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PRODUCTIVITY DISPERSION AND INPUT PRICES:

THE CASE OF ELECTRICITY

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CES 08-33 September, 2008

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Abstract

We exploit a rich new database on Prices and Quantities of Electricity in Manufacturing (PQEM) to study electricity productivity in the U.S. manufacturing sector. The database contains nearly 2 million customer-level observations (i.e., manufacturing plants) from 1963 to 2000. It allows us to construct plant-level measures of price paid per kWh, output per kWh, output per dollar spent on electric power and labor productivity. Using this database, we first document tremendous dispersion among U.S. manufacturing plants in electricity productivity measures and a strong negative relationship between price per kWh and output per kWh hour within narrowly defined industries. Using an IV strategy to isolate exogenous price variation, we estimate that the average elasticity of output per kWh with respect to the price of electricity is about 0.6 during the period from 1985 to 2000. We also develop evidence that this price-physical efficiency tradeoff is stronger for industries with bigger electricity cost shares. Finally, we develop evidence that stronger competitive pressures in the output market lead to less dispersion among manufacturing plants in price per kWh and in electricity productivity measures. The strength of competition effects on dispersion is similar for electricity productivity and labor productivity.

* We thank colleagues at the Center for Economic Studies, the University of Chicago, and the 2006 Comparative Analysis of Enterprise (Micro) Data Conference for many helpful comments. Davis and Haltiwanger gratefully acknowledge research support from the U.S. National Science Foundation under grant number SBR-9730667. This work is unofficial and thus has not undergone the review accorded to official Census Bureau publications. All results have been reviewed to ensure that no confidential information is disclosed. The views expressed in the paper are those of the authors and not necessarily those of the U.S. Census Bureau.

1. Introduction

The average price paid per kilowatt-hour (kWh) of electricity varies enormously across U.S. manufacturing plants (Davis et al., 2007a). Price differences persist over time, and they vary closely with the manufacturer's electricity demand level and the sources of power generation in its region (coal, hydro, nuclear, etc.). The exogenous components of this price variation offer a natural source of leverage for estimating how the efficiency of electricity usage responds to persistent price differences. To investigate this type of response, we exploit a rich new database with nearly 2 million customer-level observations (manufacturing plants) from 1963 to 2000.

Price per kWh also depends on manufacturer decisions with respect to its load factor, voltage level, responsiveness to peak-load pricing, proximity to high-voltage power lines, and other factors that affect the cost of supplying its power. Our earlier work provides evidence that much of the plant-level price variation reflects differences in customer supply costs that are partly under control of the manufacturer. This evidence gives rise to the concept of electricity "price efficiency" for manufacturing plants, which is distinct from the usual concept of physical efficiency in the use of electric power. Thus, a manufacturer can respond to higher electricity tariffs by taking steps to reduce power requirements per unit of output or by taking steps to lower the per kWh cost of supplying its power (or both). The first option raises physical efficiency in electricity usage, and the second option leads to a lower price paid per kWh. Both types of efficiency gains raise output per dollar spent on electric power.

In this paper, we take these observations as a starting-point for analysis and explore several aspects of plant-level differences in electricity productivity. To set the stage, we first show that physical efficiency, price per kWh and output per dollar spent on electricity vary tremendously among U.S. manufacturing plants in the same year and narrowly defined industry. We also document a powerful and pervasive cross-sectional tradeoff between electricity price efficiency and physical efficiency within industries. In other words, plants with relatively low price efficiency (those that pay a relatively high price per kWh) compared to other plants in the same industry also have a strong tendency towards a high value of output per kWh. We find the same type of strong tradeoff when we sort plants by number of employees: larger plants in an industry pay substantially less per kWh, but they also produce substantially less output per kWh.

The strong cross-sectional tradeoff between price efficiency and physical efficiency survives when we instrument the price measure using variables exogenous to the plant, e.g., variables that capture the cost of power generation in the plant's region. For example, we estimate that the average elasticity of physical efficiency with respect to exogenous components of price per kWh is about 0.6 in the period from 1985 to 2000. This estimate implies a powerful long-run gain in physical efficiency in response to higher electricity prices.

Next, we study how production technology and market structure affect these patterns in the data. Cost minimization and market selection forces imply stronger pressures to economize on the use of electric power when the production technology is more electricity intensive. In line with this implication, we test whether the cross-sectional tradeoff between price efficiency and physical efficiency is stronger for industries with a bigger electricity cost share. We find strong support for this hypothesis throughout the four decades covered by our sample.

With respect to market structure, we investigate how competition affects cross-sectional dispersion in price per kWh, physical efficiency, electricity productivity (output per dollar spent on electricity) and labor productivity. This part of our study builds on Syverson (2004a, 2004b). He models an environment with imperfect product substitutability, productivity heterogeneity among plants and entry costs. In this type of environment, more competition in the form of greater market density yields lower mean output prices and less dispersion in output prices and productivity. These effects arise because less productive firms are less able to survive in more competitive markets – they are squeezed out by stronger market selection pressures. Melitz and Ottaviano (2008) derive similar results in a model that highlights the role of international trade in determining the intensity or "toughness" of competition.

Using market density as a measure of competition, Syverson finds that greater competition leads to less dispersion in output prices and productivity for locally traded goods. Our tests are in the same spirit, and we find results that are similar in character. According to our results, the impact of local market competition on the dispersion of electricity productivity for locally traded goods is about the same as its impact on the dispersion of labor productivity. Moving from one producer to two or more producers in the same local market lowers estimated dispersion by about nine percent for both productivity measures. We also find that the lower dispersion of electricity productivity in response to greater competition reflects two separate effects: less dispersion in output per kWh, and less dispersion in price per kWh. This finding is consistent with the view that competition spurs efficiency in both senses described above – greater physical efficiency in the use of electric power and lower electricity supply costs.

Our study contributes to a large literature on productivity differences among plants and firms. Bartlesman and Doms (2000) survey the early literature on plant-level productivity differences. Tybout (2003) reviews several studies that investigate the impact of import competition and trade liberalization programs on firm-level and plant-level productivity outcomes. Recent studies that investigate the impact of competitive pressures on the distribution of productivity outcomes include Galdon-Sanchez and Schmitz (2002), Bloom and Van Reenen (2007), Eslava et al. (2007), Syverson (2007), Foster et al. (2008), and Martin (2008). Relative to previous work, our study offers several innovations: a rich new source of plant-level data on electricity price and productivity outcomes; an analysis that isolates physical efficiency in electricity usage and studies its relationship to the price of electricity; evidence of how the technology of production affects the tradeoff between price efficiency and physical efficiency; and new evidence that competition compresses the distribution of productivity outcomes.

The paper proceeds as follows. Section 2 describes the data and measures used in the analysis. Section 3 documents the tremendous cross-sectional dispersion of electricity productivity and prices. Section 4 explores the tradeoff between physical efficiency in the use of electric power and price per kWh within narrow industries. Section 5 investigates the impact of electricity intensity in production on the tradeoff between price efficiency and physical efficiency. Section 6 analyzes the impact of competition on the dispersion of productivity and price measures. Section 7 offers concluding remarks.

2. Data and Measures

2.1 Data Sources and Analysis Samples

To measure plant-level inputs and outputs, we rely on a new database called Prices and Quantities of Electricity in Manufacturing (PQEM). The PQEM contains roughly 50,000 plant-level observations in 1963, 1967 and each year from 1972 to 2000. Variables in the PQEM include expenditures for purchased electricity during the calendar year, quantity of purchased electricity (watt-hours), employment, labor costs, materials costs, shipments, and detailed information about industry and location. We constructed the PQEM mainly from the U.S. Census Bureau's Annual Survey of Manufactures (ASM) and various files produced by the U.S. Energy Information Administration.[1] The ASM is a series of nationally representative, five-year panels refreshed by births as a panel ages. Sampled plants account for about one-sixth of all manufacturing plants and three-quarters of manufacturing employment. Our analysis makes use of ASM sample weights, so that our results are nationally representative.

We exclude certain PQEM observations in forming our analysis samples. First, we delete plants with part-year operations or highly seasonal patterns of production, because they typically face special tariff schedules with higher charges. In particular, we drop a plant-year observation when its number of production workers in any single quarter is less than five percent of its average number of production workers during the year. This restriction reduces the sample size by 1.7 percent. Second, we drop plant-year observations for which value added is non-positive. We measure value added as the value

[1] We identified and resolved several issues with ASM data on electricity prices and quantities in the course of constructing the PQEM. We also checked ASM data on electricity prices and quantities against data from the Manufacturing Energy Consumption Survey, another plant-level source that relies on a different survey. See Davis et al. (2007b) for details.

of shipments plus changes in finished goods and work-in-progress inventories less costs for parts and materials, resales, contract work, electricity and fuels. [2] We also drop all observations in an industry-year, if plants with non-positive value added account for more than five percent of shipments by the industry, i.e., the four-digit SIC code. These two restrictions reduce the sample size by a further 6.8 percent. Finally, to focus on plant-level variation within narrowly defined industries, we omit industry categories styled as "miscellaneous" or "not elsewhere classified." This last requirement cuts the sample size by 9.8 percent of the remaining observations. The resulting primary analysis sample has nearly 1.5 million plant-level observations, ranging from 34,000 to 68,000 per year.[3]

We create a second analysis sample limited to plants in industries that produce homogeneous products. Following Foster et al. (2008), we consider seven homogeneous products: corrugated and solid fiber boxes, hardwood plywood, ice, motor gasoline, ready-mixed concrete, roasted coffee, and white-pan bread.[4] Foster et al. develop a list of plants that produce these homogeneous products in the Census years 1977, 1982, 1987, 1992 and 1997.[5] Our homogeneous products sample includes all observations for the plants identified by Foster et al., provided that the observation appears in the primary analysis sample and has an industry code consistent with the Foster et al. product classification. Our resulting homogeneous products sample contains about 48,000 plant-

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[2] We deflate value added to 1987 $ using the NBER-CES Manufacturing Industry Database price indices for shipments, energy, and materials. Data and information for the NBER-CES Manufacturing Industry Database can be found at http://www.nber.org/nberces/nbprod96.htm.

[3] We adjust the original ASM sample weights to account for dropped observations, following the methodology of Hough and Cole (2004). See Appendix A for a description of the weight adjustment methodology.

[4] See Foster et al. (2008) for a detailed definition of each homogenous product. Unlike Foster et al., we combine block ice and processed ice into a single product category.

[5] Foster et al. (2008) require that the product of interest account for at least 50 percent of a plant's revenue in order to classify that plant as a producer of one of their homogeneous products. See Foster et al. (2008) for a more detailed description of their methodology.

level observations. We use this sample to assess whether results for our primary sample are driven by product heterogeneity and quality differences within four-digit industries.

2.2 Productivity and Efficiency Measures

We define electricity productivity at plant *e* in year *t* as

$$\varphi_{et} = \frac{VA_{et}}{EE_{et}} = \frac{VA_{et}}{P_{et} KW_{et}}, \tag{1}$$

where VA is value added, EE is expenditures for purchased electricity, P is price per unit of electricity and KW is the number of units. Taking logs, we decompose electricity productivity into two pieces, one that captures physical efficiency in the use of electricity and a second that reflects "price efficiency":

$$\log(\varphi_{et}) = \log\left(\frac{VA_{et}}{EE_{et}}\right) = \log\left(\frac{VA_{et}}{KW_{et}}\right) - \log(P_{et}) \equiv \gamma_{et} - p_{et}. \tag{2}$$

We often interpret (the negative of) p as a measure of price efficiency, because a firm makes deliberate choices regarding location, scale, equipment voltage, load factor and responsiveness to peak-load pricing incentives that affect its average price per kWh. In Davis et al. (2007), we show that most of the plant-level variation in price per kWh is explained by the plant's location and its annual purchase quantity. We also provide evidence that price differentials on these dimensions reflect differences in customer supply costs for utilities. Thus, our earlier work provides a strong rationale for interpreting price per kWh as one aspect of the efficiency with which manufacturers make use of electrical power. However, much of our evidence and interpretation does not require us to take a stand on the precise reason for plant-level variation in price per kWh.

3. Dispersion in Electricity Productivity and Efficiency

Table 1 summarizes the distribution of electricity productivity, physical efficiency and price efficiency within narrowly defined manufacturing industries. The clear message is one of tremendous dispersion in these measures among plants in the same four-digit industry. In the primary analysis sample, the intra-industry standard deviation of output per unit of electricity (physical efficiency) is about 90 log points, and the 90-10 differential is about 200 log points.[6] By way of comparison, the intra-industry standard deviation of labor productivity is about 70 log points, and the 90-10 differential is about 140 log points.[7] These results are similar to those found in Syverson (2004b) for labor productivity.

The homogeneous products sample exhibits similar dispersion of physical efficiency within even narrower product categories. As seen in Table 2, there is considerable dispersion in output per unit of electricity in all seven homogeneous product categories. The evidence in Table 2 indicates that high productivity dispersion in the primary analysis sample is not simply an artifact of product heterogeneity within industries.

The dispersion in electricity prices paid by manufacturing plants is also large. In the primary analysis sample, the intra-industry standard deviation of price per kWh is about 35 log points, and the 90-10 differential is about 85 log points. Table 2 shows considerable price dispersion in all seven narrow product categories. These results

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[6] The 90-10 differential of 213 log points is roughly an 8 to 1 difference between the 90th and 10th percentiles.

[7] We calculate plant-level labor productivity as real value added divided by total hours worked. However, the ASM, and hence the PQEM database, only includes data on production worker hours so we must estimate total worker hours. We use a simple estimation method: total workers hours equals production workers hours times the ratio of total salaries and wages to production worker wages.

constitute a dramatic violation of the law of one price, and they suggest that unmeasured input price variation is an important source of error in standard plant-level productivity measures. While Tables 1 and 2 consider the price of electricity inputs only, casual empiricism suggests that quantity discounts and other sources of price differences are prevalent for many intermediate inputs including office supplies, computer software, legal services, information goods and airline travel.

In the analysis below, we study the relationship between electricity price and physical efficiency, the effects of electricity's cost share on the price-physical efficiency tradeoff, and the impact of product market competition on the intra-industry dispersion of physical efficiency and electricity prices. The economic forces identified by our empirical work are likely to operate for other inputs as well.

4. The Tradeoff between Electricity Price Efficiency and Physical Efficiency

4.1 Two Hypotheses

Consider the relationship between a plant's physical efficiency in the use of electricity and its price per kWh. There are two competing hypotheses regarding this relationship. The first hypothesis maintains that physical efficiency and price efficiency are positively correlated in the cross section; in other words, plants with greater physical efficiency tend to pay less per kWh. This hypothesis follows from the notion that general managerial quality varies among plants, so that plants with better managers achieve higher efficiency in terms of both output per kWh and price paid per kWh.

The second hypothesis maintains that the two aspects of electricity efficiency are negatively correlated in the cross section. One motivation for this hypothesis follows from cost minimization – plants that face higher electricity tariffs have stronger cost incentives to purchase electricity-saving equipment and to modify the production process in other ways that economize on electricity usage. Another motivation follows from market selection pressures. Plants with low efficiency in both respects have relatively high costs and, thus, are less likely to survive and grow. As a result, they are systematically selected out of the distribution of surviving producers.

There is probably a role for each of these economic forces in the cross-sectional relationship between physical efficiency and price efficiency, but we do not seek to separately identify them here. Instead, our goal is to determine the prevailing cross-sectional relationship between physical efficiency and price efficiency among plants in the same industry. That is, we investigate whether the first or second hypothesis provides a better characterization of the data. We also investigate, in the next section, how the plant-level relationship between physical efficiency and price efficiency varies with the importance of electricity in the production process.

4.2 Evaluating the Two Hypotheses

To evaluate the two hypotheses, we pool the plant-level data over years, compute deviations of the plant-level efficiency measures about their respective industry-year means, and run regressions of the form:

$$\tilde{\gamma}_{ei} = \beta_i \, \tilde{p}_{ei} + \varepsilon_{ei}, \tag{3}$$

where *e* indexes establishments, *i* indexes industry (four-digit SIC), and a tilde indicates a plant-level deviation about an industry-year mean. The left side of (3) is the natural log of value added per kWh for plant *e* in industry *i* deviated about its mean value for plants in the same industry and year. The $\tilde{p}_{ei}$ term on the right side of (3) is the log price per kWh for plant *e* in industry *i* deviated about the log price for plants in the same industry and year. We fit (3) on our primary analysis sample, pooled over years. The key parameters of interest are the β_i coefficients, which quantify the intra-industry relationship between price and physical efficiency.

In estimating the regressions (3), we break the sample into four distinct periods in the evolution of real electricity prices. See Figure 1. The first period runs from 1963 to 1973 and covers the latter part of a many-decades-long decline in real electricity prices. The second and third periods cover the years from 1974 to 1978 and 1979 to 1984, respectively. The oil price shock of 1973-74 and a less favorable regulatory climate for the industry in the 1970s led to a reversal in the earlier pattern of declining real prices.[8] Indeed, the real price per kWh for electricity purchases by U.S. manufacturers roughly doubles from 1973 to 1984. We break this period of rising prices into two pieces to allow for a surprise element in the shift from falling to rising prices and a gradual adjustment to the changed outlook for electricity prices. The fourth period, which covers the years from 1985 to 2000, is characterized by a resumption of the secular decline in real electricity prices.

Table 3 summarizes our results from estimating (3) by industry for each of the four periods. The evidence very strongly favors the second hypothesis – namely, that cost minimization incentives and market selection pressures generate a positive cross-sectional relation between physical efficiency in the use of electricity and its price per kWh. According to the least squares estimation results in panel A, the β coefficients are negative in only 1 or 2 percent of industries. They are positive and statistically significant

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[8] See Section 2 of Davis et al. (2007a) for an overview of these regulatory developments and references to more detailed treatments.

at the 5 percent level in more than 90 percent of the industries in all four periods. The mean elasticity of physical efficiency with respect to price ranges from 0.62 to 0.98, depending on time period. Elasticities in this range imply a very strong substitution response that ameliorates most of the cost increase induced by higher electricity prices.

4.3 Dealing with Measurement Error and the Endogeneity of Plant-Level Price Variation

A concern about least squares estimation of (3) is the potential for measurement error to bias the estimated β coefficients. Recall that the PQEM measure of price per kWh on the right side of (3) is constructed as the ratio of annual expenditures on purchased electricity to annual quantity of purchased electricity. Noise in the annual expenditures measure creates an attenuation bias that causes least squares estimation of (3) to understate the tradeoff between physical efficiency and price. In contrast, because it appears in the denominator on both sides of (3), errors in the purchase quantity measure cause least squares estimation to overstate the price-physical efficiency tradeoff.

To address these sources of bias, we exploit the fact that the identity of the power supplier (i.e., the electric utility) accounts for a high percentage of electricity price differences among manufacturing plants.[9] In particular, utility fixed effects account for 20 to 58 percent, depending on year, of the between-plant variance in the log of electricity prices. This result implies that the plant's utility is a good instrument for its price per kWh. For numerical reasons, we reduce the dimension of the instrument vector to one by first running cross-sectional regressions of log price on utility fixed effects. The predicted value of log price in this regression then serves as an instrument for $\tilde{p}$ in (3).

[9] For this purpose, we use utility assignments based on the county "best-match" utility indicator in the PQEM database. There are 347 county "best-match" utilities in the PQEM. See Davis et al. (2007b) for information on the creation of the "best-match" utility indicator.

To capture only industries for which utility acts as a reasonable instrument, we restrict the instrumental variables estimation to industries with first-stage R-square values greater than 0.20.[10]

Panel B of Table 3 shows the results of the instrumental variables estimation of (3). While there are fewer positive estimated β coefficients in the instrumental variables estimation than in the least squares estimation, a majority of estimated β coefficients are still positive in every time period. Less than twelve percent of the estimated β coefficients are negative and statistically significant. The mean elasticity of physical efficiency with respect to price is notably lower for the instrumental variables estimation, ranging from 0.59 to 0.77, depending on time period. Panel C shows least squares estimation results for the same set of industries used in the instrumental variables estimation and, when compared to panel B, shows that the instrumental variables estimation produces lower mean elasticities than the least squares estimation. While we still see a strong substitution response to higher electricity prices, it appears that the least squares estimation of (3) overstates the true strength of that response.

One possible criticism of the instrumental variables specification described above is that the utility instrument, which is location-based, might be correlated with omitted factors that affect physical efficiency in electricity usage. Another possible criticism is that there are too many (347) utility instruments. To address these issues, we instrument for price per kWh with three variables that measure the shares of electric power generated from hydro, nuclear, and petroleum/natural gas in the state. As before, we restrict the

[10] We also estimated the instrumental variables specification with first-stage R-square cutoffs of 0.10 and 0.15, obtaining very similar results for these specifications.

instrumental variables estimation to industries with first-stage R-square values greater than 0.20. The power share instrument results shown in Table 4 are similar to the utility instrument results in Table 3. The mean elasticity of physical efficiency with respect to price is notably lower for the instrumental variables estimation, ranging from 0.53 to 0.87, depending on time period.

4.4 The Price-Physical Efficiency Tradeoff and Manufacturer Size

A core prediction of standard models of dispersion in firm productivity is that more productive firms and establishments should be larger. That is, either for reasons of decreasing returns from factors such as span of control (e.g., Lucas (1978)) or because of product differentiation (e.g., Melitz (2003)) it is standard to assume some concavity in the profit function. Establishments and firms with higher profitability/productivity draws in an industry will be larger, but given the concavity of profits, the establishments with the highest draws will not take over the market.

We examine the respective roles of productivity and price efficiency in the context of the relationship between electricity productivity and size. Table 5 shows mean log electricity efficiency and productivity measures by deciles of the employment size distribution. We construct the statistics in Table 5 as follows. First, in each industry and year, we rank plants by number of employees and then sort them into deciles, each accounting for roughly one-tenth of industry-level employment in the year. We then pool the data over years.[11] As before, we compute all price and productivity measures as deviations from industry-year means.

[11] For this exercise, we trim the sample by dropping plants in the primary analysis sample that make up the lowest 1% of employment in each year.

As reported in Table 5, electricity productivity (output per dollar spent on electric power) is nearly flat across employment deciles. This overall relationship between size and electricity productivity masks large, roughly offsetting, differences in price per kWh and output per kWh. Larger plants prices pay less per kWh, but they produce less output per kWh. Plants in the largest employment decile are 13 percent *less* physically efficient in their use of electricity (i.e., they have 13 percent fewer dollars of value added per kWh of purchased electricity). These patterns suggest that since larger establishments are able to obtain lower prices they have less incentive to undertake costly investments to be more physically efficient.

5. The Impact of Electricity Intensity on the Price-Physical Efficiency Tradeoff

The results in Tables 3 and 4 strongly support the hypothesis of a tradeoff between price efficiency and physical efficiency in the cross section of manufacturing plants. We identified two economic forces that produce this tradeoff – cost minimization and market selection. Economic theory suggests that these forces bite harder when electricity is a more important factor input and a bigger share of costs. That is, the bigger electricity's cost share, the greater the incentive to adopt electricity-conserving production methods in response to a higher price, and the greater the force of market selection on electricity productivity (physical efficiency and price).

This line of reasoning yields a third hypothesis: the plant-level tradeoff between price efficiency and physical efficiency strengthens as electricity's cost share rises. To test this hypothesis, we consider industry-level regressions of the form:

$$\hat{\beta}_i = a + b\kappa_i + u_i, \qquad (4)$$

where $\hat{\beta}_i$ is the estimated elasticity of physical efficiency with respect to price for industry *i*, and κ_i is electricity's cost share in industry *i*. We measure the industry cost share by electricity expenditures as a fraction of industry value added, averaged over years within one of the four time periods defined above.

Figure 2 implements (4) and tests the null hypothesis that $b = 0$ using the least squares estimates for $\beta.$ Each data point in the figure corresponds to a four-digit industry in one of the four time periods. As seen in Figure 2, the data strongly support rejection of $b = 0,$ providing strong support for the hypothesis that a higher cost share for electricity leads to a stronger tradeoff between physical efficiency in the use of electricity and efficiency in the price paid per kWh. The effect is powerful and tightly estimated. For example, a five percentage point increase in electricity costs as a share of value added at the industry level raises the plant-level elasticity of physical efficiency with respect to price by 16 log points.

Figure 3 implements (4) separately for each time period. The effect of electricity intensity on the price-physical efficiency tradeoff is less precisely estimated when we split the sample, but a bigger cost share for electricity leads to a stronger tradeoff in all four periods.

Figure 4 shows results of the implementation of (4) with estimated elasticities from the power share instrumental variables estimation of (3) for all four time periods, and Figure 5 shows analogous plots individually for each time period. Both of these figures provide further support for the hypothesis that the tradeoff between electricity physical efficiency and price is stronger for more electricity intensive industries.

6. Competition Effects on Productivity and Price Dispersion

The results thus far show tremendous intra-industry dispersion in electricity price and physical efficiency plus evidence of an important tradeoff between the two in the cross section of plants. The evidence further shows that this tradeoff strengthens as electricity's cost share rises. As we discussed above, one explanation for the impact of cost share on the price-physical efficiency tradeoff involves the role of market selection pressures. We now exploit another implication of market selection to formulate and test additional hypotheses.

Other things equal, market selection pressures operate with greater force when product market competition is more intense. In particular, greater competitive intensity truncates the lower tail of the plant-level efficiency distribution. To translate this implication into a testable hypothesis, we follow Syverson (2004a) and exploit the fact that some manufacturing goods are produced and sold primarily in local markets. For local goods, an increase in the number of producers who sell the same good in the same local market means an increase in competitive intensity. Thus, we hypothesize that (a) the dispersion of electricity productivity, physical efficiency and price declines with the number of local producers for local goods, and (b) the impact of the number of local producers is less important for national goods.[12]

To test these hypotheses, we use a difference-in-difference approach. Since dispersion within any given industry may reflect many factors, we abstract from unobserved factors by exploiting differences in the local vs. national nature of the goods produced by each industry. That is, some goods (e.g., ready-mixed concrete) are

[12] As discussed in Syverson (2004b) many national goods also ship a relatively large fraction of their goods locally.

produced primarily for local use while other goods (e.g., roasted coffee) are produced for a national market. Using data collected in the 1977 Commodity Transport Survey, we have estimates by industry of the distances that goods are shipped.[13] For this exercise, we designate industries as local if more than 60 percent of the shipments for the industry are shipped less than 100 miles. Using this local/non-local distinction, we estimate regressions of the absolute value of the deviation of plant-level electricity prices and physical efficiency on an indicator variable for the number of local competitors the establishment has in the local market interacted with the local/non-local measure while controlling separately for the local nature of the industry and the density of the local market. For the latter, we use Bureau of Economic Analysis (BEA) component economic areas (CEAs) to define the local market.[14] Given substantial variation across industries in the number of local competitors, we construct a simple dummy variable for local market density indicating whether the local market has only one plant or two or more competitors.[15] This *DENS* variable should matter for dispersion more for locally produced goods, and we exploit this in our difference-in-difference specification.

Our specification consists of two stages. In the first stage, we estimate a plant-level regression of log electricity productivity on a fully interacted set of industry and year effects. Additionally, we examine electricity physical efficiency and prices using this specification. It is important to control for industry effects, particularly when examining physical efficiency dispersion, given the inherent differences in measures of

[13] Chad Syverson provided us with these industry estimates. He discusses the compilation of these estimates from the publicly available 1977 Commodity Transport Survey data in Syverson (2004b).
[14] There are 348 CEAs in the U.S. The CEAs are mutually exclusive and cover the entire U.S. See the BEA Internet site (http://www.bea.gov) for more information on CEAs.
[15] We construct this variable using the Census of Manufactures (CM) and for CM years only (1963 and years ending in '2' or '7') so that we have the universe of plants. For this reason, the regressions that follow pool only over CM years.

output across industries. As both a point of comparison and as an interesting exercise on its own, we also consider a specification where the first stage regression is plant-level log labor productivity regressed on a fully interacted set of industry and year effects.

In the second stage, we estimate difference-in-difference specifications for electricity productivity, electricity price, electricity physical efficiency and labor productivity with county-level demand controls. These specifications pool plants across Census of Manufactures (CM) years and are of the following form:

$$abs(residual_{et}) = \alpha + \beta LOCAL_{et} + \gamma DENS_{et} + \delta\left(LOCAL_{et} * DENS_{et}\right) + \phi \mathbf{X}_{c,et} + \varepsilon_{et}, \quad (5)$$

where $LOCAL_{et}$ is an indicator variable for the plant that is equal to 1 if the plant is in an industry where more than 60 percent of the goods are shipped less than 100 miles, $DENS_{et}$ is an indicator variable for the plant that is equal to 1 if the plant is in a local CEA with 2 or more plants producing in the same industry, and $\mathbf{X}_{c,et}$ is a vector of county-level demand controls. The dependent variable in (5) is the absolute value of the residual from the first stage regression. The county-level demand controls include the fraction of the population that is non-white, the fraction of the population that is over 25 years old, the fraction of the population with a college education, the fraction of occupied housing units that are owner-occupied, the natural log of median house value, and the natural log of median family income.[16] We include the controls for many of the same reasons advocated in Syverson (2004a) who uses analogous controls – our density measure is likely correlated with other factors that impact dispersion such as the local demand structure.

[16] The county-level demand controls were obtained from various editions of the 'County and City Data Book' and from the U.S. Census Bureau's 'USA Counties' data. See the References section of this paper for a detailed list of sources.

Table 6 contains the regression results from our difference-in-difference regressions. The results in Table 6 are based upon a specification with value added weighting since the market selection effects should operate on the basis of the most efficient producers of output. The primary effect of interest is the change in dispersion as the market density increases for local markets. This effect can be quantified by combining estimated coefficients from Table 6. Namely, the effect of interest is the sum of the coefficient on the density variable and the interaction of the local and density variable. This combined effect (along with standard errors) is reported in Table 7. This is the effect of interest as it reflects the implied change in dispersion from the density indicator changing from zero to one for local markets.

We find that this effect of density for local markets is negative and statistically significant for all measures of dispersion. In terms of quantitative significance, it is useful to compare the implied effect with the mean of the dispersion measure of interest (the mean of the dependent variable). In the second row of Table 7, we see that the change in dispersion with increased market density in local markets is large. The implied reduction in dispersion for local goods is about 8 percent for electricity productivity, 9 percent for electricity physical efficiency, and 4 percent for electricity prices. For purposes of comparison, the decline in dispersion for labor productivity is about 9 percent as well. These substantial changes in dispersion indicate that market forces associated with market density operate for electricity price and productivity dispersion in a manner analogous to the effects Syverson (2004a) identified for output price and productivity dispersion in the concrete industry. Our findings on labor productivity dispersion (also consistent with Syverson (2004a)) imply that the quantitative impact of market density is quite similar for electricity and labor productivity. This finding is interesting on many dimensions especially since the share of electricity costs in total costs is much smaller than the share of labor costs in total costs.

7. Concluding Remarks

Even within narrow industries and product classes, establishments in U.S. manufacturing exhibit substantial dispersion in electricity productivity and each of its components, physical efficiency and price "efficiency". The dispersion in electricity physical efficiency is larger in magnitude than the comparable dispersion in labor productivity that has been emphasized in the literature.

The substantial dispersion in electricity physical efficiency and prices raise the question: how is it that plants seemingly competing in the same market can exhibit such large dispersion in physical efficiency and price efficiency? We explore two possible answers to this question. First, we show that there is a tradeoff within industries between the price efficiency and physical efficiency of electricity. That is, high price electricity plants tend to be high physical efficiency plants. We find this tradeoff is more pronounced in electricity intensive industries.

Another answer we explore is that plants producing in the same industry (or producing the same product) may not, in fact, be competing in the same market especially if the good is primarily locally traded. That is, plants producing locally traded goods are primarily competing with other plants in that same industry in that local market. To explore the impact of market structure, we build on Syverson (2004a, 2004b) to investigate the impact of market density for locally produced goods on physical efficiency and price dispersion. Using a difference-in-difference specification, we find evidence that an increase in local market density for locally traded goods yields a reduction in the dispersion of electricity productivity and physical efficiency.

In considering the broader implications of our findings, we think the findings are of interest both for understanding firm dynamics more generally but also for understanding the response of the economy to changes in the price of energy. As we have shown, producers exhibit substantial dispersion in electricity prices and productivity, there is a tradeoff between these factors across producers (high price producers are more energy efficient) and the dispersion in both electricity prices and productivity responds to competitive pressures. For firm dynamics, the evidence suggests that many of the same factors playing a role for output price and productivity dispersion are also at work for input price and productivity dispersion. That is, our findings are consistent with the forces of cost minimization, market selection and in turn the role of competition on market selection in the presence of frictions yielding dispersion and tradeoffs in productivity, input and output prices.

Taking an even broader perspective, the dispersion, tradeoffs and response to market competition are potentially important in considering the economy-wide response to changes in energy prices. The findings on dispersion and tradeoffs highlight the different choices of location, technology, and specific products of different producers. In response to a change in energy prices, the aggregate response will depend in a complicated manner on the substitution responses within and between producers of goods. Given our findings, the response will involve shifts in the allocation of activity across high and low productivity and price producers, and this shift will depend critically on the types of frictions that underlie the observed productivity and price dispersion. In a related way, the dispersion in prices and productivity in the PQEM offers considerable variation to estimate the short run and long run elasticities of substitution to energy price changes at the producer level and in turn the aggregate level taking into account the potential shifts across producers. Given the findings here, tracing such responses using data such as the PQEM should be a high priority for future research.

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Table 1. Plant-Level Dispersion in Electricity Productivity, Physical Efficiency, Prices, and Labor Productivity

Statistics for log deviations about industry-year or product-year means	**Primary Analysis Sample**				**Homogeneous Products Sample**			
	Electricity Productivity	**Physical Efficiency**	**Price per kWh**	**Labor Productivity**	**Electricity Productivity**	**Physical Efficiency**	**Price per kWh**	**Labor Productivity**
Sample Weighted								
Mean of Absolute Value	0.63	0.68	0.28	0.47	0.62	0.68	0.28	0.48
Standard Deviation	0.87	0.92	0.38	0.66	0.85	0.91	0.38	0.69
90-10 Dispersion	1.96	2.13	0.86	1.44	1.94	2.12	0.87	1.44
90-50 Dispersion	0.95	1.05	0.45	0.72	0.95	1.05	0.45	0.70
50-10 Dispersion	1.01	1.08	0.42	0.71	0.99	1.07	0.42	0.74
Value Added Weighted								
Mean of Absolute Value	0.62	0.64	0.25	0.53	0.75	0.80	0.27	0.47
Standard Deviation	0.87	0.90	0.32	0.71	1.08	1.15	0.35	0.61
90-10 Dispersion	1.90	1.97	0.78	1.66	2.26	2.32	0.86	1.46
90-50 Dispersion	0.97	1.01	0.40	0.86	1.30	1.36	0.45	0.79
50-10 Dispersion	0.93	0.96	0.38	0.81	0.96	0.96	0.41	0.67
Purchase Weighted*								
Mean of Absolute Value	0.60	0.62	0.25	0.46	0.58	0.56	0.26	0.42
Standard Deviation	0.82	0.85	0.33	0.67	0.79	0.78	0.34	0.60
90-10 Dispersion	1.84	1.92	0.76	1.41	1.82	1.72	0.85	1.30
90-50 Dispersion	0.92	0.96	0.40	0.67	0.91	0.92	0.43	0.61
50-10 Dispersion	0.92	0.96	0.36	0.74	0.91	0.80	0.42	0.69

* Labor productivity statistics are hours weighted rather than purchase weighted.

Source: Authors' calculations on the PQEM database for pooled years 1963, 1967, and 1972-2000.

Notes: The Primary Analysis Sample excludes industries styled as "miscellaneous" and "not elsewhere classified." See text Section 2.1 for other sample restrictions. The Homogeneous Products Sample is limited to plants in the following product categories: corrugated and solid fiber boxes, hardwood plywood, ice, motor gasoline, ready-mixed concrete, roasted coffee, and white-pan bread. Statistics are for log deviations around four-digit industry or product means. All statistics make use of sample weights in addition to any other weighting that is indicated.

Table 2. Plant-Level Dispersion around Product-Year Means by Product Category

Product Category	Mean Absolute Value of Log Deviations				Standard Deviation of Log Deviations			
	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity
Boxes	0.51	0.57	0.26	0.33	0.68	0.75	0.33	0.45
Hardwood Plywood	0.44	0.46	0.27	0.38	0.59	0.61	0.35	0.48
Ice	0.75	0.74	0.25	0.46	1.05	1.03	0.33	0.64
Motor Gasoline	0.77	0.80	0.27	0.49	1.13	1.20	0.36	0.64
Ready-Mixed Concrete	0.65	0.72	0.28	0.53	0.88	0.96	0.36	0.76
Roasted Coffee	0.89	0.78	0.67	0.94	1.09	1.02	0.93	1.14
White-Pan Bread	0.45	0.48	0.24	0.39	0.60	0.63	0.31	0.54

Source: Authors' calculations on the PQEM database for pooled years 1963, 1967, and 1972-2000.

Note: Statistics computed on a sample-weighted basis.

Table 3. The Plant-Level Empirical Relationship between Physical Efficiency and Price

Plant-Level Regression Specification: $\tilde{\gamma}_{ei} = \beta_i \ \tilde{p}_{ei} + \varepsilon_{ei}$, where $\tilde{\gamma}$ and $\tilde{p}$ are log value added per kWh and log price per kWh deviated about their respective industry-year means.

Summary of Results for Industry-Level β Estimates

A. Least Squares Estimation	**Time Period**			
	1963-1973	**1974-1978**	**1979-1984**	**1985-2000**
Percent Positive	98.9	98.1	96.8	98.0
Percent Positive & Statistically Significant	93.5	91.4	90.4	92.7
Percent Negative & Statistically Significant	0.5	0.0	1.1	0.6
Number of Industries	372	374	374	504
Simple Mean of β Estimate	0.98	0.83	0.85	0.87
Value Added Weighted Mean of β Estimate	0.85	0.74	0.74	0.62
B. Utility IV Estimation (Industries with first-stage R^2 > 0.20.)	**Time Period**			
	1963-1973	**1974-1978**	**1979-1984**	**1985-2000**
Percent Positive	86.4	73.1	90.9	89.4
Percent Positive & Statistically Significant	70.5	42.3	58.2	79.1
Percent Negative & Statistically Significant	4.5	3.8	0.0	4.1
Number of Industries	44	26	110	464
Simple Mean of β Estimate	0.77	0.59	0.72	0.76
Value Added Weighted Mean of β Estimate	0.63	0.31	0.56	0.61
C. Least Squares Estimation (Same set of industries as in panel B.)	**Time Period**			
	1963-1973	**1974-1978**	**1979-1984**	**1985-2000**
Percent Positive	97.7	96.2	99.1	98.1
Percent Positive & Statistically Significant	88.6	76.9	90.0	93.1
Percent Negative & Statistically Significant	2.3	0.0	0.0	0.4
Number of Industries	44	26	110	464
Simple Mean of β Estimate	1.08	0.79	0.84	0.87
Value Added Weighted Mean of β Estimate	0.72	0.52	0.72	0.83

Notes: We estimate the regressions by industry for each time period using our Primary Analysis Sample. We drop industries with fewer than 20 plant-level observations during the time period. Panels A and B report results for weighted LS and weighted IV estimation, respectively, with weighting by value added (and sample weights). The instrument in Panel B is the plant's predicted log price in a cross-sectional regression on 347 utility fixed effects. Panels B and C report LS and IV results for a reduced set of industries for which the first-stage regression R-squared value exceeds 0.20. Statistical significance is at the 5 percent level. Shipments weights and equal weights yield highly similar results.

Table 4. The Plant-Level Empirical Relationship between Physical Efficiency and Price

Plant-Level Regression Specification: $\tilde{\gamma}_{ei} = \beta_i \ \tilde{p}_{ei} + \varepsilon_{ei}$, where $\tilde{\gamma}$ and $\tilde{p}$ are log value added per kWh and log price per kWh deviated about their respective industry-year means.

Summary of Results for Industry-Level β Estimates

A. Power Share IV Estimation (Industries with first-stage R^2 > 0.20.)	**Time Period**			
	1963-1973	**1974-1978**	**1979-1984**	**1985-2000**
Percent Positive	85.2	76.2	81.8	86.2
Percent Positive & Statistically Significant	67.2	55.4	61.2	74.5
Percent Negative & Statistically Significant	1.6	11.9	8.9	5.0
Number of Industries	61	101	214	318
Simple Mean of β Estimate	0.87	0.53	0.74	0.83
Value Added Weighted Mean of β Estimate	0.80	0.40	0.57	0.61
B. Least Squares Estimation (Same set of industries as in panel A.)	**Time Period**			
	1963-1973	**1974-1978**	**1979-1984**	**1985-2000**
Percent Positive	96.7	93.1	96.3	97.5
Percent Positive & Statistically Significant	83.6	81.2	88.3	90.9
Percent Negative & Statistically Significant	1.6	0.0	1.9	0.6
Number of Industries	61	101	214	318
Simple Mean of β Estimate	0.98	0.77	0.86	0.86
Value Added Weighted Mean of β Estimate	1.05	0.58	0.71	0.77

Notes: We estimate the regressions by industry for each time period using our Primary Analysis Sample. We drop industries with fewer than 20 plant-level observations during the time period. Panel A reports results for weighted IV estimation with weighting by value added (and sample weights). The instruments in Panel A are shares of power generated by hydro, nuclear, and petroleum/natural gas. Panels A and B report LS and IV results for a reduced set of industries for which the first-stage regression R-squared value exceeds 0.20. Statistical significance is at the 5 percent level. Shipments weights and equal weights yield highly similar results.

Table 5. Mean Electricity Price and Physical Efficiency by Manufacturer Size

Employment Decile	Number of Observations	Mean					
		Log Electricity Price		Log Electricity Physical Efficiency		Log Electricity Productivity	
1	341,018	-3.18	(0.001)	1.08	(0.001)	4.26	(0.001)
2	216,407	-3.19	(0.001)	1.08	(0.002)	4.27	(0.002)
3	173,604	-3.20	(0.001)	1.06	(0.002)	4.26	(0.002)
4	147,573	-3.22	(0.001)	1.03	(0.003)	4.24	(0.002)
5	127,092	-3.23	(0.001)	1.00	(0.003)	4.23	(0.003)
6	108,439	-3.25	(0.001)	0.99	(0.003)	4.24	(0.003)
7	91,127	-3.27	(0.002)	0.98	(0.004)	4.24	(0.004)
8	74,708	-3.29	(0.002)	0.95	(0.005)	4.25	(0.004)
9	57,228	-3.32	(0.002)	0.93	(0.006)	4.25	(0.005)
10	41,712	-3.36	(0.003)	0.94	(0.007)	4.30	(0.006)

Source: Authors' calculations on the PQEM.

Notes:

1. Results are for pooled years, 1963, 1967, and 1972-2000.
2. Employment deciles are numbered 1 to 10 from smallest to largest employers. Employment deciles each contain 10% of sample-weighted employment by year-industry.
3. Year-industry means have been removed from the log efficiency measures (the grand mean was added back in).
4. We drop plants in the primary analysis sample that make up the lowest 1% of employment in each year.

Table 6. Local Market Competition Effects on Dispersion in Productivity and Prices

Dependent Variable: absolute value of the residual in a regression of the (log) indicated variable on a fully interacted set of year and industry effects

	Electricity Productivity	Electricity Price	Electricity Physical Efficiency	Labor Productivity
	(1)	(2)	(3)	(4)
Intercept	-0.042	0.035	0.007	-0.440
	(0.026)	(0.009)	(0.028)	(0.020)
LOCAL	-0.040	0.003	-0.028	0.030
	(0.008)	(0.003)	(0.008)	(0.006)
DENS	0.018	-0.009	0.022	0.010
	(0.002)	(0.001)	(0.002)	(0.002)
*LOCAL*DENS*	-0.062	-0.002	-0.074	-0.053
	(0.009)	(0.003)	(0.009)	(0.006)
Adjusted R^2	0.007	0.034	0.006	0.014
N	394,288	394,288	394,288	394,288

Source: Authors' calculations on the PQEM database for pooled CM years: 1963, 1967, 1972, 1977, 1982, 1987, 1992, and 1997.

Notes: All four regressions are estimated by weighted least squares with weighting by value added (and sample weights). All regressions include a number of control variables for the local market (coefficients not reported but they are generally statistically significant with plausible signs). The control variables are the fraction of the population that is non-white (*RACE_NONWHITE*), the fraction of the population that is over 25 years old (*AGE25*), the fraction of the population with a college education (*COLLEGE*), the fraction of occupied housing units that are owner-occupied (*OWNOCC*), the natural log of median house value (*HOUSEVALUE*), and the natural log of median family income (*INCOME*).

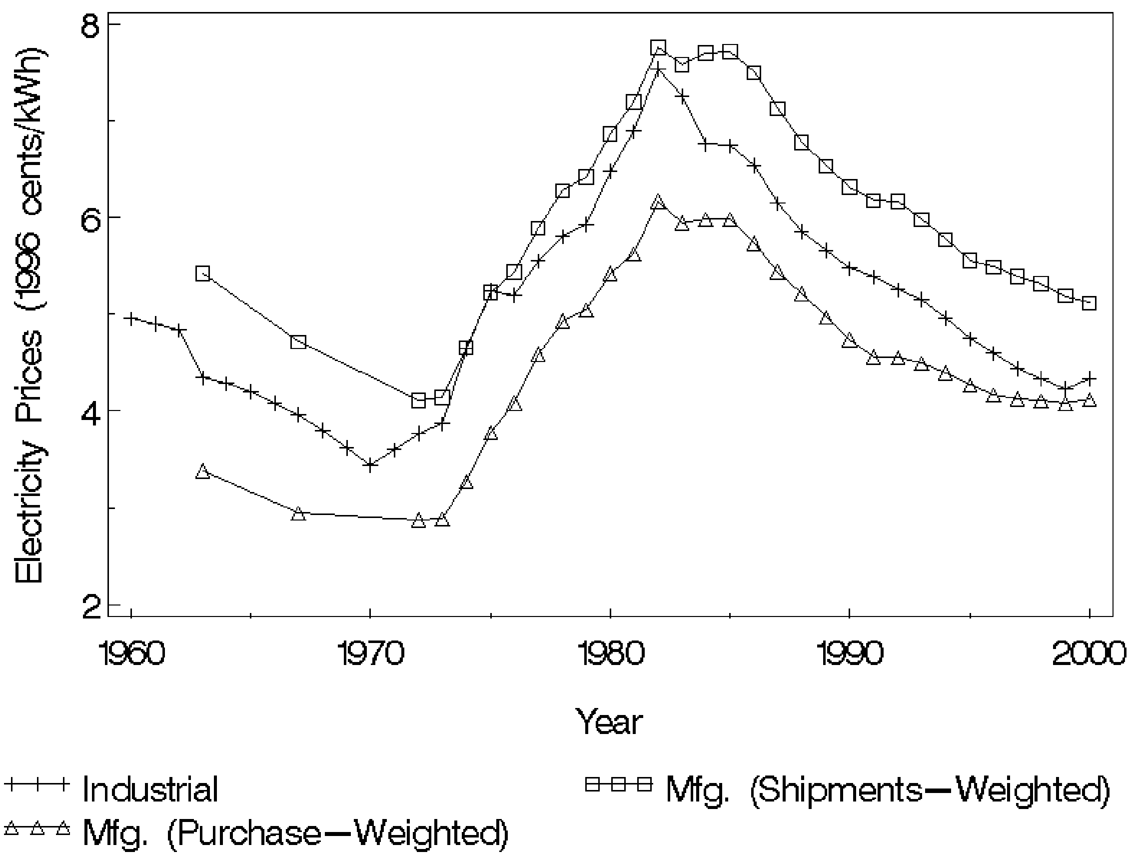
Table 7. Effects of Increased Local Market Density on Dispersion for Local Market Goods

	Electricity Productivity	Electricity Price	Electricity Physical Efficiency	Labor Productivity
	(1)	(2)	(3)	(4)
Change in dispersion from an increase in local market density for local market goods	-0.044 (0.008)	-0.011 (0.003)	-0.052 (0.009)	-0.043 (0.006)
Above change in dispersion divided by mean dispersion times 100	-8.27	-4.38	-9.34	-8.66

Source: Authors' calculations on the results from Table 5.

Notes:

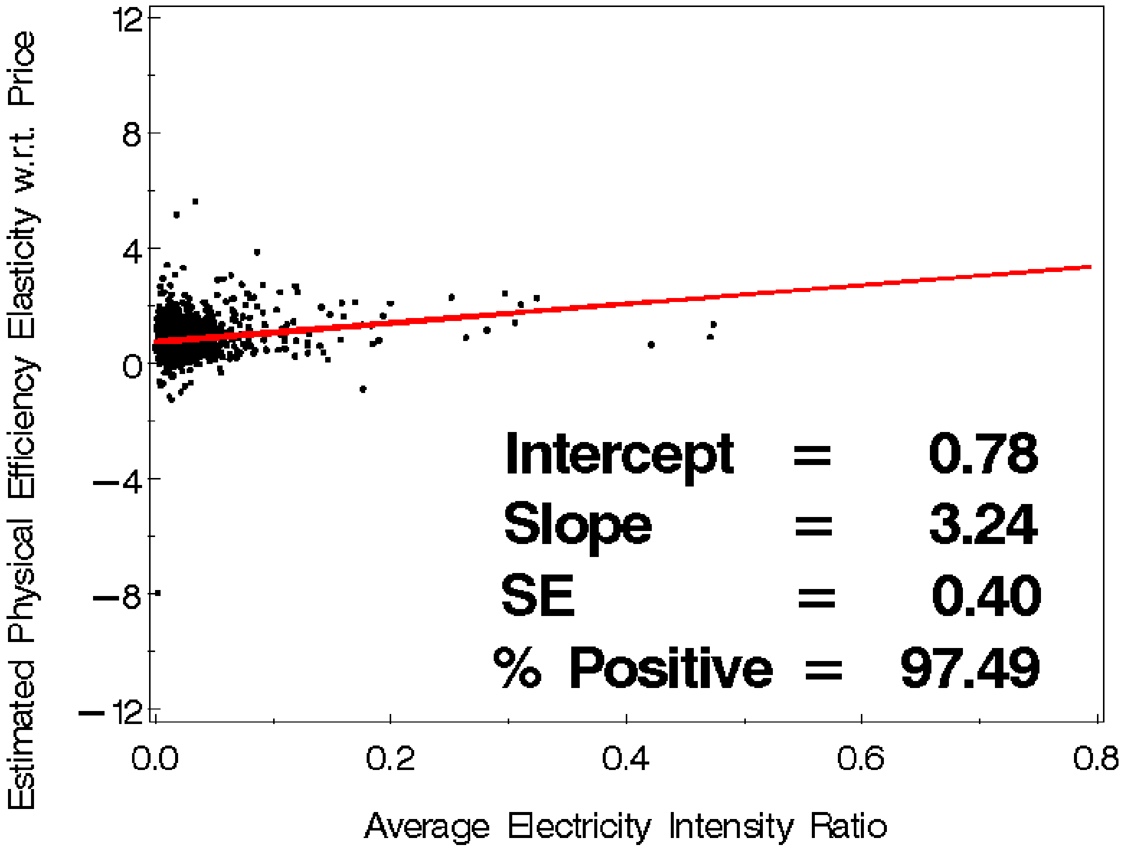
1. Dispersion is measured based upon the dependent variable in Table 5 – the absolute value of the residual of a regression of the log of the variable on fully interacted set of industry and year effects. The columns of this table correspond to the columns in Table 5.
2. Market density is measured as in Table 5. That is, the density variable (*DENS*) is a plant-level indicator variable equal to one if the plant is in a CEA with two or more plants producing in the same industry.
3. The change in dispersion from an increase in market density is calculated by combining estimated coefficients from Table 5 (*DENS* + *LOCAL*DENS*).
4. The numbers in the last row are calculated as (*DENS* + *LOCAL*DENS*) divided by the mean dispersion (dependent variable from Table 5) conditional on *LOCAL* = 1 times 100.



Source: Energy Information Administration for the Industrial series; authors' calculations on PQEM data for Manufacturing.

Note: Nominal values deflated by the GDP implicit price deflator.

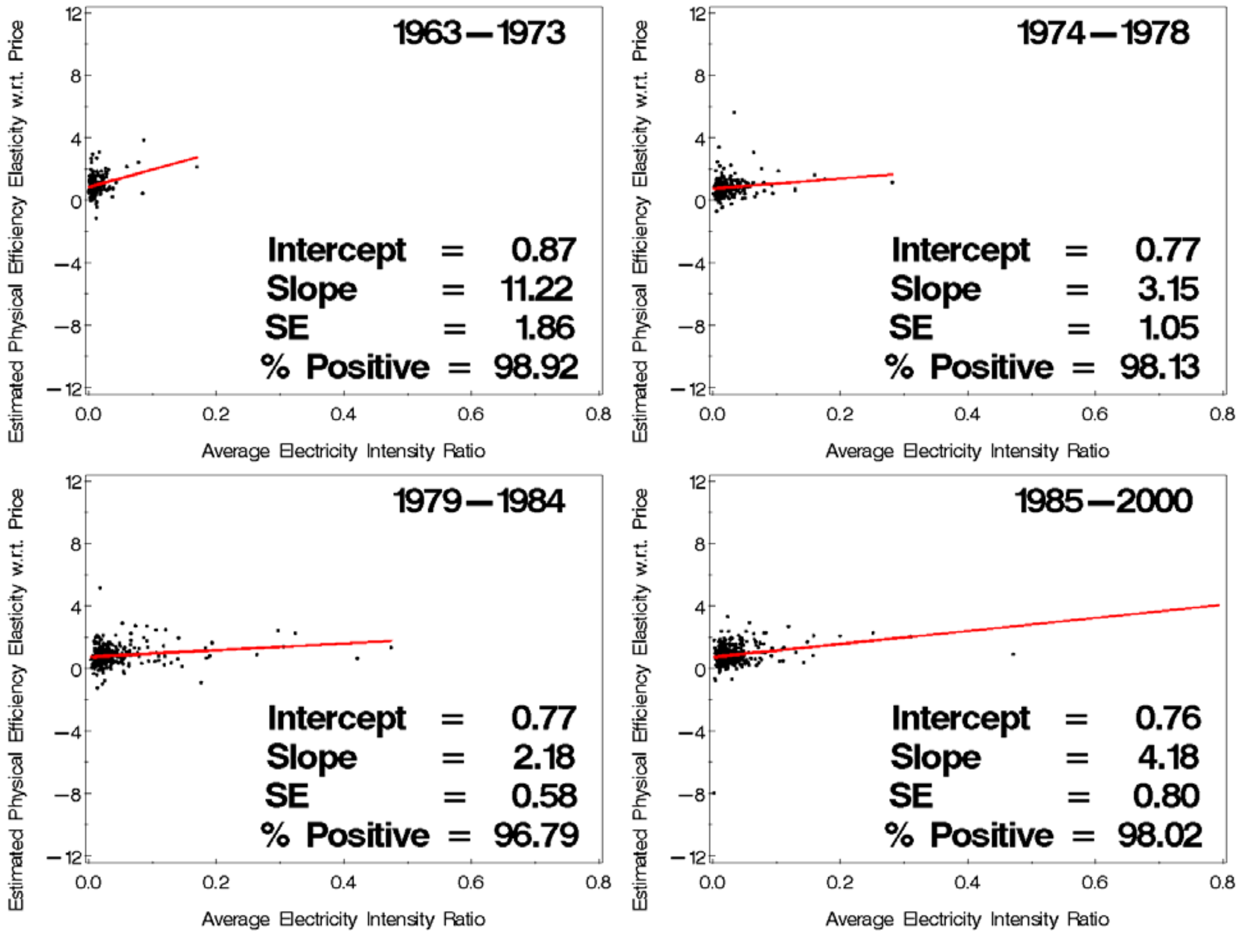
Figure 1. Real Electricity Prices, Industrial and Manufacturing Customers, 1960-2000



Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by weighted least squares as described in the text and Table 3. The electricity intensity ratio is the time-averaged value for electricity expenditures as a fraction of industry value added. Each point in the figure corresponds to a single four-digit industry in one of the four time periods, 1963-1973, 1974-1978, 1979-1984 and 1985-2000. The plotted regression line is fit by OLS to the industry-level data.

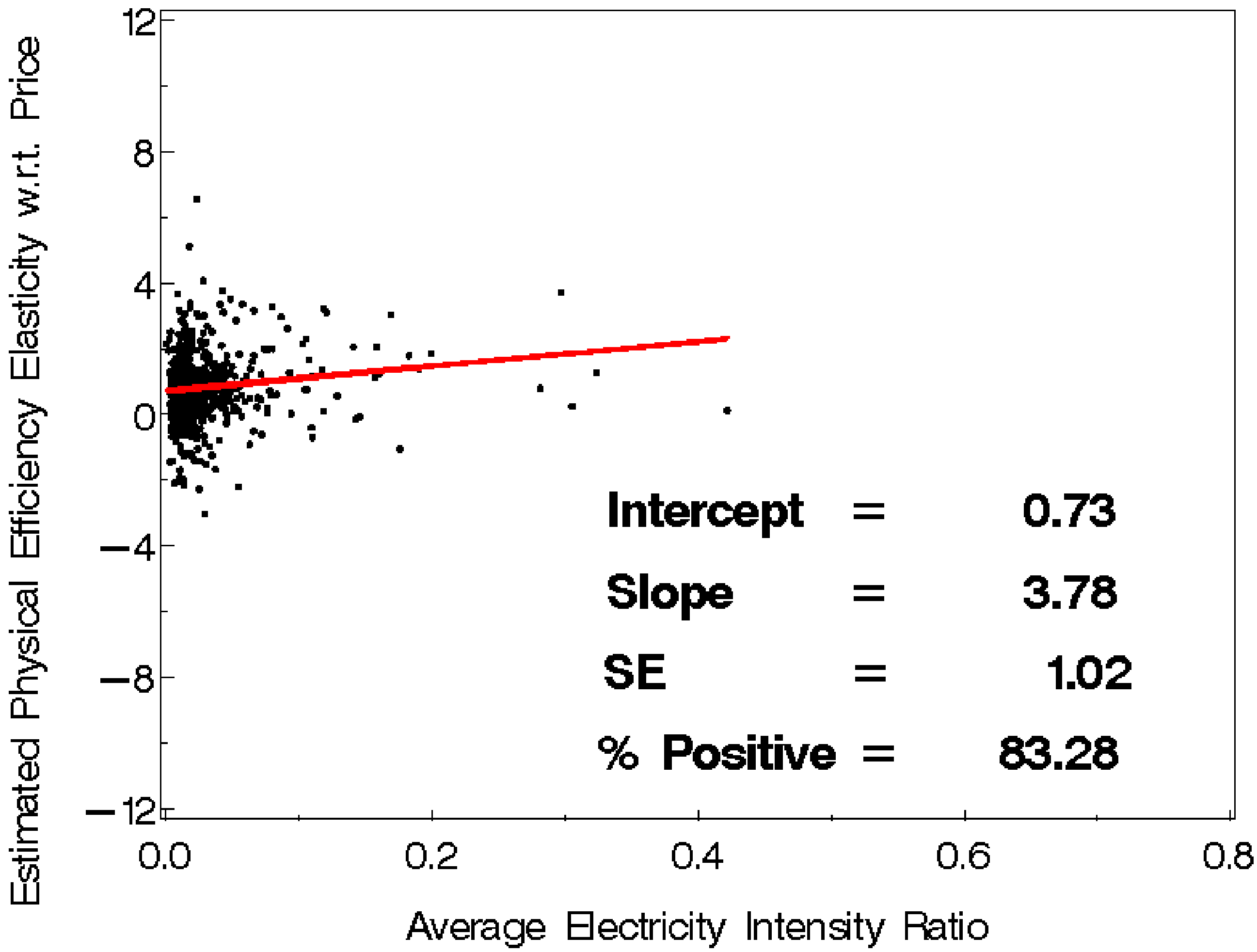
Figure 2. The Effect of Electricity Intensity on the Price-Physical Efficiency Tradeoff



Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by weighted least squares as described in the text and Table 3. The electricity intensity ratio is the time-averaged value of electricity expenditures as a fraction of industry value added. Each point in the figures corresponds to a single four-digit industry in the indicated time period. The plotted regression lines are fit by OLS to the industry-level data.

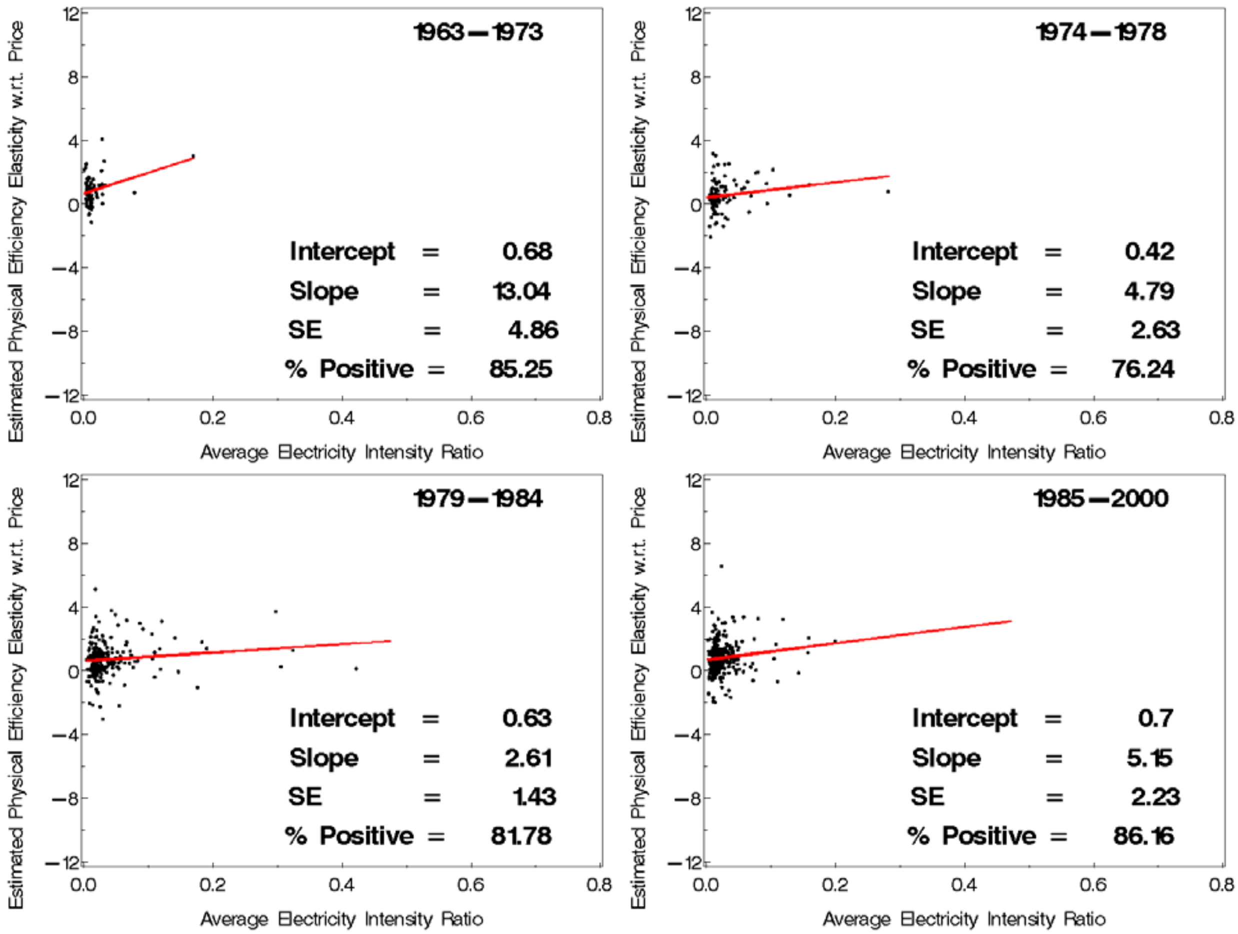
Figure 3. The Effect of Electricity Intensity on the Price-Physical Efficiency Tradeoff by Time Period



Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by instrumental variables regression as described in the text and Table 4. The electricity intensity ratio is the time-averaged value for electricity expenditures as a fraction of industry value added. Each point in the figure corresponds to a single four-digit industry in one of the four time periods, 1963-1973, 1974-1978, 1979-1984 and 1985-2000. The plotted regression line is fit by OLS to the industry-level data.

Figure 4. The Effect of Electricity Intensity on the Price-Physical Efficiency Tradeoff, Power Share Instrumental Variables Specification



Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by instrumental variables regression as described in the text and Table 4. The electricity intensity ratio is the time-averaged value of electricity expenditures as a fraction of industry value added. Each point in the figures corresponds to a single four-digit industry in the indicated time period. The plotted regression lines are fit by OLS to the industry-level data.

Figure 5. The Effect of Electricity Intensity on the Price-Physical Efficiency Tradeoff by Time Period, Power Share Instrumental Variables Specification

Appendix A: Sample Weight Adjustment Methodology

We create adjusted sample weights for our primary analysis sample to account for observations dropped from the PQEM database. We consider the PQEM database to be the full sample and use 4-digit SIC industry-total employment class cells with the total value of shipments (*TVS*) to adjust the sample weight.[17] We follow the methodology of Hough and Cole (2004), adjusting for the fact that the PQEM database is not a true population.

The weighted mean of shipments for each industry-employment class stratum for the full sample should be equal to the weighted mean of shipments for each industry-employment class stratum for the sub-sample. In other words, (A.1) should be an equality, but it is not.

$$\sum_{e=1}^{N_{is}} w_e \times TVS_e \neq \sum_{e=1}^{n_{is}} w_e \times TVS_e \qquad \text{(A.1)}$$

where i = 4-digit SIC industry

s = total employment class

e = establishment

N_{is} = number of establishments in stratum *i*-*s* in PQEM

n_{is} = number of establishments in stratum *i*-*s* in primary analysis sample

TVS_e = total value of shipments of establishment *e*

w_e = PQEM weight for establishment *e*

The goal is to create an adjusted weight, $\hat{w}_e$, such that

$$\sum_{e=1}^{N_{is}} w_e \times TVS_e = \sum_{e=1}^{n_{is}} \hat{w}_e \times TVS_e \qquad \text{(A.2)}$$

[17] Employment classes are: 0-19 employees, 20-49 employees, 50-99 employees, 100-249 employees, and greater than or equal to 250 employees.

Step 1: Decompose the right-hand-side of (A.1).

$$\begin{aligned}\sum_{e=1}^{n_{is}} w_e \times TVS_e &= \sum_{e=1}^{n_{is}} w_e \times TVS_e + \sum_{e=1}^{n_{is}} TVS_e - \sum_{e=1}^{n_{is}} TVS_e \\ \sum_{e=1}^{n_{is}} w_e \times TVS_e &= \sum_{e=1}^{n_{is}} TVS_e + \sum_{e=1}^{n_{is}} (w_e - 1) TVS_e\end{aligned} \tag{A.3}$$

Step 2: Resolve the inequality in (A.1).

$$\begin{aligned}\sum_{e=1}^{N_{is}} w_e \times TVS_e &= \sum_{e=1}^{n_{is}} TVS_e + K_{is} \sum_{e=1}^{n_{is}} (w_e - 1) TVS_e \\ \sum_{e=1}^{N_{is}} w_e \times TVS_e &= \sum_{e=1}^{n_{is}} [1 + K_{is} (w_e - 1)] TVS_e\end{aligned} \tag{A.4}$$

Step 3: The last line in (A.4) implies the following.

$$\hat{w}_e = 1 + K_{is} (w_e - 1) \tag{A.5}$$

Step 4: Solve for K_{is} from the first line of (A.4).

$$\begin{aligned}\sum_{e=1}^{N_{is}} w_e \times TVS_e &= \sum_{e=1}^{n_{is}} TVS_e + K_{is} \sum_{e=1}^{n_{is}} (w_e - 1) TVS_e \\ K_{is} &= \frac{\sum_{e=1}^{N_{is}} w_e \times TVS_e - \sum_{e=1}^{n_{is}} TVS_e}{\sum_{e=1}^{n_{is}} (w_e - 1) TVS_e}\end{aligned} \tag{A.6}$$

K_{is} can be undefined if the industry-employment size class stratum contains only certainty cases. Following Hough and Cole (2004) and adjusting for the fact that we are starting with a sample rather than a population, we define the adjusted weight as shown in (A.7) if K_{is} is undefined.

$$\hat{w}_e = \frac{\sum_{e=1}^{N_{is}} w_e \times TVS_e}{\sum_{e=1}^{n_{is}} TVS_e} \tag{A.7}$$