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A Study of Electricity Retail Rate Deregulation in San Diego

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Abstract

Utility services employ nonlinear tariff structures that attempt, though occasionally fail, to convey information effectively on cost convexities. This paper examines how customers respond to noisy and volatile tariffs by measuring deregulated retail rates' impact on electricity consumption in San Diego. In 2000, when rates doubled over three summer months, consumers appear to have reacted more to recent past bills than to more timely price information. By summer's end, we find consumption fell 6% while lagging price increases. Even months after the utility restored low historic rates customers continued curtailing demand. We conclude that rate structures relying upon lagged wholesale price averages produce delayed responses to scarcities or high costs.

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1 Introduction

Consumers of utility services often face complex nonlinear tariff structures such as the increasing-block rates that are common among natural gas, electricity, water, and telecommunications services. While in many industries that utilize nonlinear pricing, the objective of profit maximization motivates firms to discriminate, in the context of regulated utilities, firms employ complex tariffs primarily as an incentive for conservation. Regulators justify providing this incentive on the grounds of perceived scarcity, or severe cost convexities in general, for the service's provision. While motivated by a desire to make retail prices consistent with costs, complex tariffs often fall short of this goal. Given weak correlations between costs and aggregate consumption over a billing cycle, such as a month, these tariffs fail to make valid substitutes for pure peak-load pricing.[1] Furthermore, complex tariffs require customers to calculate their expected marginal price, which can be extremely challenging in some instances. In studying the deregulation of electricity retail rates in San Diego, this paper explores how consumers behave when these complex tariffs result in noisy and volatile price signals.

Even in circumstances with stable, nonlinear rate structures, determining the marginal rate at any given time requires customers to estimate their aggregate consumption over the entire billing period. Under increasing-block tariffs, Shin (1985) rejects that consumers form accurate perceptions of their marginal price. When firms offer a menu of tariff options, people must make *ex ante* estimates of consumption levels. Some research concludes that customers fail to make optimal choices but for search costs such as acquiring tariff information.[2] In addition, extremely volatile wholesale costs, which occur in industries such as natural gas and electricity, further magnify these problems. Historically,

[1] In order to better reflect wholesale costs, Steiner (1957) and others devise tariff structures more advanced than simple increasing block rates, though such tariffs have not been widely adopted.

[2] Research in other subscription markets have found mixed evidence on the consistency of consumer behavior with rational choice theory. Kridel, Lehman, and Weisman (1993), for example, argue that consumer demand for telecommunication services appear inconsistent with economic theory that ignores option value. While Train, McFadden, and Ben-Akiva (1987) find that households readily switch telecommunication services, switching occurs less so than cost minimization would suggest. In contrast, a recent paper by Miravete (2003) finds evidence of low search costs and argues that rational choice theory does hold for even small price changes. Furthermore, he concludes that consumers optimize tariff choices given realized consumption and that their expectations are critical to subscription choices.

the mismatch between wholesale and retail costs have been internalized within vertically integrated utilities. The onset of retail deregulation in these industries, however, have left retail providers more exposed to wholesale price fluctuations. Utilities in many restructured electricity markets have been required to provide a 'default' retail rate that remains fixed or relatively constant during a transition period of several years. Such a freeze was largely responsible for the financial difficulties of California's electric utilities during 2000 and 2001.

One obvious and frequently mentioned alternative allows the standard default rate to move with the wholesale price of electricity. A more frequent updating of retail rates would better reflect volatile wholesale costs than a constant increasing-block rate schedule. In the absence of improved metering technologies, however, such rates cannot be updated more frequently than once a month. Therefore, over the next several years, a large number of electricity consumers in the U.S. may find their default retail rates adjusted as frequently as monthly, according to wholesale market conditions.

Retail prices that adjust monthly better capture any seasonality in wholesale prices, but still fail to capture most of the volatility of such commodities as natural gas and electricity. Furthermore, much of the efficiency benefits from such updating hinges upon an extraordinary degree of sophistication and effort from end-use customers who must make consumption decisions before realizing the actual price. The situation in gas and electricity provides an interesting contrast to that studied in markets such as local telephony and cellular service. In the latter, customers must project their probable usage and calculate the best rate plan based upon that projection. Using information on wholesale markets, energy market customers must make additional projections about the retail *price* in order to optimize consumption. Beyond tracking wholesale prices, the only other information available to customers is recent billing data, which can at times be a very poor predictor of current prices.

Thus, while such a retail pricing structure may constitute a positive step, it remains unclear how effective such tariffs will be in communicating wholesale costs to end-users. The bulk of studies that examine the price elasticity of electricity demand do not examine environments with frequent and dramatic price changes. Some studies take advantage of the individual price variation that can be provided by varying block rates, but rely upon an assumption of fully rational awareness of prices by customers.[3] Because rate structures were stable, the calculation of the proper marginal rate only depended upon tracking one's consumption. Other studies examine programs where consumers opted into time-varying pricing tariffs.[4] No previous study has been able to examine a circumstance where a large number of customers were involuntarily exposed to substantial monthly price volatility. The experiences of customers in San Diego during 2000 provide us with such a test case.

Between the summers of 1999 and 2000, ratepayers in the service territory of San Diego Gas and Electric (SDG&E) were subject to substantial retail rate fluctuation. During this period, rates for most SDG&E electricity customers were based upon a five-week moving average of wholesale power prices. These wholesale prices increased more than four-fold during this time span, leading to a doubling of most customers' rates. Around September 1, 2000, in response to the mounting public pressure over these rate increases, state legislators mandated a retail rate freeze–retroactive to June of 2000–for some customer classes.

In this paper, we examine the impact of these events on the consumption of electricity by SDG&E customers. Because of the complexity of how SDG&E implemented and then rescinded rate increases during this period, this is as much a study of customer expectations about price as it is an examination of the response to a specific price signal. Fortunately, we have a control group, customers of a neighboring region served by the Los Angeles Department of Water and Power (LADWP), whose rates remained constant throughout this period. We examine the consumption behavior of SDG&E customers, who

[3] For example, Reiss and White (2001) study individual consumer response to increasing-block tariff structures using 1993 California data. Maddock, Castano, and Vella (1992) examine customer response to a similar tariff structure in Medellin, Columbia.

[4] Time-of-use (TOU) prices vary somewhat by time-of-day but, for a given hour, do not fluctuate from day to day. Hausman, Kinnucan, and McFadden (1979) study a TOU experimental pricing program in Connecticut. Caves and Christensen (1980) examines a pricing experiment in Wisconsin during 1977. Many time-of-use pricing programs have also been voluntary, creating the concern that those who choose to enroll do so not because they plan to alter their consumption in response to prices, but because they have relatively flat consumption patterns. These adverse selection issues have been examined in a number of studies. See Ham, Mountain, and Chan (1987), Caves, Herriges, and Kuester (1989) and Train and Mehrez (1994). Another tariff structure, real-time pricing, requires consumers to pay the actual wholesale price of electricity, varying by hour and day, in addition to transmission and distribution charges. Patrick and Wolak (1997) study the response of voluntary real-time pricing customers in the United Kingdom.

experienced a sharp increase in rates, and LADWP customers, whose electricity prices remained constant, while accounting for additional factors affecting demand such as local temperature and economic activity.

Section 2 discusses the background of the California electricity industry and the retail rate structure in San Diego. In section 3, we treat retail deregulation in SDG&E as a natural experiment. The section describes the set up and results of a difference-in-differences model testing demand behavior during various periods. We discuss the overall effect of higher prices as well as look at what times of day consumers reduced demand. Retail prices peaked in August, but were retroactively capped for most customers at 1999 levels by September. We find a reduction in average consumption of approximately six percent in August 2000. Perhaps most striking, we find an even larger eight percent reduction in September, indicating that customers respond more to the rate levels implied in their most recent bills rather than impute current rates from available information. Even though SDG&E increased rates uniformly across all hours of the day, we find larger demand effects during some hours of this period; notably, in the peak demand hours, we see a decrease of approximately nine percent.

Section 4 attempts to more explicitly model price response. These results provide further support the hypothesis that customers were responding more to the out-dated prices of their last bill than to current market conditions. During the months when retail rates were deregulated for all SDG&E customers, we estimate an elasticity of demand with respect to lagged prices (which roughly doubled by August 2000) equal to -0.068, supporting our results in section 3. The effect of lagged prices on current consumption is much stronger than that of current prices. These pricing results must be taken with the caveat that customers who anticipated a retroactive rate cut would have perceived the price increase to be less than that reflected in their bill at that time. While this effect is likely to bias downward our estimates of customers' perceived price elasticity of electricity demand, there is no obvious reason why it would alter our conclusions that customers were responding primarily to their last bill's price rather than current prices. In section 5, we conclude that, in periods of scarcity or high costs, demand will have a delayed, and likely inefficient, response to rate structures that rely upon lagged averages of wholesale prices.

2 Background

Although the wholesale market for electricity was restructured in April 1998, retail rates to customers in most of California continued to be fixed. This rate freeze was implemented as a mechanism for recovering the sunk costs of assets many believed would become 'stranded' by the transition to market based wholesale pricing. The original transition plan called for rates to be set at ten percent below 1996 levels, which were expected to be well above average wholesale price levels, for at most four years. The IOUs were allowed to apply the difference between wholesale prices and the retail energy price of energy implied by this rate freeze to the collection of their stranded costs. If wholesale price levels allowed for all utility stranded costs to be recovered before the end of the four year transition period, the energy component of retail rates were to 'drop' to wholesale levels.

The two largest California IOUs, Pacific Gas & Electric (PG&E) and Southern California Edison (SCE), both had significant investments in nuclear capacity as well as extensive contractual commitments to independent power producers. These investments, viewed as uneconomic in 1996, meant that both PG&E and SCE were perceived to have far greater stranded costs than SDG&E, the third California IOU. Having made relatively modest commitments to both nuclear and independent power, SDG&E recovered its stranded costs by mid-year 1999. Unlike ratepayers in the rest of California, after July 1, 1999, those in San Diego paid retail rates that more directly reflected the current wholesale price of power.

2.1 Retail Rate Structures in San Diego

Between July of 1999 and August of 2000, the bulk of SDG&E electricity customers were billed at a rate based upon the average wholesale cost of power for the month in which they consumed it. Approximately one-fifth of customers received their bills in any given week, each reflecting the moving average of the previous five weeks. SDG&E offered large customers the option of seeing 'real-time' rates that passed along the hourly wholesale cost of power. However, no customer ever took this option. In contrast, some large customers do pay 'time-of-use' rates. There are also rate schedules based upon four to twelve week moving averages of wholesale costs, rather than the basic five-week average. There are about 50 different tariff schedules resulting in nearly 600 prices for each week.

For expositional purposes, we note the changes in the most prominent of these rates over the period of study: the five-week, load-weighted, non-baseline (second tier), residential weekly price.[5] Table 1 shows the monthly average retail electric rate for residential customers in San Diego and the average price for electric energy in the California Power Exchange (PX), the wholesale market upon which those rates were based, for the southern California zone SP15. Figure 1 plots these averages on a weekly basis. Also included in Table 1 are two key drivers of the wholesale electricity price, wholesale natural gas prices and prices for nitrogen oxides pollution credits in the Los Angles basin (or RECLAIM permits).

Retail rates also include charges for transmission and distribution costs. In June of 1999 these other (non-energy) charges accounted for roughly 60 percent of residential rates. Since most customers are metered only on a monthly basis, the hourly PX price was mapped to a weekly average using a standardized load profile for each customer class.[6] In other words, the retail rate reflects the average hourly wholesale power cost, where that average is weighted according to the estimated average hourly consumption for all customers in that rate class.[7]

[5] The standard retail rate was a two-tier increasing-block tariff. During the sample period, wholesale price changes were reflected equally in both tiers. The difference between tiers is minor compared to the changes in the overall levels. Load is defined as end-use demand for electricity.

[6] SDG&E has seven main customer classes: agriculture, large commercial and industrial, medium commercial and industrial, residential, schedule A6, schedule AD, and small commercial.

[7] In addition to the energy price in the PX, wholesale power costs for an energy service provider also include the costs of ancillary services as well as other miscellaneous fees like those paid to scheduling coordinators (such as the PX) and the California Independent System Operator (ISO), which is responsible for operating the transmission network. As a result, the June 1999 price for energy charges was \$0.046/kWh, much greater than the \$0.026/kWh shown in Table 1 that only reflects the PX wholesale electricity price.

Table 1
Monthly Residential Rates and Wholesale Prices

Month	Wholesale Nat. Gas[a] ($/Therm)	RECLAIM NOx credits[b] ($/lb.)	Average PX Price[c] ($/kWh)	Residential Elec. Rate[d] ($/kWh)
January 1999	0.19	0.27	0.02	0.13
February	0.18	0.58	0.02	0.13
March	0.17	0.62	0.02	0.13
April	0.21	0.30	0.03	0.13
May	0.22	0.34	0.03	0.13
June	0.23	0.33	0.03	0.13
July	0.23	0.65	0.03	0.12
August	0.27	0.59	0.04	0.13
September	0.26	0.73	0.03	0.12
October	0.29	0.77	0.04	0.12
November	0.25	0.75	0.03	0.13
December	0.24	0.89	0.03	0.12
January 2000	0.24	1.07	0.03	0.11
February	0.26	1.53	0.03	0.11
March	0.28	2.83	0.03	0.11
April	0.30	3.60	0.03	0.11
May	0.36	4.12	0.06	0.11
June	0.46	4.00	0.13	0.14
July	0.46	11.92	0.12	0.17
August	0.52	10.07	0.16	0.23
September	0.60	26.46	0.12	0.30[d]
October	0.55	36.59	0.09	0.23
November	1.01	37.05	0.14	0.22
December	2.50	38.25	0.23	0.23

Notes:

a) Source: Natural Gas Intelligence (http://intelligencepress.com/)

b) Source: South Coast Air Quality Management District (http://www.aqmd.gov/)

c) SDG&E load-weighted average of SP15 PX prices. Source: Power Exchange (http://www.calpx.com/)

d) The retroactive rate freeze, passed around September 1, 2000, capped retail rates at $0.14/kWh for June to August of 2000 and at $0.15/kWh from September to December of 2000.

Source: SDG&E (http://www.sdge.com/)

As can be seen from both Table 1 and Figure 1, residential rates declined modestly with the end of the retail rate freeze in July 1999 and then rose sharply after May of 2000 in response to rapidly increasing wholesale prices. By August of 2000, wholesale energy prices had more than tripled from the end of 1999 and the corresponding residential rates (including non-energy related costs) had roughly doubled.[8] Various cost factors such as higher natural gas prices and environmental compliance contributed to this rise, but several studies have also found the market power of suppliers to be significant throughout this period.[9]

By late June of 2000, there was a tremendous outcry from ratepayers who were for the first time directly exposed to the cost impact of these factors. Throughout much of July, the California Public Utilities Commission and the California Legislature debated proposals for rate relief for San Diegans. Governor Davis signed Assembly Bill 265 on August 27. This legislation froze rates for small and medium-sized (those under 100 kW) retail customers of SDG&E at 6.5 cents/kWh retroactive to June 1, 2000.[10] In Figure 1, the retroactive rate freeze is represented by the dashed line. As a result of this legislation, the difference between wholesale costs and retail rates for these customers has been accumulating in a tracking account since June 2000. The future liability for this revenue shortfall remains uncertain, but it is widely expected that future ratepayers will be expected to cover a significant portion of these costs.

The widely publicized rate increases, followed by calls for non-payment, a one-time refund, and finally a retroactive rate decrease undoubtedly created a great deal of confusion in the minds of end-use customers over the true retail price of the electricity they were consuming during the summer of 2000. It is reasonable to assert that for at least

[8] Wholesale electric energy price-cap in the California ISO, which also served as a *de facto* ceiling on prices in the PX, was increased from \$250/MWh to \$750/MWh in October, 1999. The rate was lowered to \$500/MWh on July 1, 2000, and lowered again back to \$250/MWh on August 7, 2000.

[9] See for example Borenstein, Bushnell and Wolak (2002), Joskow and Kahn (2001) and Puller (2001) as well as various analyses by the Dept. of Market Analysis of the California ISO (for example, Dept. of Market Analysis 2001).

[10] The rate freeze applied to the price of energy. Transmission and distribution charges were also paid by the small consumers as reflected in Table 1 and Figure 1. AB 265 overrode the Public Utilities Commission's decision on August 21 to hold SDG&E's monthly residential utility bills to \$68 for the first 500 kWh per month.

two months, customers expected that the price they would pay for electricity would be considerably higher than in the previous year. In the following sections, we analyze the impact such expectations had on end-use consumption in the SDG&E service territory.

3 A Natural Experiment Approach to Measuring Demand Response

Although several news accounts and anecdotal stories told of large-scale reductions in demand in the San Diego area during the summer of 2000, demand grew relative to previous years. Figure 2 plots the average hourly demand by week from 1997 through 2000. Of course, there are many confounding factors as to why demand did not decrease from 1999 to 2000. For example, there were lower than normal temperatures during 1999 while records were set throughout the West in 2000. In addition, economic growth continued to be robust throughout this period. By comparison, LADWP also displays a similar upward trend in demand during this period (see the dashed line in Figure 2).

Our goal in this paper is to determine the extent to which the changes in rates, as well as the uncertainty surrounding those rates, influenced end-use consumption in the San Diego area. Because of the uncertainty about prices at this time, we begin by testing for any behavioral changes during the period. In other words, we determine the degree to which factors other than price *fail* to describe consumption patterns during this time. By isolating distinct time periods that have differing price levels, price variability, and consumer expectations, we are able to estimate price responsiveness. Then, once determining whether consumers behavior changed, we explicitly attempt to identify the effect of price on consumption in the following section.

We begin by studying electricity consumption using a panel of several California regions over a period from January 1, 1997, to December 31, 2000. We model the log of daily aggregate demand in region i during month-year j on day t, $\ln(Q_{ijt})$, as a function of four sets of variables: the "intervention" effect (Z_{ij}); regional-specific variables capturing economic activity ($ECON_{ij}$) and weather ($WEATHER_{ijt}$); variables common to California capturing emergency stages and demand periodicity (X_{jt}). In addition, we model idiosyncratic shocks (u_{ijt}). Allowing the coefficients on all independent variables to vary by region, the econometric model we estimate is shown in (1) below:

$$\ln(Q_{ijt}) = \alpha_i + Z'_{ij}\beta_i + ECON'_{ij}\delta_i + WEATHER'_{ijt}\gamma_i + X'_{jt}\theta_i + u_{ijt}. \tag{1}$$

We use several economic variables that reflect variation by time and region in order to capture the size and status of the economy. These include unemployment rate, size of labor force, and new building permits, where all variables are modeled in logs, assuming a constant elasticity of demand response.

For each region, the weather variables include daily minimum and maximum temperatures, and cooling and heating degree days. Cooling degree days are the number of degrees the mean daily temperature exceeded 65° F. Heating degree days are the number of degrees the mean daily temperature was below 65° F. All weather variables were modeled as quadratic functions. An additional weather variable approximates daily hours of sunlight.[11]

The indicator variables (X_{jt}) account for stage 1, 2, or 3 emergencies, the day of the week, and the month of the year. The indicators of stage emergencies account for days in which the ISO issued a warning that the system-wide quantity demanded approached the total capacity of suppliers. Each stage alert is accompanied by increasingly emphatic requests for voluntary reductions in demand. The alerts also activate load reductions from customers on interruptible rates, though by different amounts throughout the state.

Some idiosyncratic shocks (u_{ijt}) resulting from economic or other 'non-price' demand shocks were common throughout southern California while others were region specific. As such, we model $u_{ijt} = \eta_j + \varepsilon_{ijt}$, where η_j are common month-year shocks and ε_{ijt} are region-specific shocks. Finally, because of the confusion surrounding rates, in this section, we model the price shocks, or "intervention" effects, as month-year fixed effects (Z_{ij}) for each month after retail rate deregulation: July 1999 to December 2000.

A potential drawback to any such fixed effects approach is that factors other than price that are also not considered in these estimates may have impacted demand during this

[11] We model sunlight hours as a sinusoidal function of the days to the nearest winter solstice.

time. This implies that *any* local shocks to demand will be captured by Z_{ij} that we are interpreting as a price effect. To address this concern, we use control groups where rates did not change but whose regional proximity would imply that their customers would be subject to the same regional non-price shocks within a month, η_j, as those in SDG&E. The primary control group that we utilize in this paper is the retail electricity demand of the Los Angles Department of Water and Power (LADWP). We also examine using the retail demand of Southern California Edison (SCE) as an alternative control group. These control groups are described in more detail in the following subsection. We feel that these utilities provide adequate control groups for San Diego. However, as these control groups are of greater size than SDG&E, we model the common shocks η_j as a multiplicative, rather than additive, shocks. Therefore, we use a difference-in-differences model of log of daily quantity demanded electricity in each region.

3.1 Control Groups

LADWP, the largest municipally-owned utility in the United States, provides electric service to residential customers within the city of Los Angeles and to portions of the Owens Valley. Like most municipal utilities in California, LADWP successfully resisted participating in the restructuring undertaken by the State's large investor-owned utilities. It is not a member of the California ISO's system and therefore retains control of its transmission assets and acts as its own control area operator. Having retained ownership of a surplus of generation capacity, LADWP was able to pay down over $4 billion of its debt by virtue of its position as a net seller into the lucrative California wholesale market during 2000 and 2001. Despite the rapid improvement in its financial position, retail rates in LADWP remained constant throughout the period we examine.

Southern California Edison distributes electricity to the bulk of southern California, excluding the cities of Los Angeles and San Diego. Like SDG&E, SCE divested most of its generation assets and opened its system to a form of retail competition, subject to a transition charge that essentially froze rates at ten percent below 1996 levels. Unlike SDG&E, the transition period in SCE had not expired by the summer of 2000. The inability of SCE to adjust rates to levels that reflected its wholesale costs during this time were the primary cause of its subsequent financial difficulties. These financial problems caused SCE to suspend payments to its wholesale suppliers in late 2000 and, along with similar defaults by Pacific Gas and Electric, set the stage for the crisis conditions experienced in the market during the winter of 2000-01.

Table 2 shows the hourly average and the peak electricity demand for SCE, LADWP and SDG&E during 2000. For each region, the table also displays the market share of demand among major customer classes.[12] SCE is by far the largest utility and, to the extent the distinction is meaningful in southern California, serves a more suburban population. Demand in LADWP averaged about 40 percent higher than that in San Diego. Demand from large customers was more skewed towards the industrial category in SDG&E and towards the commercial category in LADWP. SDG&E served a larger proportion of residential customers. Although the customer class differences raise potential concerns about the quality of the control groups, as we describe below, the results were in fact quite robust to the choice of control group.

Table 2
Summary of Demand Data in 2000

	SCE	SDG&E	LADWP
Hourly Average Demand (GWh)	8.41	1.73	2.41
Hourly Peak Demand (GWh)	19.51	3.53	5.30
<u>Market Shares</u>			
Residential	0.35	0.42	0.29
Commercial	0.35	0.41	0.57
Industrial	0.29	0.17	0.12
Other	0.01	0.01	0.02

3.2 Data

In Table 3, we summarize those data that are specific to one of the three utility regions. The data describe electricity demand, economic activity, and weather characteristics. For each variable, the number of observations, frequency, data source, mean, and standard deviation are given. While we have data on the quantity of electricity demanded by hour,

[12] The customer class data are from the Energy Information Administration's form 861.

none of the independent variables in this paper displays as great a frequency. Therefore, for most of the paper, we aggregate the electricity demand to daily observations in order to be consistent with weather data (the most frequent of our independent variables). As noted in Table 2, SDG&E is about 76 percent the size of LADWP and 20 percent that of SCE. Daily demand is less variable in SDG&E relative to the other regions.[13] The utility demand data are taken from the Federal Energy Regulatory Commission, form 714.

For a given Metropolitan Statistical Area (MSA), we use three measures of economic activity with monthly frequency. The San Diego area enjoyed a lower overall unemployment rate (the San Diego MSA unemployment rate was half of the size as that in the Los Angeles MSA). The San Diego MSA experienced a slightly more rapid percent decline in unemployment and increase in labor force over our sample period.[14] The data on unemployment rates and labor force size are taken from the Bureau of Labor Statistics. Data on permits for new buildings are taken from the U.S. Census Bureau.

For each region, we examine the mean, minimum and maximum daily temperature. For San Diego, we average daily data over four weather stations: Miramar, Brown Field, Gillespie, and Lindberg. In LADWP, the weather data are averaged over two weather stations located in Burbank and Los Angeles Airport. When SCE is used as a control group, weather data are averaged over Ontario and Santa Ana as well as Burbank and Los Angeles Airport. The two smaller utilities, SDG&E and LADWP, serve primarily coastal communities with similar climates while SCE has considerable load further inland. Climate in these regions of southern California is quite temperate, with 90 percent of daily means between 52 and $76°F$ in each of the three regions. The weather data are provided by the National Climate Data Center.

[13] The coefficient of variation, the ratio of standard deviation to mean, is 0.10 in SDG&E but is 0.13 in LADWP and SCE.

[14] Both labor markets grew approximately three percent per year from 1997 to 2000: in San Diego the labor force increased from 1.26 to 1.42 million (3.1 percent annual growth) while in LA, it went from 4.38 to 4.85 million (2.7 percent annual growth). The unemployment rate in San Diego fell from 0.049 to 0.024 from 1997 to 2000 (a 51 percent reduction) while the L.A. rate fell from 0.078 to 0.047 (40 percent drop).

3.3 Estimation Issues

We address three potential estimation issues in estimating our econometric model (1). First, the observations are daily and as such are likely to be serially correlated. Second, demand across seasons and regions will likely be heteroskedastic. Finally, some variables are measured monthly while others are observed weekly or even daily. The relative lack of frequency of the economic variables, which are measured monthly, may cause an error-in-variables problem. Tests of serial correlation and heteroskedasticity were significant at the one percent level when estimating (1) using LADWP as a control group.[15]

To address these concerns, we use generalized least squares (GLS) in order to account for a first order auto-regressive error structure. The Prais-Winsten method is used to estimate a common AR(1) coefficient for both regions. We perform a few robustness checks of this modeling structure of serial correlation.[16] A White correction of the standard errors is done to account for the heteroskedasticity. Finally, to account for potential errors-in-variables problems, we cluster the model's errors by month-year in order to allow them to be correlated. Shocks in daily unemployment rates, labor force size, or new building permits would result in measurement error and thus would bias our estimates.

3.4 Results

Table 4 shows the regression results of estimating (1) using LADWP as a control group. The sample size, based on daily observations in both SDG&E and LADWP from January 1997 to December 2000, equals 2912 observations. The model explains most of the variation

[15] A Breusch-Godfrey LM test failed to reject an AR(1): $\chi^2 = 809$; P-value = 0.00). The Cook-Weisberg test for homoscedasticity was rejected ($\chi^2 = 79$, p-value of 0.000).

[16] First, we model the error structure non-parametrically using Newey-West standard errors. Assuming a seven-day moving average lag structure, we find results consistent with those shown in the paper. The coefficient on August 2000 is -0.069 (0.016) and the coefficient on September 2000 is -0.060 (0.019).

Second, we run ordinary least squares using a lagged dependent variable and also find consistent, though slightly smaller results. The coefficient on August 2000 is -0.040 (0.010) and the coefficient on September 2000 is -0.035 (0.010).

Third, we run a generalized least squares regression assuming the errors are heteroskedastic with cross-sectional correlation and allow for panel-specific AR(1) coefficients. The coefficient on August 2000 is -0.067 (0.016) and the coefficient on September 2000 is -0.055 (0.015).

in the dependent variable, the log of daily aggregate demand (MWh) by region, $\ln(Q_{ijt})$.[17]

For most months following retail rate deregulation, SDG&E demand was not statistically different, nor economically significant (less than two percent change in most months), from expectations based on the control group and variables measuring economic activity and the weather.[18] However, two notable exceptions are August and September of 2000. In August, demand fell six percent below levels explained by the model. Most strikingly, the September reduction is slightly *larger* in magnitude (eight percent) than the August reduction, *despite* the fact that rates had been substantially reduced by September 1st.[19]

In October 2000, consumption in SDG&E remained five percent below expectations, while in the months following it was not statistically different from expectations.[20] This latter period is at least one month after the price caps had been reinstated for smaller customers. Given the five-week cycle in the billing period, most customers would have received bills reflecting the lower rate levels by mid-October. These results are consistent with a hypothesis that consumers were basing their consumption decisions on the prices reflected in their most recent bills rather than on a rational estimation of their current price. We explore this further in section 4.

When SDG&E reimposed the rate freeze in September, the largest commercial and industrial customers were ineligible. These customers, who comprise approximately one-third of energy consumption in the San Diego area, continued paying high retail rates. Even though their November and December retail bills remained as high as in August or

[17] R^2 equals 0.97. The first order auto-regressive ρ coefficient is 0.60. Various joint tests of economic, weather, and the various indicator variables rejected common coefficients across regions.

[18] The regression includes month-year fixed effects for July 1999 through December 2000 for both LADWP and SDG&E, as well as for SDG&E only. Other regressors include regional, day of week, and monthly fixed effects, and indicators of stage 1, 2, and 3 emergency alerts. We include quadratic functions of several weather variables averaged over a region: daily maximum and minimum temperatures, cooling degree-days (degrees daily mean below 65° F), and heating degree-days (degrees mean above 65° F). Finally, we account for hours of sunlight in a day.

Those month-year fixed effects in SDG&E that were not reported in Table 4 but were significant include July 1999 (0.036) and January 2000 (-0.024), both of which are driven by changes in LADWP relative to SDG&E, where we estimate coefficients of -0.027 and 0.021, respectively.

[19] A Wald test indicates that the coefficients for August and September are significantly different (F-statistic of 5.4 and a p-value of 0.02).

[20] A Wald test indicates that the October coefficient was significantly different from September 2000 (F-statistic of 5.9 and a p-value of 0.02), though not from August 2000 (F-statistic of 1.7 and a p-value of 0.20).

October of 2000, the overall market demand for electricity was not significantly different, given our controls. This suggests that the September and October effects resulted from some behavioral response beyond any that may have come from the large customers.

The impact of the economic variables conformed to expectations. As with all regressors, the impact of economic measures varied by region. The coefficient on the unemployment rate in LADWP implies a demand elasticity of -0.22. The labor force size, indicating of both population growth and economic activity, is expected to be positively related with electricity demand. We estimate the elasticity of demand with respect to labor force size to be 1.61 in SDG&E. The coefficients on unemployment in SDG&E, labor force in LADWP, and new housing starts in both regions were not significant.[21]

3.4.1 Robustness Checks

As a robustness check, we examine the sensitivity of our main demand response findings to factors such as our choice of control group, economic variables, and functional form. Table 5 summarizes the results of these variations. The first two variations test the importance of the control group by first substituting SCE for LADWP and then using no control group. We then examine whether economic variables affect our results while using either LADWP or SCE as controls. Then, we remove the weather and indicators but keep the economic variables using LADWP as a control group. Finally, we test the importance of functional form. We model η_j as a proportional shock by modeling demand in levels. For each region, the daily demand is normalized by average daily demand before retail deregulation.[22] The monthly impact results are robust to the choice (or presence) of a control group, functional form, and even to weather variables. However, the results are sensitive to the presence of the economic variables, although less so when SCE is the control group.

[21] A joint test of all economic variables is significant at the one percent level (Wald test F stat=33.1; P-value = 0.00).

[22] The average daily demand in region before retail deregulation, namely from January 1997 through July 1999, was 51,211 MWh in SDG&E and 67,913 MWh in LADWP. To impute the percent change in demand in August 2000, divide the coefficient by 1.22 (implying a 6.7 percent reduction). For September 2000, divide by 1.13 (implying a 5.2 percent reduction).

3.4.2 Hourly Effects

We examine whether the demand effects measured in section 3.4 were uniform across the day for each month of interest. As previously mentioned, our data on demand are available for each hour from 1997 to 2000. Using this hourly variation, we estimate (1) by hour. In other words, we estimate the parameters $(\alpha_{ih}, \beta_{ih}, \delta_{ih}, \gamma_{ih}, \theta_{ih})$ for each hour h, effectively interacting the respective variables (a constant, $Z_{ij}, ECON_{ij}, WEATHER_{ijt}, X_{jt}$) with hourly indicator variables. Table 6 shows the estimates of the hour-month-year fixed effects variables for SDG&E $(\widehat{\beta}_{ih})$ for June to December, 2000. This analysis reveals that the reduction in demand during August and September was *not* uniform across hours. Figure 3 plots the hourly coefficients and 95 percent confidence interval of the percent change in demand for the month of August. The largest reductions in demand came primarily in the afternoon hours, reaching approximately nine percent around 3:00 P.M. and 6:00 P.M.

4 Explicit Tests for a Price Impact on Demand

The analyses of the previous section take an event study, or natural experiment, approach to determine whether demand in San Diego behaved differently relative to a control group during the summer of 2000. The results indicate that demand in the 2 months *after* customers received their largest bills, August and September, was in fact lower than would have been expected after accounting for various non-price factors. In this section, we directly test for the significance of the impact of retail prices on this demand behavior. We employ the same regression approach as in section 3, but replace monthly fixed effects with different measures of retail price as independent variables.

Although the presence of a price effect would be informative, there are many caveats that must be applied to interpreting the results of this kind of analysis. First, a *single* price for all customers in SDG&E does not exist. There are many different customers on different rate schedules. However, only the aggregate SDG&E demand is available as there are no reliable measures of demand by rate class on an hourly basis. We do know that the rates of each customer class moved linearly with a weighted average of the wholesale PX price. The *changes* in rates were therefore roughly common across customers and rate classes. The duration of the averaging linkages varied by customer class. As discussed in the data subsection below, we construct a measure of the energy portion of the retail price based on the five-week weighted average PX price.

A second important caveat is the fact that there was much contradictory information about retail prices being provided to customers during this time period. These rates were eventually retroactively adjusted to levels different than those indicated by the movement of the five-week weighted average PX price. To the extent that customers anticipated this retroactive rate decrease, they would have responded less aggressively to the price increases as they were happening. There is no way to credibly measure the extent to which these expectations were affecting consumer behavior.

Finally, it is important to realize that results from this study will likely understate the price response that could be expected from exposing customers to higher prices over a longer period of time. As with any good or service, the long run price elasticity will be greater than that in the short run. For example, customers can change consumption behavior by investing in more energy efficient technology. In addition, changing behavior can take time. It may take longer exposure to higher prices to "convince" people to turn off lights in rooms not being used or to lower the thermostat when not home on cold days. For these reasons, the price response we model should be considered a lower bound of an elasticity measure.

4.1 Model of Demand

In this section, we model demand as a linear function of price because of aggregation concerns. Without customer level data, we are only able to estimate the aggregate demand response to prices. We model demand for customer of class k, on billing cycle b, in region i, at month-year j, and day t. We assume demand to be linear in the expected price $E[P_{kbi}^{jt}|\Omega_{kbi}^{jt}]$, where Ω_{kb}^{jt} is the set of information the customer has available at that time:

$$q_{kbi}^{jt} = \phi_{kbi} - \sigma_{kbi} \cdot E[P_{kbi}^{jt} | \Omega_{kbi}^{jt}]. \tag{2}$$

We can rewrite (2) as:

$$q_{kbi}^{jt} = \phi_{kbi} + \sigma_{kbi} \cdot \overline{P}_{ki}^{j<\widehat{j}} - \sigma_{kbi} \cdot E[P_{kbi}^{jt} - \overline{P}_{ki}^{j<\widehat{j}} | \Omega_{kbi}^{jt}] \equiv \widetilde{\phi}_{kbi} - \sigma_{kbi} \cdot E[\Delta P_{kbi}^{jt} | \Omega_{kbi}^{jt}], \tag{3}$$

where $\overline{P}_{ki}^{j<\widehat{j}}$ is the average price paid by customer class k before retail deregulation ($\widehat{j}$ is the month when retail rates were deregulated). $E[\Delta P_{kbi}^{jt} | \Omega_{kbi}^{jt}]$ is the change in price from the frozen rates prior to deregulation that a customer of class k on billing cycle b expects to pay at time (j, t), given his or her information set.

For a given time period, we assume that $E[\Delta P_{kbi}^{jt} | \Omega_{kbi}^{jt}]$ is the same for all classes and billing cycles. We write daily aggregate demand, Q_{ijt}, by aggregating q_{kbi}^{jt} over K classes and B cycles:

$$Q_{ijt} = \sum_{k=1}^{K} \sum_{b=1}^{B} q_{kbi}^{jt} = \Phi_{ijt} - \Sigma_i \cdot E[\Delta P_i^{jt} | \Omega_i^{jt}]. \tag{4}$$

In order to estimate (4), we normalize daily demand (in region i during month-year j on day t) using data on a region's average daily demand prior to retail deregulation:

$$\widetilde{Q}_{ijt} = Q_{ijt} / \overline{Q}_{i,j<\widehat{j}}. \tag{5}$$

Similar to section 3, we model $\widetilde{Q}_{ijt}$ as a function of four sets of variables: the price effect (P_{ijt}); regional-specific variables capturing economic activity ($ECON_{ij}$) and weather ($WEATHER_{ijt}$); variables common to California capturing emergency stages and demand periodicity (X_{jt}). In addition, we model idiosyncratic shocks ($\widetilde{u}_{ijt}$). Allowing the coefficients on all independent variables to vary by region, the econometric model we estimate is shown in (6) below:

$$\widetilde{Q}_{ijt} = \widetilde{\alpha}_i + P'_{ijt}\widetilde{\beta}_i + ECON'_{ij}\widetilde{\delta}_i + WEATHER'_{ijt}\widetilde{\gamma}_i + X'_{jt}\widetilde{\theta}_i + \widetilde{u}_{ijt}. \tag{6}$$

The independent variables, other than prices, are as defined in section 3. The error term ($\widetilde{u}_{ijt}$) is again modeled as the sum of common month-year shocks ($\widetilde{\eta}_j$) and region-specific shocks ($\widetilde{\varepsilon}_{ijt}$).

4.2 Data

In addition to the variables described in section 3.2, this analysis requires some price measure. As mentioned above, the various customer classes had different rates before retail deregulation, *but* the rate changes were similar, in levels, after deregulation. Therefore, we construct a measure of price based on the PX wholesale price. For each week, we calculate a quantity weighted average PX price, where the weights are the aggregate consumption of electricity in SDG&E. Since bills are typically received monthly, we construct a monthly moving average of these quantity weighted average PX prices. This we denote the "retail price index."

Due to the complexity of the interaction between our price index and aggregate customer behavior, we test four different models of price response. Our main measure accounts for two facts about billing: only one-fifth of customers are billed in a given week; and bills typically arrive five to ten days after the cycle ends. Customers at the end of a billing cycle are expected to respond to prices throughout the previous five weeks since they are billed based on an average of all those prices, not only on the current price. As such, the first measure of price is a backward-looking model based upon a five-week moving average of the retail price index ending with the week prior to the date of the observation.

The additional models of price are as follows. The second model utilizes only the current week's retail price index. A third model simply uses the previous week's retail price index. The last measure utilizes a five-week average of this price centered upon the week of the observation. This is more consistent with a rational expectations model of demand in which customers would have to base current consumption upon estimates of recent, current and near-future prices. That is, we examine each of the following models of price:

Model	Description
1	Five-week moving average of retail price index (last bill)
2	Current week's retail price index
3	Previous week's retail price index
4	Expected retail price index

Finally, we recognize three periods when aggregate demand possibly responded to prices differently. The control period, prior to retail deregulation, was from January 1997 through June 1999: $j < \widehat{j}$. The retail deregulation period was from July 1999 through August 2000: $\widehat{j} < j < \widetilde{j}$, where $\widetilde{j}$ is the month when the retroactive rate freeze was enacted. Lastly, the period after the retroactive rate freeze for small customers, the "post-deregulation" period, was from September 2000 to the end of our sample, December 2000. For a given price measure, we examine demand response for the three periods separately. In addition, we use LADWP as a control group in order to account for any spurious correlation between price movements and regional economic activity. Therefore, each model of price response includes six price measures, the three period price effects in LADWP and the three for SDG&E.

4.3 Estimation Issues

As in the previous section, we test for and address issues of serial correlation and heteroskedasticity in estimating (6).[23] We also correct for potential errors-in-variables in using economic variables with monthly frequency by clustering errors by month-year. In addition to these previous concerns, the question of the endogeneity of prices is inherent to any demand estimation model when prices are determined in equilibrium by a system of equations.

However, we model retail prices as exogenous for several reasons. Models using measures of price based on previous bills, like the first and third models described above, cannot be directly affected by current demand shocks. In addition, San Diego represents a relatively small share of the southern California wholesale electricity market and is not likely to significantly impact wholesale prices. Also, the retail pricing formula further dilutes the impact of consumption in any given hour on retail prices. Of course, the retail pricing formula may also introduce endogeneity as we construct the retail price index using SDG&E demand as weights. To formally test the hypothesis of endogeneity, we use the Durbin-Wu-Hausman procedure. For all four measures of price, we conclude that price is exogenous to demand (see appendix).

[23] A Breusch-Godfrey LM test failed to reject an AR(1): $\chi^2 = 789$; P-value = 0.00). The Cook-Weisberg test for homoscedasticity was rejected ($\chi^2 = 212$, p-value of 0.000).

4.4 Results

Table 7 summarizes our results using various models of retail price response. In general, the historical retail prices produce apparently stronger effects than do current or near-future ones. Our primary model, using a backward-looking five-week moving average of retail prices, produces the strongest price effect; the coefficient for the retail price index during the retail deregulation period (July 1999 to August 2000) is -0.525. One measure of demand price “elasticity” implied by this estimation is -0.068.[24] From July of 1999 to August of 2000, the residential retail rate had approximately doubled. For August 2000, the price coefficient from our primary model of price response implies a five percent reduction in quantity demanded of electricity, as is consistent with the results of the previous section.[25] In contrast, the second measure of price, which only looks at the current week's retail index, has a coefficient of -0.274 for the same “retail deregulation” period and an implied price “elasticity” of demand of -0.035. The price coefficients of models (1) and (2) bracket those of models (3) and (4), which use last week's price index and the expected price index respectively, for the second and third periods in SDG&E.

After the retroactive rate freeze, demand was not as responsive to the price for some models. For model (1), the coefficient on price index is only -0.477, though not statistically different from the coefficient during retail deregulation. The implied “elasticity” during this period is greater in magnitude (-0.102) because of substantial increases in rates, which reflect high PX prices, paid by the large commercial and industrial customers. For models (2) to (4), the price coefficients on SDG&E after the retroactive rate freeze are similar to those during retail deregulation. Before deregulation, the coefficient on SDG&E price is insignificant for all four models, as is consistent with expectations.

[24] In order to provide a proxy of demand price “elasticity” for a given period, we multiplied the price coefficient by the ratio of a given consumer group's retail electricity price to the normalized quantity demanded in SDG&E. During the retail deregulation period, the residential rate (as shown in Table 1) averaged $0.13/kWh while the normalized demand in SDG&E was 1.07 on average. Using other customer classes' prices would result in slightly smaller measures of elasticity.

[25] In August, 1999, the residential retail rate was $0.126/kWh. In August of 2000, it had risen to $0.232/kWh (see Table 1). This price change times the price coefficient for SDG&E during the retail deregulation period from model (1) imply a 0.065 reduction in the normalized demand from 1.177 to 1.121, or by 4.7 percent.

We test whether or not these price response effects are statistically different from each other. Namely, were customers more responsive to their last bills, as reflected in model (1), or for example, to model (2) current retail prices. Since there does not exist a mapping of one price variable to the other, a non-nested test is required. We follow the methodology of an encompassing test.[26] With this test, we find that the coefficients on price from the SDG&E customers' last bills during and after deregulation are significant with the expected negative sign. Current prices also explain consumer behavior conditional on historic prices. However, the coefficients on current prices in SDG&E during and after deregulation are *positive*, which is not consistent with economic theory. This suggests that a more accurate measure of consumer behavior is historic prices. By comparing model (1) with either model (3) or with model (4), we draw similar conclusions: the most accurate measure of consumer behavior is the backward-looking five-week moving average of the retail price index.

We perform two robustness checks of our main model of price response. First, we look at the price effect without using a control group. In this case, the price coefficients for SDG&E during the retail deregulation period and the post-deregulation period are -0.444 and -0.405, respectively. These imply slightly smaller price "elasticities." Finally, we test functional form by modeling demand as a logarithmic function but keeping prices linear as the price shocks were similar for all customers in levels. The implied "elasticities" are similar to the linear model (-0.077 and -0.104, respectively).

All told, the results indicate that consumer behavior best fits the hypothesis that customers were responding to the prices contained in their last bill rather than to an expectation of current prices. This is consistent with the results of the previous section, where some of the greatest conservation was observed in the month following a dramatic reduction in rates. Considering the caveats given above, it is more difficult to interpret these results as estimates of the price elasticity of demand. Although we observe a reduction in demand of six and eight percent during August and September, 2000, it is nearly

[26] The encompassing test, as described in Davidson and MacKinnon (1993, pages 386-387), is done by testing one hypothesis and including the variables from the second hypothesis that are not already in the model. In our case, this simply means adding the current price variables to model (1).

impossible to estimate what level of price customers *thought* they were going to pay at that time.

5 Conclusions

As the trend of deregulation continues in various utility services, wholesale price volatility will, almost certainly, increase. Such volatility makes the accurate transmission of price signals to retail customers even more important than it was under regulation. To date, utilities and their regulators have relied upon complex tariff structures to convey this information. Among other shortcomings, such tariffs demand an unusually high level of attention from customers.

In electricity and natural gas, greater wholesale price volatility will require more frequent retail rate updating. In the absence of advanced metering, this means that customers will pay a rate based on an average of the wholesale costs during their period of consumption. If such rates are to even approach the desired effect of a reduction in end-use during periods of high wholesale costs, customers will have to be alert to what is going on in the wholesale market. If they are not, the most likely scenario is that they will simply set consumption levels based upon the prices reflected in their most recent bill.

With these issues in mind, we have attempted to reconstruct the pattern of electricity consumer behavior in San Diego during the volatile summer of 2000. Because of the uncertainty surrounding prices, we first approach this analysis as an event study. We examine whether consumption in San Diego during key time periods of the summer of 2000 followed a different pattern than at other times. We also account for shocks to consumption from other, non-price sources that were common to all southern Californians by incorporating into our estimates the changes in consumption in the utilities neighboring San Diego.

We find that consumption in August 2000, the period with the highest retail rates, was about six percent lower than could be explained by non-price factors. We also find the reduction in demand in September 2000 slightly larger than in August (eight percent), even though retail rates had been significantly lowered for the majority of demand by September 1. This implies that, given the confusion surrounding prices, customers were indeed reacting to the prices reflected in their most recent bills rather than to the currently relevant rates.

We also explicitly test for a price impact on consumption in San Diego and explore which price movements best explain consumer behavior. Using a backward-looking five-week moving average of a retail price index, we find that a doubling in retail price, which was reached in August, accounted for a five percent reduction in demand. These results support our previous findings. Estimates based on current, rather than historic, retail prices produce a weaker implied price response. We view this as further evidence that customers primarily base their expectation of current prices upon the prices reflected in recent bills. These results indicate that rate structures that rely upon lagged averages of wholesale prices will produce a delayed, and likely inefficient, response to periods of scarcity and high costs.

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Appendix

The method we use to test for the endogeneity of prices is similar to a Hausman test. We test whether the vector of coefficients that is based on a model *accounting for endogeneity* differs from the vector of coefficients that is based on a model *assuming the exogeneity* of prices. The Durbin-Wu-Hausman (DWH) test for endogeneity requires constructing fitted values of the variables in question that will be orthogonal to the error term in the second stage regression of quantity demanded on price, economic, weather and other indicator variables.

For each of the four models of price response, there are six price measures: the three period price effects in LADWP and the three for SDG&E. In order to construct the fitted values, we regress each price variable on the set of exogenous variables in (6) – namely those measuring economic activity, weather, emergency stages, and demand periodicity – in addition to a set of instruments. These instruments include temperature variables from San Francisco (SFO), similar to those variables described for SDG&E and our control groups. In addition, we consider input prices for supplying electricity. Two input prices that are important in determining the marginal cost of producing electricity are wholesale natural gas prices in southern California (TOPOK) and the nitrogen oxides pollution permit prices for the LA region (RECLAIM). Monthly average prices for wholesale natural gas and RECLAIM permits are included in Table 1.[27]

In the first stage of the DWH test, we allow the coefficients on the instruments to vary before and after retail deregulation. The first stage regressions are, therefore, price on SFO weather, input prices, SFO weather after retail deregulation, input prices after retail deregulation, and the exogenous variables in (6). In order to test the strength of the instruments, we account for the error structure of the first stage. Rather than explicitly modeling a particular structure, we calculate the Newey-West standard errors taking into account a seven day moving average process. For our primary model of price response, we

[27] The results are robust to excluding wholesale natural gas prices as they could potentially affect demand for electricity other than through the wholesale electricity price. For example, consumers use natural gas for heating and cooking. Natural gas and electricity could be substitutes or complements. In addition, SDG&E bills consumers for natural gas and electricity simultaneously. Customers may have difficulty separating out billing information.

reject weak instruments for all six first stage regressions (see Table A1).[28] In the second stage, we regress the normalized, daily demand for a given region (again using LADWP as a control group for SDG&E) on the actual prices, the fitted prices, and the other independent variables from (6). The standard errors are corrected as in section 4. We do not correct for the estimation of the first stage as doing so will only increase the estimates of the standard errors.

Given this approach, we find that the coefficients on the five-week moving average of the retail price index in SDG&E during and after the retail deregulation period are highly significant and similar to that in model (2) of Table 7; the coefficient during deregulation is -0.521 (0.125) while the coefficient after the retroactive rate freeze is -0.472 (0.096). In contrast, none of the fitted prices from the first stage are significant at the ten percent level, either individually or jointly.[29] This implies that the five-week moving average of the retail price index is exogenous to demand. We repeat the exercise for models (2) to (4) and also reject weak instruments in the first stages and conclude that all of our measures of price are exogenous to demand.

[28] The Wald tests had F-statistics ranged from 4.9 to 77.5 for the six price variables, all significant at the one percent level.

[29] A Wald test of joint significance was insignificant (F-statistic of 0.8 and a p-value of 0.57).

Weekly Price Averages in PX and SDGE Residential

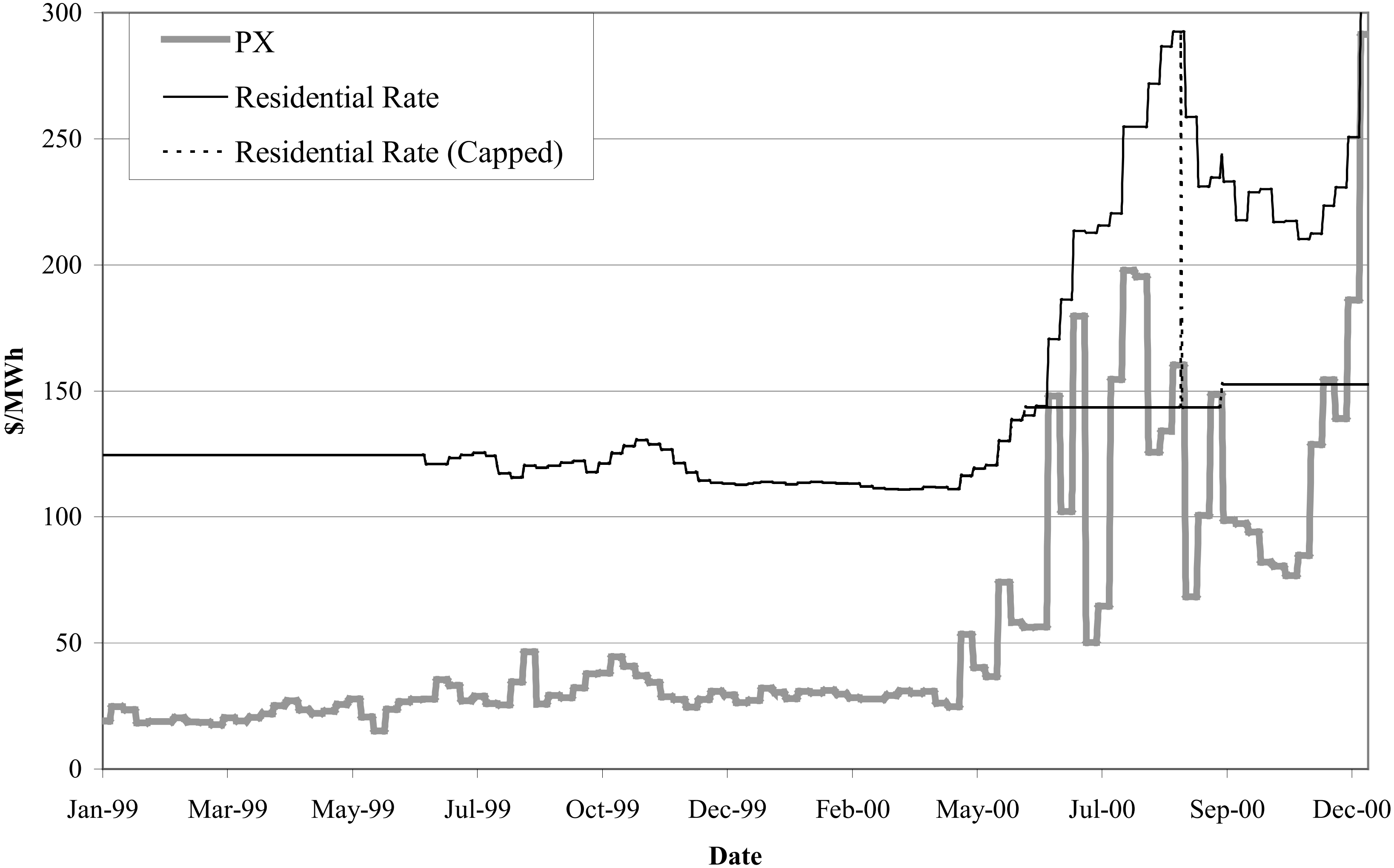

Figure 1: Five-Week Averages for PX SP15 Price and SDGE Residential Rates.

Note: Prices in $/MWh in Figure 1 while, in Table 1, they are in $/kWh where 1 MWh = 1000 kWh.

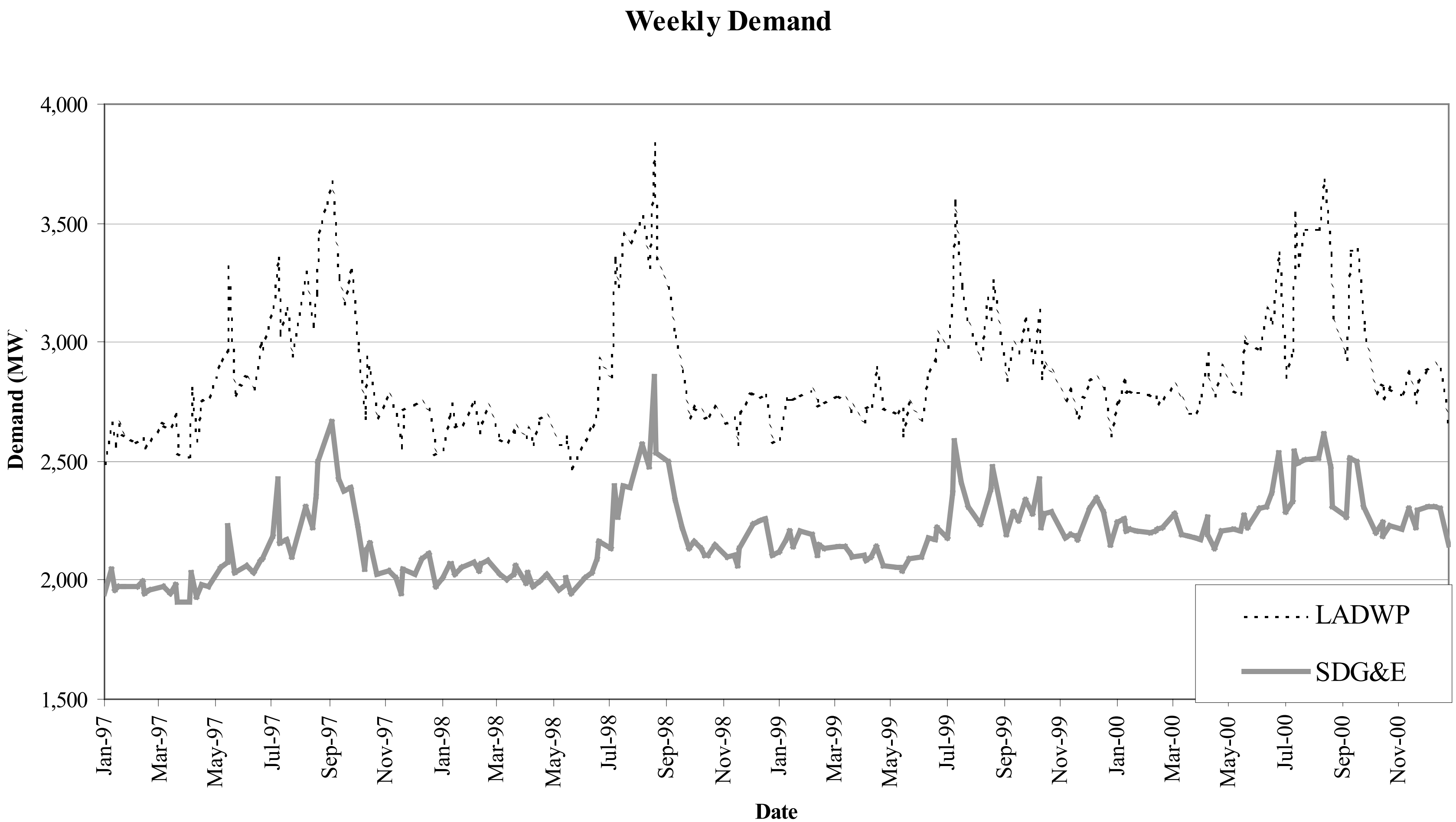

Figure 2: Weekly Average of Hourly Electricity Demand for SDG&E and LADWP.

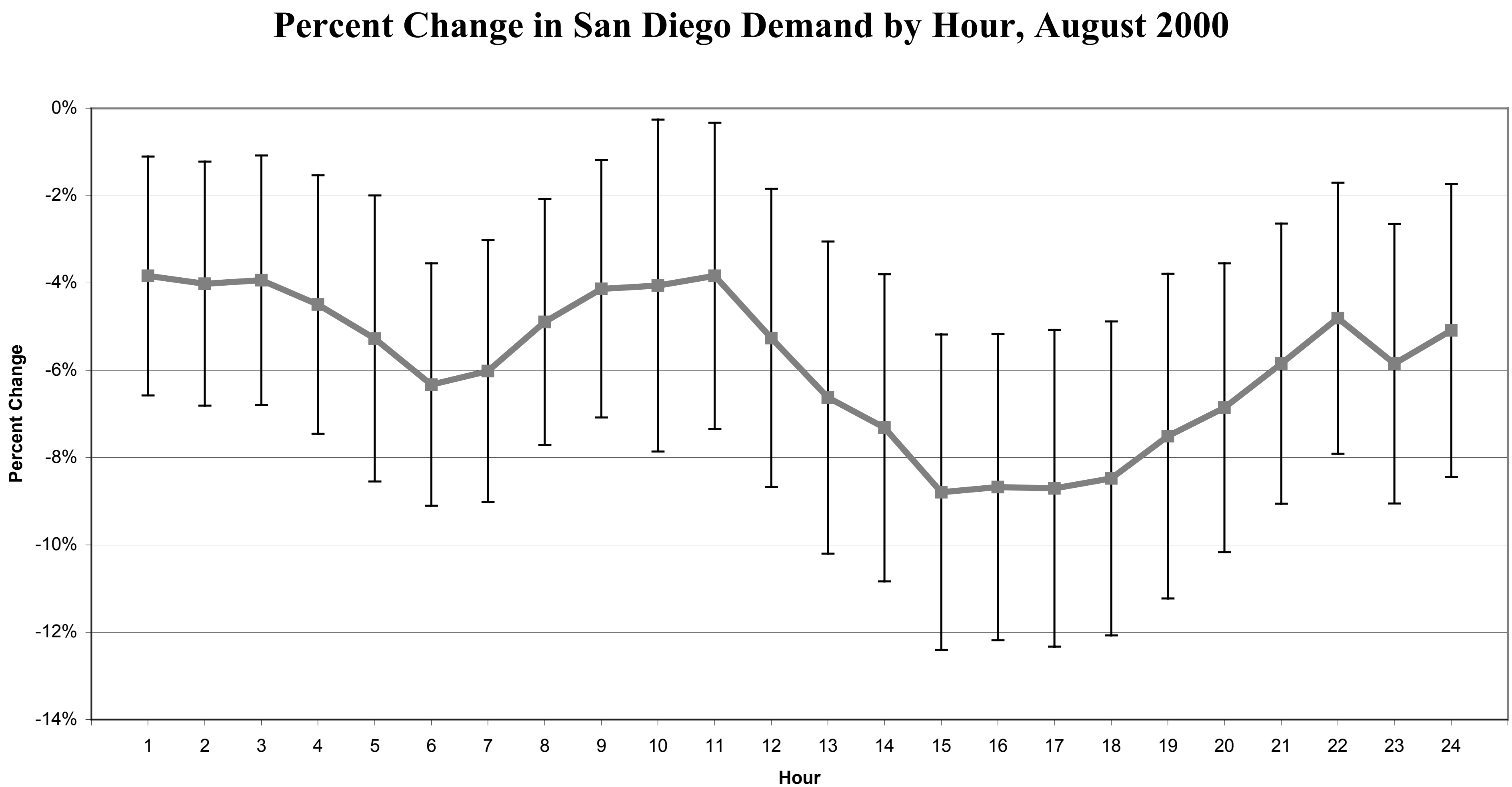

Figure 3: Percent Change in San Diego Demand by Hour, August 2000.

Table 3
Summary Statistics of Regional Variables, 1997-2000[a]

Variable	Frequency	Observations	Region SDG&E	LADWP	SCE[b]
Daily aggregate demand[c] (GWh)	Daily	1,461	52.51	68.85	257.98
			[5.10]	[8.67]	[33.06]
Economic variables					
Unemployment rate[d] (%)	Monthly	48	3.46	6.15	6.15
			[0.59]	[0.71]	[0.71]
Labor force size[d] (X 10,000)	Monthly	48	134.32	464.08	464.08
			[4.76]	[11.51]	[11.51]
Housing starts[e] (X 100)	Monthly	48	11.24	39.04	39.04
			[4.16]	[9.97]	[9.97]
Temperature variables					
Daily mean[f] (° F)	Daily	1,456	63.24	63.24	63.83
			[7.01]	[7.36]	[7.60]
Daily minimum[f] (° F)	Daily	1,456	53.69	54.68	54.66
			[8.05]	[7.86]	[7.87]
Daily maximum[f] (° F)	Daily	1,456	73.45	73.91	75.10
			[7.93]	[8.57]	[9.00]

Notes:

a) For each region and variable, the sample mean is given with the standard deviation in brackets.
b) Economic variables for SCE use Los Angeles MSA data.
c) Source: Federal Energy Regulatory Commission, form 714.
d) Source: United States Bureau of Labor Statistics.
e) Source: United States Census Bureau.
f) Source: National Oceanic and Atmospheric Association's National Climate Data Center.

Table 4
Difference-in-Differences Demand Response Effects

Dependent variable: Log of daily aggregate demand (MWh) by region.

Variables	Control Effect	Treatment Effect
June, 2000	0.019#	-0.021
	(0.011)	(0.017)
July	-0.020	-0.004
	(0.013)	(0.021)
August	-0.013	-0.064*
	(0.019)	(0.016)
September	0.004	-0.078*
	(0.014)	(0.016)
October	0.011	-0.049*
	(0.019)	(0.021)
November	-0.008	-0.013
	(0.013)	(0.016)
December	-0.026	-0.012
	(0.023)	(0.016)
Economic variables		
Log unemployment rate	-0.216*	0.046
	(0.078)	(0.059)
Log labor force	-0.025	1.611*
	(0.251)	(0.347)
Log housing starts	0.013	-0.004
	(0.026)	(0.007)

Notes:

a) Table presents GLS coefficients accounting for a first order auto-regressive error structure using the Prais-Winsten method.
b) Robust standard errors are in parentheses. Errors are clustered into 48 groups by month-year.
c) Significance at the 5% level with (*) and at the 10% level with (#).
d) Regression includes regional, day of week, and monthly fixed effects. Other regressors include month-year fixed effects for July 1999 through May 2000 and indicators of stage 1, 2, and 3 emergency alerts. We include quadratic functions of several weather variables averaged over a region: daily maximum and minimum temperatures, cooling degree-days (degrees daily mean below 65° F), and heating degree-days (degrees mean above 65° F). Finally, we account for hours of sunlight in a day.
e) The sample size of the regression is 2,912 (daily observations in each region from January 1997 to December 2000). R^2 is 0.97. First order auto-regressive ρ coefficient is 0.60.
f) Joint test of all economic variables is significant (Wald test F stat=33.1; P-value = 0.00).
g) Control effect corresponds to the overall effect in both regions: the control (LADWP) and the treatment (SDG&E). Treatment effect is an interaction of an indicator variable for the treatment region (SDG&E) and the variable of interest. For example, for the variable "June, 2000" the control region demand grew 1.9% (coefficient of 0.019) while the treatment region demand decreased by 2.1% (coefficient of -0.021) *relative* to the control region; the overall effect on demand in the treatment region was a 0.2% decrease (adding 0.019 and -0.021).

Table 5
Robustness Checks of Difference-in-Differences Demand Response Effects

Dependent Variable: In columns (1) to (5), it is the log of daily aggregate demand by region. In column (6), it is daily demand by region, normalized by average daily demand in region before retail deregulation.

	(1)	(2)	(3)	(4)	(5)	(6)
June, 2000	-0.043[#]	-0.002	0.034*	-0.007	-0.112*	-0.005
	(0.022)	(0.015)	(0.009)	(0.007)	(0.050)	(0.021)
July	-0.052*	-0.024	0.066*	0.012[#]	-0.167*	0.012
	(0.023)	(0.021)	(0.011)	(0.007)	(0.047)	(0.020)
August	-0.090*	-0.078*	-0.004	-0.034*	-0.211*	-0.066*
	(0.017)	(0.021)	(0.006)	(0.007)	(0.038)	(0.015)
September	-0.096*	-0.073*	-0.015	-0.038*	-0.146*	-0.080*
	(0.016)	(0.013)	(0.011)	(0.007)	(0.035)	(0.016)
October	-0.075*	-0.039*	0.011	-0.012*	-0.170*	-0.051*
	(0.023)	(0.014)	(0.008)	(0.005)	(0.041)	(0.020)
November	-0.036*	-0.021	0.028*	0.000	-0.114*	-0.015
	(0.018)	(0.013)	(0.012)	(0.004)	(0.041)	(0.016)
December	-0.015	-0.038*	0.037[#]	0.020[#]	-0.066[#]	-0.016
	(0.016)	(0.016)	(0.019)	(0.010)	(0.038)	(0.017)
Control group	SCE	NO	LADWP	SCE	LADWP	LADWP
ECON	YES	YES	NO	NO	YES	YES
WEATHER and indicators	YES	YES	YES	YES	NO	YES
AR(1) ρ coefficient	0.65	0.61	0.70	0.74	0.61	0.62

Notes:

a) GLS coefficients and robust standard errors (in parentheses) are for treatment effects only (SDG&E relative to control area where applicable).

b) See Table 4 for other details.

c) Prior to retail deregulation, namely from January 1997 to June 1999, the average daily demand in region was: 51,024 MWh in SDG&E; 67,604 MWh in LADWP; and 250,122 MWh in SCE.

Table 6
Hourly Analysis of Difference-in-Differences Demand Response Effects
Dependent variable: Log of hourly demand (MWh) by region.

Hour	June, 2000	July	August	September	October	November	December
1:00	-0.024#	0.011	-0.038*	-0.062*	-0.029	0.007	-0.002
A.M.	(0.014)	(0.014)	(0.014)	(0.012)	(0.021)	(0.013)	(0.016)
2:00	-0.028*	0.013	-0.040*	-0.066*	-0.017	0.017	0.001
	(0.013)	(0.013)	(0.014)	(0.013)	(0.019)	(0.015)	(0.013)
3:00	-0.040*	-0.000	-0.039*	-0.065*	-0.029	0.014	-0.005
	(0.015)	(0.014)	(0.015)	(0.014)	(0.021)	(0.015)	(0.013)
4:00	-0.046*	-0.009	-0.045*	-0.075*	-0.037	0.007	-0.011
	(0.015)	(0.015)	(0.015)	(0.014)	(0.022)	(0.015)	(0.012)
5:00	-0.052*	-0.018	-0.053*	-0.083*	-0.052*	-0.012	-0.022#
	(0.016)	(0.017)	(0.017)	(0.014)	(0.023)	(0.016)	(0.013)
6:00	-0.067*	-0.022	-0.063*	-0.092*	-0.060*	-0.008	-0.043*
	(0.015)	(0.016)	(0.014)	(0.013)	(0.022)	(0.012)	(0.011)
7:00	-0.042*	-0.019	-0.060*	-0.096*	-0.056*	-0.023#	-0.042*
	(0.017)	(0.019)	(0.015)	(0.014)	(0.020)	(0.014)	(0.011)
8:00	-0.032#	-0.011	-0.049*	-0.090*	-0.053*	-0.020	-0.031*
	(0.016)	(0.017)	(0.014)	(0.013)	(0.018)	(0.014)	(0.012)
9:00	-0.014	-0.002	-0.041*	-0.078*	-0.052*	-0.019	-0.025#
	(0.016)	(0.018)	(0.015)	(0.014)	(0.017)	(0.014)	(0.013)
10:00	-0.004	0.013	-0.041*	-0.068*	-0.050*	-0.018	-0.004
	(0.018)	(0.022)	(0.019)	(0.016)	(0.020)	(0.017)	(0.018)
11:00	0.004	0.018	-0.038*	-0.061*	-0.042*	-0.008	-0.005
	(0.017)	(0.021)	(0.018)	(0.015)	(0.019)	(0.016)	(0.016)
Noon	0.002	0.021	-0.053*	-0.064*	-0.043*	-0.004	-0.002
	(0.018)	(0.022)	(0.017)	(0.016)	(0.020)	(0.017)	(0.016)
1:00	0.004	0.020	-0.066*	-0.070*	-0.046*	-0.009	-0.005
P.M.	(0.019)	(0.024)	(0.018)	(0.017)	(0.021)	(0.017)	(0.017)
2:00	-0.001	0.016	-0.073*	-0.077*	-0.041#	-0.007	-0.005
	(0.019)	(0.024)	(0.018)	(0.017)	(0.021)	(0.016)	(0.016)
3:00	-0.010	-0.001	-0.088*	-0.088*	-0.045*	-0.014	-0.011
	(0.021)	(0.025)	(0.018)	(0.017)	(0.021)	(0.017)	(0.016)
4:00	-0.007	-0.002	-0.087*	-0.091*	-0.052*	-0.011	-0.017
	(0.020)	(0.024)	(0.018)	(0.017)	(0.023)	(0.016)	(0.018)
5:00	-0.013	-0.009	-0.087*	-0.094*	-0.054*	-0.011	-0.018
	(0.021)	(0.025)	(0.019)	(0.017)	(0.024)	(0.018)	(0.020)
6:00	-0.018	-0.019	-0.085*	-0.095*	-0.048#	-0.010	-0.017
	(0.022)	(0.025)	(0.018)	(0.018)	(0.024)	(0.018)	(0.019)
7:00	-0.015	-0.016	-0.075*	-0.086*	-0.047#	-0.002	-0.008
	(0.023)	(0.024)	(0.019)	(0.018)	(0.024)	(0.017)	(0.020)
8:00	-0.028	-0.014	-0.069*	-0.074*	-0.046*	-0.005	-0.015
	(0.019)	(0.021)	(0.017)	(0.016)	(0.022)	(0.016)	(0.019)
9:00	-0.023	-0.006	-0.058*	-0.063*	-0.043*	-0.006	-0.011
	(0.018)	(0.020)	(0.016)	(0.015)	(0.020)	(0.016)	(0.018)
10:00	-0.021	0.001	-0.048*	-0.054*	-0.035#	-0.012	-0.015
	(0.016)	(0.020)	(0.016)	(0.014)	(0.019)	(0.016)	(0.016)
11:00	-0.029#	-0.004	-0.058*	-0.063*	-0.048*	-0.019	-0.017
	(0.016)	(0.018)	(0.016)	(0.015)	(0.022)	(0.017)	(0.016)
Midnight	-0.032#	0.002	-0.051*	-0.080*	-0.049*	-0.016	-0.012
	(0.017)	(0.020)	(0.017)	(0.016)	(0.022)	(0.016)	(0.020)

Notes:

a) GLS coefficients and robust standard errors (in parentheses) are for hour-specific treatment effects only (SDG&E relative to LADWP control area).

b) For each hour of the day, we ran a separate regression including the same regressors as described in Table 4, including the economic variables.

c) Each regression by hour has a sample size of 2,912. R^2 ranged from 0.91 to 0.98. The first order auto-regressive ρ coefficients ranged from 0.39 to 0.62.

Table 7
Price Response Regressions

Dependent Variable: In columns (1) to (5), it is daily demand by region, normalized by average daily demand in region before retail deregulation. In column (6), it is the log of daily aggregate demand by region.

Price Variables	(1) Five- Week Ave Index	(2) Current Week's Price Index	(3) Last Week's Price Index	(4) Expected Price Index	(5) (1) w/o control	(6) Log-linear of (1)
Price: Jan 97-Jul 99 ($/kWh)	0.087 (0.346)	0.735# (0.373)	0.337 (0.377)	0.763* (0.372)	. .	0.165 (0.330)
Price: Aug 99-Aug 00	0.087 (0.113)	0.127 (0.086)	-0.001 (0.095)	0.165# (0.087)	. .	0.075 (0.105)
Price: Sep 00-Dec 00	0.074 (0.094)	0.047 (0.081)	-0.009 (0.076)	0.150* (0.066)	. .	0.054 (0.092)
SDGE * Price: Jan 97-Jul 99	0.144 (0.396)	-0.001 (0.374)	0.153 (0.390)	-0.060 (0.391)	0.220 (0.362)	-0.086 (0.363)
SDGE * Price: Aug 99-Aug 00	-0.525* (0.126)	-0.274* (0.105)	-0.314* (0.122)	-0.319* (0.124)	-0.444* (0.150)	-0.555* (0.114)
SDGE * Price: Sep 00-Dec 00	-0.477* (0.095)	-0.270* (0.081)	-0.315* (0.091)	-0.353* (0.111)	-0.405* (0.077)	-0.454* (0.097)
Sample size	2,786	2,856	2,842	2,796	1,393	2,786

Notes:

a) Table presents GLS coefficients accounting for a first order auto-regressive error structure using the Prais-Winsten method.
h) Robust standard errors are in parentheses. Errors are clustered into 48 groups by month-year.
b) Significance at the 5% level with (*) and at the 10% level with (#).
c) The average daily demand in region before retail deregulation, namely from January 1997 to June 1999, was 51,024 MWh in SDG&E and 67,604 MWh in LADWP.
d) Other regressors are as described in Table 4. Economic variables are expressed as linear functions in columns (1) to (5) and are logarithmic functions in column (6). The economic variables are jointly significant at the 1% level for all regressions.
e) R^2 ranges from 0.87 to 0.97. First order auto-regressive ρ coefficient ranges from 0.62 to 0.66.

Table A. Durbin-Wu-Hausman Test of Endogeneity of Prices

First stage dependent variables: Five-week moving average of the retail price index, by time period and region.

Second stage dependent variable: Daily demand by region, normalized by average daily demand in region before retail deregulation.

Variables	First Stage F-statistic	Second Stage Prices	Second Stage Fitted Prices
Price: Jan 97-Jul 99 ($/kWh)	77.5*	0.828 (0.653)	-1.122 (2.607)
Price: Aug 99-Aug 00	32.6*	0.045 (0.129)	-0.123 (0.721)
Price: Sep 00-Dec 00	68.2*	0.144 (0.158)	-0.270 (0.496)
SDGE * Price: Jan 97-Jul 99	7.9*	0.183 (0.398)	0.282 (4.662)
SDGE * Price: Aug 99-Aug 00	7.2*	-0.521* (0.125)	0.405 (1.395)
SDGE * Price: Sep 00-Dec 00	4.9*	-0.472* (0.096)	0.399 (0.882)

Notes:

a) In the first stage, we regress each of the prices (varying by time period and region) on the independent variables from Table 4, including the economic variables, and a set of instruments (including temperature effects in San Francisco and prices of RECLAIM permits). The errors are adjusted for a 7-day moving average lag structure using the Newey-West procedure. The first column in Table A presents F-statistics of the joint significance of these instruments for each of the six price regressions. All are significant.

b) In second and third columns, we report the GLS coefficients for the second stage. This is a single regression of demand on both actual and fitted prices as well as the other independent variables described in Table 4. The model accounts for a first order auto-regressive error structure using the Prais-Winsten method. Robust errors are clustered by month-year.

c) Significance at the 5% level with (*) and at the 10% level with ($^{\#}$).

d) In second stage regression, the sample size is 2,844, R^2 is 0.88, and the first order auto-regressive ρ coefficient is 0.64.

e) Wald test of significance of fitted price variables has an F-statistic of 2.00 (p=0.09).