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.

---

1 University of Chicago, NBER and American Enterprise Institute; Bureau of the Census; University of Maryland, Bureau of the Census and NBER; and Bureau of Economic Analysis, respectively. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau, the Bureau of Economic Analysis or the U.S. Department of Commerce. All results have been reviewed to ensure that no confidential information is disclosed.

2 459 counties are served by a single utility, 776 are served by 2 utilities, 791 are served by 3 utilities, 535 are served by 4 utilities, 441 are served by 5-7 utilities, and the remaining 29 counties are served by 8-12 utilities. To the best of our knowledge, data on the list of counties served by each electric utility are not available prior to 1999. Hence, we apply each utility’s county list for 2000 to all years.
Second, we use Geographic Information System (GIS) maps of electric utility service areas for Kansas, Kentucky, Maine, Minnesota, Ohio and Wisconsin.\(^3\) 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

---

\(^3\) 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.4 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

---

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. 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.

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


**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
