Electricity Pricing to U.S. Manufacturing Plants, 1963-2000

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Abstract

We construct a large customer-level database to study electricity pricing to U.S. manufacturing plants. We document tremendous dispersion in price paid per kWh and trace the dispersion to quantity discounts and spatial differentials. Quantity discounts diminish through the late 1970s and then stabilize. Spatial price dispersion declines markedly until the late 1980s for large purchasers, but it rises in the lower deciles of the purchases distribution.

We also develop a new method to estimate how electricity supply costs vary with customer purchase quantity in the cross section. The method exploits large differences among utilities in the size distribution of customer purchase quantities. Estimated supply costs per kWh fall by more than half in moving from smaller to bigger purchasers, providing a strong cost-based rationale for quantity discounts.

Finally, we combine the price measurements and cost estimates to test a key implication of efficient pricing in the cross section of customers. Before the mid 1970s, marginal price and marginal cost schedules with respect to customer purchase quantity are nearly identical, as required by efficient pricing. In later years, there is some evidence that marginal supply costs exceed marginal prices for smaller customers.

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1. Introduction

Longstanding concerns and recent developments have combined to intensify interest in the performance of the U.S. electric power industry. These include persistent regional disparities in retail prices, growth in wholesale power markets, a wave of restructuring and deregulation initiatives in the 1990s, difficulties in the transition to a more competitive electricity sector, and, perhaps most spectacularly, the California electricity crisis of 2000-2001. Despite these concerns and developments, there are few broad empirical studies of electricity prices paid by end users, and there are major gaps in our knowledge of retail pricing patterns and their evolution over time. These gaps hamper efforts to place recent developments in historical perspective, to evaluate the impact of regulatory changes on electricity users, and to assess theories of electricity pricing.

To help address these issues, we construct a rich micro database – Prices and Quantities of Electricity in Manufacturing (PQEM) – and use it to study electricity pricing to U.S. manufacturing plants from 1963 to 2000. The PQEM includes data on electricity expenditures, purchases (watt-hours) and other variables for more than 48,000 manufacturing plants per year, linked to additional data on the utilities that supply electricity. Our customer-level data are limited to manufacturers, but they are informative about pricing practices for a broader class that includes other industrial customers and large and mid-size commercial customers.

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1 Hirsh (1999), EIA (2000), Besanko et al. (2001), Borenstein (2002), and Joskow (2005), among others, describe and analyze these matters.
2 We inspected electricity tariffs for several utilities and found that they offered the same menu of pricing terms to manufacturers, other industrial customers, and large and mid-size commercial customers. In addition, average electricity prices behave similarly for the manufacturing sector and the industrial sector as a whole, as we show below. Industrial purchasers account for 45% of retail electricity sales (watt-hours) in 1963 and 31% in 2000 (EIA, 2003a, Table 8.5). Manufacturing accounts for the lion’s share of electricity purchases by the industrial sector.
Figure 1 displays several measures of dispersion in the distribution of log electricity prices from 1963 to 2000. The price measure is the ratio of the plant’s annual expenditures on purchased electricity to its annual purchases (watt-hours). The figure shows purchase-weighted and shipments-weighted price distributions, where the former weights each customer-level observation by watt-hours of electricity purchases, and the latter weights by its shipments. As seen in Figure 1, there is tremendous dispersion in the price per kWh paid by manufacturing plants. The purchase-weighted standard deviation exceeds 38% in all years and reaches 55% in some years. By way of comparison, the hours-weighted standard deviation of log hourly production worker wages among manufacturing plants in the PQEM ranges from 39% to 43% between 1975 and 1993. In other words, the dispersion in electricity prices among manufacturing plants is at least as great as the dispersion in their average hourly wages.

Figure 1 also reveals that the log price distribution underwent a large compression from 1967 to the late 1970s. The between-plant standard deviation fell from 55% in 1967 to 44% in 1979 on a purchase-weighted basis and from 47% to 35% on a shipments-weighted basis. Over the same time frame, the 90-10 price differential shrank by about 37 log points under both weighting methods. The 90-10 differential later widened but never returned to the peaks of the 1960s. To the best of our knowledge, we are the first to quantify the remarkable extent of electricity price dispersion for a major end-user group and the first to document the price compression that played out by the late 1970s.

3 The natural log transformation is convenient for characterizing the magnitude of price dispersion. In addition, electricity transmission over power lines and the process of transforming voltage levels involve costs in the form of electrical energy dissipated as heat energy. The dissipation of electrical energy rises with transmission distance, other things equal, so that spatial price differentials are aptly described in log terms. For these reasons, we often consider log price differentials in this paper, but we also consider prices measured in natural units.

4 These weighting methods mirror the use of input-weighted and output-weighted distributions in plant-level studies of productivity growth. Examples include Foster et al. (2001) and van Biesebroeck (2004).


6 The temporary widening of dispersion in the mid 1970s reflects the 1973-74 oil price shock and differences among state public utility commissions in how rapidly they moved to approve higher electricity tariffs. In later years, automatic fuel price adjustment clauses came into widespread use in tariff schedules for industrial customers.
We show below that this compression episode reflects a sharp erosion of quantity discounts. On a purchase-weighted basis, the cross-sectional average elasticity of price with respect to annual purchase quantity shrank from -22% in 1967 to about -9% in the late 1970s, partially recovering after the mid 1980s. Because the range of electricity purchases among manufacturers is enormous, these elasticities translate into very large price differentials. For example, prices for the biggest purchasers were two-thirds below the median price in the 1960s. Plant-level differences in purchase amounts account for 75% of overall price dispersion among manufacturers in 1963 but only 30% by 1978.

Quantity discounts in the form of declining-block tariffs are a well-known feature of retail electricity pricing for industrial and commercial customers and a sometimes contentious topic in ratemaking proceedings and legislative hearings. They are also the object of careful analysis in theoretical treatments of nonlinear pricing (e.g., Wilson, 1993) and public utility pricing in particular (e.g., Brown and Sibley, 1986). Insofar as the cost of supplying electric power declines with a customer’s purchase quantity, an efficient two-part tariff or other marginal-cost pricing scheme requires quantity discounts. If demand is also more elastic at higher purchase levels, Ramsey pricing by a revenue-constrained utility entails lower markups for bigger customers and, hence, is another potential explanation for quantity discounts.

These cost and demand determinants of quantity discounts are well understood as a matter of theory, but their importance in practice is unclear. Brown and Sibley (1986) and Borenstein and Holland (2003), for example, argue that the approach to rate setting by electric utilities and their regulators, and the resulting tariff schedules, do not seem well designed to

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7 Cudahy and Malko (1976) discuss quantity discounts and other aspects of rate design from the perspective of public utility regulators in a prominent case involving the Madison Gas & Electric Company. Hirsh (1999) recounts the political struggles over federal legislative efforts to reform rate-making practices, efforts that culminated in the Public Utilities Regulatory Policies Act (PURPA) of 1978, a major component of President Carter’s National Energy Plan.
achieve efficient pricing. Moreover, previous research offers no quantitative, theoretically grounded explanation for the magnitude of quantity discounts. To address these matters, we develop a novel method for estimating the contribution of cost factors to quantity discounts. In particular, we exploit the considerable variation across electric utilities in the size distribution of customer purchases to estimate how supply costs per watt-hour vary with customer purchase quantities in the cross section. The results reveal that supply costs fall by more than half in moving from smaller to bigger purchasers. This pattern holds throughout the past four decades, providing a strong cost-based rationale for quantity discounts.

To test a key implication of pricing efficiency, we ask whether the marginal price schedule with respect to customer purchase quantity coincides with the corresponding marginal cost schedule. This is a demanding requirement in our context, because the range of customer purchases in the data is enormous. As it turns out, the evidence is highly consistent with marginal cost pricing in the early years of our sample. Indeed, marginal price schedules are nearly identical to marginal cost schedules before the mid 1970s. In the upper half of the customer purchase distribution, they are nearly identical from 1967 to 2000. Among smaller manufacturing customers, however, estimated marginal supply costs exceed marginal prices by 10% or more after 1980. Perhaps surprisingly, we find no support for the standard Ramsey pricing view that quantity discounts partly reflect smaller markups for more elastic demanders.

We also consider the dispersion in average electricity prices among counties and utilities. Spatial price differentials are large, and they display three interesting and somewhat surprising time-series patterns. First, in the lower deciles of the purchases distribution, spatial price

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8 Although pricing efficiency on the customer purchase quantity margin has received much careful theoretical attention – e.g., Goldman et al. (1984), Brown and Sibley (1986), and Wilson (1993) – we are unaware of any previous study that tests the implication. The biggest barrier to testing has been the inability to quantify how supply costs vary with customer purchase quantity. As we discuss below, there is a small empirical literature that tests other aspects of retail pricing efficiency in the electric power industry.
dispersion widened over time. Second, and in sharp contrast, spatial price dispersion in the top decile of the purchases distribution fell sharply from the 1960s to the late 1980s. Third, in the 1990s – when wholesale power markets grew rapidly – spatial price dispersion at the retail level did not diminish and even rose modestly over much of the purchases distribution.

The next section describes the PQEM database. Section 3 quantifies the dispersion of electricity prices between and within industries, counties, utilities, and purchase size classes. Section 4 discusses cost and demand influences on electricity pricing, describes key features of electricity tariffs, and develops evidence on electricity price-quantity schedules and their evolution over time. Section 5 develops and implements a method to estimate supply costs as a function of customer purchase levels. Section 6 investigates whether marginal price schedules comport with efficient pricing and Ramsey pricing. The concluding section summarizes our main findings and identifies some directions for future research.

2. The PQEM Database

The PQEM database derives principally from the U.S. Census Bureau’s Annual Survey of Manufactures (ASM) and various files produced by the Energy Information Administration (EIA). We draw our data on electricity prices and quantities and other variables for individual manufacturing plants from ASM micro files for 1963, 1967, and 1972-2000. The ASM is a series of nationally representative, five-year panels refreshed by births as a panel ages. Large manufacturing plants with at least 250 employees are sampled with certainty, and smaller plants with at least 5 employees are sampled randomly with probabilities that increase with the number of employees.\(^9\) ASM plants account for about one-sixth of all manufacturing plants and about

\(^9\) The number of employees required to be a certainty case is lower in 1963 and 1967. In 1963, all plants in a multi-plant firm with 100 or more employees were sampled with certainty. The same was true in 1967 except for plants in apparel (SIC 23) and printing and publishing (SIC 27), which had certainty thresholds of 250 employees.
three-quarters of manufacturing employment. Our statistics make use of ASM sample weights, so that our results are nationally representative.

ASM plants report expenditures for purchased electricity during the calendar year and annual purchases (kWh). As mentioned above, we calculate the plant-level price as expenditures on purchased electricity divided by quantity purchased. The ASM includes street address and county and state codes, which are helpful in assigning manufacturing plants to electricity suppliers. As described in a companion paper (Davis et al., 2007b), we identified and resolved several issues with ASM electricity price and quantity measures in the course of preparing this study. We also checked the ASM data against the Manufacturing Energy Consumption Survey, another plant-level data source at the U.S. Census Bureau that relies on a different survey.

We linked ASM plants to their electricity suppliers using several sources of information. The Annual Electric Utility Reports, also known as the EIA-861 files, include each utility’s revenue from sales to industrial customers (by state) and a list of the counties in which the utility has industrial customers. The EIA-861 files provide an immediate match to the utility for plants in counties served by a single utility. For many states, we are able to supplement the EIA-861 files with Geographic Information System (GIS) maps, a list of zip codes served by each utility or printed maps showing utility service territories. These supplemental sources of information enable us to construct accurate matches for counties served by more than one utility. We have supplemental geographic information for 18 states, accounting for 49% of electricity purchases and 54% of manufacturing shipments. For plants in states without this type of information, we created a “best match” utility indicator using the method described in the web appendix.
We also exploit publicly available information on the identity of plants that purchase electricity directly from the six largest public power authorities.\textsuperscript{10} Direct purchasers from public power authorities typically consume large quantities of electricity, and they often accept high-voltage power, operate their own transformers, and obtain electric power at heavily discounted rates. While few in number, these direct purchasers account for a large fraction of electricity purchases in some counties, and they constitute a distinct segment of the retail electricity market. We identified between 56 and 93 direct purchasers from public power authorities per year.

Finally, we incorporated the State Energy Data 2000 files into the PQEM.\textsuperscript{11} These files include annual data on fuel sources used for electricity generation by state from 1960 to 2000. We construct annual state-level fuel shares in electric power generation for the following five categories: coal, petroleum and natural gas, hydropower, nuclear power, and other (includes geothermal, wind, wood and waste, photovoltaic, and solar).

Table 1 reports selected characteristics of the PQEM. The database contains more than 1.8 million plant-level observations over the period from 1963 to 2000. There are 3,031 counties with manufacturing plants and 697 utilities, counting multi-state utilities once for each state in which they sell to industrial customers. The table shows that electricity purchases and cost shares vary enormously across manufacturing plants. For example, the 90\textsuperscript{th} quantile of the purchases distribution is 381 times the 10\textsuperscript{th} quantile on a shipments-weighted basis and 739 times on a purchase-weighted basis. The median ratio of electricity costs to labor costs is 4.7\% on a shipments-weighted basis and 17.2\% on a purchase-weighted basis. While electricity costs are a

\textsuperscript{10} They are the Tennessee Valley Authority, Bonneville Power Administration, Santee Cooper, New York Power Authority, Grand River Dam Authority, and Colorado River Commission of Nevada. Fourteen public power authorities supplied electricity directly to industrial customers in 2000, but the six largest accounted for nearly 98\% of the revenues from direct sales to industrial customers (EIA-861 file).

\textsuperscript{11} This data is from the State Energy Data System (SEDS) on the Energy Information Administration Internet site, http://www.eia.doe.gov.
modest percentage of labor costs for most plants, they exceed 62% of labor costs in the top quartile and 200% in the top decile.

3. Electricity Price Dispersion

After trending down for nearly a century, real electricity prices began to rise after 1973. They continued to rise for about ten years, before resuming the historical pattern of steady declines. See Figure 2, which shows that these broad trends held for all major end-user groups.\(^\text{12}\) We discuss the market, technological, regulatory and other factors behind these broad trends in Davis et al. (2007a). Here, we focus on price dispersion among manufacturing customers.

To decompose the variance of log electricity prices into within-group and between-group components (industry, region, etc.), write the overall variance as

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V = \sum_{e} s_e (p_e - \bar{p})^2 = \sum_{g} \sum_{eg} s_e (p_e - \bar{p})^2
\]

\[
V = \sum_{g} s_g \left( \sum_{eg} s_e (p_e - \bar{p}_g)^2 \right) + \sum_{g} s_g (\bar{p}_g - \bar{p})^2
\]

\[
V = \sum_{g} s_g V^W_g + V^B = V^W + V^B
\]

where \(p_e\) is the log price for plant \(e\), \(s_e\) is the weight, \(\bar{p}\) is the overall weighted mean log price, \(\bar{p}_g\) is the weighted mean log price for group \(g\), \(s_g = \sum_{eg} s_e\) is the sum of weights for plants in group \(g\), \(V^W_g\) is the weighted variance within \(g\), and \(V^B\) is the between-group variance. Table 2 reports shipments-weighted and purchase-weighted versions of (1) for selected years, with \(s_e\) set to the product of the plant’s ASM sample weight and its shipments or purchases value.

\(^{12}\) The electricity price series in Figure 2 for the residential, commercial and industrial sectors are from the Energy Information Administration (EIA), and the two series for the manufacturing sector are constructed from the PQEM. The EIA data rely on reports from electric utilities, and the PQEM data rely on reports from electricity customers (manufacturing plants). EIA prices are calculated as revenue from retail electricity sales divided by kilowatt hours delivered to retail customers. Real prices are calculated using the BEA implicit price deflator for GDP (1996 = 100). In the EIA data, the industrial sector encompasses manufacturing, mining, construction and agriculture.
According to Table 2, the shipments-weighted standard deviation of log electricity prices across manufacturing plants stood at 47% in 1967, fell sharply to 37% by 1977, and then changed little over the next 23 years. Price dispersion also fell sharply on a purchase-weighted basis, from 55% in 1967 to 43% in 1977 and then further in the 1990s to stand at 38% in 2000. Following a similar path, the between-industry dispersion of electricity prices fell rapidly through 1982 and to even lower levels in the 1990s on a purchase-weighted basis. All told, the purchase-weighted dispersion of industry prices fell by almost half over the past four decades.

Table 2 also documents several other facts. First, spatial price differentials are large. County effects, for example, never account for less than 65% of the overall price variance on a purchase-weighted basis. Second, customer groups defined by electricity purchase quantities also account for a high percentage of overall price dispersion, especially in the 1960s. Price dispersion among purchase centiles fell by nearly half during our sample period, mostly between 1967 and 1977. Third, purchase level and utility jointly account for a high percentage of price dispersion throughout the past four decades. Groups defined by utility crossed with purchase centile account for 85-95% of the purchase-weighted variance.

Trends in spatial price dispersion show a complex pattern. For example, the purchase-weighted between-county standard deviation fell by nearly one-third from 1963 to 2000, while the analogous shipments-weighted measure rose by one-fifth. Closer examination reveals that spatial dispersion fell in the top decile of the purchases distribution (more heavily weighted in purchase-weighted analyses), but it rose in the lowest deciles (more heavily weighted in shipments-weighted analyses). We highlight this pattern in Figure 3, which shows the evolution of spatial price dispersion for three selected deciles. To control for purchase quantity within deciles, Figure 3 uses residuals from annual customer-level regressions of log price on a polynomial in log purchases. As seen in Figure 3, there is an enormous decline from the late
1960 to the late 1980s in spatial dispersion within Decile 10 (comprising the biggest purchasers). A similar, but more muted, pattern holds for Decile 9. The middle deciles exhibit little trend change in spatial dispersion, as illustrated by Decile 6. The lower deciles exhibit trend increases in spatial dispersion, as illustrated by Decile 1. Another noteworthy pattern highlighted by Figure 3 is the lack of a downward trend in spatial price dispersion during the 1990s, when wholesale power markets grew rapidly. Sales of electricity for resale rose from 41% of generated power in 1991 to 61% in 2000 (EIA, 2003b, Tables ES and 6.2).

We summarize the empirical findings to this point in three statements. One, there is tremendous dispersion among manufacturing plants in price paid per kWh. Two, the plant-level distribution of electricity prices underwent a large compression through the late 1970s. Three, readily observed plant characteristics such as utility and customer purchase quantity capture most of the cross-sectional price variation. The rest of the paper more fully explores the role of utility characteristics and customer purchase quantity in electricity pricing and supply costs.

4. Electricity Price-Quantity Schedules

4.1 Cost and Demand Influences on the Electricity Price-Quantity Relationship

Supply costs per kWh of electricity tend to be lower for larger industrial and commercial customers for several reasons. Large purchasers are more likely to locate near generating facilities to minimize transmission losses. High-voltage transmission lines can lead all the way to the customer’s doorstep, further reducing transmission costs. A large power user is also more likely to operate equipment at high voltage levels, circumventing or reducing the need for step-down transformers and complex distribution networks. Large power users may operate and maintain their own step-down transformers as well, relieving the utility of this task and associated costs. Larger electricity customers also have stronger incentives to respond to pricing structures that discourage volatile consumption patterns and peak-period consumption. In turn,
these incentive responses economize on generating and transmission facilities and mute the
effect of system-wide demand fluctuations on generating costs. Similarly, larger customers have
stronger incentives to consider provisions for interruptible and curtailable power as a means of
lowering electricity costs. These customer supply characteristics provide a cost basis for quantity
discounts in electricity pricing.

Customer demand characteristics also lead to quantity discounts under plausible
conditions. Ramsey pricing logic suggests that a utility should price at a smaller markup over the
cost of supply for more price-sensitive customers. If demand is more price-elastic for
manufacturing plants that use more electric power, then the Ramsey logic translates into prices
that decline with customer purchase quantity.\(^\text{13}\) Of course, customer supply costs and customer
demand characteristics can contribute to quantity discounts at the same time.

4.2 Electricity Tariffs for Industrial Customers

Electricity tariffs for industrial customers usually include separate energy and “demand”
charges.\(^\text{14}\) The energy charge depends on total kilowatt-hours of consumption during the billing
period, and the demand charge depends on the highest consumption over 15- or 30-minute
intervals within the billing period or longer time period. Roughly speaking, the demand charge
reflects the customer’s maximal requirements for power. By discouraging uneven and erratic
patterns of power consumption, the separate demand charge economizes on the need for
generating, transmission and transformer facilities. Eligibility for the most favorable tariff
schedules is usually limited to large customers who make long term commitments to minimum
contract demand levels that place a high floor on monthly charges.

\(13\) We state the Ramey pricing condition precisely and provide a fuller discussion in Section 6 below.
\(14\) See Cowern (2001) for a concise introduction to electricity tariffs for industrial customers. Caywood (1972)
provides a detailed description of electricity tariffs and rate-setting practices.
Traditionally, electric utilities have offered declining-block rate schedules, whereby the marginal price per kWh of energy and the marginal price per kW of demand decline as step functions (Caywood, 1972). For bigger purchasers, in particular, electricity tariffs also depend on other factors such as voltage level and willingness to accept power interruptions or curtailments. Differential rates by time of day and other applications of peak-load pricing principles came into wider use after the mid 1970s (ELR, 1975, and Cudahy and Malko, 1976). Moves toward more finely differentiated tariff schedules for industrial customers continued through at least the late 1980s (Wilson, 1993, pages 36-38). The California Electricity Crisis of 2000-2001 intensified interest in retail pricing structures (Borenstein and Holland, 2003).

As an illustration, Table 3 summarizes the menu of electricity tariff schedules offered to industrial customers by Santee Cooper Power.\textsuperscript{15} There are three main charges: a monthly customer charge, monthly demand charges, and monthly energy charges. Larger customers face smaller energy charges per kWh and smaller demand charges per kW but higher monthly minimum charges. For example, the Medium General Service schedule offers an energy charge of 2.6¢ per kWh, a demand charge of $11.85 per kW, and a minimum monthly payment of $29. The Large Power and Light schedule offers a lower energy charge of 2.19¢ per kWh and a lower demand charge of $10.76 per kW, but a much higher minimum monthly payment of $11,960.\textsuperscript{16} Large Santee Cooper customers who locate near transmission lines and provide their own transformers receive discounts of roughly 4% on demand charges. Optional riders to the Large Power and Light schedule offer big discounts on demand charges for off-peak power and power subject to curtailment or interruption. The Large Power and Light schedule and its optional riders

\textsuperscript{15} Santee Cooper is also known as the South Carolina Public Service Authority. Among utilities with positive industrial revenue, Santee Cooper is close to average size with industrial sales of $238 million in 2000. The Santee Cooper schedules reflected in Table 3 are in effect as of July 2004 and date back to 1996. They are available for download at http://www.santeecooper.com/.

\textsuperscript{16} This monthly minimum holds for a customer who contracts for at least 1,000 kW of firm power. Lower minimum charges are available to customers who accept interruptible or curtailable power.
require a five-year customer commitment to a contract demand level of at least 1,000 kW and the implied demand charges. These basic features of the Santee Cooper tariff schedules are similar to the tariff menu offered to industrial customers by Pacific Gas & Electric in 1988, as described in Wilson (1993), and to the illustrative tariff schedule for industrial customers reported by Caywood in the 1956 and 1972 editions of Electric Utility Rate Economics.

The PQEM reports the average price per kWh paid by a plant in the calendar year; it does not capture the full complexity of the underlying electricity tariff schedules. In this respect, the PQEM is analogous to individual and establishment-level data sets that report hourly wages and hours worked but not the details of underlying compensation arrangements. To be sure, the lack of data on the underlying tariff schedules (or compensation terms) is a limitation, but it does not preclude an informative analysis. Despite the complexity of compensation arrangements, there is a vast body of informative research on wage structure and labor demand that fruitfully exploits relatively simple data on wage rates for individual workers and employers. Our empirical analysis of the retail pricing structure for electricity proceeds in the same spirit.

4.3 Empirical Price-Quantity Schedules

We now present evidence on empirical price-quantity schedules for electric power. When a plant operates for only part of the calendar year, the PQEM measure of kWh purchases does not accurately indicate where the plant fits into the purchases distribution. For this reason, we henceforth exclude part-year observations. We also exclude observations that display extreme seasonality or within-year variation in production activity. Customers with highly variable loads typically face special tariff schedules with higher charges.18

17 Specifically, we exclude observations for which the number of production workers in any single quarter is less than 5 percent of the annual average number of production workers. These observations represent less than 2 percent of shipments and electricity purchases in each year.

18 For example, Santee Cooper tariff schedule TP for temporary service (e.g., ballpark lighting) specifies a flat rate of 7.23¢ per kWh. Schedule GV for Seasonal General Service specifies energy charges of 2.34¢ per kWh and demand charges of $14.35 per kW.
Figure 4 displays empirical price-quantity schedules for selected years. Each curve shows the fit from a customer-level regression of log price on a fifth-order polynomial in the log of annual purchases. We run the regressions separately by year, weighting each observation by its shipments value and ASM sample weight. The regression fits show a dramatic flattening of the price-quantity schedule between 1967 and 1978. The fitted price differential between the 25th and 75th quantiles of the purchase distribution shrinks from 46 log points in 1967 to 26 log points in 1978, and the gap between the 5th and 95th quantiles shrinks from 103 to 51 log points. In short, there was a remarkable erosion of quantity discounts between 1967 and the late 1970s. As we show shortly, the extent of quantity discounts was relatively stable after the late 1970s.

4.4 Spatial Sorting of Production Activity

If bigger purchasers locate in areas with cheaper electricity, the pooled data will show a negative relationship between price and purchase quantity even if all utilities offer flat price-quantity schedules. More generally, any tendency by bigger purchasers to buy from utilities with cheaper electricity contributes to a negative price-quantity relationship in the pooled data. To investigate this issue, we fit two plant-level regressions of log price on a fifth-order polynomial in log purchases for each year. One regression specification includes utility fixed effects to control for the identity of the plant’s electricity supplier, and the other specification omits utility effects. We then use the fitted regressions to calculate the average elasticity of electricity price with respect to customers’ annual purchase levels. To isolate the role of spatial sorting, we compare the elasticity values calculated from regressions with and without utility fixed effects.

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19 We also considered nonparametric regression fits for the price-quantity schedule using the SAS GAM procedure (spline option, 100 degrees of freedom). Except at the extreme upper end of the purchase distribution, accounting for less than one percent of shipments, the nonparametric fits are highly similar to the fifth-order polynomial fits. Given this similarity and the much longer run times for the nonparametric fits, especially when we add covariates, we focus on polynomial fits throughout the paper. See the web appendix for a nonparametric description of how price per kWh varies with purchase quantity and how the price-quantity relationship evolves over time.

20 We also created analogs to Figure 4 for the five utilities with the largest number of customer-level observations (several hundred per year). All five utilities show the same basic pattern as in Figure 4.
Figure 5 shows the results. It confirms a dramatic flattening of price-quantity schedules through the late 1970s, and it conveniently summarizes the magnitude of quantity discounts. In the 1960s, the average price-quantity elasticity is -22% on a purchase-weighted basis, and it ranges from -12% to -14% on a shipments-weighted basis. The inclusion of utility fixed effects has only a modest impact on the elasticity values prior to 1974. Thus, in the early part of our sample period the huge purchase-level price differentials in Figure 4 overwhelmingly reflect within-utility price variation, not spatial sorting by customers. Spatial sorting plays a bigger role after 1973, especially on a purchase-weighted basis. Evidently, the onset of rising real electricity prices in 1973 (Figure 2) encouraged the migration of electricity-intensive manufacturing activity to areas served by utilities with cheaper electricity. The bigger role for spatial sorting on a purchase-weighted basis suggests that bigger purchasers are more sensitive to spatial price differences in their choice of location.

Even though spatial sorting plays a larger role after 1973, it is important to emphasize that the two main patterns in Figure 4 are robust to controlling for utility fixed effects. That is, utilities charge much less per kWh to customers that purchase more power, and there was a substantial erosion of quantity discounts through the late 1970s. The web appendix provides additional evidence of these two strong patterns in the data.

4.5 Other Behavioral Responses by Customers

In addition to location choice, other behavioral responses by customers influence the empirical price-quantity schedule. Bigger purchasers have greater opportunity and incentive to reduce price paid per kWh by managing load factors (ratio of average to peak demand), taking high-voltage power, responding to peak-load pricing incentives, and accepting curtailable or interruptible power. In the web appendix, we provide evidence that these behavioral responses account for much of the negative relationship between price per kWh and annual purchase
quantity documented in Figures 4 and 5. Specifically, we compare the price-quantity schedule for firm power implied by the Santee-Cooper tariff menu to the empirical price-quantity schedule. In tracing out the implied Santee-Cooper schedule, we fix the customer load factor and exclude discounts for off-peak or high-voltage power. In this way, we foreclose quantity discounts that arise from behavioral responses and isolate a “built-in”, mechanical customer size effect. By comparing the implied and fitted price-quantity schedules, it is apparent that both sources of quantity discounts are important features of the data. Mechanical discounts are important in the lower and middle part of the customer size distribution, and discounts associated with behavioral responses are important in the upper half. These behavioral responses contribute to lower supply costs per kWh for larger customers. We turn next to a method for quantifying the relationship between supply costs per kWh and customer purchase quantity.

5. Customer Purchase Quantity and Electricity Supply Costs

5.1 A Method for Estimating Supply Costs as a Function of Purchase Amount

We now develop a method for estimating supply costs as a function of customer purchase quantity. The method exploits the cross-sectional richness of the PQEM and, to the best of our knowledge, offers a new approach to the estimation of customer supply cost schedules. To be clear, it is not our aim to estimate how supply costs vary with power generation at the level of a region, utility or generating facility. Rather, we seek to estimate how supply costs vary with customer purchase quantity in the cross section.

Our method involves three main steps. Step one uses customer-level data on purchase quantities to calculate utility-level statistics for the location and shape of the purchase distribution. Step two exploits the utility’s revenue constraint to obtain average cost per kWh from data on average price per kWh. Step three uses cross-utility variation in the purchase distribution to estimate how costs per kWh of delivered electricity vary with customers’ annual
purchases. By explicitly treating the aggregation from customers to utilities, we can infer the supply cost schedule from the results in the third step. We carry out step three using regression methods to control for other factors that affect supply costs. The chief concern in this respect are factors that affect supply costs and are correlated in the cross section of utilities with the customer size distribution. We now develop the method in detail.

A portion of a utility’s costs is common to all customers, and the remaining portion can be allocated to particular customers. Let $\theta_g$ be the common cost per kWh at utility $g$. Write the allocable portion of costs per kWh for customer $e$ that purchases $q_e$ as $C_g(q_e) + k_e$, where the first term captures cost differences that vary systematically by purchase level and the second term captures idiosyncratic supply cost differences unrelated to purchase level. By construction, $\sum s_e k_e = 0$, where $s_e$ is the share of purchases from utility $g$ by plant $e$. Thus, letting $TC$ denote total cost, we can write the average cost per kWh at utility $g$ as

$$AC_g \equiv \frac{TC_g}{\sum_{eeg} q_e} = \theta_g + \sum_{eeg} s_e C_g(q_e)$$

(2)

The revenue constraint says that a utility’s average cost per kWh (inclusive of profit and payments to capital) equals its average price per kWh. Imposing this requirement in (2) yields

$$P_g = \theta_g + \sum_{eeg} s_e C_g(q_e) + \nu^p_g$$

(3)

where $P_g$ is the purchase-weighted mean price per kWh at utility $g$, and $\nu^p_g$ is an error term introduced by sampling variation in $P_g$ as well as non-sampling error discussed in more detail below. We do not directly observe the utility’s average price per kWh in the PQEM, but we can estimate it using the price and quantity observations on the utility’s manufacturing customers.
To obtain an estimable specification from (3), we adopt three assumptions. First, we postulate that the \( C_g(q) \) functions are the same for all \( g \) up to a utility-specific additive term; i.e., \( C_g(q) = C(q) + \alpha_g \). Second, we approximate \( C(q) \) as a polynomial in \( \log (q) \). Third, we model the sum of the utility’s additive and common cost components as a function of observable utility characteristics \( X \); namely, \( \alpha_g + \theta_g = X_g b + u_g \). Applying these assumptions to (3) yields an estimating equation with four error components:

\[
P_g = X_g b + \sum_{n=1}^{N} \gamma_n \sum_{e \in g} s_e \left[ \log (q_e) \right]^n + u_g + \gamma^p + \gamma^q + \xi_g
\]

where \( N \) is the order of approximation to the \( C \) function, \( \sum_{e \in g} s_e \left[ \log (q_e) \right]^n \) is the \( n \)th uncentered sample moment of the log purchase distribution at \( g \), and the \( \gamma \)'s are the key parameters of interest for the supply cost schedule. The error component \( \gamma^p \) arises from sampling variation in the moments of the purchase distribution, and \( \gamma^q \) arises from the polynomial approximation to \( C \). Though not our main focus, the \( b \) parameters are also interesting, because they provide information about how average costs per kWh vary with utility characteristics when we control for the size distribution of customer purchases.

We estimate (4) by weighted least squares (WLS) and weighted instrumental variables (IV) regression. We then use the \( \gamma \) estimates to trace out the supply cost schedule as a function of customer purchase quantity. Before turning to the results, a number of econometric issues require some discussion.

First, consider the error term \( u_g \) in (4) that arises from unobserved determinants of the additive and common costs. If these unobserved cost determinants vary systematically with the size distribution of customer purchases, they give rise to an omitted variables problem that biases
the estimates of $\gamma$. As a case in point, municipal and cooperatively owned utilities tend to serve smaller manufacturing customers. If these same utilities also have lower supply costs conditional on customer size, then the regression (4) understates the extent to which costs per kWh decline with purchase amount, unless we control for utility type. Hence, we include the utility’s organizational form in the $X$ vector, distinguishing among cooperative and municipal utilities, state and federal power authorities, and private investor-owned utilities. For similar reasons, we include controls for the size of the utility and for the shares of electric power generated from hydro, nuclear, coal, and petroleum and natural gas. A potential omitted variables problem also arises in connection with non-sampling components of the error term $\nu_g^P$ in (3) and (4). In particular, the revenue constraint might fail for manufacturing customers as a group because of cross-subsidization between classes of customers within the utility. Thus, we control for the fraction of the utility’s revenues derived from sales to industrial customers.

Second, the error term $\nu_g^q$ that arises from sampling variation in the moments of the purchase distribution creates a standard errors-in-variables problem. To address this potential source of bias, we exploit the fact that consecutive ASM panels are independently drawn from the universe of manufacturing plants. It follows that the sampling error in the purchase distribution statistics for utility $g$ at time $t$ is uncorrelated with the sampling error at $t + k$, provided that a new ASM panel has commenced between $t$ and $t + k$. Thus, we instrument the moments of the utility’s log ($q$) distribution with the corresponding statistics for the same utility calculated from a nearby year that draws on a different ASM sample.

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21 Davis et al. (2007b) display the distribution of mean log purchases by manufacturing customers for private investor owned utilities and the analogous distribution for municipal and cooperatively owned utilities. Their evidence confirms that average customer size is considerably smaller at municipal and cooperatively owned utilities. For $k=1$, we can construct instruments across ASM panels for 12 years. For $k=5$, we can construct instruments across ASM panels for all years. We tried both approaches.
Third, the number of annual customer-level observations per utility in the PQEM ranges widely from a small handful to hundreds. Hence, the sampling error components in (4) have a heteroscedastic structure. To improve the efficiency of our estimates, we weight each observation in the regression (4) by the square root of the number of manufacturing plants used to calculate the utility-level quantities. As a side benefit, this weighting method mitigates the errors-in-variable problem under least squares.

To summarize, we seek consistent estimates for the $\gamma$ parameters that approximate the cross-sectional supply cost schedule $C(q)$. To obtain consistent estimates from the regression (4), we must control for factors affecting average cost per kWh that are also correlated with the customer size distribution in the cross section of utilities. Our baseline specification controls for the utility’s organizational form, its size, its fraction of revenues from industrial customers, and power generation sources.

5.2 Supply Cost Schedule Estimation Results

Table 4 reports WLS regressions of the form (4) on the utility-level data. We approximate the supply cost schedule $C(q)$ as a third-order polynomial in $\log(q)$. We normalize the purchase-weighted mean price per kWh to 100 in each year, so that slope coefficients on the indicator variables reflect percentage differences from the omitted category. We report results for selected years to economize on space, but our discussion below draws on results for all years.

Municipal and cooperative utilities have lower estimated supply costs in the 1960s and early 1970s, after controlling for other factors, and their cost advantage over private investor-owned utilities re-emerges in the 1990s. Relative to coal-powered electricity generation, greater reliance on nuclear power yields higher supply costs; hydroelectric power yields lower supply costs until the 1990s; and petroleum and natural gas yield higher supply costs after the 1970s.
The estimated effects of power source are sizable. For example, the 1967 estimates imply that shifting 10% of power generation from coal to hydro involves a 3.6% reduction in cost per kWh.

Turning to our main focus, the moments of the customer purchase distribution are jointly significant at the 0.1% level in all years, strongly confirming the statistical significance of purchase quantity as a determinant of supply costs. Table 5 and Figure 6 report the estimated supply cost schedules. Figure 6 also shows a scatter of mean log customer purchases for each utility, $\bar{q}_{lg}$, plotted against the sum of the corresponding fitted cost value

$$\hat{P}_g = \left( \hat{\beta}' g \right) + \hat{\gamma}_1 \bar{q}_{lg} + \hat{\gamma}_2 \left( \bar{q}_{lg} \right)^2 + \hat{\gamma}_3 \left( \bar{q}_{lg} \right)^3$$

and the utility’s regression residual. As seen in Figure 6 and Table 5, supply costs per kWh fall by a factor of 2 or 3 or more over the range of purchases spanned by the utilities in our sample. This pattern holds in all years from 1963 to 2000. We re-estimated the supply cost regressions by IV using the approach described above, and obtained essentially the same findings. These results provide strong evidence of powerful, cost-based reasons for large quantity discounts in electricity pricing to industrial customers.

Despite the controls in our baseline specification, there could be other unobserved cost determinants that are correlated with the purchase size distribution of the utility. Spatial sorting by electricity-intensive manufacturing customers is a possible source of concern in this regard, given the results in Section 4.4. We have already controlled for power sources and other factors that potentially affect cost and drive location decision, but there could be other, omitted, cost factors as well. To the extent that spatial sorting in response to unobserved cost factors is a concern, it is most acute for the most electricity-intensive manufacturing plants. Thus, we re-estimated the supply cost relationships on a restricted sample that omits all customer-level observations for which electricity costs exceed twenty percent of the value of shipments. This
restricted sample yields results very similar to Table 5 and Figure 6, which suggests that spatial sorting by manufacturing plants is not a serious problem in our estimated supply cost schedules. We also computed the average elasticity of supply costs with respect to customer purchase quantity for each year and compared it to the average elasticity of price with respect to purchase quantity in Figure 5. The comparison yields two interesting results. First, the average cost elasticity is consistently somewhat larger in magnitude than the average price elasticity, indicating that (average) supply costs fall more rapidly with purchase quantity than (average) price per kWh. Second, longer term swings in the average cost elasticity closely mirror the swings in the average price elasticity seen in Figure 6. This time-series pattern reinforces the inference derived from the cross-sectional evidence that cost factors drive large quantity discounts in electricity pricing. We examine this issue more rigorously in the next section.

6. **Evaluating the Pricing Structure**

6.1 **Pricing Conditions on the Purchase Quantity Margin**

Consider a utility that prices electricity to maximize consumer surplus subject to the constraint that revenues equal costs. As shown by Goldman et al. (1984), Brown and Sibley (1986) and Wilson (1993), among others, the optimal nonlinear pricing schedule for successive increments of electricity satisfies the Ramsey pricing condition:

\[
\frac{M(q) - C(q;Q)}{M(q)} = \frac{-\alpha}{\eta[M(q),q]}, \text{ for all } q,
\]

(5)

where \(M(q)\) is the marginal price for the customer’s \(q\)th unit of electricity, \(C(q;Q)\) is the marginal cost of the \(q\)th unit when the utility’s total quantity supplied is \(Q\), \(\eta[M(q),q]\) is the elasticity of demand for the \(q\)th unit with respect to the marginal price, and the Ramsey number \(\alpha \in [0,1]\) is a constant chosen to satisfy the revenue constraint.
According to (5), the markup of price over marginal supply cost depends on the elasticity of demand when the revenue constraint binds ($\alpha > 0$). For example, if the revenue constraint binds and demand is more elastic at higher purchase quantities, then Ramsey pricing implies that the marginal price schedule declines more steeply with purchase quantity than the marginal cost schedule. If supply costs per kWh are the same for all customers, Ramsey pricing implies that $M(q)$ declines with $q$ when demand is more elastic for bigger purchasers.

Efficient pricing can be interpreted as a special case of Ramsey pricing when $\alpha = 0$. Pricing efficiency in the cross section of customers requires that the marginal price schedule for electric power be identical to the marginal supply cost schedule; i.e.,

$$M(q) = C(q;Q) \text{ for all } q,$$

where, as before, $q$ is the customer purchase quantity. Three observations about this marginal cost pricing condition are in order. First, as noted above, it is a special case of Ramsey pricing when $\alpha = 0$ in (5). Second, the marginal cost pricing condition (6) is consistent with competitive, regulated and monopolistic behavior. With respect to the latter, (6) says that a utility should exercise its monopoly power in ways that do not distort marginal prices by, for example, charging high monthly access fees while setting marginal prices to marginal supply costs. Third, in contrast to the general Ramsey pricing condition (5), the demand side of the market for electric power does not enter into the efficient pricing condition (6). Thus, we can test (6) without identifying the demand structure of the market. In other words, the relevant marginal

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23 The revenue constraint does not preclude marginal cost pricing, even for a utility with declining costs over the relevant range. For example, consider a two-part tariff with a fixed access fee for each customer and marginal price set to marginal cost. Set the access fees so that total revenues cover total costs. Then, provided that the access fees are not so high as to deter participation by any consumer who values (some) electricity at more than its marginal supply cost, this type of two-part tariff is fully efficient (Brown and Sibley, 1986). In this case, $\alpha = 0$ and the Ramsey pricing condition (5) reduces to the marginal cost pricing condition (6). When efficient pricing is infeasible, the Ramsey pricing condition (5) minimizes the allocative distortions induced by deviating from (6).

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price schedule in (6) is not a structural object derived from a demand curve. It is, instead, an empirical object that we can derive from the within-utility price-quantity schedule.

To evaluate whether and how closely the data conform to (6), we use the average within-utility price schedules fitted in Section 4 and the average supply cost schedules estimated in Section 5. We compute the corresponding marginal schedules and then test whether they satisfy (6). We should note one limitation of our approach at the outset: we cannot test whether (6) holds utility by utility because we rely on between-utility variation to estimate the cost schedules. Instead, we test whether (6) holds on average across all utilities or a subset of utilities.

Several previous empirical studies consider retail pricing efficiency in the electric power industry. Examples include Meyer and Leland (1980), Hayashi, Sevier and Trapani (1985) and Nelson, Roberts and Tromp (1987). However, these studies evaluate pricing differences across broad classes of customers – residential, industrial and commercial – from the vantage point of marginal cost pricing, Ramsey pricing, and rate of return regulation. They do not consider pricing efficiency on the purchase quantity margin. Indeed, we are unaware of any previous study that tests marginal cost or Ramsey pricing conditions on the purchase quantity margin, even though they receive much attention in theoretical works.24 See Brown and Sibley (1986) and Wilson (1993) and references therein. Our empirical assessment of pricing on the purchase quantity margin complements the well-developed theoretical literature on the topic.

6.2 Is Electricity Pricing Efficient on the Purchase Quantity Margin?

To facilitate an apples-to-apples comparison between price and cost schedules, we make two modest adjustments to the fitting of price-quantity schedules in Section 4. First, because we cannot identify the cost schedule outside the range of mean purchases in the utility-level data (except through functional form restrictions), we drop plant-level observations outside this range.

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24 Peltzman (1971) considers electricity pricing on the purchase quantity margin, but he lacks the cost data needed for an assessment of pricing efficiency.
Second, when we re-estimate the price-quantity schedules on the restricted sample, we regress price per unit (not logged) on a third order polynomial in log customer purchases so as to parallel the specification used to estimate the cost schedules. We also include utility fixed effects to isolate the (average) within-utility variation. The resulting price-quantity schedules (not shown) are very similar to ones in Figure 4.

Using the fitted price-quantity schedules, it is easy to calculate the corresponding marginal schedules. Let \( T(q) = qP(q) \) be the total tariff for a customer that purchases \( q \) kWh, where \( P(q) \) is the customer’s average price per kWh. We compute the marginal schedule as

\[
\hat{M}(q) = \hat{P}(q) + (q/\epsilon)\left[ \hat{P}(q+(\epsilon/2)) - \hat{P}(q-(\epsilon/2)) \right]
\]

where \( \hat{P}(q) \) is the fitted value of the price-quantity schedule at \( q \), and \( \epsilon \) is a small positive number. We follow the same approach in calculating marginal cost schedules from estimated supply cost schedules of the type displayed in Figure 6. That is, \( TC(q) = qAC(q) \) so we can derive \( MC(q) \) from the estimated \( AC(q) \) curves in Figure 6.

One challenge is the limited number of utilities with enough customer-level observations to reliably estimate the moments of the customer purchases distribution and average price per kWh; both are inputs to the estimation of cost schedules. To improve precision in this respect, we exploit the fact that each ASM panel is an independently drawn random sample. Specifically, we pool customer-level observations over year-pairs that straddle ASM panel changeovers before we construct the utility-level data.\(^{25}\) This pooling method yields more customer-level observations per utility and a larger number of usable utility-level observations, thereby improving estimation efficiency in the supply cost regressions. We estimate these regressions using the same specification and WLS method as before except for adding a year control.

\(^{25}\) We cannot use this method in 1967 but, fortunately, the ASM was considerably larger then, so we obtain roughly the same precision.
Figure 7 displays the marginal price and marginal cost schedules for selected years, along with bootstrapped standard error bands for the marginal cost schedules. (Standard errors for marginal prices are extremely small, and we ignore them in the discussion that follows.) The marginal price and cost schedules are remarkably similar in both 1967 and 1973/74, strongly confirming the central implication of pricing efficiency on the purchase quantity margin. After 1973/74, however, a gap opens between marginal cost and marginal price in the lower deciles of the purchases distribution. The gap is sizable, with marginal supply cost exceeding marginal price by 10% or more for smaller purchasers.

An interesting feature of Figure 7 is that shifts over time in the location and shape of the marginal price schedules largely mimic shifts in the marginal cost schedules, except for small purchasers after 1973/74. In Section 5, we noted the similarity of long-term swings in the mean elasticity of the average price per kWh and the mean elasticity of the average supply cost per kWh. These two sets of results suggest that much of the flattening of price-quantity schedules through the late 1970s was driven by factors that altered the relationship between customer supply costs and purchase quantity. Identifying the specific factors that drove the shifts in the customer supply cost schedules is beyond the scope of this study.

To construct a more powerful and formal test of the null hypothesis of pricing efficiency, we now pool the data over several years. We evaluate pricing efficiency in the “early years” 1963, 1967, 1973 and 1974 and the “recent years” 1988, 1993, 1998 and 1999. The early years predate the departures from pricing efficiency suggested by Figure 7, and the recent years postdate them. We selected these particular years because they involve eight independently drawn samples of manufacturing plants in the ASM and PQEM. In pooling the data over years, we introduce year controls that allow marginal costs to shift over time in a manner that is uniform with respect to purchase quantity.
Table 6 reports the pooled-sample estimates and bootstrapped standard errors for early and late years. The upper panel extends our previous pooling method for calculating utility-level statistics from customer-level observations. This method results in many customer-level observations per utility but only one observation per utility in the supply cost regression. Hence, the method relies exclusively on between-utility variation to estimate the cost schedules. The lower panel calculates utility-level statistics from customer-level data before pooling over years. This method results in fewer customer-level observations per utility but up to four observations per utility in the supply cost regression. The method combines between-utility variation and utility-level changes over time to estimate the cost schedules. When we calculate standard errors under this method, we assume that utility-level error terms in the supply cost regression are uncorrelated over time.

The two pooling methods yield a similar pattern of point estimates that show sizable departures from pricing efficiency in the later years for smaller customers. Marginal prices are roughly 10% below marginal costs at the 20th percentile of the purchase quantity distribution in the later years, and the difference is statistically significant at the 5 percent level. There is also weaker evidence of smaller departures in the same direction for smaller customers in the earlier years. In line with Figure 7, Table 6 yields no statistically significant evidence of departures from pricing efficiency in the middle and upper portions of the purchase quantity distribution.

We conducted three robustness exercises in connection with the results in Table 6. First, we recreated Table 6 for a sample that drops states with a program to restructure the retail electricity market, in the year of enactment and thereafter. California, Massachusetts, New Hampshire, New York, and Rhode Island enacted retail market restructuring in 1998. Five more states followed in 1999 (Arizona, Delaware, Illinois, New Jersey, Pennsylvania), and three more
followed in 2000 (Connecticut, Maryland, Maine).\textsuperscript{26} The Panel A results for this restricted sample are nearly identical to the ones shown in Table 6. The Panel B results are also similar, but there is no longer a statistically significant departure from marginal cost pricing at the 20th percentile of the customer size distribution.

Second, motivated by potential concerns about spatial sorting of production activity, as discussed in Section 5.2, we recreated Table 6 for a sample that excludes customers with electricity costs greater than 20\% of the value of shipments. This sample also produces results very similar to the full sample but with larger standard errors. We again find no evidence of departures from marginal cost pricing in the middle and upper parts of the purchase quantity distribution. At the 20\textsuperscript{th} percentile, the point estimates again yield a fairly large gap between marginal cost and marginal price in the later years – 0.64 cents per kWh in Panel A and 0.49 cents per kWh in Panel B. However, the gaps are no longer statistically significant.

Third, we investigated whether the results in Figure 7 and Table 6 were caused by inaccuracies in our assignments of customers to utilities. Recall that when a county is served by a single utility, we know the correct assignment of customer to utility from the EIA-861 files. We also know the correct assignment with near certainty in those states with detailed GIS data on utility service territories. We used the detailed GIS information for certain states to estimate how the cruder information available in other states affects the probability of an accurate assignment. Our method, detailed in Davis et al. (2007b), yields an estimated probability of an accurate assignment for each customer and an estimated rate of correct assignments for each utility. In the full sample that underlies Table 6 and Figure 7, we estimate that at least 67\% of customers are assigned to the correct utility.\textsuperscript{27} To construct a restricted sample, we discarded customers with

\textsuperscript{26} These dates are from Joskow (2005), who also discusses the changes involved in retail restructuring.

\textsuperscript{27} The estimated accuracy rate is calculated in a shipments-weighted manner. The actual accuracy rate is probably higher than the 67\% figure, because the figure does not account for the hand-adjusted assignments that we made.
low probabilities of an accurate assignment and discarded utilities with low accuracy rates. The restricted sample has an estimated match accuracy rate of at least 88 percent. The number of utility-level observations available for the Table 6 analysis in the restricted sample is about 70% smaller than before for Panel A and about 45% smaller for Panel B.

The Table 6 results for this restricted sample are also very similar to the full sample results, except that standard errors are bigger. As before, there is no evidence of departures from marginal cost pricing in the middle or upper parts of the purchase quantity distribution. Under the pooling method of Panel A, the point estimate for marginal cost minus marginal price at the 20th percentile is actually larger than in the full sample, but we can no longer reject the null hypothesis of no difference at conventional significance levels. The gap between marginal price and marginal cost at the 20th percentile is statistically significant at the 10% level under the pooling method of Panel B. In short, the restricted sample results are consistent with the full sample results, but the statistical evidence for departures from marginal cost pricing is weaker.

In summary, these robustness exercises provide little reason to doubt the inferences based on Figure 7 and Table 6. However, the restricted samples involve a loss of power to reject the null. As a result, these samples yield weaker evidence of departures from marginal cost pricing for manufacturing plants that purchase relatively small amounts of electric power.

6.3 Does Ramsey Pricing Play a Role in Quantity Discounts?

Equation (5) implies that we cannot estimate the general Ramsey pricing schedule without identifying the demand side of the market for electricity purchases. That is a formidable undertaking and beyond the scope of this paper. However, we can still assess whether the data are qualitatively consistent with a standard Ramsey pricing interpretation of the quantity discounts documented in Section 3. The standard interpretation rests on two assumptions. First, based on visual inspections of utility service territory maps in nine states. The same point applies to the 88% accuracy rate for the restricted sample.
that $\alpha > 0$ for regulatory or market reasons, so that a utility cannot cover total costs through marginal cost pricing. Second, that demand is more sensitive to price for larger customers or, more precisely, that the absolute value of $\eta[M(q), q]$ increases in $q$. Taken together, these two assumptions and the pricing condition (5) imply that the marginal price schedule lies above the marginal cost schedule, with a shrinking gap as we move from smaller to larger values of $q$.

Figure 7 and Table 6 provide no support for this Ramsey pricing view. Indeed, where we find departures from marginal cost pricing, they are in the opposite direction from the usual Ramsey pricing story. Instead of a marginal cost schedule that lies above the marginal price schedule, we find some evidence that marginal price exceeds marginal cost for smaller purchasers. Instead of smaller markups for larger purchasers, we find evidence of bigger markdowns for smaller purchasers. That the data do not conform perfectly to Ramsey pricing is perhaps no surprise. However, our evidence supports a much stronger conclusion: the usual Ramsey pricing rationale for quantity discounts plays no role in electricity pricing to manufacturing plants. Instead, the explanation for quantity discounts is largely a cost-based one.

It is worth remarking, however, that the data can be reconciled with Ramsey pricing under the unusual premise that marginal cost pricing raises too much revenue; i.e., that efficient pricing raises more revenue than required to cover costs and a normal return on equity. In this circumstance, Ramsey pricing logic implies that the second-best pricing structure involves bigger markdowns of marginal prices relative to marginal costs in the less elastic portion of the purchases distribution. That is essentially the pricing structure that emerges after 1973. The premise that yields this rationalization is greatly at odds with the traditional view that electric utilities operate with declining costs in the relevant region. However, it resonates with the view that regulatory changes over the course of the 1970s led to tight capacity constraints.
7. Concluding Remarks

In this study, we document tremendous dispersion in the price per kWh that manufacturers pay for electricity. Spatial price differentials and quantity discounts account for all but a small fraction of the dispersion in prices. We also develop and implement a new method for estimating how electricity supply costs vary with customer purchase quantity in the cross section. The method may have useful applications in other settings. In our application, the estimation results imply that annual supply costs per kWh fall by more than half in moving from smaller to bigger purchasers, providing a strong cost-based rationale for quantity discounts.

We apply the fitted price schedules and estimated cost schedules to test for pricing efficiency on the purchase quantity margin and to assess a traditional Ramsey pricing interpretation of quantity discounts. To our surprise, the data are remarkably consistent with efficient pricing – i.e., marginal price schedules are nearly identical to marginal cost schedules over a range of purchases that spans several hundred log points. The main exception is pricing to smaller manufacturing customers after the mid 1970s. By our estimates, the marginal cost of supplying power to these customers exceeds the marginal price by about 10% in the 1980s and 1990s.

What might have caused the departure from pricing efficiency for smaller customers after the mid 1970s? We do not know the answer, but we suggest two avenues for future investigation. First, sizable deviations from marginal cost pricing began to emerge at the same time as real electricity prices began to rise (Figure 2). As mentioned in Section 3, the rise in real electricity prices from 1973 to 1983 reversed a decades-long trend. Perhaps utility companies or their regulators sought to insulate smaller industrial customers from the full impact of rising energy costs. A difficulty with this story is its failure to explain the persistence of deviations from marginal cost pricing after real electricity prices resumed a downward trend. Another difficulty is that, under two-part tariffs, subsidies need not involve departures from marginal cost pricing.
Second, during the 1970s public utility commissions began to focus greater effort on the review and design of electricity tariff schedules, as discussed by Cudahy and Malko (1976) in their treatment of the landmark Madison Gas and Electric case. The Madison case, initiated in 1972, stimulated similar reviews in other states. By 1977, a dozen state utility commissions held hearings on the reform of retail electric rate structures (Joskow, 1979, page 794). Ironically, these moves toward more aggressive intervention in rate design were often promoted in the name of marginal cost pricing principles. Our evidence shows that greater involvement in the design of rate structures by public utility commissions coincided with significant steps away from efficient pricing on the margin we measure. A careful study of whether intervention by public utility commissions drove the deviations from efficient pricing merits investigation.

Our results also identify some noteworthy aspects of spatial price differentials that merit further study. Spatial price differentials fell sharply from the late 1960s to the late 1980s for the largest purchasers, but they rose over time in the lower part of the purchases distribution. The expansion of wholesale power markets in the 1990s had no apparent effect on spatial price dispersion at the retail level for manufacturing customers. It strikes us as something of a puzzle that rapid expansion of wholesale power markets in the 1990s had so little impact on spatial price dispersion at the retail level for industrial customers.
References


Table 1. Selected Characteristics of the PQEM Database

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<tr>
<td>Years covered</td>
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<tr>
<td>Number of plant-level</td>
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<td>Total number of annual</td>
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<tr>
<td>utilities(^c)</td>
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<td>Mean annual electricity</td>
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</tr>
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<td>(GWh)(^d)</td>
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</tr>
</tbody>
</table>

Weighting Method

| Quantiles of Annual Electricity Purchases, Gigawatt-hours\(^e\) |
|-----------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                             | 1               | 5               | 10              | 25              | 50              | 75              | 90              | 95              | 99              |
| Shipments                   | .07             | .30             | .70             | 3.22            | 16.4            | 89.2            | 267             | 444             | 1,500           |
| Purchases                   | .20             | 1.08            | 2.84            | 13.58           | 85.9            | 452             | 2,100           | 4,185           | 14,241          |

Weighting Method

| Quantiles of Electricity Costs as a Percent of Total Labor Costs\(^e\) |
|-----------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Shipments                   | 0.4             | 1.1             | 1.5             | 2.5             | 4.7             | 10.2            | 25.7            | 46.3            | 197.2           |
| Purchases                   | 1.1             | 2.1             | 3.0             | 6.1             | 17.2            | 61.7            | 201.0           | 305.3           | 3,461           |

Notes:

\(^a\) The initial sample contains 1,945,813 records. We drop 107 records because of invalid geography codes and 128,058 (6.6%) because of missing values for electricity price, total employment, value added or shipments. We also trim the bottom 0.05% of the electricity price distribution in each year (928 observations over all years).


\(^c\) There are 684 best-match utilities not counting public power authorities: Tennessee Valley Authority, Bonneville Power Administration, New York Power Authority, Santee Cooper, Grand River Dam Authority, and the Colorado River Commission of Nevada. By construction, a best-match utility does not cross state lines.

\(^d\) Weighted by shipments (electricity purchases).

\(^e\) For disclosure reasons, the quantiles shown above are averages of plant-level observations in three quantiles, the quantile shown and the two surrounding quantiles (e.g., quantile 50 as shown is the average of observations in quantiles 49, 50, and 51).
Table 2. The Distribution of Log Electricity Prices Paid by U.S. Manufacturing Plants, Dispersion and Variance Decompositions

<table>
<thead>
<tr>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall Standard Deviation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>.409</td>
<td>.468</td>
<td>.429</td>
<td>.369</td>
<td>.359</td>
<td>.347</td>
<td>.373</td>
<td>.388</td>
<td>.360</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>.524</td>
<td>.552</td>
<td>.478</td>
<td>.433</td>
<td>.439</td>
<td>.429</td>
<td>.477</td>
<td>.437</td>
<td>.383</td>
</tr>
<tr>
<td><strong>Price Dispersion Between Groups As a Percent of the Total</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>4-Digit SIC Industries (447/458)&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>36.6</td>
<td>36.3</td>
<td>28.0</td>
<td>20.6</td>
<td>19.4</td>
<td>23.1</td>
<td>26.4</td>
<td>25.1</td>
<td>23.8</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>71.3</td>
<td>61.4</td>
<td>48.8</td>
<td>40.9</td>
<td>37.9</td>
<td>46.8</td>
<td>59.0</td>
<td>44.5</td>
<td>37.5</td>
</tr>
<tr>
<td><strong>Utilities (697)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>20.4</td>
<td>22.1</td>
<td>23.5</td>
<td>44.3</td>
<td>58.3</td>
<td>45.7</td>
<td>52.9</td>
<td>48.9</td>
<td>47.3</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>67.2</td>
<td>58.4</td>
<td>52.3</td>
<td>60.0</td>
<td>65.2</td>
<td>56.8</td>
<td>59.1</td>
<td>55.0</td>
<td>52.7</td>
</tr>
<tr>
<td><strong>Counties (3,031)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>31.4</td>
<td>32.0</td>
<td>32.2</td>
<td>53.0</td>
<td>67.2</td>
<td>54.3</td>
<td>61.6</td>
<td>57.6</td>
<td>56.3</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>77.9</td>
<td>69.6</td>
<td>64.9</td>
<td>73.5</td>
<td>78.6</td>
<td>74.9</td>
<td>77.5</td>
<td>69.9</td>
<td>65.4</td>
</tr>
<tr>
<td><strong>Purchase Deciles (10)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>57.2</td>
<td>54.2</td>
<td>33.2</td>
<td>16.4</td>
<td>19.3</td>
<td>26.2</td>
<td>29.0</td>
<td>30.6</td>
<td>25.6</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>62.8</td>
<td>56.3</td>
<td>36.2</td>
<td>27.4</td>
<td>24.7</td>
<td>38.0</td>
<td>49.5</td>
<td>41.3</td>
<td>38.1</td>
</tr>
<tr>
<td><strong>Purchase Centiles (100)&lt;sup&gt;b&lt;/sup&gt;</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>61.1</td>
<td>57.2</td>
<td>35.8</td>
<td>18.6</td>
<td>21.6</td>
<td>28.7</td>
<td>31.9</td>
<td>32.7</td>
<td>29.0</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>74.7</td>
<td>65.5</td>
<td>41.5</td>
<td>33.8</td>
<td>31.8</td>
<td>45.0</td>
<td>60.8</td>
<td>45.9</td>
<td>43.4</td>
</tr>
<tr>
<td><strong>Utility x Purchase Centile (32,142)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shipments-Weighted</td>
<td>84.1</td>
<td>79.6</td>
<td>67.7</td>
<td>71.5</td>
<td>83.1</td>
<td>78.5</td>
<td>85.1</td>
<td>83.8</td>
<td>81.9</td>
</tr>
<tr>
<td>Purchase-Weighted</td>
<td>94.7</td>
<td>91.1</td>
<td>81.6</td>
<td>84.5</td>
<td>88.4</td>
<td>88.3</td>
<td>91.7</td>
<td>87.5</td>
<td>86.3</td>
</tr>
</tbody>
</table>

<sup>a</sup> Years prior to 1987 are classified using the 1977 SIC system (447 4-digit industries). Years 1987 and later are classified using the 1987 SIC system (458 4-digit industries).

<sup>b</sup> We group plants by where they fit into the distribution of electricity purchases in the indicated year, allow the centile boundaries to vary by year.

Source: Authors’ calculations on PQEM data.
<table>
<thead>
<tr>
<th>Service Type and Schedule</th>
<th>Energy Charge Per kWh</th>
<th>Monthly Demand Charge Per kW</th>
<th>Minimum Monthly Demand Charge</th>
<th>Own Transformer Discount?</th>
<th>Monthly Customer Charge</th>
<th>Customer Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Service, GN-96</td>
<td>6.56¢</td>
<td>None</td>
<td>None</td>
<td>No</td>
<td>$6.85</td>
<td>Less than 90 MWh per year</td>
</tr>
<tr>
<td>Medium General Service, GS-96</td>
<td>2.60¢</td>
<td>$11.85</td>
<td>$11.85</td>
<td>No</td>
<td>$16.15</td>
<td>Greater than 90 MWh and less than 1,080 MWh per year</td>
</tr>
<tr>
<td>Large General Service, GL-96 (Optional provision for interruptible power)</td>
<td>2.32¢ ($8.57 for interruptible portion)</td>
<td>$13.20</td>
<td>$3,960</td>
<td>Yes, $0.50 per kW</td>
<td>$24.00</td>
<td>Greater than 1,080 MWh per year, and delivery points near transmission line</td>
</tr>
<tr>
<td>General Service Time of Use, GT-96</td>
<td>2.32¢</td>
<td>$13.20 peak, $3.87 off-peak</td>
<td>No</td>
<td>$24.00</td>
<td>Greater than 90 MWh per year</td>
<td></td>
</tr>
<tr>
<td>Large Power and Light, L-96 (Requires 5-year contract with high floor on demand charges)</td>
<td>2.19¢ ($6.00 per kW in excess of contract level)</td>
<td>$10.76</td>
<td>$10,760 (for 1,000 kW of Firm Power)</td>
<td>Yes, $0.50 per kW</td>
<td>$1,200</td>
<td>Demand greater than 1,000 kW and delivery points near transmission lines; minimum 5-year commitment.</td>
</tr>
</tbody>
</table>

**Optional Riders to Large Power and Light Schedule**

- **Curtailable Supplemental Power, L-97**
  - Different energy charges and a discount of 72% on demand charges for supplemental power that is subject to temporary or permanent curtailment or interruption with six months notice.

- **Interruptible Power, L-02-I**
  - Discount of 36% on demand charges for power subject to curtailment or interruption on short notice (2.5 hours); limitations on frequency and duration of curtailments and interruptions; one-year advance notice required by customer to reduce interruptible portion of demand.

- **Off-Peak Service, L-96-OP**
  - Discount of 80% on demand charges for off-peak power in excess of contracted levels for Firm, Supplemental and Interruptible Demands; subject to curtailment or interruption on short notice.

- **Economy Power, L-02-EP**
  - Discounted energy charges offered, at Santee Cooper’s sole discretion, to customers with Contract Demand greater than 2,000 kW. Available on short notice during specified clock hours.

- **Standby Power, L-96-SB**
  - Available at Santee Cooper’s discretion to customers with alternative non-emergency power sources.
Notes:

1. The charges listed above exclude South Carolina Sales Tax and other taxes and fees levied by governmental authorities.
2. Electricity is metered and billed separately for each delivery point and voltage level, so that the Monthly Customer Charge and Minimum Monthly Demand Charge apply per delivery point and voltage level.
3. All service types are subject to a Fuel Adjustment Clause (FAC-96) whereby the energy charge per kWh is adjusted by an additive factor that depends on Santee Cooper’s fuel costs in the preceding three months, an allowance for its capital improvements and distribution losses, and other considerations. The energy charge adjustment per kWh is similar for all service types, but the adjustment is less sensitive to capital improvements and distribution losses under the Large Power and Light schedule. Under all schedules, standard “firm-requirements” service is also subject to a Demand Sales Adjustment Clause (DSC-96) that credits Santee Cooper customers with specified shares of its demand-related and capacity-related revenues. The Demand Sales Adjustment can be positive or negative. It is applied as a proportional adjustment to the monthly demand charge under the Large Power and Light schedule and as a proportional adjustment to the monthly energy charge under the General Service schedules.
4. The kW level used to calculate the Monthly Demand Charge can be greater than “Measured Demand” during the billing period, defined as “the maximum 30-minute integrated kW demand recorded by suitable measuring device during each billing period.” For example, the Medium General Service schedule states that the “monthly Billing Demand shall be the greater of (i) the Measured Demand for the current billing period or (ii) fifty percent (50%) of the greatest Firm Billing Demand computed for the preceding eleven months.” The Large General Service schedule specifies a 70% figure.
5. The discounted Demand Charge under the General Service Time-of-Use Schedule applies to the difference between the customer’s Off-Peak Measured Demand and the customer’s On-Peak Measured Demand.
6. The transformer discount requires that the customer take delivery at available transmission voltage (69kV or greater).
7. Customers that opt for curtailable or interruptible power forfeit all discounts previously received during the calendar year for such power in the event they fail to meet a request for power curtailment or interruption. In addition, future discounts for curtailable and interruptible power can be withdrawn.
8. Under the Large Power and Light schedule, the customer must commit to a Firm Contract Demand level for a five-year period. The Firm Contract Level places a floor on the demand level used to compute the Monthly Demand Charge. Lower minimum monthly demand charges are available under certain conditions. The Large Light and Power Schedule also includes an Excess Demand Charge of $6.00 per kW for Measured Demand in excess of the Firm Contract Demand, a charge of $0.44 per kVar of Excess Reactive Demand, and a Monthly Facilities Charge equal to 1.4% of the original installed cost of any facilities that Santee Cooper provides in addition to the facilities it normally provides to its customers.

**Table 4. Regression Results for Electricity Supply Costs, Selected Years**

Dependent Variable: Purchase-weighted mean price per kWh for the utility’s manufacturing customers

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Public Ownership</td>
<td>26**</td>
<td>7</td>
<td>-4</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>(9)</td>
<td>(8)</td>
<td>(12)</td>
<td>(10)</td>
</tr>
<tr>
<td>Private Ownership</td>
<td>35***</td>
<td>21***</td>
<td>14***</td>
<td>8*</td>
</tr>
<tr>
<td></td>
<td>(4)</td>
<td>(3)</td>
<td>(4)</td>
<td>(3)</td>
</tr>
<tr>
<td>Fraction of Utility Revenue from Industrial Customers &lt; 25%</td>
<td>-6</td>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>(7)</td>
<td>(6)</td>
<td>(5)</td>
<td>(4)</td>
</tr>
<tr>
<td>Fraction of Utility Revenue from Industrial Customers 25-50%</td>
<td>-5</td>
<td>-4</td>
<td>-5</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>(7)</td>
<td>(6)</td>
<td>(5)</td>
<td>(4)</td>
</tr>
<tr>
<td>Share of Power From Hydro</td>
<td>-35***</td>
<td>-48***</td>
<td>-58***</td>
<td>16*</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(5)</td>
<td>(6)</td>
<td>(8)</td>
</tr>
<tr>
<td>Share of Power From Nuclear</td>
<td>417***</td>
<td>49***</td>
<td>13</td>
<td>46***</td>
</tr>
<tr>
<td></td>
<td>(82)</td>
<td>(13)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Share of Power From Oil and Natural Gas</td>
<td>-4</td>
<td>-5</td>
<td>7</td>
<td>43***</td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(7)</td>
</tr>
</tbody>
</table>

Adjusted R-Square          | 0.76 | 0.65 | 0.60 | 0.63 |

P-Value for Test: Utility Size Measures = 0 | 0.00 | 0.35 | 0.47 | 0.62 |

P-Value for Test: Customer Size Measures = 0 | 0.00 | 0.00 | 0.00 | 0.00 |

P-Value Test: Ownership Measures = 0 | 0.00 | 0.00 | 0.00 | 0.07 |

N                          | 253  | 272  | 298  | 290  |

* p<0.05, ** p<0.01, *** p<0.001

Notes:

1. Regressions are on utility-level data by weighted least squares. Weights are proportional to the square root of the number of customer observations used to calculate the utility-level statistics. The sample is limited to utilities for which there are at least 8 customer-level observations. The dependent variable is normalized so that the purchase-weighted mean price over utilities equals 100.

2. In addition to the variables shown in the table, the regressions also include the first three uncentered moments of the utility’s log customer size distribution and a quadratic polynomial in the log of the utility’s electricity sales to industrial customers.

3. The ownership variables and the fraction of revenue from industrial customers are from the 2000 EIA-861 file. Public and private ownership variables are dummy variables, and the omitted category is cooperative and municipal ownership. Fuel share variables are state-level data from the State Energy Data 2000 files. Both coal and “other” (includes geothermal, wind, wood and waste, photovoltaic, and solar) are omitted since “other” is always very small. Moments of the customer size distribution are constructed from the PQEM.

Source: Authors’ calculations on data from the PQEM, EIA-861 files, and State Energy Data 2000.
Table 5. Estimated Electricity Supply-Cost Schedules as a Function of Customer Purchase Quantity, Selected Years

<table>
<thead>
<tr>
<th>Annual Purchase Amount (GWh)</th>
<th>Percentile of Purchases Distribution</th>
<th>Supply Cost per kWh in 1996 Cents</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.53</td>
<td>10</td>
<td>8.03</td>
</tr>
<tr>
<td>2.43</td>
<td>25</td>
<td>5.68</td>
</tr>
<tr>
<td>13.1</td>
<td>50</td>
<td>4.20</td>
</tr>
<tr>
<td>73.9</td>
<td>75</td>
<td>3.44</td>
</tr>
<tr>
<td>229</td>
<td>90</td>
<td>3.10</td>
</tr>
<tr>
<td>422</td>
<td>95</td>
<td>2.91</td>
</tr>
<tr>
<td>1,130</td>
<td>99</td>
<td>2.49</td>
</tr>
</tbody>
</table>

Notes:
1. The supply-cost schedules are derived from the regressions reported in Table 4 and described in Section 5.1. The schedules are evaluated at sample mean values of the other regression covariates.
3. We do not report supply costs for the bottom tail of the purchases distribution, because small purchase values are outside the range we used to fit the utility-level regressions in Table 4.

Source: Authors’ calculations on PQEM data.
Table 6. Tests of Pricing Efficiency with Alternative Pooling Methods

A. Customer-Level Data Pooled over Years before Calculating Utility-Level Statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>20th Percentile</td>
<td>Marginal Price (1996 ¢ / kWh)</td>
</tr>
<tr>
<td>50th</td>
<td>3.66</td>
</tr>
<tr>
<td>80th</td>
<td>3.20</td>
</tr>
<tr>
<td>20th Percentile</td>
<td>6.25</td>
</tr>
<tr>
<td>50th</td>
<td>5.06</td>
</tr>
<tr>
<td>80th</td>
<td>4.20</td>
</tr>
</tbody>
</table>

B. Utility-Level Statistics Calculated from Customer-Level Data before Pooling

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>20th Percentile</td>
<td>Marginal Price (1996 ¢ / kWh)</td>
</tr>
<tr>
<td>50th</td>
<td>3.68</td>
</tr>
<tr>
<td>80th</td>
<td>3.19</td>
</tr>
<tr>
<td>20th Percentile</td>
<td>6.29</td>
</tr>
<tr>
<td>50th</td>
<td>5.09</td>
</tr>
<tr>
<td>80th</td>
<td>4.26</td>
</tr>
</tbody>
</table>

Notes: See text for a description of the underlying specifications and estimation methods.
Source: Authors’ calculations on PQEM data.

Figure 1. Electricity Price Dispersion Among U.S. Manufacturing Plants, 1963-2000
Source: Energy Information Administration for Residential, Commercial and Industrial series; authors’ calculations on PQEM data for Manufacturing.

**Figure 2.** Real Electricity Prices by End-Use Sector, 1960-2000
Source: Authors’ calculations on PQEM data.

Note: The between-county standard deviations are calculated in a purchase-weighted manner using residuals from annual customer-level regressions of log price on a fifth-order polynomial in log purchases.

**Figure 3.** Spatial Price Dispersion by Selected Deciles of the Purchases Distribution, 1963-2000
Source: Authors’ calculations on PQEM data.


**Figure 4.** Log Electricity Price Fit to Fifth-Order Polynomials in Log Purchases, Selected Years
Source: Authors’ calculations on PQEM data.

Note: Elasticity values are calculated from shipments-weighted regressions of the log price on a fifth-order polynomial in log purchases.

Figure 5. Average Elasticity of Price with Respect to Purchase Quantity, 1963-2000
Source: Authors’ calculations on PQEM data.

Notes: Each curve shows the fitted relationship between supply costs per kWh and annual customer purchases, evaluated at sample means of other covariates in the regression. The vertical coordinate for each plotted point is the sum of the fitted supply cost and the regression residual for a particular utility in the sample, as described in the text.

**Figure 6.** Electricity Supply Costs per kWh as a Function of Annual Customer Purchase Level, Selected Years
Source: Authors’ calculations on PQEM data.


Figure 7. Marginal Cost and Marginal Price Schedules Compared, Selected Years
1. Assigning Manufacturing Plants to Electric Utilities

This section provides an overview of our methods for assigning manufacturing plants to electric utilities. Davis et al. (2007) provide a more detailed discussion and an evaluation of assignment accuracy.

The EIA-861 data do not determine a unique, unambiguous assignment in counties served by more than one electric utility. We addressed this issue using several approaches, depending on available information. First, we created a “best-match” utility indicator for each county. Given a list of utilities with industrial customers in the county, the indicator identifies the utility with the largest statewide revenues from sales to industrial customers. Based on each manufacturing plant’s county of operation, our default assignment method (in the absence of better information described below) is to assign the plant to the utility selected by the best-match indicator. We introduce a separate utility code for each state in which a utility operates, because state laws and state-level public utility commissions govern rate setting.
Second, we use Geographic Information System (GIS) maps of electric utility service areas for Kansas, Kentucky, Maine, Minnesota, Ohio and Wisconsin. These six states account for 13.4% of plants, 14.2% of employment, 14.8% of payroll, 17.3% of electricity purchases, 15.3% of electricity expenditures and 15.1% of shipments in the PQEM. We use street address to assign latitude and longitude to manufacturing plants and then overlay the GIS service area map to determine the electric utility that serves the plant. Using this approach, we can construct highly accurate matches for most plants in states with GIS maps of utility service areas.

Third, for California, New York and Rhode Island, we obtained a list of utilities that operate in each zip code. These three states account for 18.2% of plants, 16.6% of employment, 17.5% of payroll, 9.8% of electricity purchases, 13.3% of electricity expenditures and 14.7% of shipments in the PQEM. Because zip codes cover much smaller areas than counties, the zip code data enables us to construct a unique match in most cases. When more than one utility serves a given zip code, we assigned plants based on the same type of “best match” approach as described above.

Fourth, we adjusted our county-based assignments in some cases based on visual inspections of maps showing utility service territories in Florida, Illinois, Louisiana, Maryland, Michigan, Missouri, Pennsylvania, South Dakota and Wyoming. These states account for 23.3% of plants, 23.7% of employment, 24.1% of payroll, 21.4% of electricity purchases, 23.2% of electricity expenditures and 24.3% of shipments in the PQEM. We inspected the utility service territories for each county, and if one utility clearly covers most of the county’s population, we assign that utility to all plants in the

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3 The Minnesota GIS map we obtained is an unofficial version.
county. If the county is not covered primarily by a single utility, we retained the county-based utility match based on the best-match indicator.

As noted in the main text, we exploit publicly available information on the identity of plants that purchase electricity directly from the six largest public power authorities. In all other cases, our assignment procedures rely on the assumption that a plant’s location determines its electricity supplier. This assumption works for the period of time covered by our data, because electric utilities were monopolies at the retail distribution level. According to Joskow (2005), the “first retail competition programs began operating in Massachusetts, Rhode Island and California in early 1998 and spread to about a dozen states by the end of 2000.” These developments on the retail side occur at the very end of the period covered by our data. One of the robustness exercises in Section 6.1 considers a sample that omits all observations potentially affected by these state-level retail restructuring and competition programs.

2. **Additional Empirical Results**

   a. **Electricity Price Per kWh by Purchase Decile, 1963-2000**

   Figure W1 shows the mean log real price of electricity by purchase decile from 1963 to 2000. The figure shows that the purchase deciles are almost perfectly rank ordered by price during the past four decades. Price differentials peak in 1967, when the gap in mean price between the top and bottom deciles exceeds 100 log points. Purchase-level price differentials shrink dramatically from 1967 through the first half of the 1970s, and they continue to shrink through the end of the decade. The gap between mean prices in the top and bottom deciles of the purchase distribution remains large throughout the past four decades, amounting to about 50 log points in 2000.
b. **Empirical Price-Quantity Schedules with Controls for Utility Effects**

Figure W2 shows price-quantity schedules fitted exclusively from within-utility variation for the same years as in Figure 4. Except for the inclusion of utility fixed effects, the specification underlying Figure W2 is identical to the specification underlying Figure 4. It is apparent that, even after controlling for utility fixed effects, there are large quantity discounts in all years and a substantial erosion of quantity discounts in the 1970s.

c. **Behavioral Responses and the Price-Quantity Schedule**

As briefly discussed in Section 4.5, we compared the price-quantity schedule implied by the menu of tariff schedules offered by Santee Cooper to the fitted price-quantity schedule for manufacturing plants in the 2000 PQEM. In calculating the implied price-quantity schedule, we assume the customer takes firm power, we fix the load factor at 50%, and we exclude discounts for off-peak or high-voltage power. These assumptions serve to foreclose quantity discounts that arise from behavioral responses to pricing incentives, isolating a “built-in” (non-behavioral) customer size effect. In contrast, the empirical price-quantity schedule fit to the PQEM reflects the built-in size effect and any behavioral responses by electricity customers.

Figure W3 plots the implied Santee Cooper price-quantity schedule and the within-utility price-quantity schedule in the 2000 PQEM data. We do not have enough customer-level observations to estimate an empirical price-quantity schedule for Santee Cooper alone. As in Figure 4, the fitted empirical schedule is based on a fifth-order

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4 Specifically, we compute the lower envelope of the price-quantity schedules implied by the General Service, Medium General Service, Large General Service, and Large Power and Light schedules. Recall that the tariff schedules described in Table 3 do not include taxes or adjustments specified by the Fuel Adjustment Clause and the Demand Sales Adjustment Clause.
polynomial specification, but we now include utility fixed effects in the plant-level regression to isolate within-utility price variation.

Figure W3 suggests that both mechanical and behavioral sources of quantity discounts are important features of the data. Over the middle part of the distribution that roughly spans the interquartile range of purchases by manufacturing plants, the price per kWh implied by the Santee Cooper tariff menu declines with purchase quantity by 30 to 40 log points. That is, over this range, large quantity discounts are built into the Santee Cooper menu of tariff schedules.\(^5\) In contrast, Figure W3 suggests that large quantity discounts in the upper quartile of the distribution reflect behavioral responses to pricing incentives. This evidence reinforces the view – often expressed in the public utility and Ramsey pricing literatures – that demand is more price elastic at higher purchase levels.

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\(^5\) The implied schedule declines more rapidly than the empirical schedule over this range, which indicates that the Santee Cooper tariff menu involves bigger “built in” quantity discounts than the average utility.
Source: Authors' calculations on shipments-weighted PQEM data.

**Figure W1.** Mean of Log Real Electricity Prices by Purchase Deciles, 1963-2000
Source: Authors’ calculations on PQEM data.

Note: Vertical lines depict the simple average of the 5\textsuperscript{th}, 25\textsuperscript{th}, 50\textsuperscript{th}, 75\textsuperscript{th}, and 95\textsuperscript{th} percentiles of the shipments-weighted distribution of annual purchases for 1967, 1973, 1978, and 2000.

\textbf{Figure W2.} Log Electricity Price Fit to Fifth-Order Polynomials in Log Purchases controlling for utility fixed effects, Selected Years
Source: Authors’ calculations on PQEM data and Santee Cooper tariff schedules.


**Figure W3.** Comparison of Empirical and Implied Price-Quantity Schedules, 2000

**References**
