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CONSUMPTION UNDER NOISY PRICE SIGNALS: A STUDY OF ELECTRICITY RETAIL RATE DEREGULATION IN SAN DIEGO*

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Abstract

Utility services employ nonlinear tariffs that attempt to convey information 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. When rates doubled in 2000, consumers appear to have reacted more to recent past bills than to current 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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I. INTRODUCTION

THIS PAPER explores demand response to noisy and volatile price signals. Electricity, natural gas, telecommunications, and water services frequently use nonlinear tariff structures to convey information on cost convexities. However, customers typically do not know the marginal price until after they decide to consume. Complex tariffs require consumers to calculate their expected marginal price, which can be extremely challenging when prices are volatile. Previous literature estimating electricity demand response to such tariffs has been complicated by selection issues and limited retail price volatility. By contrast, we study the San Diego retail electricity market where a large number of customers were involuntarily exposed to substantial monthly price volatility.

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. Weekly wholesale price averages increased more than four-fold during this time span, leading to a doubling of most customers' rates. Around September 1, 2000, state legislators responded to mounting public pressure over these rate increases. They mandated a retail rate freeze that was retroactive to June of 2000. 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 Because of the complexity of how SDG&E implemented and then rescinded rate increases during this period, this is as much a study of customer expectations about price as it is an examination of the response to a specific price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.

Price signals may be difficult to estimate even given stable nonlinear rate structures. Customers must estimate their aggregate consumption over the entire billing period in order to determine the marginal rate at any given time. 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. These problems are magnified further in industries such as natural gas and electricity that have extremely volatile wholesale costs. 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. As electricity restructuring progresses, consumers may find their 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.[1] 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.

Whether or not such tariffs effectively communicate wholesale costs to retailers remains unclear. 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.[2] 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.[3] No previous study has been able to examine a case when all customers were forced to face significant price volatility. The experiences of customers in San Diego during 2000 provide us with such a test case.[4]

We measure consumer response with two approaches. First we estimate the price responsiveness of San Diego customers using a demand model. Second, we examine the average monthly effects using difference-in-differences (DID) estimation because of the uncertainty surrounding prices. We control for general southern California trends by examining demand in the neighboring areas where rates remained constant. Both models account for other factors affecting demand such as temperature and economic activity.

Our findings in both models support the hypothesis that customers respond more to out-dated prices from 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 nearly doubled by August 2000) equal to

-0.10. By contrast, the effect of current prices on current consumption is not significant after retail rates were deregulated. With our DID model, we find a reduction in average consumption of approximately 5% when prices peaked in August and an even larger 7% reduction in September, *after* most customers' prices returned to historic levels. Finally, 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 14%.

These 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.

Section II discusses the background of the California electricity industry and the retail rate structure in San Diego. Section III explicitly models price response. In section IV, we examine retail deregulation in SDG&E using DID estimation. In section V, 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.

II. CALIFORNIA ELECTRICITY MARKETS

In April of 1998, California restructured its wholesale electricity market. The traditional utilities divested most of their generation assets but continued to serve retail customers. During our sample period, from January of 1997 to December of 2000, generating firms sold electricity in the now defunct Power Exchange (PX). The utilities purchased power in the PX to meet their customers' demand. The PX ran a double auction that cleared at a uniform price from the intersection of supply offers and demand bids. Every hour, a single price cleared the market except when transmission lines were congested. In that case, southern California had a separate 'SP15' price. While the wholesale market restructured in 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. Having made relatively modest commitments to both nuclear and independent power, SDG&E recovered its stranded costs by mid-year 1999. After July 1, 1999, ratepayers in San Diego paid retail rates that more directly reflected the current wholesale price of power. Customers in the rest of California stayed on frozen rates throughout our sample. We exploit this pricing experience that resulted from these exogenous historic commitment decisions.

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. The seven different customer classes are on about 50 different tariff schedules.[5] 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.[6] Figure 1 shows the weekly average retail electric rate for residential customers in San Diego, including what these rates *would have been* in late 2000.[7] In addition, the figure shows the average PX wholesale price for SP15 (grey line).

Place Figure 1 approximately here.

As can be seen from 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]

By late June of 2000, there was a tremendous outcry from ratepayers who were for the first time directly exposed to these wholesale costs. Politicians told customers to not pay bills and debated several policies.[9] 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] When AB 265 was signed, it overrode another policy: 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 (which was not retroactive). While this policy change is not exogenous to market conditions and therefore should not be viewed as a 'natural experiment,' it is still informative to test whether price response changed after this law went into effect. In Figure 1, the retroactive rate freeze is represented by the dashed line.

In the following sections, we analyze the impact these noisy price signals had on end-use consumption using two alternative methods. In section III we test the price impacts on demand in the deregulated retail electricity SDG&E market. Because of the caveats about customer price perceptions described below and the potential for a regional demand shock during this period, in section IV we utilize a Difference-in-Differences model of monthly demand utilizing neighboring utilities as control groups.

III. MEASURING PRICE IMPACTS

III(i). *Methodology of Price Impacts*

In this section, we study daily demand as a function of retail price. As this price is modeled as a function of the wholesale price, this section's sample period ranges from April 1, 1998, until December 31, 2000. We model average hourly demand per customer (q_t) during day t as a function of the retail price (P_t), economic variables ($ECON_t$), weather variables ($WEATHER_t$), and variables capturing demand periodicity (X_t). In addition, we model idiosyncratic shocks (u_t) and estimate this econometric model:

$$q_t = \alpha + \beta P_t + ECON_t'\delta + WEATHER_t'\gamma + X_t'\theta + u_t. \tag{1}$$

We use several economic variables that capture the status of the San Diego economy. These include unemployment rate, size of labor force, and new building permits. The weather variables include quadratic functions of daily minimum and maximum temperatures, and cooling and heating degree-days.[11] An additional weather variable approximates daily hours of sunlight.[12] The indicator variables (X_t) account for the day of the week and the month of the year.

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, 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. The price response we model should be considered a lower bound of a long run elasticity measure.

A second important caveat is the fact that there was much contradictory information about retail prices being provided to customers during this time period. Eventually, the rates were retroactively adjusted to levels different than those indicated by the movement of the five-week weighted average PX price. Although the retroactive aspect of the rate-freeze reversed a CPUC decision of eight days previous, to the extent that customers anticipated this retroactive rate decrease they would have responded less aggressively to the price increases as they were happening. Given the uncertainty over policy, it is extremely difficult to measure the extent to which these expectations were affecting consumer demand.

Finally, 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 daily demand data are available; not even utilities have reliable measures of daily demand by customer or rate class. We do know that the rates of each customer class moved linearly with the wholesale price. While prices vary by customer class, the *changes* in rates were roughly common across customers and rate classes as they were all tied to the PX price. See the Appendix for a discussion of our general model of consumer behavior and assumptions regarding aggregation.

We estimate equation (1) using instrumental variables as there are several potential reasons why an OLS estimate on these price measures would be biased: endogeneity due to simultaneity; aggregation induced error-in-variables bias; quantity weighting the average price variable; and endogeneity due to non-linear pricing. Valid instruments will be correlated with the true price that each customer faces but not correlated with the residual in equation equation (1). For price instruments, we use data on weather, natural gas, and pollution permits.[13]

III(ii). *Data for Price Impacts*

We first define a wholesale price measure that is used to construct alternative measures of the retail price P_t. The price is a five-week weighted average of the wholesale (PX) price that reflects only the energy, not the transmission and distribution, portion of retail prices. 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 moving average we denote the 'wholesale price index.'

Recall that the price paid by each individual customer reflects the wholesale price index for the five-weeks prior to their billing date. Since there are 5 different billing cycles, aggregate demand depends on four lagged prices, the current price, and four forward prices. Due to the complexity of the interaction between our price index and aggregate customer demand, we test four different models of price response. These models differ in the assumptions made regarding the information set of each customer.

The first model tests whether consumers respond primarily to the current week's weighted average wholesale price. Given that the PX posted this information on the internet and prices were of such great concern over this period, one might expect that consumers focused on the current wholesale prices. This model does not account for the fact that current consumption is billed based on five weeks of prices.

A second model assumes an information set that accounts for the longer time period of the average price. This model is consistent with customers responding to the previous week's wholesale price index. Bills typically arrive five to ten days after the cycle ends. This is a model that assumes price dissemination through people discussing their latest bills. It is consistent with everyone reacting to the price contained in the bill most recently received by anyone.

In our third model, customers calculate their exact prices. This is consistent with a model of demand in which customers base current consumption upon estimates of recent, current, and near-future wholesale prices. It accounts for the fact that only one-fifth of customers are billed in a given week. We recognize that consumers' demand today will be billed anywhere from the average of the last five weeks (including the current one) for some customers up to the average of next five weeks (including the current one) for others. This measure utilizes a five-week average of the wholesale price index centered upon the week of the observation.

Our last model is consistent with the hypothesis that customers are responding primarily to the price contained in their own most recent bill. This combines the information about the lag in the billing process with the staggering of the billing cycles. This is similar to the third model but with prices lagged by five weeks. 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 on the current price. As such, this measure of price is a backward-looking model based upon a five-week moving average of the wholesale price index ending with the week prior to the date of the observation.

In summary, we examine each of the following models of price:

Model	Description
1	Current week's wholesale price average
2	Last week's wholesale price index
3	Expected bill: average predicted wholesale price index
4	Last bill: average historic wholesale price index

Finally, we recognize three periods when aggregate demand possibly responded to prices differently. The control period, prior to retail deregulation, was from April 1998 through June 1999. The retail deregulation period was from July 1999 through August 2000. 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.

Table I summarizes data on electricity demand, economic activity, and weather characteristics for the SDG&E, regions. These data are also summarized for two neighboring utilities, the Los Angles Department of Water and Power (LADWP) and Southern California Edison (SCE).[14] We use these regions as controls in section IV.

Place Table I approximately here.

While we have data on the quantity of electricity demanded by hour, 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). Daily demand is less variable in SDG&E relative to the other regions.

For a given Metropolitan Statistical Area (MSA), we use three measures of economic activity - unemployment rate, housing starts, and labor force size - with monthly frequency. Table I discusses all data sources. The San Diego MSA experienced a slightly more rapid decline in unemployment and increase in labor force over our sample period. For each region, we examine the mean, minimum, and maximum daily temperature.[15] 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% of daily means between 52 and $76°F$ in each of the three regions.

III(iii). *Results of Price Impacts*

Table II summarizes our results using various models of retail price response. The first stage regressions are not shown. Joint tests on the instruments are significant at the 1% level in all regressions, suggesting that the instruments are not weak. We test and correct for serial correlation and heteroskedasticity.[16] We use the Newey-West [1987] autocorrelation consistent covariance estimator assuming a seven day lag structure.[17] An overidentifying restriction test shows that the instruments are not correlated with the residuals in the second stage.[18]

Place Table II approximately here.

The price impacts in the second stage regressions differ by pricing model. In models (1) and (3), which rely upon current rather than lagged prices, the wholesale price is insignificant both during retail deregulation (July 1999 to August 2000) and after the retroactive rate freeze (September 2000 to December 2000). The second model, which looks at a one week lag of the wholesale price index, was significant but only after the retroactive rate freeze. The coefficient of -0.484 implies a modest response. The average customer demand would fall by a 0.05 kWh per hour if rates increased ten cents per kWh.

Models (1) and (3) do predict price to be positively correlated with demand during the early period even though wholesale prices had no impact on retail prices. This is likely due to aberrant prices in the wholesale market during its first few months of operation.[19] Many studies of California's markets ignore this early period because of the inconsistencies. If we exclude April-June 1998 from the pricing analysis, the coefficients on price in models (1) and (3) are no longer significant and the results for other models and time epochs are qualitatively unchanged.

The fourth model produces the largest price effects that are significant after retail rate deregulation. It uses a backward-looking five-week moving average of retail prices. The coefficient for the wholesale price index during the retail deregulation period is -1.34 (with a standard error of 0.520). One measure of demand price 'elasticity' implied by this estimation is -0.096.[20] From July of 1999 to August of 2000, the residential retail rate had approximately doubled. For August, 2000, the price coefficient from this model implies a 6% reduction in quantity demanded of electricity.[21]

For the fourth model, demand response is less strong but is still significant after the retroactive rate freeze. The price coefficient is only -0.843 (s.e. of 0.270), and differs significantly from the coefficient during retail deregulation at the 10% level. The implied 'elasticity' during this period is similar (-0.101) because of high PX prices. For both the deregulated period and after the retroactive rate freeze, the coefficients in the fourth model are approximately twice those of model two.

Many of the other covariates on economic activity, weather, and demand periodicity were significant. While the fourth model had the highest R^2, all models fit demand reasonably well (the R^2 range from 0.90 to 0.92). Here we mention the covariates that are significant at the 5% level. Our first measure of economic activity is the unemployment rate. The greater the rate, we expect there to be less demand for electricity. This is consistent with our findings in model one. The variable was insignificant in the other models. For all models, the coefficient on population is positive and significant. Monthly coefficients were jointly significant for all models. The quantity demanded on each day of the week is significantly greater than that on Sunday for all models.

Recall that the weather variables include quadratic functions of daily minimum and maximum temperatures, and cooling and heating degree-days. For all models, the two coefficients comprising the quadratic function on daily minimum were jointly significant. We find similar results for cooling degree-days and heating degree-days. Almost all of the temperature effects are captured by cooling degree-days. For all models, a $10°F$ increase in mean temperature above $65°F$ results in an increase in the quantity of electricity demanded of approximately 14%. Finally, demand is decreasing in sunlight. All of these results are consistent with expectations.

These results imply that demand is particularly responsive to lagged prices. We hypothesize that customers respond to information contained in their last bill rather than to an expectation of current prices. Our findings are consistent with this hypothesis. Considering the caveats given above, it is more difficult to interpret these results as estimates of the price elasticity of demand as we do not know what level of price customers *thought* they were going to pay at that time. Therefore, in the next section we abstract away from direct measures of price.

IV. DIFFERENCE-IN-DIFFERENCES (DID) ESTIMATION

In this section, we test the robustness of our findings in section III by determining the degree to which factors other than price *fail* to describe consumption patterns. By isolating distinct time periods that have differing price levels, price variability, and consumer expectations, we are able to estimate customers' aggregate price responsiveness in an indirect manner.

IV(i). *Methodology of DID Estimation*

We study electricity consumption using a panel of the three California regions over a period from January 1, 1997, to December 31, 2000. We estimate a modified version of equation (1) using DID estimation instead of price and allow the coefficients on all independent variables to vary by region i. Similar to equation (1), the dependent variable is the hourly average demand per customer (q_{ijt}) for region i, month of deregulation j, and day t. The resulting econometric model we estimate is:

$$(2) \qquad q_{ijt} = \alpha_i + \psi_j + \phi_j SDGE_{ijt} + ECON'_{ijt}\delta_i + WEATHER'_{ijt}\gamma_i + X'_{ijt}\theta_i + u_{ijt},$$

where $SDGE_{ijt}$ is an indicator variable of whether the region is SDG&E.

Price shocks, or 'intervention' effects, are now modeled as month-year fixed effects (ϕ_j) for each month after retail rate deregulation (July 1999 to December 2000): $j = \{1, .., 18\}$. While retail prices do change weekly, given the limited number of daily observations in each week and the presence of serial correlation, such a fine definition of an intervention would have little power. 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 time. This implies that *any* local shocks to demand will be captured by ϕ_j that we are interpreting as a price effect.

To address this concern, we use a control group where rates did not change but whose regional proximity would imply that their customers would be subject to the same regional non-price as those in SDG&E. We control for general month-year effects after retail rate deregulation (ψ_j) that are common to southern California. The control group consists of daily observations from two neighboring utilities: LADWP and SCE. Retail rates for customers of both LADWP and SCE remained constant throughout the period examined.

Furthermore, as this period was prior to the rolling blackouts, there was little effort made statewide to encourage conservation.

As with any DID estimation, we mention several caveats. Besley and Case [2000] point out that policies are often endogenous and therefore treating them as 'natural experiments' is incorrect. As we mentioned, the initial lifting of the price freeze in 1999 was likely exogenously determined while the second policy change, that of the retroactive rate freeze, is likely to be endogenous. People were calling for the rates to be reduced and may have anticipated that the current price was not the true price. For this reason, we interpret our findings as lower bounds of how responsive customers would be to the observed price shocks.[22]

In a recent paper, Bertrand, Duflo, and Mullainathan [2004] argue that many papers using DID estimation are problematic due to the correlation of the intervention effects (ϕ_j) and the autocorrelation in the residuals u_{ijt}. They argue for using an arbitrary variance-covariance matrix that is equivalent to using the Newey-West method and letting all lags be important. Given that we have only three states, we modify their approach and account for the serial correlation by using the Newey-West autocorrelation consistent covariance estimator assuming a seven day lag structure. Our results are not sensitive to the length of the lag structure.

IV(ii). *Results of DID Estimation*

Table III shows the regression results of estimating equation (2). For most months following retail rate deregulation, SDG&E demand was not significantly different from expectations based on the control group and covariates for economic activity, weather, and periodicity.[23] However, three notable exceptions are August through October of 2000. The coefficient on August implies a 0.113 reduction in per customer hourly demand, or 5% below levels explained by the model. Most strikingly, the September reduction is slightly *larger* in magnitude (a coefficient of -0.145, or 7%) than the August reduction, *despite* the fact that rates had been substantially reduced by September 1^{st}. In October 2000, consumption in SDG&E remained 5% below expectations, a coefficient of -0.089.[24]

Place Table III approximately here.

The control group helps us identify the San Diego intervention effects. The control group has significantly positive effects during August, September, and October of 2000. The quantity of electricity demanded per customer increased in all of southern California by about 2.7% during these months. The overall impact on San Diego (namely the sum of ϕ_j and ψ_j) was significantly negative for August and September.

By October, the price caps had been reinstated for smaller customers for over a month. Given the five-week cycle in the billing period, most customers received bills reflecting the lower rate levels by mid-October. 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 October of 2000, the overall market demand for electricity was not significantly different than that in other regions, given our controls. This suggests that the September and October effects resulted from some demand response beyond any that may have come from the large customers. 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. This is consistent with our findings in section III.

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 SDG&E implies a reduction of 0.05 kWh per customer for every 1% increase in unemployment. The labor force per customer, indicating economic activity, has a positive impact on electricity demand in all three regions, though to different degrees (an additional labor force participant increases demand five times as much in SCE as in LADWP). Each new housing start per 1000 customers in SCE increase demand by 0.11 kWh per customer. The weather effects in San Diego for this model are similar to those we estimate in section III.

We perform various robustness checks. Our main findings are robust to different models of the covariance matrix such as clustering by month given the low frequency of the economic variables. We find a similar but stronger reduction in consumption during the notable months when SCE is the only control group. With no control group or only using LADWP, the effects are attenuated and the reduction in consumption in October is no longer significant at the 5% level. The results are robust to the presence of the weather variables. However, the results are sensitive to the presence of the economic variables. The San Diego intervention effects are still negative, but smaller and no longer significant in the absence of economic controls.

Finally, we find that these intervention effects were not uniform across the day.[25] For each hour of the day, Figure 2 reports the coefficient on hourly demand in San Diego during August of 2000 (ϕ_{jh}), plus and minus 1.96 times the standard error. The largest reductions in demand came primarily in the afternoon hours, reaching approximately 17% in August, 2000, from 3:00 to 7:00 P.M.[26] By contrast, consumption during early morning hours increased up to 5% in August, indicating a shift in consumption within the day despite the fact that prices remained constant across hours.

Place Figure 2 approximately here.

We offer two possible interpretations of this pattern. First, customers may be more price responsive in the late afternoon when demand peaks. A second possibility is that elasticity varies more across customer classes rather than across time of day. Since the share of demand by customer class varies by hour, this would imply that a subset of customers is responsible for most reductions. We examine the correlation between our coefficient estimates and average hourly demand by customer type.[27] Of all customer classes, residential demand was by far the most correlated with the intervention effects (-0.67). This is consistent with an interpretation that residential customers were responsible for a large part of the reduced consumption.

V. 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 demand in San Diego during the volatile summer of 2000. First, we explicitly test for a price impact on consumption in San Diego and explore which price movements best explain consumer demand. Using a backward-looking five-week moving average of a wholesale price index, we find that a near doubling in retail price, which was reached in August, accounted for a 6% reduction in demand. Estimates based on current, rather than historic, retail prices imply no price response. We view this as evidence that customers primarily base their expectation of current prices upon the prices reflected in recent bills.

Because of the uncertainty surrounding prices, we also 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 5% lower than could be explained by non-price factors. We also find the reduction in demand in September 2000 slightly larger than in August (7%), even though retail rates had been significantly lowered for the majority of demand by September 1. This further implies that customers were indeed reacting to the prices reflected in their most recent bills rather than to the currently relevant rates. 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

Our empirical analysis uses aggregate consumption and price data. This appendix outlines the assumptions underlying our demand model relating individual demand with aggregate data. The traditional aggregation issue applies in that customers have different *preferences*. In addition, we must address aggregating over customers facing different *prices*.

We begin by modeling daily demand for electricity of customer j (Q_{jt}^{bk}) for weekly billing cycle b, customer class k, and day t. As previously mentioned, most consumers are on one of five cycles: $b = \{0, .., 4\}$ and in one of K customer classes. One-fifth of the population is assumed to be on each of the billing cycles. We assume demand to be linear in the expected price $E[P_t^{bk}|\Omega_{jt}]$ and an idiosyncratic shock υ_{jt}^{bk}, where Ω_{jt} is customer j's information set at day t:

$$Q_{jt}^{bk} = \widehat{A}^k + \widehat{B}^k E[P_t^{bk}|\Omega_{jt}] + \upsilon_{jt}^{bk}. \tag{3}$$

During the initial rate freeze, customer j consumed $\widehat{Q}_{jt}^{bk} \equiv Q_{jt}^{bk}(\widehat{P}^k)$, where $\widehat{P}^k$ is a constant retail price for all t. After retail deregulation, the expected price may deviate from this historically frozen rate:

$$E[P_t^{bk}|\Omega_{jt}] = \widehat{P}^k + \Delta\overline{P}_{bt}^k + \mu_{jt}^{bk}, \tag{4}$$

where $\Delta\overline{P}_{bt}^k$ is the portion of the deviation of the actual price from the historic level that is common to all customers in a given billing cycle and class. This portion is an average price shock, as a function of the wholesale price, over the weeks $w_t + b - 4$ to $w_t + b$, where w_t is an index counting the week in which day t falls. The term μ_{jt}^{bk} captures the portion of the deviation that is customer specific.

We aggregate over customers in a given cycle–class pair (b, k):

$$Q_t^{bk} = \sum_{j\in(b,k)} Q_{jt}^{bk} = \sum_{j\in(b,k)} \left[(\widehat{A}^k + \widehat{B}^k \widehat{P}^k) + \widehat{B}^k \Delta \overline{P}_{bt}^k + (\upsilon_{jt}^{bk} + \widehat{B}^k \mu_{jt}^{bk})\right] \tag{5}$$
$$\equiv A^k + B^k \Delta \overline{P}_{bt}^k + \varepsilon_t^{bk}.$$

Then we define aggregate demand Q_t as the sum of Q_t^{bk} over all customer classes and billing cycles. Recall that one fifth of the population is on each billing cycle:

$$Q_t = \sum_{k=1}^{K}\sum_{b=0}^{4} Q_t^{bk} = A + \sum_{k=1}^{K} \cdot \sum_{b=0}^{4} B^k \Delta \overline{P}_{bt}^k + \varepsilon_t. \tag{6}$$

Given N_t customers at time t, the average demand equation per consumer ($q_t \equiv Q_t/N_t$) is a function of 5K price deviations:

$$q_t = \alpha + \sum_{k=1}^{K} \cdot \sum_{b=0}^{4} \beta^k \Delta \overline{P}_{bt}^k + \xi_t, \tag{7}$$

where ξ_t may depend on shocks to the economy, weather, etc. Demand is normalized by the number of customers so we can compare SDG&E with our control group in section IV.

This can be further simplified. As noted above, the *changes* in rates were roughly common across customers and rate classes: $\Delta \overline{P}_{bt}^k = \Delta \overline{P}_{bt}$ for all k. Let $\Delta \overline{P}_{bt}$ be the (unweighted) average of the wholesale price shocks ($\Delta P_{w_t+b+l-4}$) over the five weeks from $l = 0$ to 4: $\Delta \overline{P}_{bt} = \frac{1}{5}\sum_{l=0}^{4} \Delta P_{w_t+b+l-4}$. We can write the model as:

$$q_t = \alpha + \left(\sum_{k=1}^{K} \beta^k\right)\left(\sum_{b=0}^{4} \Delta \overline{P}_{bt}\right) + \xi_t \tag{8}$$
$$= \alpha + \beta\left(\frac{1}{5}\sum_{b=0}^{4}\sum_{l=0}^{4} \Delta P_{w_t+b+l-4}\right) + \xi_t.$$

Aggregate demand depends on four lagged prices, the current price, and four forward prices. We further simplify the model by looking at how aggregate consumption responds to an average price. This price shock differs slightly from the true price each customer pays.

We estimated a model with the five distinct price averages as implied by equation (7). The data are highly correlated; the correlation between this week's PX price and last week's is 0.82 and the correlation among bills is even greater. Due to the high degree of multi-collinearity, none of the coefficients were significant. For this reason, we use a single price measure in the model. Therefore, we model equation (8) as:

$$q_t = \alpha + \beta P_t + \xi_t, \tag{9}$$

where P_t is a weighted average of price calculated four separate ways as described in the text.

Notes

[1]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.

[2]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.

[3]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 [2001] study the response of voluntary real-time pricing customers in the United Kingdom.

[4]In a recent working paper, Reiss and White [2003] examine this market using confidential monthly residential billing data, which do not allow them to account for economic or regional shocks as we do here.

[5]The main customer classes are agriculture, large commercial and industrial, medium commercial and industrial, residential, schedule A6, schedule AD, and small commercial. SDG&E offered large customers the option of seeing 'real-time' rates that passed along the hourly wholesale cost of power, though no customer 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. Overall, each week may have 600 different prices.

[6]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.

[7]The retail rate reflects the average hourly wholesale power cost. That average is weighted according to the estimated average hourly consumption for all customers in that rate class. 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. As a result, the June 1999 price for energy charges was \$0.046/kWh, much greater than the \$0.026/kWh that only reflects the PX wholesale electricity price. 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.

[8]Various cost factors such as higher natural gas prices and RECLAIM pollution credits contributed to this rise, but several studies have also found the market power of suppliers to be significant throughout this period. See Borenstein, Bushnell and Wolak [2002], Joskow and Kahn [2001] and Puller [2001].

[9]On July 12, State Senator Steve Peace advised customers to defer payment of at least

half their July bills.

[10]The rate freeze applied to the price of energy. Transmission and distribution charges were also paid by the small consumers as reflected in Figure 1.

[11]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.

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

[13]The weather data for San Francisco and major cities in Arizona. Natural gas spot prices are from Natural Gas Intelligence and measured at Henry Hub, a major trading hub in Louisiana. Prices for nitrogen oxides pollution credits in the Los Angles basin (or RECLAIM permits) are from the South Coast Air Quality Management District.

[14]LADWP provides electric service to residential customers within the city of Los Angeles and to portions of the Owens Valley. SCE distributes electricity to the bulk of southern California (except the LADWP and SDG&E territories).

[15]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. SCE weather data are averaged over Ontario and Santa Ana as well as Burbank and Los Angeles Airport.

[16]The tests were significant at the 1% level. We estimated model (1) using two stage least squares. After the second stage, a Breusch-Godfrey LM test failed to reject an AR(1): $\chi^2 = 207$; P-value = 0.00). The Cook-Weisberg test for homoscedasticity was rejected ($\chi^2 = 267$, p-value of 0.000).

[17]This model is estimated in Stata using the newey2 command written by David Roodman. We test the robustness of our results to longer lag structures. We find similar results with a lag structure of 100 days.

[18]We regress the residuals on the set of instruments and adjust the standard errors using the Newey-West method with a seven day lag. A Wald test on the instruments has an F-statistic of 1.42, which is insignificant at the 10% level.

[19]The incumbent utilities had not yet divested their generation assets to deregulated suppliers. The PX price was extremely low for April, May, and June of 1998 (averaging \$15.11 compared to an average of \$31.26 for the rest of 1998. This is well below the average seen in any other month and far below estimated marginal costs (see Borenstein, et al., 2002). Including these months into our analysis introduces an artificially strong and positive relationship between PX prices and overall demand levels, which happened to be low during this period when exogenous factors depressed PX prices.

[20]Elasticity is the price coefficient times the ratio of a given consumer group's average retail electricity price to the per customer hourly average quantity demanded in SDG&E. During the retail deregulation period, the residential rate (as shown in Table I) averaged \$0.138/kWh while the per customer demand in SDG&E was 1.93 on average. Other customer classes have lower historic prices so their elasticity estimates would be smaller.

[21]In August, 1999, the residential retail rate was \$0.126/kWh. In August of 2000, it had risen to \$0.232/kWh. This price change times the price coefficient for SDG&E during the retail deregulation period from model (1) imply a 0.142 kWh reduction in per customer demand. Actual per customer consumption was 2.105 kWh in August, 2000, implying demand fell by 6.3%.

[22]Other important issues have been noted in the DID estimation literature. Abadie [2004] points out that the control group may not have the same range of exogenous regressors as the treatment and suggests using propensity score methods to adjust for this bias. We do not use a propensity score method in this paper; however, we do allow the coefficients on these exogenous regressors to vary by region. Blundell and MaCurdy [2000] provide a general overview of DID estimation and discuss whether it can ever isolate a specific behavioral parameter. This is true for all DID estimation–our findings are specific to this case of study. Some work has also examined biased estimates of standard errors in

DID. Donald and Lang [2001] show that Moulton's [1990] critique regarding using common grouped data biasing standard errors also applies to DID estimation. We test the robustness of our findings by clustering the standard errors by month, which is the periodicity of the economic variables.

[23]Those month-year fixed effects in SDG&E that were not reported in Table III 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.

[24]Wald tests indicate that the August, September, and October coefficients were indistinguishable from each other.

[25]Using hourly demand data, we estimate α_{ih}, ψ_{jh},and ϕ_{jh} for all hours h (1 to 24) in a single regression equation.

[26]We estimate Wald tests on the August coefficients that compare the difference between each of the hours from 3:00 p.m. to 7:00 p.m. with each of the other hours that month. All tests were significant at the five percent level with 4 exceptions: 3:00 p.m. was not significantly different from 9:00-11:00 p.m. and 5:00 PM was not significantly different from 7:00 PM.

[27]SDG&E predicts the distribution of consumption, absent price response, across hours for each customer class. We use the 'Annual Dynamic Load Profile' data from www.sdge.com that span January 29, 2000, to January 28, 2001. We calculated the average demand by customer class and hour of day.

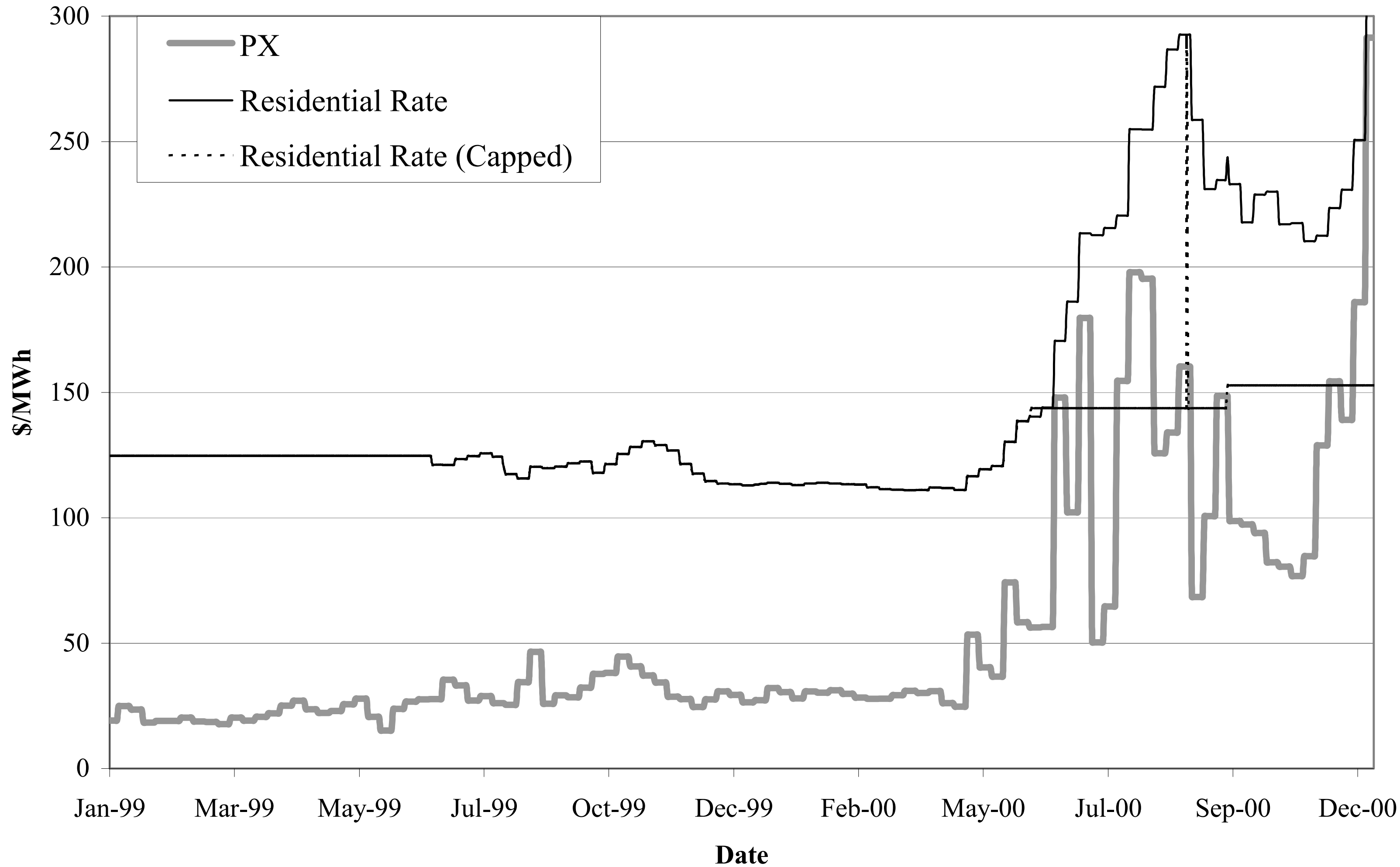

Figure 1
Five-Week Averages for PX SP15 Price and SDGE Residential Rates. Note: After September 1, 2000, the solid line represents what the residential retail rates would have been if SDG&E had been allowed to pass on its procurement costs.

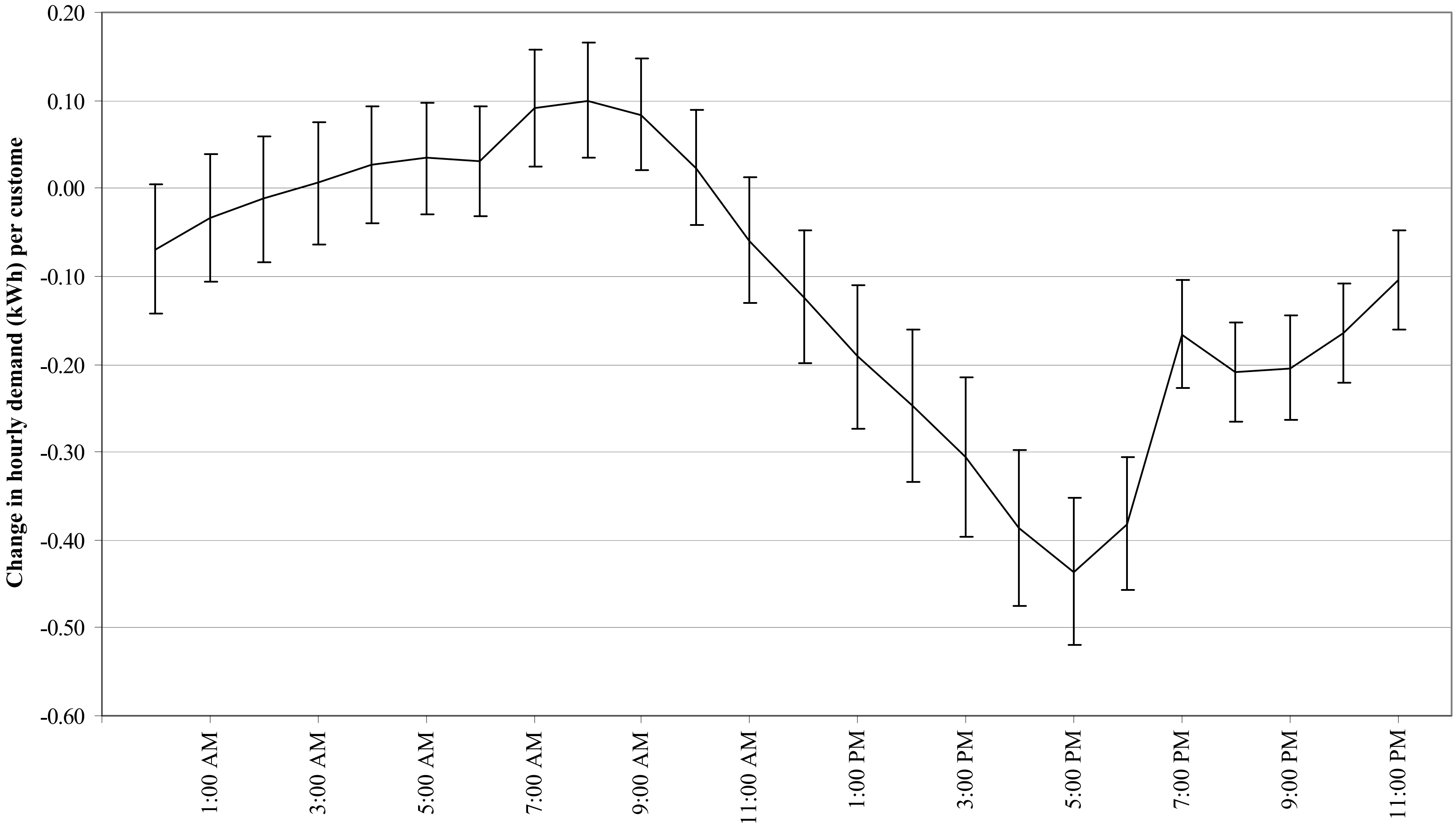

Figure 2
Change in hourly demand (kWh) per customer for SDGE in August 2000.
Figure plots coefficient estimates plus and minus 1.96 times the hourly standard error.

Table I

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

			Region		
Variable	Frequency	Observations	SDG&E	LADWP	SCE[b]
Demand					
Hourly average[c] (GWh)	Daily	1,461	2.19	2.87	10.75
Hourly peak (GWh)	Once	1	3.53	5.30	19.51
Customers[d] (millions)	Yearly	4	1.18	1.42	4.25
Customer average (kWh)	Daily	1,461	1.85	2.02	2.53
Residential Share[d]	Yearly	1	0.42	0.29	0.35
Commercial Share[d]	Yearly	1	0.41	0.57	0.35
Industrial Share[d]	Yearly	1	0.17	0.12	0.29
Economic variables					
Unemployment rate[e] (%)	Monthly	48	3.46	6.15	6.15
Labor force per customer[e]	Monthly	48	1.13	3.27	1.09
Housing starts per 1000 customers[f]	Monthly	48	0.95	2.76	0.92
Temperature variables					
Daily mean[g] (°F)	Daily	1,456	63.24	63.24	63.83
Daily minimum[g] (°F)	Daily	1,456	53.69	54.68	54.66
Daily maximum[g] (°F)	Daily	1,456	73.45	73.91	75.10

Notes:

a) The sample mean is given for each region and variable.
b) Economic variables for SCE use Los Angeles MSA data.
c) Source: Federal Energy Regulatory Commission, form 714.
d) Source: EIA form 861. Shares are for 2000 only and may sum to less than one because the “other” category is excluded.
e) Source: United States Bureau of Labor Statistics.
f) Source: United States Census Bureau.
g) Source: National Oceanic and Atmospheric Association’s National Climate Data Center.

Table II

Price Response Regressions
Dependent Variable: Daily average hourly demand (kWh) per customer.

	(1)	(2)	(3)	(4)
Price Variables	Wholesale Price	Last Week's Price Index	Expected Bill	Last Bill
Price: Apr 98-Jul 99 ($/kWh)	3.451*	1.919	4.115*	1.016
	(1.137)	(1.266)	(1.397)	(1.191)
Price: Aug 99-Aug 00	0.354	-0.516	0.309	-1.340*
	(0.248)	(0.331)	(0.401)	(0.520)
Price: Sep 00-Dec 00	-0.119	-0.484*	-0.183	-0.843*
	(0.146)	(0.179)	(0.208)	(0.270)

Notes:

a) Table presents IV coefficients and Newey-West standard errors in parentheses that assume a 7-day lag structure.

b) We denote significance at the 5% level with (*).

c) Regressions include economic variables of the unemployment rate, labor force per customer, and number of housing starts per 1000 customers. We add fixed effects for day of week and month of year. 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.

d) The instruments include temperature variables for San Francisco and Arizona (quadratic functions of minimum and maximum daily temperature as well as of cooling and heating degree-days). They also include linear functions of cost variables of natural gas prices and RECLAIM pollution permit prices.

e) Sample is daily observations in SDG&E from April 1, 1998, to December 31, 2000, and has 997 observations.

Table III

Difference-in-Differences Demand Response Effects
Dependent variable: Daily average hourly demand (kWh) per consumer by region.

Intervention variables	Control Effect (ψ_i)	Treatment Effect (φ_i)
June, 2000	0.042 (0.034)	0.013 (0.038)
July	0.026 (0.038)	0.008 (0.048)
August	0.056* (0.026)	-0.113* (0.038)
September	0.067* (0.031)	-0.145* (0.039)
October	0.063* (0.022)	-0.089* (0.029)
November	0.007 (0.026)	0.005 (0.033)
December	-0.026 (0.039)	0.009 (0.051)

Other variables	LADWP	SCE	SDG&E
Unemployment rate	0.076 (1.369)	-2.760 (2.888)	-4.971* (1.227)
Labor force per customer	0.532* (0.041)	2.434* (0.730)	1.330* (0.290)
Housing starts (per 1000 customers)	0.012 (0.015)	0.111* (0.049)	0.001 (0.012)

Notes:

a) Table presents OLS coefficients. Standard errors are in parentheses and have been corrected for serial correlation and heteroskedasticity using the Newey-West correction assuming a seven-day lag structure.
b) We denote significance at the 5% level with (*).
c) The regression includes month-year fixed effects for July 1999 through December 2000. All regressors in note c of Table 2 are allowed to vary by region.
d) The sample size is 4,368 (daily observations in three regions from 1997 to 2000).
e) The control effect corresponds to the overall effect in all regions: SDG&E, LADWP, and SCE. The 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 hourly demand grew 0.042 kWh per customer in the control regions while the treatment region demand increased by 0.013 *relative* to the control regions; the overall effect in SDG&E is the sum: 0.055.