# Energy Economics

## How price responsive is industrial electricity demand in the US?

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Title page

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**Abstract**

Accurate projections of electricity demand growth by end-use customer class (residential, commercial, industrial) are necessary for energy policy modelling, resource planning, and electricity pricing and procurement. Motivated by the expected trend of rising retail electricity prices in the US and diverse price elasticity estimates found by extant studies, we answer the substantive policy question: how price responsive is industrial electricity demand in the US? Based on a comprehensive panel data analysis that uses five parametric specifications and monthly data for the lower 48 states in 2001-2019, our answer comprises: (1) the statistically significant ($p$-value $\leq 0.05$) static own-price elasticity estimates are -0.029 to -0.130, short-run -0.021 to -0.133 and long-run -0.043 to -0.214; (2) the size of these estimates varies by elasticity type, sample period, parametric specification, and assumption of partial adjustment; (3) erroneously ignoring the highly significant ($p$-value $< 0.01$) cross-section dependence does not materially alter these elasticity estimates; (4) these elasticity estimates vary by region though not season and their size has been slowly declining over time. Hence, price-induced conservation's future effect on the US industrial electricity demand is likely small, justifying the continuation of policies to promote energy efficiency and demand side management to achieve deep decarbonization.

## 1. Introduction

Accurate projections of electricity demand growth by end-use customer class (residential, commercial, industrial) are necessary for energy policy modelling (Manne et al., 1979), resource planning (Hobbs, 1995; Wilkerson et al., 2014), and electricity pricing and procurement (Fisher et al., 1992; Orans, 2008). Figure 1 shows the industrial customer class's slowly declining share of the US total electricity consumption in the last three decades. For 2019, the industrial share is ~25%, commercial share ~35%, and residential share ~40%.

An intuitive representation of a growth projection for a given customer class is the sum of demand changes due to: (a) energy price changes; (b) non-price factors (e.g., economic growth and climate change); and (c) government policies on energy efficiency (EE) standards and demand-side management (DSM) programs (Manne et al., 1979, p.5). This paper's focus is the price-induced demand change in (a) of the US industrial customer class:

$$\Delta Q_t \quad = \quad Q_{t\text{-}1} \, \Sigma_m \, \varepsilon_m \ln(P_{mt} / P_{mt\text{-}1}), \tag{1}$$

where $\Delta Q_t$ = demand change over one period; $Q_{t\text{-}1}$ = demand in period $t$-1; $\varepsilon_m$ = elasticity of demand with respect to $P_m$, with $m$ = 1 for electricity, 2 for fuel oil, and 3 for natural gas; and $\ln(P_{mt} / P_{mt\text{-}1})$ = percentage change of $P_m$ over one period.[1] The own-price elasticity is $\varepsilon_1 < 0$. The cross-price elasticity is $\varepsilon_m > 0$ (< 0) when $P_{m\neq1}$ = price of a substitute (complement).

To underscore the policy relevance of $\{\varepsilon_m\}$, consider an electric utility planning to reliably meet its end-use demands in the next 10 years under an assumption of rising retail electricity prices, see Section 2.1 for the assumption's supporting details. The utility operates in one of the electricity grids in Figure 2: Western Interconnection, Electric Reliability Council of Texas (ERCOT), and Eastern Interconnection. If industrial customers are highly price responsive, their projected demand reductions can diminish the utility's procurement of

[1] Our choice of energy mix is based on the US and non-US industrial electricity demand studies listed in Table 1 below. There order of labelling is intentional for our subsequent derivation of energy demand equations for testing the demand effect of fuel oil price.

electrical energy (MWh) and capacity (MW) to achieve resource adequacy defined by the reliability standards set by the North American Electric Reliability Corporation (NERC) and adopted by state and federal regulators. But if these customers are price insensitive, their small demand reductions have minimal impact on the utility's procurement. Finally, should the utility have wrongly assumed high price responsiveness, it could face resource inadequacy in the forecast period.

Woo et al. (2018b) report that -0.10 to -0.25 is the range of non-residential own-price elasticities assumed by two US government agencies, the Energy Information Administration (EIA) and Environmental Protection Agency (EPA), for developing electricity demand projections. This range is larger in size than the range of -0.05 to -0.10 assumed by US electric utilities for resource planning and procurement. Both ranges correspond to the low end of the diverse elasticity estimates found by the studies listed in Table 1.

The lack of empirical consensus noted above motivates our main research question: how price responsive is industrial electricity demand in the US? Answering this question with a comprehensive panel data analysis based on a large sample informs the elasticity assumptions adopted by the US government agencies and electric utilities. When answered with data for other countries, the same question is internationally important and relevant, as exemplified by China that has replaced the US as the world's leading country in aggregate energy consumption and $CO_2$ emissions.

Responding to the preceding question, we perform panel data analysis of monthly data for the lower 48 states in 2001-2019 under five parametric specifications used by extant studies of industrial electricity demand: double-log, linear, constant elasticity of substitution (CES), Generalized Leontief (GL) and Transcendental logarithmic (TL). Our sample period's starting month reflects the EIA's first publication of monthly industrial natural gas consumption by state and ending month data available at the time of our writing.[2]

Our paper sharply differs from extant studies because of its salient features. First, its sample is large, containing 10,944 observations (= 48 states × 19 years × 12 months per year) for credible quantification of price responsiveness. Second, it accounts for the presence of cross-section dependence (CD) (Liddle and Hasanov, 2021) that reflect common shocks (e.g., federal government policies and regional weather patterns) and interdependence of regression errors among states (Li et al., 2021). Third, except for the double-log specification, its price elasticity estimates are monthly, enabling calculation of seasonal price responsiveness. Fourth, it reports regional variation in own-price elasticity estimates. Fifth, its rolling-window approach documents the declining trend of the US industrial electricity demand's small own-price elasticity estimates, revealing price-induced conservation's diminishing demand-reduction effect that justifies continuation of EE standards and DSM programs designed to achieve deep decarbonization (Williams et al., 2012; Mahone et al., 2018).

We fill several knowledge gaps in the industrial electricity demand literature, which are the presently unknown effects of parametric specification, treatment of CD, seasonality, time trend, and regionality on industrial electricity demand's price responsiveness. Our scientific innovation comprises seven contributions to the vast literature of electricity demand analysis.[3] The first six contributions are our newly developed empirics and the last is our methodology:

[2] Our sample period excludes year 2020 because of missing monthly data for some states and Covid-19's adverse effects on the US economy.

[3] Our paper does not explore very-short-run (e.g., hourly) own-price elasticities of industrial energy users exposed to time-varying wholesale electricity prices or real-time pricing programs for three reasons. First, we do not have highly disaggregate hourly data at customer level for the lower 48 states. Second, the size of hourly elasticity estimates is generally small (< 0.1) based on (a) a summary of own-price elasticity estimates from utility-sponsored real-time pricing programs (EPRI, 2021); and (b) examples of elasticity estimation for industrial firms exposed to wholesale prices (Patrick and Wolak, 2001; Zarnikau and Hallett, 2008). Finally, hourly own-price elasticity estimates seldom consider the kWh effect of inter-fuel substitution, an important aspect of an industrial electricity demand analysis like the one presented herein.

(1) The US industrial electricity demand's statistically significant ($p$-value $\leq 0.05$) static own-price elasticity estimates are -0.029 to -0.130, short-run -0.021 to -0.133 and long-run -0.043 to -0.214,[4] matching the low estimates found by extant studies.

(2) Statistically significant factors affecting the US industrial electricity demand's own-price elasticity estimates are elasticity type, parametric specification, and assumption of partial adjustment.

(3) Erroneously ignoring the highly significant ($p$-value < 0.01) presence of CD does not materially alter the US industrial electricity demand's own-price elasticity estimates.

(4) The US industrial electricity demand's own-price elasticity estimates do not vary by season.

(5) The US industrial electricity demand's price responsiveness has been slowly declining over time.

(6) The US industrial electricity demand's price responsiveness varies by region.

(7) This paper's approach is general. Subject to data availability, it is equally applicable to the commercial customer class in the US and non-residential customer classes in other parts of the world (e.g., countries in Europe or provinces in China).

The rest of our paper proceeds as follows. Section 2 explains the trend of rising retail electricity prices, discusses nonlinear pricing of industrial electricity consumption, presents a brief literature review, identifies knowledge gaps, states the theory of industrial electricity demand, derives the five parametric specifications, describes our panel data, and proposes an estimation strategy. Section 3 presents our empirics, the basis of Section 4: conclusions and policy implications.

[4] As detailed in Section 2, a static price elasticity estimate comes from a demand regression that ignores the relationship between current and past consumption. Short-run and long-run price elasticity estimates are based on a demand regression with partial adjustment.

## 2. Materials and methods

### 2.1 Trend of rising retail electricity prices in the US

An industrial customer in the US may be served by (a) an integrated electricity utility in a state without retail competition (e.g., Louisiana) (Zarnikau et al., 2020a); or (b) a retail service provider (RSP) in a state with retail competition (e.g., Texas) (Brown et al., 2020a). The utility in (a) is more likely to be investor-owned and regulated by a state public utility commission than publicly owned and overseen by a local municipality or cooperative.[5] Irrespective of the type of ownership, its retail prices aim to fully recover embedded costs (Bonbright et al., 1988). The RSP in (b) buys energy and capacity from the wholesale electricity market, transmission (T) service from a grid operator, and distribution (D) service from a local distribution company. It offers retail pricing plans designed to fully collect its procurement costs for energy, capacity, and T&D services.

The assumption of rising retail prices noted in Section 1 is underscored by the following cases in point. The first case is the technology path to deep decarbonization (Williams et al., 2012; Mahone et al., 2018). Electricity plays a pivotal role in this path, best exemplified by electrification of energy-using durables (e.g., furnace and vehicles) and large-scale development of emissions-free renewable resources (e.g., solar and wind) (Joskow, 2021).[6] Rising electrification increases an electric grid's obligation of meeting location- and time-dependent capacity and energy demands, with the ensuing incremental costs to be recovered through higher transmission charges that in turn raise retail electricity prices. In tandem, reliable integration of intermittent renewable energy increases the grid's operating reserve requirements (*aka* ancillary services) for maintaining system reliability and stability

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[5] Investor-owned utilities served 72% of U.S. electricity customers in 2017 (https://www.eia.gov/todayinenergy/detail.php?id=40913)

[6] The main drivers for renewable energy development in the US are easy transmission access, aggressive renewable portfolio standards and generous tax credits (Alagappan et al., 2011). Complementing these drivers is carbon trading described in the next paragraph.

(Zarnikau et al., 2019), thus raising retail electricity prices due to pass-through of wholesale electricity prices under retail competition (Brown et al., 2020a) or cost-of-service regulation (COSR) (Bonbright et al., 1988). Such retail electricity price increases are partially offset by renewable energy's declining per kWh cost (Woo and Zarnikau, 2019; Brown et al., 2020a) and merit order effect on wholesale electricity prices (Woo et al., 2017a, 2017b, 2018a; Zarnikau et al., 2019, 2020a).

The second case is cap-and-trade of $CO_2$ emissions permits (*aka* carbon trading) that accelerates development of renewable energy and retirement of aging coal- and natural-gas-fired power plants (Woo et al., 2017a, 2017b, 2018a). Carbon trading tends to raise retail electricity prices for two reasons. First, a RSP's pricing plans pass through wholesale prices that embody marginal costs of $CO_2$ emissions. Second, if a regulated electric utility has a generation capacity mix dominated by $CO_2$-emitting plants, its retail prices will likely increase under COSR due to procurement of $CO_2$ emissions permits.

The third case is the US wholesale natural gas price's decline attributable to the explosive growth of shale gas (Caporin and Fontini, 2017). As natural gas is becoming a dominant fuel for thermal generation in the US, its wholesale price decline reduces wholesale electricity prices (Woo et al., 2017a, 2017b, 2018a; Zarnikau et al., 2019, 2020a). The wholesale electricity price reductions are then passed through by an RSP or electricity utility to its retail prices. Further, an electric utility's retail electricity prices decrease under COSR's fuel cost adjustment clause for the natural gas used in electricity generation. Going forward, however, the US wholesale natural gas price decline will likely reverse because of environmental concerns about hydraulic fracturing (Sovacool, 2014) and projected growth of the US export of natural gas (Arora and Cai, 2014), causing the US retail electricity prices to rise in coming years.

The last case is the need to upgrade an electric grid's aging infrastructure, best illustrated by Texas's deep freeze of February 11 – 20 in 2021 that brought multiday power outages caused by generation plant shutdowns.[7] Improved protection of electrical facilities results in incremental costs to be paid by retail customers through higher electricity prices.

## 2.2 Nonlinear pricing of industrial electricity consumption in the US

Nonlinear pricing shapes our econometric modelling of the US industrial electricity demand. Specifically, our panel data analysis uses the EIA monthly average electricity price data that may be endogenous, necessitating instrumental variable (IV) estimation to obtain consistent estimates of price elasticities (Davidson and MacKinnon, 1993).

To understand average electricity price data's endogeneity, consider an industrial customer in the US that typically faces a Hopkinson tariff with per kWh charges which may be time differentiated and per kW-month charges which may be reliability differentiated (Seeto et al., 1997; Horowitz and Woo, 2006; Woo et al., 2014). This tariff's empirical implication is that the observed negative relationship between the customer's monthly usage and average price (= monthly electricity bill ÷ monthly kWh usage) can misinform the customer's price sensitivity. To see this point, consider a hypothetical manufacturing plant's average electricity price based on a simple Hopkinson tariff that has a flat per kWh charge for monthly kWh usage and a flat per kW-month charge for monthly non-coincident peak kW demand in the plant's busiest hour within a month. The plant's average electricity price for a given month increases when the plant uses less kWh due to public holiday and worker sickout. This negative relationship between the plant's monthly average price and kWh usage exists, even when the plant is ***completely insensitive*** to electricity price changes.

[7] In July 2021, the Energy Institute of the University of Texas at Austin timeline issued a report (https://energy.utexas.edu/ercot-blackout-2021) on the events of the February 2021 Texas electric grid blackouts.

Nonlinear pricing may cloud an industrial customer's understanding of the applicable per kWh and per kW charges. However, the customer is likely a sophisticated large user that closely monitors its kWh consumption and kW demand (Seeto et al., 1997), unlike a residential customer who seldom knows its kWh consumption absent smart metering (Jessoe and Rapson, 2014; Batalla-Bejerano et al., 2020). This suggests the industrial customer's electricity consumption decision for a given month is based on that month's price information, rather than the average price based on the prior month's electricity bill. Hence, current prices, instead of lagged prices, should be used when estimating the US industrial electricity demand's price responsiveness.

### 2.3 Literature review

To provide our paper's contextual background, we review a sample of industrial electricity demand studies. Intentionally brief, this review does not consider time series modelling of high-frequency (e.g., 5-minute to hourly) electricity load data, whose primary focus is seldom price responsiveness (Weron, 2006, 2014). Second, we do not consider time-of-use electricity demand studies that typically do not consider an industrial customer's inter-fuel substitution (Faruqui and Malko, 1983; Aigner, 1984; DOE, 2006; FERC, 2008-2020; Faruqui and Sergici, 2010; EPRI, 2021). Third, a comprehensive literature review is obviated by extant surveys of numerous energy demand studies (e.g., Taylor, 1975; Hartman, 1979; Bohi and Zimmerman, 1984; Dahl, 1993; Dahl and Roman, 2004; Suganthia and Samuel, 2012; Labanderia et al., 2017; Huntington et al., 2019).

Table 1 summarizes own-price elasticity estimates found by a list of selected studies.[8] For brevity, this table does not report cross-price elasticity estimates that are typically positive but smaller in size than own-price elasticity estimates.

[8] Unintended to be exhaustive, the list is found via the following steps: (1) use scholar.google.com to find the initial list based on the keywords of "price elasticity", "industrial electricity demand" and "United States"; and (2) narrow the initial list by considering each study's immediate relevance to our paper.

Emerged from Panel A of Table 1 are the following remarks in connection to the US studies. First, the regional coverage of these studies spans from a single state to lower 48 states. Second, these studies tend to use annual data, with notable exception of Woo et al. (2017c, 2018b) that use monthly data for a more granular determination of price and weather effects on industrial electricity demand. Third, all studies use natural gas price as a regressor to account for substitutability between electricity and natural gas, while five studies additionally use fuel oil price. Fourth, eight studies use the double-log specification, whose price coefficients conveniently measure price elasticities. The other three studies use the linear, CES and GL specifications. Fifth, the estimation methods range from a simple OLS regression to three-stage least squares estimation of a system of regressions. Sixth, all studies use average price data. Finally, the elasticity estimates in this panel's last three columns paint a mixed picture of highly diverse price responsiveness, with own-price elasticity estimates ranging from -0.02 to -29.7. Emerged from Panel B of Table 1 are the following remarks in connection to the non-US studies. First, the regional coverage of these studies spans from a single country to 35 countries. Second, these studies tend to use annual data, with notable exception of Labandeira et al. (2012) and Kwon et al. (2016) that use monthly data. Third, only three studies include non-electric energy prices as regressors in their regression models. Fourth, nine studies use the double-log specification and the remaining three employ TL and CES functional forms. Fifth, the estimation methods vary from a simple OLS regression to maximum likelihood estimation of a system of regressions. Sixth, all studies use average price data. Finally, the elasticity estimates in this panel's last three columns affirm industrial electricity demand's highly diverse price responsiveness, with own-price elasticity estimates ranging from -0.03 to -1.9.

## 2.4 Knowledge gaps

Identified by our literature review are the following knowledge (KG) gaps:

- **KG1**: While some studies have long sample periods, there is a lack of empirics on the time trend of price responsiveness.
- **KG2**: None of the studies investigates seasonality of price responsiveness.
- **KG3**: These studies use annual or monthly data without considering the effect of data frequency on price elasticity estimates.[9]
- **KG4**: While these studies encompass five parametric specifications, presently unknown is how price elasticity estimates vary by specification.
- **KG5**: Liddle and Hasanov (2021) is the only study that accounts for CD. There are no empirics on the impact of erroneously ignoring the statistically significant CD presence on price elasticity estimates, an important issue investigated by Li et al. (2021) for the residential customer class.
- **KG6**: Lin et al. (1987) is the only study that considers regional variation in the US electricity demand's price responsiveness. There is a lack of recent empirics on the industrial customer class's regional own-price elasticity estimates.

## 2.5 Theory and practical considerations of industrial electricity demand

Consider an industrial customer's two-stage cost minimization problem. In Stage 1 that is conditional on an installed stock of energy using durables, the customer procures electricity $Y_1$ (kWh) at price $P_1$ ($/kWh), fuel oil $Y_2$ (gallon) at $P_2$ ($/gallon) natural gas $Y_3$ (Mcf) at price $P_3$ ($/Mcf) to minimize its monthly energy cost for producing some intermediate output $Z$. We assume that $Z$ is an increasing function of a set of end-use requirements such as heating, cooling, lighting, refrigeration, and intra-plant transportation (e.g., conveyor belts and folk lifts). In Stage 2, the customer chooses the least-cost mix of $Z$ and non-energy inputs

[9] Price elasticity estimates based on annual data are likely larger in size than those based on monthly data, chiefly because an industrial customer has more flexibility in making its annual energy consumption decision.

such as labour ($L$), material ($M$) and capital ($K$) to produce output vector $\boldsymbol{V}$ according to the transformation function $G(\boldsymbol{V}, Z, L, M, K)$.

Let $Y_1^*$, $Y_2^*$ and $Y_3^*$ denote the least-cost usage levels of electricity, fuel oil and natural gas that solve the Stage 1 problem. The resulting monthly energy cost function is:

$$C(P_1, P_2, P_3, Z) = P_1\, Y_1^* + P_2\, Y_2^* + P_3\, Y_3^* > 0. \tag{2}$$

A theoretically valid $C(\bullet)$ is homogeneous of degree one in ($P_1$, $P_2$, $P_3$), increasing and concave in ($P_1$, $P_2$, $P_3$), and increasing in $Z$ (Varian, 1992).

Invoking Shephard's Lemma yields the electricity demand function (Diewert, 1971):

$$\partial C(\bullet) \,/\, \partial P_1 = Y_1^* = H(P_1, P_2, P_3, Z). \tag{3}$$

As $Y_1^*$ is homogeneous of degree zero in ($P_1$, $P_2$, $P_3$), $P_1\, \partial H(\bullet)/\partial P_1 + P_2\, \partial H(\bullet)/\partial P_2 + P_3\, \partial H(\bullet)/\partial P_3 = 0$, implying $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 0$. As $\varepsilon_1 < 0$ and $(\varepsilon_2 + \varepsilon_3) > 0$, at least one non-electricity energy input is a substitute for electricity in the customer's production of $Z$. Further, the cost function's price homogeneity property implies that $Y_1^*$ depends on energy price ratios rather than on the price levels. In addition, $\partial H(\bullet) \,/\, \partial Z > 0$ indicates that the industrial electricity demand increases with $Z$.

While $Z$ is not directly unobservable, it can be proxied by a linear function of the monthly industrial employment denoted by $X$ and weather based on cooling degree days (*CDD*) and heating degree days (*HDD*). Finally, this study employs average prices for four reasons. First, it exploits the EIA's publicly available monthly data. Second, absent disaggregate consumption data and tariff information at customer level, accurate marginal prices are impossible to find. Third, it simplifies the cost minimization problem that can become very complicated if based on a Hopkinson tariff (Woo et al., 1995). Finally, should average price data be found endogenous, the ensuing estimation bias can be corrected via IV estimation (Davidson and MacKinnon, 1993).

2.6 Parametric specifications

Our literature review leads us to consider five parametric specifications of $C(\bullet)$. In the ensuing analysis we first state the energy cost function associated with specification $j$ for $j$ = 1, …, 5, and then apply Shephard's Lemma to derive the consequent electricity demand function. Finally, we state each specification's own-price elasticity of electricity demand. For empirical implementation, we replace the unobservable $Y_m^*$ with the observable $Y_m$ = recorded usage level so that $(Y_m - Y_m^*)$ is a random error with zero mean and finite variance.

Our chosen metric for measuring price responsiveness of the industrial demand for electricity is the own-price elasticity that is the primary focus of the studies listed in Table 1 and those included in literature surveys. Further, the sum of cross-price elasticities can come from $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 0$ (e.g., $\varepsilon_1 = -\varepsilon_3$ when $\varepsilon_2 = 0$ that indicates the US industrial electricity demand's insensitivity to fuel oil price changes).

2.6.1 Double-log specification

Based on Hausman (1981), the double-log demand equation's normalized cost function is:

$$(C / P_3) = e^{\beta_0} [(P_1 / P_3)^{1+\beta_1} / (1 + \beta_1)] (P_2 / P_3)^{\beta_2} Z^{\beta_Z}. \quad (4)$$

Invoking Shephard's Lemma and using normalized prices,[10] we find the double-log demand equation:[11]

$$\ln Y_1 = \beta_0 + \beta_1 \ln(P_1 / P_3) + \beta_2 \ln(P_2 / P_3) + \beta_Z \ln Z. \quad (5)$$

[10] Some non-US studies in Table 1 ignore an industrial customer's inter-fuel substitution and use the real electricity price ($P_1 / P$) with $P$ = GDP price deflator as the only energy price regressor. This implies $\beta_2 = 0$ in equation (5) below. However, $\beta_1$ continues to have the interpretation of an own-price elasticity. Our regression results in Table 4 show that the $\beta_2$ estimate is statistically significant, thus rejecting the restriction of $\beta_2 = 0$.
[11] For expositional ease and conciseness, our discussion of demand equations excludes the additive random error, as commonly done in the electricity demand literature.

The own-price elasticity is $\varepsilon_1 = \beta_1$, which does not vary by consumption level or across time and states. As the data for $Z$ are unobservable, estimating equation (5) assumes that $\ln Z$ is a linear function of $X$, $CDD$ and $HDD$.

2.6.2 Linear specification

Based on quadratic approximation, the normalized energy cost function is:

$$(C / P_3) = \alpha_1 (P_1 / P_3) + \alpha_2 (P_2 / P_3) + 1/2\ \alpha_{11} (P_1 / P_3)^2 + \alpha_{12} (P_1 / P_3)\ (P_2 / P_3) + 1/2\ \alpha_{22} (P_2 / P_3)^2 + \alpha_{1Z} (P_1 / P_3) Z + \alpha_{2Z} (P_2 / P_3) Z. \tag{6}$$

Invoking Shephard's Lemma and the definition of normalized prices yields the linear demand equation:

$$Y_1 = \alpha_1 + \alpha_{11} (P_1 / P_3) + \alpha_{12} (P_2 / P_3) + \alpha_Z Z. \tag{7}$$

The linear demand's own-price elasticity is:

$$\varepsilon_1 = \alpha_{11} (P_1 / P_3) / Y_1. \tag{8}$$

As $\varepsilon_1$ nonlinearly depends on the price ratio and electricity usage level, it varies by consumption level and across time and states. Thus, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates. Finally, estimating equation (7) assumes that $Z$ is a linear function of $X$, $CDD$ and $HDD$.

2.6.3 CES specification

Consider a homothetic CES energy cost function (Woo et al., 2017c, 2018c):

$$C = A^{1/\rho} h(Z), \tag{9}$$

where $A = [\lambda_1 P_1{}^\rho + \lambda_2 P_2{}^\rho + \lambda_3 P_3{}^\rho]$ and $h(Z)$ = increasing function of $Z$.

Invoking Shephard's Lemma and dividing the demand function for electricity by the demand function for gas yields:

$$\ln(Y_1 / Y_3) = \phi_0 + \phi_1 \ln(P_1/P_3), \tag{10}$$

where $\phi_0 = (\lambda_1 / \lambda_3)$ and $\phi_1 = (\rho - 1)$. To recognize possible dependence of $\ln(Y_1 / Y_3)$ on non-price factors, we assume $\phi_0$ to be a linear function of $X$, $CDD$ and $HDD$.

The CES demand's own-price elasticity is:

$$\varepsilon_1 \quad = \quad \phi_1 (1 - S), \tag{11}$$

where $S = P_1\, Y_1 / C$ = electricity cost share (Woo et al., 2018c). As $\varepsilon_1$ varies by consumption level and across time and states, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates.

We would be remiss had we ignored the data mismatch in connection to the calculation of $\varepsilon_1$ under the CES specification. Specifically, equation (11) requires monthly data by state for industrial fuel oil prices and usage levels. While the EIA publishes monthly fuel oil prices, only annual fuel oil usage levels are available. To overcome this data mismatch, we first use the EIA monthly data to compute $S_{\max} = P_1\, Y_1 / (P_1\, Y_1 + P_3\, Y_3)$ under the assumption that the state's industrial customer class does not consume fuel oil. We then use the EIA annual data to compute two annual electricity cost shares: $AS_{\max} = P_1\, Y_1 / (P_1\, Y_1 + P_3\, Y_3)$ and $AS_{\text{true}} = P_1\, Y_1 / (P_1\, Y_1 + P_2\, Y_2 + P_3\, Y_3)$. Finally, we use $S_{\max}\, (AS_{\text{true}} / AS_{\max})$ to approximate $S$'s monthly missing values.

2.6.4 GL specification

Consider the following GL energy cost function (Diewert, 1971; Woo et al., 2018b):

$$\begin{aligned} C \quad = \quad & b_{11}\, P_1 + b_{22}\, P_2 + b_{33}\, P_3 + 2\, b_{12}\, P_1^{1/2} P_2^{1/2} + 2\, b_{13}\, P_1^{1/2} P_3^{1/2} + \\ & 2\, b_{23}\, P_2^{1/2} P_3^{1/2} + b_{1Z}\, P_1\, Z + b_{2Z}\, P_2\, Z + b_{3Z}\, P_2\, Z. \end{aligned} \tag{12}$$

Invoking Shephard's Lemma, we find the industrial electricity demand function:

$$Y_1 \quad = \quad b_{11} + b_{12}\, (P_2 / P_1)^{1/2} + b_{13}\, (P_3 / P_1)^{1/2} + b_{1Z}\, Z. \tag{13}$$

The GL demand's own-price elasticity is:

$$\varepsilon_1 \quad = \quad - 1/2\, [b_{12}\, (P_2 / P_1)^{1/2} + b_{13}\, (P_3 / P_1)^{1/2}\, ] / Y_1. \tag{13}$$

As $\varepsilon_1$ varies by consumption level and across time and states, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates. Finally, estimating equation (13) assumes that $Z$ is a linear function of $X$, $CDD$ and $HDD$.

### 2.6.5 TL specification

Consider a TL energy cost function (Berndt, 1976; Caves and Christensen, 1980):

$$\ln C = a_1 \ln P_1 + a_2 \ln P_2 + a_3 \ln P_3 + 1/2\,[a_{11} (\ln P_1)^2 + a_{22} (\ln P_2)^2 + a_{33} (\ln P_3)^2 + 2\,a_{12} \ln P_1 \ln P_2 + 2\,a_{13} \ln P_1 \ln P_3 + 2\,a_{23} \ln P_2 \ln P_3] + a_{1Z} \ln P_1 \ln Z + a_{2Z} \ln P_2 \ln Z + a_{3Z} \ln P_3 \ln Z, \qquad (14)$$

which obeys the linear restrictions of $a_1 + a_2 + a_3 = 1$; $a_{11} + a_{12} + a_{13} = \ldots = a_{13} + a_{23} + a_{33} = 0$; and $a_{1Z} + a_{2Z} + a_{3Z} = 0$.

Invoking Shephard's Lemma, we find the electricity cost share equation:

$$S = a_1 + a_{11} \ln(P_1/P_3) + a_{12} \ln(P_2/P_3) + a_{1Z} \ln Z. \qquad (15)$$

Estimating equation (15) assumes that $\ln Z$ is a linear function of $X$, $CDD$ and $HDD$ and the data for $S$ are the approximated values used by the CES specification's own-price elasticity calculation.

The own-price elasticity based on the TL specification is:

$$\varepsilon_1 = (a_{11} + S^2 - S) / S. \qquad (16)$$

As $\varepsilon_1$ varies by consumption level and across time and states, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates.

## 2.7 Long-run elasticity

We have thus far ignored the dependence of a current month's consumption on the prior month's consumption due to an industrial customer's slowly changing stock of electricity using durables. Hence, we include the 1-month lagged regressand as an additional regressor to reflect partial adjustment, as similarly done by some studies in Table 1.[12]

[12] We decide not to use autoregressive distributed lag (ADRL) modelling because our preliminary exploration shows that the additional estimation sophistication does not lead to better understanding of the US industrial electricity demand's empirical price responsiveness. Supporting this claim are the following reasons. First, ADRL modelling is not absolutely necessary for identifying what matters in the US industrial electricity's empirical price responsiveness. Second, the ADRL model relies on an appropriate specification of the lag structure, which cannot be *a priori* informed by our demand theory. Finally, the ARDL results cloud the relationship's presentation and explanation, unlike our clear discussion of the empirics reported in Section 3.

Let $\varphi$ denote the lagged regressand's coefficient. As will be seen in Section 3 below, the statistically significant ($p$-value $\leq 0.05$) estimate for $\varphi$ is between 0.376 to 0.507.[13] After using specification $j$'s own-price elasticity formula to compute the short-run elasticity (SRE), we calculate the long-run elasticity LRE = SRE / (1 - $\varphi$).

2.8 Selection of a parametric specification

None of the studies listed in Table 1 discusses how to select a parametric specification among multiple alternatives. For example, the TL specification may yield negative predicted cost shares and positive own-price elasticity estimates, violating the energy cost function's theoretical properties of positive cost shares and price concavity. If the number of violations is relatively large (e.g., over 20% of the sample), the TL specification is deemed empirically inappropriate.

We consider three approaches for selecting a parametric specification. First, if the choice is between the double-log and linear specifications, it can be based on estimating a Box-Cox demand regression for testing which specification is rejected by the data (Woo, 1994).

Second, the choice among the CES, GL and TL specifications can rely on their global properties investigated by Caves and Christensen (1980), whose general finding is that the TL specification tends to have more violations than the CES and GL specifications. Further, selecting a suitable specification (e.g., CES vs. GL) can be based on testing linear restrictions on the CES-GBC specification (Tishler and Lipovesky, 1997). Finally, one may use Bayesian modelling proposed by Xiao et al. (2007).

Third, the selection is based on empirical plausibility, as often done in regulatory hearings in the US (Woo et al., 2015). For example, if a particular specification (e.g., the TL)

[13] The implication of this finding is that after experiencing a demand shock (e.g., a price increase), an industrial customer achieves its equilibrium mix of electricity and natural gas usage within three months.

produces elasticity estimates that greatly differ from those found under the commonly used double-log and linear specifications, its proponent likely faces accusations of cherry-picking during cross-examination. When the elasticity estimates based on most of the specifications considered are numerically close, they are deemed empirically plausible.

Our decision to use the third approach reflects that few participants in a regulatory hearing can perform sophisticated statistical tests. It also reflects the likely lack of understanding of such tests by the hearing's general audience (e.g., lawyers, regulatory staff, consumer advocates, environmentalists, and ratepayers).

2.9 Data description

Table 2 presents the descriptive statistics of our panel data. All variables listed in this table have wide ranges defined by their minimum and maximum values. Based on the coefficient of variation (= standard deviation / mean), the data for non-weather variables are less volatile than weather variables.

The last column of Table 2 reports that $Y_1$ is positively correlated with $Y_3$ ($r$ = 0.51), suggesting that electricity and natural gas usage tend to move in tandem. It is negatively correlated with $P_1$ ($r$ = -0.452) but less so with $P_2$ ($r$ = -0.037) and $P_3$ ($r$ = -0.276). It is negatively correlated with ($P_1$ / $P_3$) ($r$ = -0.043) but positively correlated with ($P_2$ / $P_3$) ($r$ = 0.213). While it is positively correlated with $X$ ($r$ = 0.537), its correlation with $CDD$ and $HDD$ is very weak ($|r| < 0.05$). In summary, the correlation coefficients in Table 2 do not untangle the marginal effects of price ratios, employment, and weather on the US industrial electricity demand, leading to our estimation strategy presented below.

2.10 Estimation strategy

Thanks to its popularity, the double-log specification with partial adjustment is used here to illustrate our estimation strategy:

$$\ln Y_{1kt} = \beta_1 \ln(P_{1kt} / P_{3kt}) + \beta_2 \ln(P_{2kt} / P_{3kt}) + \beta_X X_{kt} + \beta_{CDD} CDD_{kt} + \beta_{HDD} HDD_{kt} +$$

$$\varphi \ln Y_{1kt\text{-}1} + \eta_k + \mu_{kt}, \qquad (17)$$

where $\eta_k$ = state-specific fixed effect; and $\mu_{kt}$ = random error with $k$ = 1 to 48 and $t$ = 2 to 228 denoting an observation's state (= 1 for Alabama, …, 48 for Wyoming) and period (= 1 for Jan-2001, …, 228 for Dec-2019).

Estimating equation (17) under the restriction of $\varphi = 0$ produces the static elasticity estimate. When the $\varphi$ estimate is statistically significant, the short- and long-run elasticity estimates are those explained in Section 2.7.

To obtain consistent estimates for the coefficients in equation (17), we use the dynamic common correlated effects (DCCE) panel estimator that accounts for CD presence (Chudik and Pesaran, 2015).[14] The DCCE estimator controls for CD by adding current and lagged cross-section averages of the dependent and explanatory variables to the dynamic panel regression. Under the restriction of $\varphi = 0$, it is not necessary to add any lags of the cross-section averages, and the resulting estimator will resemble that of Pesaran (2006).[15] Under the assumption of CD absence, cross-section averages are not included in the regression and the resulting estimator resembles that of Pesaran and Smith (1995).

We now state our multistep estimation strategy:

(1) Use the Pesaran (2020) test to determine the statistical significance of CD presence.

(2) Perform the Pesaran (2007) panel unit root test to ensure stationarity of the variables and avoid spurious regressions (Baltagi and Kao, 2001).

(3) Perform IV and non-IV estimation to estimate the coefficients of equation (17) for the four cases formed by (a) $\varphi = 0$ vs. $\varphi > 0$; and (b) CD presence vs. CD absence. The instrument for the current month's price ratio is the price ratio in the prior three months.

[14] Accommodating autocorrelation and heteroscedasticity, this estimator generates standard errors for gauging the statistical significance of the coefficient estimates.

[15] As the Pesaran (2006) estimator differs from the DCCE estimator, the resulting static own-price elasticity estimates may not lie between the short-run and long-run estimates, as exemplified by the estimates found by Woo et al. (2018b).

## 3. Empirics

### 3.1 Tests of cross-section independence and non-stationary data

Table 3 contains the test results that decisively reject ($p$-value < 0.01) the null hypotheses of cross-section independence and data non-stationarity. Hence, our panel data analysis accounts for CD presence *sans* the concern of spurious regressions.

### 3.2 General remarks on regression results

Three general remarks emerge from Table 4. First, all non-CES specifications that include CD presence have adjusted $R^2$ values $\geq 0.74$ that indicate reasonable goodness of fit. Second, the hypothesis of CD absence is decisively rejected ($p$-value < 0.01) for all specifications.[16] Third, the Durbin-Wu-Hausman test (Wooldridge, 2010) results suggest that the current price ratio data are exogenous for six (seven) out of 10 models under CD presence (CD absence).[17] Further, IV estimation leads to various anomalous elasticity estimates, lending further support to the use of non-IV estimation. These remarks lead to our preference for the results by specification shaded in light green in the panels of Table 4 that are based on CD presence and non-IV estimation.

### 3.3 Regression details

We now turn our attention to the regression details. For the double-log specification, Panel A.1 of Table 4 reports that the US industrial electricity demand has a static own-price elasticity estimate of -0.103 and increases with employment, *CDD* and *HDD*. Panel A.2 reports that the demand effects of *CDD* and *HDD* are numerically close to those in Panel A.1. The short-run own price elasticity estimate is -0.094, smaller than its long-run counterpart of

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[16] Pesaran (2020) cautions against the use of the CD test on residuals in models augmented with cross-sectional averages. Therefore, we do not report the CD test results for the models with CD presence.

[17] The average electricity price ratio data are exogenous when an industrial customer's average electricity price is almost linear when the customer has a high load factor. To see this point, consider an industrial customer's average price = $P + D$, where $P$ = per kWh charge and $D = K \times$ total kW demand / total kWh usage for $K$ = per kW-month demand charge. Let $LF$ = load factor = total kWh usage per month ÷ (total kW demand × 720 hours per month). Hence, $D = K / (LF \times 720$ hours). As $LF$ approaches 1, $D$ converges to ($K$ / 720 hours) and the customer's average price becomes almost linear.

-0.150 due to the coefficient estimate of 0.376 for lagged $\ln Y_1$. Parenthetically, the double-log specification's static and long-run elasticity estimates corroborate the -0.100 and -0.123 estimates found by Woo et al. (2018b).

For the linear specification, Panels B.1 and B.2 show that the positive coefficient estimates for employment, *CDD*, *HDD* and lagged $Y_1$. The static own-price elasticity estimate is -0.130, close to the one under the double-log specification. The short- and long-run estimates are -0.090 and -0.164, larger than those found by Woo et al. (2018b).

Panel C.1 shows that under the CES specification, $\ln(Y_1 / Y_3)$ declines with $\ln(P_1 / P_3)$. The estimated coefficient for employment is negative but statistically insignificant. Further, the coefficient estimates for *CDD* and *HDD* suggest weather's small impact on the electricity-natural gas consumption ratio. The static own-price elasticity estimate is -0.029, comparable to the -0.035 estimate for California found by Woo et al. (2017c). The short- and long-run estimate are -0.021 and -0.043, much smaller than those based on the double-log and linear specifications.

Panel D.1 and D.2 report the GL specification's coefficient estimates for employment is positive. Though statistically significant, the estimates for *CDD* and *HDD* are close to zero. The static own-price elasticity estimate is -0.087, the short-run estimate -0.115 and the long-run estimate -0.214, larger than those based on the double-log, linear and CES specifications, and those found by Woo et al. (2017c, 2018b).

For the TL specification, Panel E.1 and E.2 report that the estimated effect of employment on electricity cost share is negative though insignificant. The estimated effects of *CDD* and *HDD* are negligible. The static own-price elasticity estimate is -0.055, close to those found by Woo et al. (2017c). The short- and long-run estimates are -0.133 and -0.208, comparable to those based on the GL specification.

In summary, the own-price elasticity estimates in Table 4 are moderately diverse. Nevertheless, their small sizes generally support the elasticity assumptions made by the US government agencies and electric utilities.

3.3 Seasonal pattern of own-price elasticity estimates

Motivated by **KG2**, Panel F of Table 4 reports the seasonal pattern of own-price elasticity estimates by specification, leading to the following remarks. First, elasticity estimates within a season vary by specification. Second, elasticity estimates for a given specification do not appear to vary seasonally. These remarks suggest that energy policy modelling and resource planning can use elasticity estimates for all 12 months, without overly concerning price responsiveness's seasonality.

3.4 Factors affecting the US industrial demand's empirical price responsiveness

Motivated by **KG4** and **KG5**, we estimate an OLS dummy variable regression to delineate what moves the US industrial demand's empirical price responsiveness. Table 5 contains this regression's results that have the following interpretations:

- The positive coefficient estimates for $F_j$ for $j$ = 1 to 4 indicate that the TL specification tends to magnify the size of own-price elasticity estimates. Further, the double-log, linear and GL specifications have similar own-price elasticity estimates that are larger in size than those based on the CES specification.
- The statistically insignificant estimate for *IV* indicates that IV estimation does not have a discernible effect on elasticity estimates.
- The negative and significant coefficient estimate *LR* suggests that the long-run elasticity estimates are larger than the static estimates that are not significantly different from the short-run estimates.

- The highly insignificant ($p$-value = 0.71) coefficient estimate for *CD* suggests that erroneously ignoring CD presence does not alter the US industrial electricity demand's empirical price responsiveness.

When taken together, the preceding interpretations suggest that the elasticity estimates in Table 4 are bound by the CES specification's and TL specification's estimates. They also reveal the similarity of elasticity estimates based on the double-log, linear and GL specifications, thus lending support to these specifications' empirical plausibility.

3.5 Time trend of own-price elasticity estimates

Motivated by **KG1**, we use a rolling-window approach to find elasticity estimates by 10-yer period under the empirically plausible double-log specification with CD presence and non-IV estimation. The first period is Jan-2001 to Dec-2010, the second period Feb-2001 to Jan-2011, …, the last period Jan-2010 to Dec-2019.

Figure 3 portrays the US industrial electricity demand's diminishing price responsiveness over time, which is further confirmed by the OLS regression results shown in Table 6. Hence, price-management of the US industrial electricity demand is likely to become less effective over time.

3.6 Final checks

We choose the double-log specification with CD presence and non-IV estimation to perform several final checks of the US industrial demands' empirical price responsiveness. Our choice reflects the double-log specification's popularity evidenced by Table 1 and empirical plausibility portrayed by Table 5.

The first check repeats the panel data analysis after excluding the regressor of fuel oil – natural gas price ratio. This check's finding is that the static own-price elasticity estimate becomes -0.046, short-run -0.024 and long-run -0.041. However, these small estimates are questionable because of the statistically significant coefficient estimates for $\ln(P_2 / P_3)$ in

Panels A.1 and A.2 of Table 4 . In short, excluding fuel oil from a regression analysis of the US industrial electricity demand tends to understate own-price elasticity estimates because the exclusion implies restricting industrial inter-fuel substation opportunities.

Motivated by **KG3**, the second check uses quarterly data instead of monthly data, thereby testing if a longer decision period affects industrial electricity demand's price elasticity estimates. It cannot use annual data because the DCCE estimator requires more time series observations than what the annual data can provide. Its finding is that the quarterly static price elasticity estimate is -0.090, the short-run estimate -0.072, and the long-run estimate -0.107. Thus, reducing data frequency does not materially affect price elasticity estimates reported in Panels A.1 and A.2 in Table 4.

The third check uses aggregate, instead of per capita, energy usage and employment data for estimating the double-log demand regression. This check's finding is that using aggregate data does not alter the price elasticity estimates reported in Panels A.1 and A.2 in Table 4.

The fourth check uses price level data instead of price ratio data. Its finding is that the static price elasticity estimate becomes -0.175, the short-run estimate -0.159, and the long-run estimate -0.240. Thus, relaxing the restriction that a theoretically valid industrial electricity demand equation should depend on price ratios tends to magnify the size of price elasticity estimates.

The fifth check implements the approach of Burke and Abayasekara (2018), a panel data analysis based on the double-log specification with the "between" estimator *sans* CD presence and state-specific fixed effects. The resulting long-run own-price elasticity estimate is -1.359, close to the estimates of -1.34 to -1.44 found by Burke and Abayasekara (2018). As the -1.359 estimate is much larger than those reported in Table 4 and adopted by the US government agencies and electric utilities, we caution against its use for energy policy modelling and resource planning.

Motivated by **KG6**, the sixth check investigates regional price responsiveness:

(1) Re-estimate the double-log demand regressions for two regions defined by (a) Texas and the states in the Western Interconnection; and (b) the remaining states in the Eastern Interconnection. Table 7 shows that these two regions have similar own-price elasticity estimates.

(2) Re-estimate the double-log demand regressions for two regions defined by (a) states with retail competition by the end of 2019 (Texas, and those in the Northeast); and (b) states without retail competition. Table 7 shows that industrial customers located in (a) tend to be more price responsive than those in (b), reflecting that industrial customers who can better respond to price changes are more likely to support retail competition.

(3) Re-estimate the regressions for two subsamples based on each state's electricity generation's coal share (*CS* = sum of annual coal-fired generation for the entire sample period / sum of annual generation for the entire sample period). The first subsample contains states with below average *CS*, while the second subsample the remaining states. Table 7 indicates that industrial customers who are less able to respond to price shocks are likely in states with low and stable electricity prices made possible by relative abundance of coal-fired generation.[18]

## 4. Conclusions and policy implications

### 4.1 Conclusions

Our paper's conclusions are as follows. First, accurate projections of electricity demand growth by customer class are necessary for energy policy modelling, electricity resource

[18] Coal-fired generation units tend to have lower and less volatile per MWh fuel costs than natural-gas-fired generation units because wholesale coal prices are less and more stable than natural gas prices.

planning, and electricity pricing and procurement. Own-price elasticity estimates for industrial electricity demand are important input assumptions for such projections. However, making reasonable assumptions based on a survey of extant studies is difficult, chiefly because these studies report highly diverse price elasticity estimates. As a result, these assumptions should be based on an electricity demand analysis of a large and recent sample.

Second, a panel data analysis that uses a large and recent sample of monthly data by state over a long period is useful for estimating price responsiveness of industrial electricity demand in the US. Such an analysis, however, should recognize the significant effects on elasticity estimates of the following factors: elasticity type, sample period, parametric specification, assumption on partial adjustment, treatment of CD, time trend, and region. That said, our extensive empirics convey the key message that the US industrial electricity demand's price responsiveness is low and diminishing over time.

Finally, our own-price elasticity estimates are between -0.03 to -0.21, matching the low end of the diverse estimates found by extant studies. Importantly, they represent newly developed empirical evidence that corroborates the elasticity ranges assumed by the US government agencies and electric utilities.

### 4.2 Policy implications

Emerged from our conclusions are the following policy implications. First, price-induced conservation is unlikely to materially reduce industrial electricity consumption in the US. Hence, deep decarbonization requires continuation of EE standards and DSM programs (EPA, 2008; Williams et al., 2012; Mahone et al., 2018).

Second, enhancing the US industrial electricity demand's price responsiveness may come from electricity product differentiation enabled by smart metering, as exemplified by an electricity utility's demand response (DR) programs like dynamic pricing and demand subscription (Woo et al., 2014).[19] Notwithstanding DR's increasing popularity (FERC, 2008-2020), we find that the US industrial electricity demand's price responsiveness has been slowly declining over time. Hence, a low-carbon economy requires resolution of thorny supply-side issues that currently plague the US electricity industry.

A partial list of supply-side issues includes: (a) limited geographic scope of carbon trading that causes power laundering (Woo et al., 2017a, 2017b);[20] (b) inadequate market-based investment incentives for natural-gas-fired generation (Woo et al., 2016; Zarnikau et al., 2020b); and (c) inadequate coordination of generation and transmission investments in a competitive market environment (Wu et al., 2006; Brown et al., 2020b; Chao and Wilson, 2020).[21] Resolving these and other supply-side issues (e.g., market power abuse, inefficient generation dispatch and uneconomic capacity reserve), however, requires refining an electric grid's existing market design (e.g., Woo et al., 2019), a topic well beyond the intent and scope of this paper.

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[19] In the US, DR programs are often optional with voluntary customer participation. Industrial customers that are highly price responsive tend to prefer a real-time pricing program with hourly prices that fluctuate daily over a time-of-use program with peak and off-peak prices that are fixed within a season. The same line of reasoning extends to the residential customer class because households have heterogenous price responsiveness (Frondel et al., 2019).

[20] Using California as example, power laundering occurs when a hydro generation owner in the Pacific Northwest exports emissions-free hydro energy to California, which is made possible by the owner's large reservoirs for importing energy produced by coal- and natural-gas-fired generation plants to meet the owner's domestic load obligations. Fixing the power laundering problem requires expanding the geographic scope of California's cap-and-trade program, not an easy task to achieve due to inter-state jurisdictional issues.

[21] A good example is California based on four regulatory governance reasons. First, while the California Independent System Operator (CAISO) can assess the state's transmission needs, it cannot order new transmission investments by the state's regulated investor-owned utilities because approval of these investments resides with the California Public Utilities Commission (CPUC). Second, generation investments by independent power producers are market-based, outside the purview of CAISO and CPUC. Third, the California Energy Commission has the authority of approving power plant siting applications. Finally, power plant and transmission line construction are subject to approval by a multitude of local governments.

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Table 1. Own-price elasticity estimates from selected studies of industrial electricity demand

Panel A: Eleven US studies

| Study | Sample period | Regional coverage | Data type | Data frequency | Non-electric energy prices | Parametric specification | Estimation method | Static | Short-run | Long-run |
|---|---|---|---|---|---|---|---|---|---|---|
| Beierlein et al. (1981) | 1967-1977 | Nine Northeast states | Panel | Annual | Natural gas, fuel oil | Double-log with partial adjustment | Error component – seemingly unrelated regressions | | -0.119 | -29.70 |
| Lin et al., (1987) | 1960-1983 | Nine regions of the US | Panel | Annual | Natural gas, fuel oil | Double-log with partial adjustment | Error component – seemingly unrelated regressions | | -0.388 | -1.160 |
| Badri (1992) | 1988 | 50 states | Cross section | Annual | Natural gas, fuel oil, coal | Linear | Two-stage least squares | -0.86 | | |
| Kamerschen and Porter (2004) | 1973-1998 | National | Time series | Annual | Natural gas | Double-log | Three-stage least squares | | | -0.34 to -0.55 |
| Macfie (2008) | 1960-2004 | Arizona | Time series | Annual | Natural gas | Double-log | OLS | -0.60 to -0.65 | | |
| | 2004 | Lower 48 states | Cross section | Annual | Natural gas | Double-log | OLS | -1.68 | | |
| Ros (2017) | 1972-2009 | 72 US electricity distribution companies | Panel | Annual | Natural gas | Double-log with partial adjustment | Two-stage least squares | | -0.046 to -0.096 | -0.64 |
| Woo et al. (2017c) | 2001-2016 | California (CA) and Pacific Northwest (PNW) | Panel | Monthly | Natural gas | Constant elasticity of substitution (CES) | Iterated seemingly unrelated regressions | CA: -0.035; PNW: -0.091 | | |
| Eryilmaz et al. (2017) | 2000 - 2013 | Thirteen Midwest states | Panel | Annual | Natural gas | Double-log with partial adjustment | Three-stage least squares | | -0.109 | -0.241 |
| Gautam and Paudel (2018) | 1997-2011 | Nine Northeast states | Panel | Annual | Natural gas, fuel oil | Double-log with autoregressive distributed lag | Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) | | | -0.63 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Burke and Abayasekara (2018) | 2003-2015 | Lower 48 states | Panel | Annual | Natural gas | Double-log | Panel data analysis with and without instrumental variable (IV) estimation | | -0.100 | IV: -1.34 Non-IV: -1.44 |
| Woo et al. (2018b) | 2001-2016 | Lower 48 states | Panel | Monthly | Natural gas, fuel oil | Generalized Leontief (GL) system of energy intensities with and without partial adjustment | Iterated seemingly unrelated regressions | -0.100 | -0.024 | -0.123 |

Notes: (1) Natural gas price enters an electricity demand equation because electricity and natural gas are substitutes.

(2) Badri (1992) is the only study that includes coal price as a regressor.

(3) Panel data are often used to obtain a large sample with sufficient data variation.

(4) A commonly used parametric specification is the double-log because its electricity price coefficient measures own-price elasticity.

(5) Due to nonlinear pricing, average industrial electricity prices are endogenous, necessitating the use of IV estimation to obtain consistent price elasticity estimates.

(6) None of the panel data studies considers the impact of cross-section dependence (CD) on the US industrial electricity demand's empirical price responsiveness.

(7) The very large estimate of -29.70 for Beierlein et al. (1981) is based on the lagged dependent variable's coefficient estimate of 0.96.

(8) We classify an elasticity estimate reported by a given study as static when (a) the estimate is based on a regression that does not use the lagged dependent variable as a regressor; or (b) the estimate is not explicitly stated as short- or long-run by the study.

Panel B: Twelve non-US studies

| Study | Sample period | Regional coverage | Data type | Data frequency | Non-electric energy prices | Parametric specification | Estimation method | Static | Short-run | Long-run |
|---|---|---|---|---|---|---|---|---|---|---|
| Bjørner (2001) | 1983 - 1996 | Denmark | Panel for 2,949 companies | Annual | None | Double-log | OLS with and without fixed effects (FE) | FE: -0.442 Non-FE: -1.33 | | |
| Bölük and Koç (2010) | 1980 - 2001 | Turkey | Time series | Annual | None | TL | Three-stage least squares | -0.85 | | |
| Labandeira et al. (2012) | 2005 - 2007 | Spain | Panel | Monthly | Natural gas | Double-log | Generalized least squares with error components | -0.0308 to -0.0518 | | |
| Cox et al. (2014) | 2003 | Germany | Cross section of sector data based on 60,000 firms | Annual | None | TL | Seemingly unrelated regressions | -0.20 | | |
| Bernstein and Madlener (2015) | 1970 - 2007 | Germany | Panel for 8 subsectors of the German manufacturing industry | Annual | None | Double-log | Vector error correction model | | -0.31 to -0.57 | 0.0 to -0.53 |
| Kwon et al. (2016) | 2004 - 2012 | Korea | Panel for 16 regions | Monthly | None | Double-log with partial adjustment | Two-stage least squares | | -0.051 | -0.207 |
| Wang and Mogi (2017) | 1989 - 2014 | Japan | Time series | Annual | None | Double-log | Time-varying coefficient model | -0.797 in 1995 to -0.289 in 2007 | | |
| Su (2018) | 1998 - 2015 | Taiwan | Panel for 23 industries | Annual | Petroleum | Double-log with and without partial adjustment | Generalized method of moments | -0.24 | -0.14 | -0.82 |
| Alarenan et al. (2020) | 1986 - 2016 | Saudi Arabia | Time series | Annual | None | Double-log with partial adjustment | Maximum likelihood | | -0.18 | -0.34 |
| Csereklyei (2020) | 1996 - 2016 | Europe | Panel for EU countries | Annual | None | Double-log with partial adjustment | Generalized method of moments | | -0.11 to -0.19 | -0.40 to -0.68 |
| Agnolucci and De Lipsisa (2020) | 1990 - 2014 | UK | Panel for 8 subsectors | Annual | Natural gas, oil, and coal | System of log[fuel share / (1 | Vector error correction model | | | -0.22 to -1.90 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | – fuel share)] regressions | | | | |
| Liddle and Hasanov (2021) | 1980 – 2016 | 35 OECD countries | Panel | Annual | None | Double-log | Autoregressive distributed lag model with cross-section dependence | | | -0.25 |

Notes: (1) The short-run estimates reported by Bernstein and Madlener (2015) are larger than the long-run estimates for some subsectors.
(2) Most of this panel's cited studies do not include non-electricity prices as regressors.
(3) The double-log is often used among the cited studies, which is followed by the TL. Further, the specification of Agnolucci and De Lipsisa (2020) based on fuel shares resembles those derived from the CES specification by Woo et al. (2017c).
(4) Liddle and Hasanov (2021) is the only study that accounts for the presence of cross-section dependence.
(5) We classify an elasticity estimate reported by a given study as static when (a) the estimate is based on a regression that does not use the lagged dependent variable as a regressor; or (b) the estimate is not explicitly stated as short- or long-run by the study.

Table 2. Descriptive statistics for the monthly data in Jan-2001 to Dec-2019 for the lower 48 states; number of observations = 10,944

| Variable (Source) | Definition | Mean | Standard deviation | Minimum | Maximum | Correlation with $Y_1$ |
|---|---|---|---|---|---|---|
| $Y_1$ (EIA and BLS) | Per capita electricity consumption (kWh) | 448.26 | 306.57 | 51.78 | 2177.51 | 1.0 |
| $Y_3$ (EIA and BLS) | Per capita natural gas consumption (Mcf) | 2.800 | 3.426 | 0.020 | 28.332 | 0.509 |
| $P_1$ (EIA) | Electricity price ($/kWh) | 0.067 | 0.024 | 0.027 | 0.182 | -0.452 |
| $P_2$ (EIA) | Fuel oil price ($/gallon) | 2.080 | 0.819 | 0.507 | 4.335 | -0.037 |
| $P_3$ (EIA) | Natural gas price ($/Mcf) | 7.280 | 2.650 | 1.710 | 22.750 | -0.276 |
| $P_1$ / $P_3$ | Electricity – natural gas price ratio | 0.010 | 0.004 | 0.002 | 0.052 | -0.043 |
| $P_2$ / $P_3$ | Fuel oil – natural gas price ratio | 0.317 | 0.166 | 0.061 | 1.499 | 0.213 |
| $X$ (BLS) | Per capita industrial employment | 0.093 | 0.023 | 0.042 | 0.173 | 0.537 |
| $CDD$ (NOAA) | Cooling degree days | 94.48 | 147.07 | 0 | 761 | 0.045 |
| $HDD$ (NOAA) | Heating degree days | 431.62 | 423.97 | 0 | 1919 | -0.001 |

Notes: (1) EIA is the US Energy Information Administration, BLS the US Bureau of Labor Statistics, and NOAA the US National Oceanic and Atmospheric Administration.
(2) This table excludes the industrial customer class's fuel oil consumption due to the lack of monthly data from the EIA.
(3) $P_1$, $P_2$ and $P_3$ are nominal prices. Converting these prices to real prices is unnecessary for our regression analysis because all specifications use price ratio data.
(4) $CDD$ = monthly sum of max(daily average temperature - 65°F, 0).
(5) $HDD$ = monthly sum of max(65°F - daily average temperature, 0).

Table 3. Test statistics for cross-section independence and non-stationarity data; *p*-values in ( )

| Variable | $H_0$: cross-section independence | $H_0$: Non-stationary data |
|---|---|---|
| $Y_1$ | 123.60<br>(0.000) | -2.310<br>(0.000) |
| $P_1$ / $P_3$ | 301.70<br>(0.000) | -4.420<br>(0.000) |
| $P_2$ / $P_3$ | 430.95<br>(0.000) | -4.498<br>(0.000) |
| $X$ | 401.98<br>(0.000) | -2.093<br>(0.010) |
| $CDD$ | 454.32<br>(0.000) | -6.145<br>(0.000) |
| $HDD$ | 480.78<br>(0.000) | -6.184<br>(0.000) |

Table 4. Regression results by specification; sample period: Jan-2001 to Dec-2019; statistically significant coefficient/elasticity estimates ($p$-value ≤ 0.10) in **bold**; coefficient/elasticity estimates with wrong sign in *italic*; each specification's preferred results shaded in light green

Panel A.1: Double-log specification without partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.08 | 0.08 | 0.11 | 0.11 |
| Adjusted $R^2$ | 0.83 | 0.95 | 0.67 | 0.68 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **-0.103** | -0.090 | **-0.109** | **-0.112** |
| $\ln(P_2 / P_3)$ = ln(fuel oil price / natural gas price) | **0.102** | 0.078 | **0.056** | **0.056** |
| $X$ = per capita industrial employment | 4.143 | 5.110 | **6.091** | **6.127** |
| $CDD$ = cooling degree days | **0.0002** | **0.0002** | **0.0003** | **0.0003** |
| $HDD$ = heating degree days | 0.0000 | 0.0000 | **0.0000** | **0.0000** |
| Static own-price elasticity | **-0.103** | -0.090 | **-0.109** | **-0.112** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel A.2: Double-log specification with partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.05 | 0.05 | 0.07 | 0.07 |
| Adjusted $R^2$ | 0.93 | 0.93 | 0.88 | 0.88 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **-0.094** | -0.0004 | **-0.054** | **-0.042** |
| $\ln(P_2 / P_3)$ = ln(fuel oil price / natural gas price) | **0.097** | 0.008 | **0.027** | **0.023** |
| $X$ = per capita industrial employment | **2.874** | **2.273** | **2.681** | **2.720** |
| $CDD$ = cooling degree days | **0.0001** | **0.0001** | **0.000** | **0.0002** |
| $HDD$ = heating degree days | **0.0000** | **0.0000** | **0.000** | **0.0000** |
| Lagged $\ln Y_1$ | **0.376** | **0.350** | **0.515** | **0.508** |
| Short-run own-price elasticity | **-0.094** | -0.0004 | **-0.054** | **-0.042** |
| Long-run own-price elasticity | **-0.150** | -0.001 | **-0.111** | **-0.085** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel B.1: Linear specification without partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.04 | 0.04 | 0.05 | 0.05 |
| Adjusted $R^2$ | 0.78 | 0.90 | 0.67 | 0.68 |
| ($P_1$ / $P_3$) = (electricity price / natural gas price) | -0.034 | -0.030 | **-0.041** | **-0.040** |
| ($P_2$ / $P_3$) = (fuel oil price / natural gas price) | 0.111 | 0.116 | **0.080** | **0.081** |
| $X$ = per capita industrial employment | **2.007** | **2.305** | **1.841** | **1.940** |
| $CDD$ = cooling degree days | **0.0001** | **0.0001** | **0.0001** | **0.0001** |
| $HDD$ = heating degree days | **0.0000** | **0.0000** | 0.0000 | 0.0000 |
| Static own-price elasticity | **-0.130** | **-0.114** | **-0.158** | **-0.156** |
| $p$-value for testing $H_0$: CD is absent | | | 0.000 | 0.000 |

Panel B.2: Linear specification with partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.02 | 0.02 | 0.03 | 0.03 |
| Adjusted $R^2$ | 0.92 | 0.83 | 0.85 | 0.86 |
| ($P_1$ / $P_3$) = (electricity price / natural gas price) | **-0.023** | -0.017 | **-0.021** | **-0.016** |
| ($P_2$ / $P_3$) = (fuel oil price / natural gas price) | **0.083** | 0.074 | **0.039** | **0.034** |
| $X$ = per capita industrial employment | **1.674** | **1.252** | **0.791** | **0.858** |
| $CDD$ = cooling degree days | **0.0001** | **0.0001** | **0.0001** | **0.0001** |
| $HDD$ = heating degree days | **0.0000** | 0.0000 | 0.0000 | 0.0000 |
| Lagged $Y_1$ | **0.452** | **0.425** | **0.511** | **0.499** |
| Short-run own-price elasticity | **-0.090** | **-0.066** | **-0.080** | **-0.062** |
| Long-run own-price elasticity | **-0.164** | **-0.115** | **-0.164** | **-0.123** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel C.1: CES specification without partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.16 | 0.16 | 0.21 | 0.20 |
| Adjusted $R^2$ | 0.74 | 0.96 | 0.58 | 0.59 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **-0.070** | -0.073 | **-0.248** | **-0.276** |
| $X$ = per capita industrial employment | -2.423 | -3.108 | 2.434 | 1.860 |
| *CDD* = cooling degree days | **0.0002** | **0.0002** | **0.0003** | **0.0003** |
| *HDD* = heating degree days | **-0.0002** | **-0.0002** | **-0.0003** | **-0.0003** |
| Static own-price elasticity | **-0.029** | **-0.030** | **-0.102** | **-0.114** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel C.2: CES specification with partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.12 | 0.11 | 0.15 | 0.15 |
| Adjusted $R^2$ | 0.85 | 0.92 | 0.78 | 0.79 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **-0.052** | *0.017* | **-0.123** | **-0.135** |
| $X$ = per capita industrial employment | -1.048 | -0.788 | 0.577 | 0.335 |
| *CDD* = cooling degree days | 0.0001 | 0.0000 | **0.0002** | **0.0002** |
| *HDD* = heating degree days | **-0.0002** | **-0.0002** | **-0.0002** | **-0.0002** |
| Lagged $\ln(Y_1 / Y_3)$ | **0.507** | **0.504** | **0.546** | **0.534** |
| Short-run own-price elasticity | **-0.021** | ***0.007*** | **-0.051** | **-0.056** |
| Long-run own-price elasticity | **-0.043** | ***0.014*** | **-0.112** | **-0.120** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel D.1: GL specification without partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.04 | 0.04 | 0.05 | 0.05 |
| Adjusted $R^2$ | 0.77 | 0.89 | 0.64 | 0.65 |
| $(P_2 / P_1)^{1/2}$ = (natural gas price / electricity price) $^{1/2}$ | -0.018 | -0.042 | 0.013 | 0.013 |
| $(P_3 / P_1)^{1/2}$ = (fuel oil price / electricity price) $^{1/2}$ | 0.127 | 0.066 | **0.079** | **0.074** |
| *X* = per capita industrial employment | 1.426 | **2.003** | **1.718** | **1.682** |
| *CDD* = cooling degree days | **0.0001** | **0.0001** | **0.0001** | **0.0001** |
| *HDD* = heating degree days | **0.0000** | **0.0000** | 0.0000 | 0.0000 |
| Static own-price elasticity | **-0.087** | ***0.015*** | **-0.098** | **-0.094** |
| *p*-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel D.2: GL specification with partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.02 | 0.02 | 0.03 | 0.03 |
| Adjusted $R^2$ | 0.92 | 0.81 | 0.85 | 0.86 |
| $(P_2 / P_1)^{1/2}$ = (natural gas price / electricity price) $^{1/2}$ | -0.005 | -0.008 | 0.010 | 0.008 |
| $(P_3 / P_1)^{1/2}$ = (fuel oil price / electricity price) $^{1/2}$ | **0.132** | -0.020 | **0.043** | **0.033** |
| *X* = per capita industrial employment | **1.170** | **1.110** | **0.724** | **0.705** |
| *CDD* = cooling degree days | **0.0001** | **0.0001** | **0.0001** | **0.0001** |
| *HDD* = heating degree days | 0.0000 | **0.0000** | 0.0000 | 0.0000 |
| Lagged $Y_1$ | **0.462** | **0.442** | **0.516** | **0.507** |
| Short-run own-price elasticity | **-0.115** | ***0.034*** | **-0.058** | **-0.045** |
| Long-run own-price elasticity | **-0.214** | ***0.061*** | **-0.121** | **-0.092** |
| *p*-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel E.1: TL specification without partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.03 | 0.03 | 0.04 | 0.04 |
| Adjusted $R^2$ | 0.89 | 0.85 | 0.83 | 0.83 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **0.198** | **0.179** | **0.190** | **0.187** |
| $\ln(P_2 / P_3)$ = ln(fuel oil price / natural gas price) | -0.012 | 0.001 | **-0.038** | **-0.037** |
| $X$ = per capita industrial employment | -0.969 | -1.073 | -0.122 | -0.169 |
| $CDD$ = cooling degree days | **0.0000** | **0.0000** | **0.0000** | **0.0000** |
| $HDD$ = heating degree days | **0.0000** | **0.0000** | **-0.0001** | **-0.0001** |
| Static own-price elasticity | **-0.055** | **-0.088** | **-0.069** | **-0.074** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel E.2: TL specification with partial adjustment

| Variable | CD presence | | CD absence | |
|---|---|---|---|---|
| | IV estimation: No | IV estimation: Yes | IV estimation: No | IV estimation: Yes |
| RMSE | 0.02 | 0.03 | 0.03 | 0.03 |
| Adjusted $R^2$ | 0.93 | 0.94 | 0.90 | 0.88 |
| $\ln(P_1 / P_3)$ = ln(electricity price / natural gas price) | **0.154** | -0.116 | **0.130** | **0.066** |
| $\ln(P_2 / P_3)$ = ln(fuel oil price / natural gas price) | -0.006 | **0.237** | **-0.020** | -0.004 |
| $X$ = per capita industrial employment | -0.369 | -0.523 | -0.062 | **-0.285** |
| $CDD$ = cooling degree days | 0.0000 | 0.0000 | **0.0000** | **0.0000** |
| $HDD$ = heating degree days | **0.0000** | **0.0000** | **-0.0001** | **-0.0001** |
| Lagged $S$ | **0.357** | **0.460** | **0.371** | **0.520** |
| Short-run own-price elasticity | **-0.133** | **-0.622** | **-0.177** | **-0.292** |
| Long-run own-price elasticity | **-0.208** | **-1.150** | **-0.281** | **-0.610** |
| $p$-value for testing $H_0$: CD is absent | - | - | 0.000 | 0.000 |

Panel F. Seasonal pattern of elasticity estimates based on CD presence and non-IV estimation

Results for all 12 months

| Specification *j* | Static own-price elasticity estimate | Short-run own-price elasticity estimate | Long-run own-price elasticity estimate |
|---|---|---|---|
| (1) Double-log | -0.103 | -0.094 | -0.150 |
| (2) Linear | -0.130 | -0.090 | -0.164 |
| (3) CES | -0.029 | -0.021 | -0.043 |
| (4) GL | -0.087 | -0.115 | -0.214 |
| (5) TL | -0.055 | -0.133 | -0.208 |

Results for the spring months of March, April and May

| Specification *j* | Static own-price elasticity estimate | Short-run own-price elasticity estimate | Long-run own-price elasticity estimate |
|---|---|---|---|
| (1) Double-log | -0.103 | -0.094 | -0.150 |
| (2) Linear | -0.129 | -0.089 | -0.161 |
| (3) CES | -0.030 | -0.022 | -0.044 |
| (4) GL | -0.089 | -0.118 | -0.220 |
| (5) TL | -0.059 | -0.139 | -0.216 |

Results for the summer months of June, July and August

| Specification *j* | Static own-price elasticity estimate | Short-run own-price elasticity estimate | Long-run own-price elasticity estimate |
|---|---|---|---|
| (1) Double-log | -0.103 | -0.094 | -0.150 |
| (2) Linear | -0.130 | -0.089 | -0.163 |
| (3) CES | -0.026 | -0.019 | -0.039 |
| (4) GL | -0.081 | -0.107 | -0.199 |
| (5) TL | -0.038 | -0.110 | -0.172 |

Results for the fall months of September, October and November

| Specification *j* | Static own-price elasticity estimate | Short-run own-price elasticity estimate | Long-run own-price elasticity estimate |
|---|---|---|---|
| (1) Double-log | -0.103 | -0.094 | -0.150 |
| (2) Linear | -0.135 | -0.093 | -0.169 |
| (3) CES | -0.028 | -0.021 | -0.042 |
| (4) GL | -0.089 | -0.117 | -0.218 |
| (5) TL | -0.052 | -0.129 | -0.200 |

Results for the winter months of December, January and February

| Specification *j* | Static own-price elasticity estimate | Short-run own-price elasticity estimate | Long-run own-price elasticity estimate |
|---|---|---|---|
| (1) Double-log | -0.103 | -0.094 | -0.150 |
| (2) Linear | -0.128 | -0.088 | -0.161 |
| (3) CES | -0.032 | -0.024 | -0.049 |
| (4) GL | -0.088 | -0.118 | -0.219 |
| (5) TL | -0.070 | -0.156 | -0.243 |

Note: While the double-log specification's elasticity estimates do not vary monthly, the same cannot be said for the other specifications.

Table 5. OLS dummy variable regression whose regressand is the US industrial electricity demand's own-price elasticity estimate; sample size = 60 observations = 5 specifications × 3 elasticity types × 2 CD treatments ×2 estimation methods

| Variable | Estimate | Standard error | *p*-value |
|---|---|---|---|
| Adjusted $R^2$ | 0.267 | | |
| RMSE | 0.152 | | |
| Intercept | -0.263 | 0.070 | 0.000 |
| $F_1$ = 1 if double-log specification, 0 otherwise | 0.234 | 0.091 | 0.013 |
| $F_2$ = 1 if linear specification, 0 otherwise | 0.195 | 0.090 | 0.035 |
| $F_3$ = 1 if CES specification, 0 otherwise | 0.259 | 0.091 | 0.006 |
| $F_4$ = 1 if GL specification, 0 otherwise | 0.246 | 0.092 | 0.011 |
| $IV$ = 1 if IV estimation, 0 otherwise | -0.028 | 0.039 | 0.478 |
| $SR$ = 1 if short-run, 0 otherwise | -0.011 | 0.034 | 0.748 |
| $LR$ = 1 if long-run, 0 otherwise | -0.100 | 0.055 | 0.074 |
| $CD$ = 1 if CD present, 0 otherwise | 0.001 | 0.039 | 0.975 |

Note: At $F_1 = F_2 = F_3 = F_4 = 0$, the reference specification is TL.

Table 6. OLS time trend regression: Own-price elasticity estimate = intercept + *b* *ID* + error; sample size = 109 observations for each elasticity type

Panel A: Static elasticity

| Variable | Estimate | Standard error | *p*-value |
|---|---|---|---|
| Regressand's mean | -0.103 | | |
| Adjusted $R^2$ | 0.881 | | |
| RMSE | 0.020 | | |
| Intercept | -0.196 | 0.003 | 0.000 |
| *ID* | 0.002 | 0.0001 | 0.000 |

Panel B: Short-run elasticity

| Variable | Estimate | Standard error | *p*-value |
|---|---|---|---|
| Regressand's mean | -0.120 | | |
| Adjusted $R^2$ | 0.822 | | |
| RMSE | 0.013 | | |
| Intercept | -0.169 | 0.003 | 0.000 |
| *ID* | 0.001 | 0.00004 | 0.000 |

Panel C: Long-run elasticity

| Variable | Estimate | Standard error | *p*-value |
|---|---|---|---|
| Regressand's mean | -0.143 | | |
| Adjusted $R^2$ | 0.836 | | |
| RMSE | 0.014 | | |
| Intercept | -0.199 | 0.003 | 0.000 |
| *ID* | 0.001 | 0.0001 | 0.000 |

Notes: (1) The elasticity estimates included in this regression analysis are based on the double-log specification with CD presence and non-IV estimation.

(2) The first observation (*ID* = 1) corresponds to the first 10-year period of 2001 – 2010. The last observation (*ID* = 109) is based on the last 10-year period of 2000 – 2019.

(3) The small but highly significant *b* estimate for ID in each panel's last row indicates that the US industrial electricity's price responsiveness has been slowly shrinking over time.

Table 7. Regional own-price elasticity estimates based on the double-log specification with CD presence and non-IV estimation

| Regional comparison of price responsiveness | Region definition | Static elasticity | Short-run elasticity | Long-run elasticity |
|---|---|---|---|---|
| Western states vs. Eastern states | Texas plus states in the Western Interconnection | -0.111 | -0.072 | -0.132 |
| | States in the Eastern Interconnection | -0.108 | -0.108 | -0.169 |
| States with retail competition vs. states without retail competition | States that have adopted retail competition | -0.228 | -0.200 | -0.286 |
| | States that have not adopted retail competition | -0.075 | -0.072 | -0.136 |
| States with relatively less coal-fired generation vs. states with relatively more coal-fired generation | States with below average coal shares of total generation | -0.083 | -0.088 | -0.127 |
| | States with above average coal shares of total generation | -0.123 | -0.109 | -0.217 |

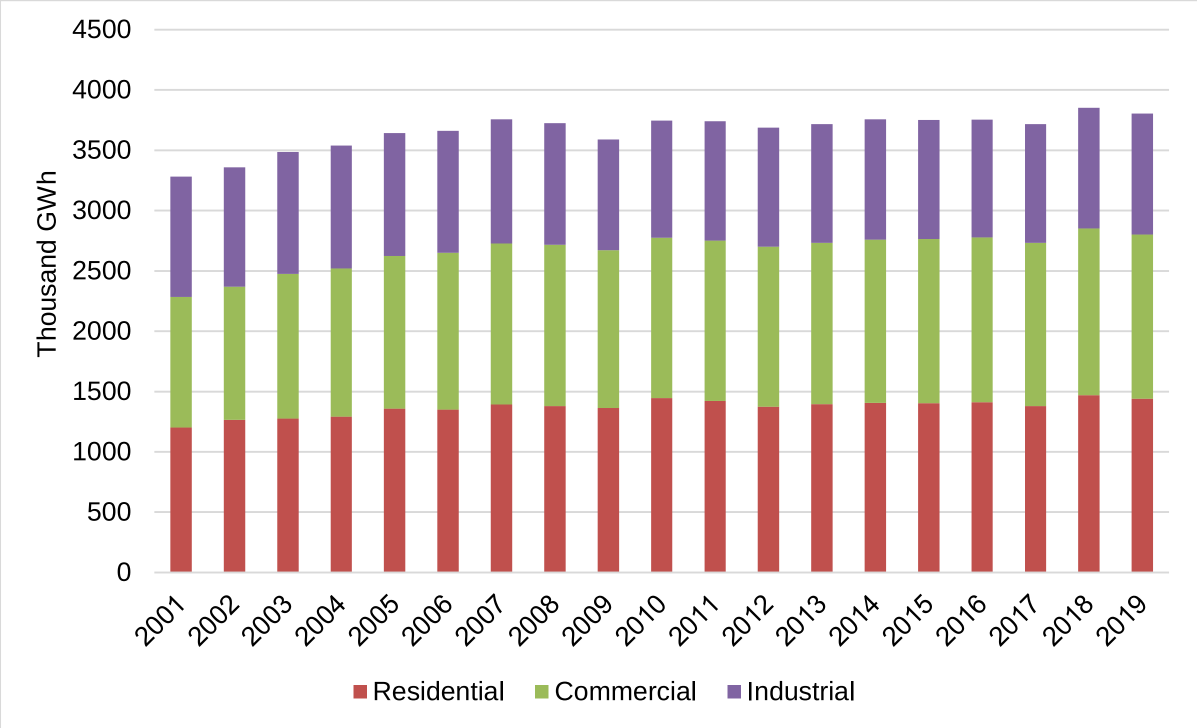



Figure 1. US annual electricity consumption by customer class in 2001-2019 (Data source: US Energy Information Agency).

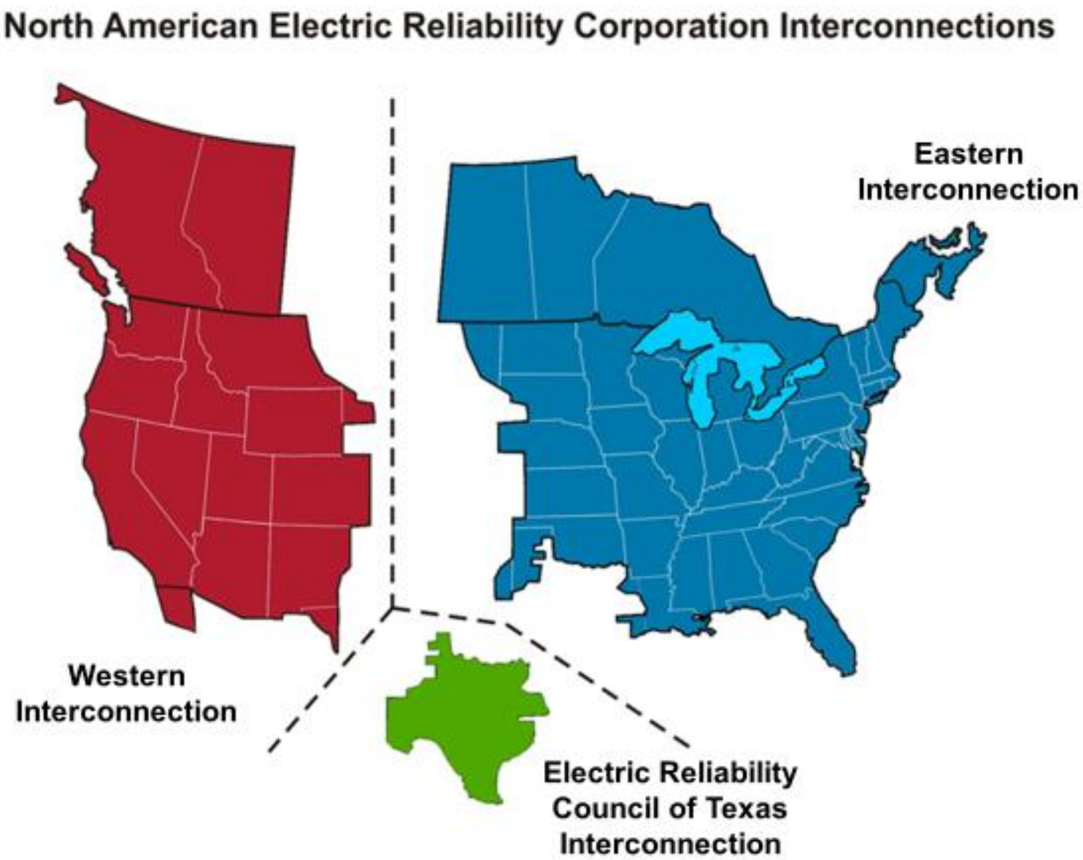
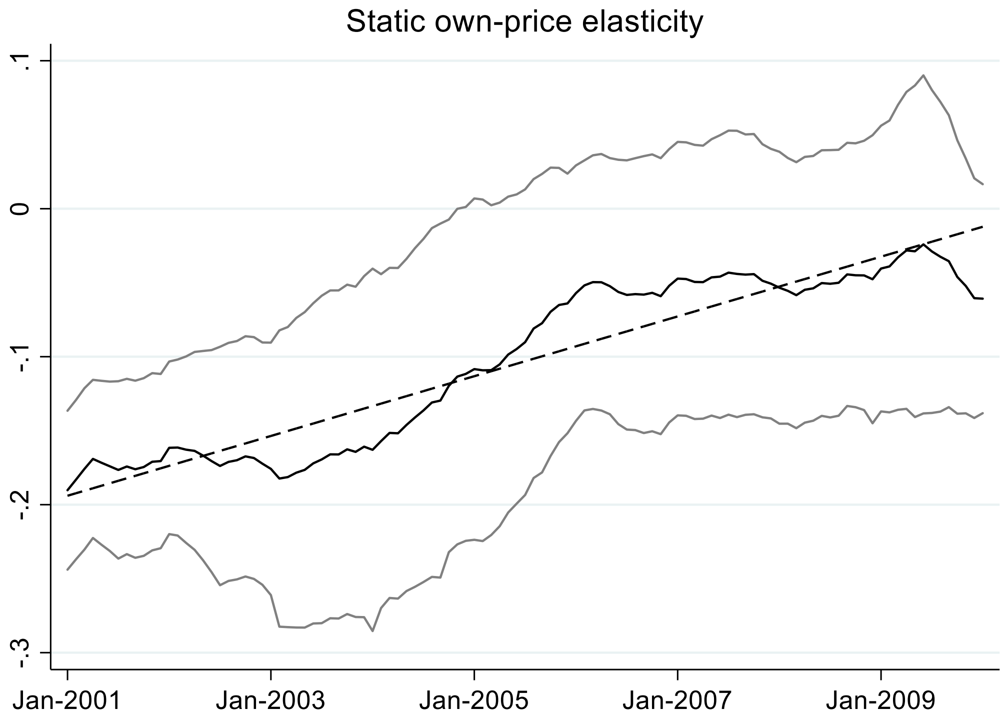
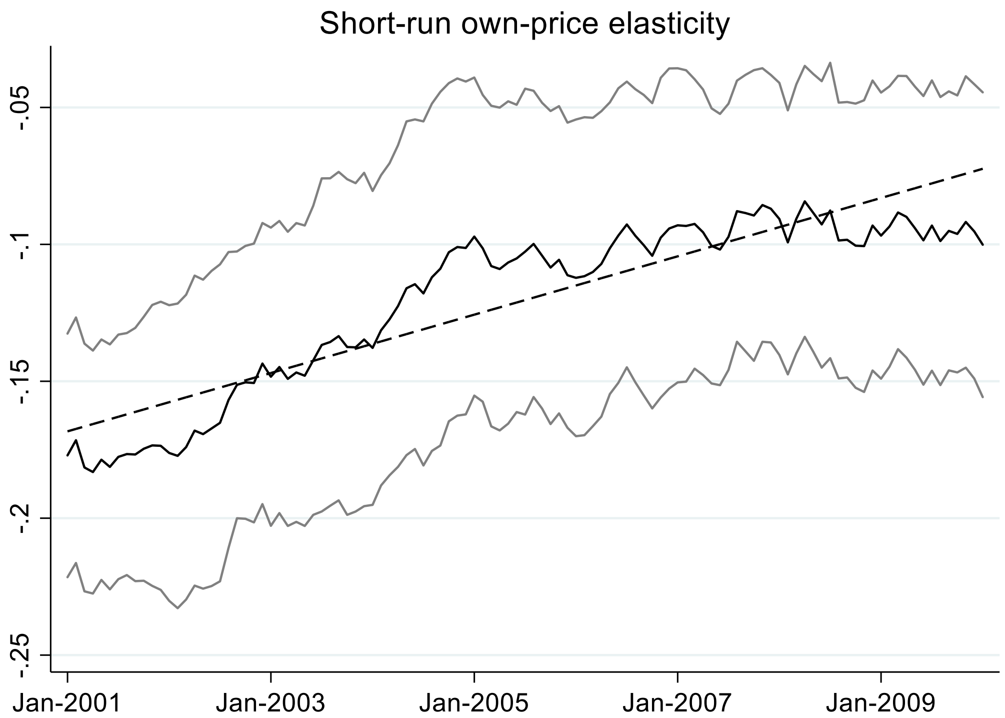



Figure 2: Major electricity grids in the US (Source: the US Environmental Protection Agency)


Static own-price elasticity
.1
0
-.1
-.2
-.3
Jan-2001
Jan-2003
Jan-2005
Jan-2007
Jan-2009


Short-run own-price elasticity
-.05
-.1
-.15
-.2
-.25
Jan-2001
Jan-2003
Jan-2005
Jan-2007
Jan-2009

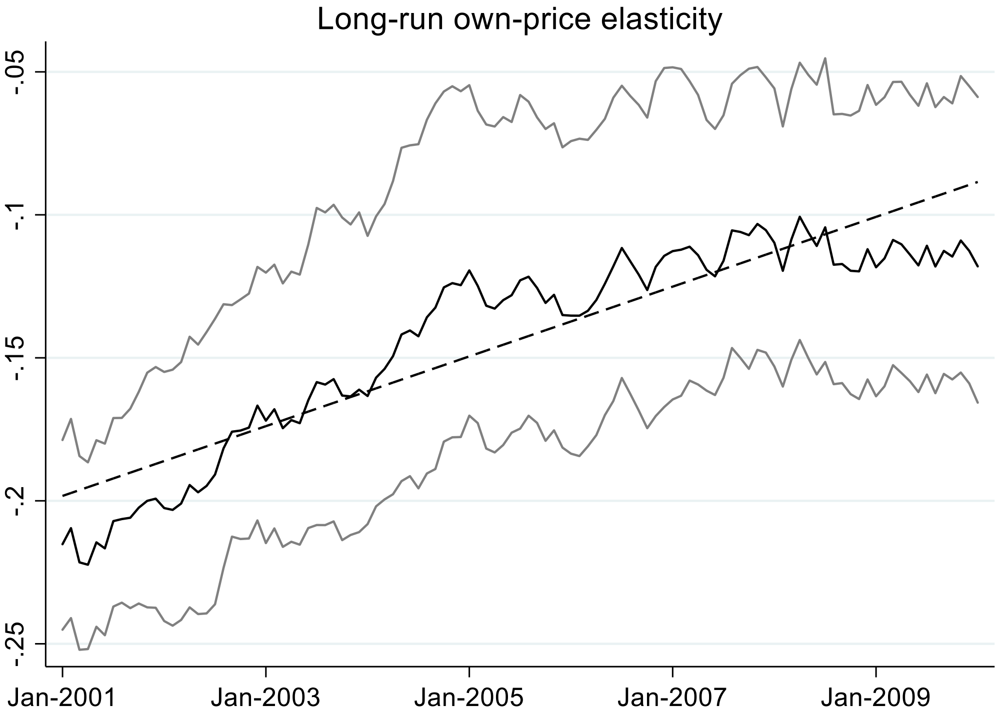



Figure 3. Own-prices elasticity estimates from a rolling-window analysis that uses the double-log specification with CD presence and non-IV estimation. The middle solid black line portrays an elasticity estimate. The lower and upper solid grey lines form the estimate's 95% confidence interval. The dashed line is the estimate's linear time trend.

**Abstract**

Accurate projections of electricity demand growth by end-use customer class (residential, commercial, industrial) are necessary for energy policy modelling, resource planning, and electricity pricing and procurement. Motivated by the expected trend of rising retail electricity prices in the US and diverse price elasticity estimates found by extant studies, we answer the substantive policy question: how price responsive is industrial electricity demand in the US? Based on a comprehensive panel data analysis that uses five parametric specifications and monthly data for the lower 48 states in 2001-2019, our answer comprises: (1) the statistically significant ($p$-value $\leq 0.05$) static own-price elasticity estimates are -0.029 to -0.130, short-run -0.021 to -0.133 and long-run -0.043 to -0.214; (2) the size of these estimates varies by elasticity type, sample period, parametric specification, and assumption of partial adjustment; (3) erroneously ignoring the highly significant ($p$-value $< 0.01$) cross-section dependence does not materially alter these elasticity estimates; (4) these elasticity estimates vary by region though not season and their size has been slowly declining over time. Hence, price-induced conservation's future effect on the US industrial electricity demand is likely small, justifying the continuation of policies to promote energy efficiency and demand side management to achieve deep decarbonization.

Click here to access/download
**Simulation Code and Data (.ZIP)**
EE_program.zip