**How price responsive is industrial demand for natural gas in the US?**

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**Abstract**

To assess price responsiveness of industrial demand for natural gas in the US, our panel data analysis uses five parametric specifications and 10,944 monthly observations for the lower 48 states in 2001-2019 to document statistically significant (*p*-value ≤ 0.05) static own-price elasticity estimates of -0.027 to -0.062, short-run -0.029 to -0.125 and long-run -0.060 to -0.179. These estimates with relatively small absolute values support continuation of energy efficiency standards and demand-side-management programs for deep decarbonization. Further, diverse price responsiveness among heterogenous industrial customers suggests using demand response programs to efficiently allocate the limited supply available during a natural gas shortage.

**Introduction**

Natural gas consumption of the industrial customer class in the US has been slowly rising in the last decade. Using Figure 1 as backdrop and noting that price elasticity estimates are necessary for policy evaluations, this paper empirically answers the substantive question of how price responsive is industrial demand for natural gas in the US? This question is partly motivated by the likely future trend of rising natural gas prices that reduce the industrial customer class’s natural gas consumption.[[1]](#footnote-2) It is also motivated by our interest in using own-price elasticity estimates to calculate the industrial customer class’s natural gas shortage cost.[[2]](#footnote-3) Our proposed shortage cost calculation is real-world relevant for two reasons. First, while the US presently has abundant supply of natural gas due to large-scale development of shale gas, a regional shortage can occur because of insufficient pipeline capacity.[[3]](#footnote-4) Second, the recent long frigid winter in the US and Europe drained regional natural gas inventories and unforeseen supply disruptions have caused international shortages of natural gas.[[4]](#footnote-5)

Reflecting the preceding question’s importance in policy development is the need for accurate price elasticity estimates in numerous applications in an economy’s quest for a clean and sustainable future. Such applications include energy policy modelling (Bhattacharyya and Timilsina, 2009), resource planning (Logan et al., 2013; Abrell and Weigt, 2016; Holz et al., 2016; Çalcı et al., 2022), the development of consumption projections (Huntington, 2007; Bianco et al., 2014; Dilaver et al., 2014), the analyses of the consumption effect of a carbon tax (Xiang and Lawley, 2019), better understanding a natural gas shortage’s adverse effect on an economy (Leahy et al., 2012; Alcaraz and Villalvazo, 2017), the price increase required to achieve a consumption reduction target (Rowland et al, 2017), an energy system’s responses to price shocks (Brown et al., 2021), optimal pricing (Davis and Muehlegger, 2010; Gong et al., 2016), and welfare analysis of market liberalization (Lee et al., 2004) and shale gas development (Hausman and Kellogg, 2015; Gillingham and Huang, 2019).

Table 1 presents diverse own-price elasticity estimates for natural gas demand, complicating the choice of which elasticity assumptions to use in the applications stated above. In response, we estimate the own-price elasticities of industrial natural gas demand in the US for comparison with those shown in Table 2 and the US Energy Information Administration’s (EIA’s) short-run estimate of -0.269 found by Costello (2006).

Our estimation is a panel data analysis that uses five parametric specifications and a newly-developed sample of 10,944 monthly observations (= 48 states × 19 years × 12 months per year) for the lower 48 states in 2001-2019. Our sample contains industrial natural gas consumption levels and average prices by state which were available from the EIA at the time of our writing.[[5]](#footnote-6) Guided by a review of existing studies listed in Table 2, our chosen parametric specifications are the double-log, linear, constant elasticity of substitution (CES), generalized Leontief (GL) and transcendental-logarithmic (TL).[[6]](#footnote-7) These model specifications lead to vastly different formulae for calculating the static, short-run and long-run own-price elasticities.[[7]](#footnote-8) However, little is known about whether these different formulae are a material reason for the highly diverse price elasticity estimates in Table 2.

Our paper makes six contributions to the natural gas demand literature:

1. Based on our regression results for the double-log, linear, CES and GL specifications, the US industrial natural gas demand’s statistically significant (*p*-value ≤ 0.05) static own-price elasticity estimates are -0.027 to -0.062, short-run -0.029 to -0.125 and long-run -0.060 to -0.179. These newly-found estimates match the estimates that are low (in absolute value) reported by existing studies and are smaller in absolute value than the EIA’s short-run estimate of -0.269.
2. Statistically significant factors affecting the US industrial natural gas demand’s own-price elasticity estimates are elasticity type, the model specification chosen, treatment of cross-section dependence (CD),[[8]](#footnote-9) and whether partial adjustment is assumed.
3. Erroneously ignoring the highly significant (*p*-value < 0.01) presence of CD can quadruple the US industrial natural gas demand’s own-price elasticity estimates.
4. The US industrial natural gas demand’s own-price elasticity estimates vary by region and their size (in absolute value) has been rising slowly over time.
5. A hypothetical one-day natural gas shortage that causes curtailment of 10% of industrial demand increases industrial energy cost by less than 4%.
6. This paper’s methodology is similarly applicable to the commercial customer class in the US and to non-residential customer classes in other regions of the world for which similar data exist.

The rest of this paper proceeds as follows. Section 2 explains the expected trend of rising retail natural gas prices, presents a brief literature review, presents the five parametric specifications, calculates the natural gas shortage costs, describes our panel data, and proposes an estimation strategy. Section 3 presents our empirics, the basis for Section 4: conclusions and policy implications.

**2. Materials and methods**

2.1 Industrial sector’s use of natural gas

According to the EIA,[[9]](#footnote-10) the industrial sector uses natural gas as a fuel for process heating; a feedstock for producing chemicals, fertilizer, and hydrogen; a fuel for well, field, and lease operations (e.g., drilling operations, heaters, dehydrators, and field compressors); and a fuel used by a natural gas processing plant. As electricity and fuel oil can play a similar role as natural gas in some of these uses, they are potential substitutes for natural gas in the sector’s production of final outputs. See Appendix 1 that shows industrial natural gas demand’s sum of own- and cross-price is equal to zero. [[10]](#footnote-11) Rising output levels, however, tend to increase the sector’s energy consumption levels.[[11]](#footnote-12)

2.2 Industrial natural gas prices in the US

Many of the larger industrial consumers of natural gas in the US are “bypass” or “pipeline customers”. Instead of buying natural gas through a local distribution company (LDC), these consumers have direct access to a pipeline and contract for a supply of natural gas directly with a producer or through a marketer. For pipeline customers, natural gas prices are largely deregulated. Both firm and interruptible supplies of natural gas are generally available. An industrial consumer can sign contracts containing different terms and conditions. Futures prices for one to 36 months in advance and spot prices for the deregulated natural gas commodity are set on the NY Mercantile Exchange and the Intercontinental Exchange, as well as through less-formal markets. Smaller industrial natural gas consumers are likely to be served through an LDC and pay prices set by regulatory authorities, although many states permit consumers to bypass LDCs and work with marketers or competitive retail natural gas suppliers to obtain a supply of the fuel. In summary, the average price of natural gas to industrial energy consumers in the US or for any particular state in the US reflects a variety of different contracts, pricing approaches, and regulatory policies, as well as market forces.

Figure 2 presents the annual box plots of monthly average industrial natural gas prices for the lower 48 states in 1991-2019. It shows that these prices exhibit discernible variations across space and time, aiding our estimation of the US industrial natural gas demand’s price responsiveness.

Industrial natural gas prices in the US are expected to rise in the coming years for three reasons.[[12]](#footnote-13) The first reason is an economy’s path to deep decarbonization (Williams et al., 2012; Mahone et al., 2018). Natural gas plays a pivotal role in this path as a bridge fuel for displacing electricity sector’s coal-fired generation and industrial sector’s consumption of petroleum products (Woo et al., 2018b; Gillingham and Huang, 2019). Further, electrification of energy-using durables (Williams et al., 2012) necessitates large-scale development of emissions-free renewable resources (Alagappan, et al., 2011; Joskow, 2021), whose reliable grid integration may benefit from flexible capacity of natural gas-fired generation (Zarnikau et al. 2019, 2020b) and fast ramping resources like demand response (e.g., load curtailment triggered by underfrequency), battery, and pumped storage (Hargreaves et al., 2015).

The second reason is cap-and-trade (CAP) of CO2 emissions permits (*aka* carbon trading), as exemplified by California’s CAP program (Woo et al., 2017a). Carbon trading has the following effects on energy prices. First, it raises retail natural gas prices that embody the marginal costs of CO2 emissions. Second, it raises the retail prices for petroleum products with relatively high CO2 emissions, inducing industrial inter-fuel substitution that increases industrial demand for natural gas. Third, it increases wholesale electricity prices when natural gas is the dominant marginal fuel for electricity generation (Woo et al., 2017a, 2017b). However, this expected electricity price increase is moderated by the merit order effect of rising solar and wind generation (Woo et al., 2017a, 2017b, 2017c; Zarnikau et al., 2019, 2020a).[[13]](#footnote-14)

The third reason is related to the decline in natural gas prices in the US resulting from shale gas’s explosive growth (Caporin and Fontini, 2017). This decline is expected to reverse, owing to serious concerns about hydraulic fracturing’s environmental damage (Sovacool, 2014) and the projected growth of the export of natural gas from the US (Arora and Cai, 2014; Çalcı et al., 2022).

2.3 Nonlinear pricing of industrial natural gas consumption in the US

An industrial customer in the US typically faces a two-part tariff with a fixed customer charge ($/customer-month) and a variable commodity charge ($/Mcf) (Woo et al., 2014b). When the commodity charge is linear, the fixed customer charge causes the customer’s monthly average natural gas price (= monthly bill ÷ monthly usage) to decrease with consumption. Under a declining block tariff design, the customer’s monthly average natural gas price further decreases with consumption. This negative relationship between average price and consumption exists, even if the customer is totally price insensitive with an own-price elasticity equal to zero. Hence, nonlinear pricing of industrial natural gas consumption may overstate the size of price elasticity estimates.

Our panel data analysis uses the EIA’s monthly average prices since accurate marginal prices are unavailable. Should the average price data be found endogenous, the ensuing estimation bias could be readily corrected by instrumental variable (IV) estimation (Davidson and MacKinnon, 1993).

2.4 Literature review

To place our paper in context, we review a sample of industrial natural gas demand studies.[[14]](#footnote-15) Our review is intentionally brief, thanks to the existing surveys of natural gas demand (Al-Sahlawi, 1989) and energy demand (Taylor, 1977; Hartman, 1979; Bohi and Zimmerman, 1984; Dahl, 1993; Dahl and Roman, 2004; Suganthia and Samuel, 2012; Labandeira et al., 2017; Huntington et al., 2019).

We make the following remarks based on the eleven US studies listed in Panel A of Table 2. First, the regional coverage of these studies spans from a single state to the entire US. Second, these studies generally use annual data. Third, all studies use non-natural-gas energy prices as regressors to reflect inter-fuel substitution by industrial customers. Fourth, half of the studies use the double-log specification, whose price coefficients equal the sought-after price elasticities. The remaining six studies use the linear, CES and GL specifications. Fifth, the estimation methods span from OLS regression to maximum likelihood estimation. Sixth, all studies use average prices, rather than marginal prices. Finally, the elasticity estimates in this panel’s last three columns reinforce Table 1’s key message of highly diverse price responsiveness, with own-price elasticity estimates ranging from -0.048 to -3.82.

The following remarks emerge from Panel B of Table 2 that lists seven non-US studies. First, the regional coverage of these studies ranges from one to 44 countries. Second, most of these studies employ annual data. Third, five studies use the double-log specification, while the remaining two adopt the CES and TL functional forms. Fourth, the estimation methods vary from OLS regression to vector error correction modelling. Fifth, all studies use average price data. Finally, the elasticity estimates in this panel’s last three columns affirm Table 1’s key message, with own-price elasticity estimates varying from 0.0 to -7.8.

Our literature review of the studies listed in Table 2 reveals the following knowledge (KG) gaps to be filled by our panel data analysis and shortage cost assessment. The first gap is KG1: these studies do not analyse the time trend of price responsiveness. The second gap is KG2: these studies do not consider the effect of data frequency on price elasticity estimates. The third gap is KG3: none of these studies estimates the impact of CD on price elasticity estimates. The fourth gap is KG4: there is a lack of recent empirics on the US industrial customer class’s regional own-price elasticity estimates, as the regional study of Lin et al. (1987) is over 30 years old. The fifth gap is KG5: none of these studies estimates the industrial customer class’s natural gas shortage costs.

2.5 Five parametric specifications

For readability, Appendix 1 derives the five parametric specifications used by our panel data analysis. These specifications are considered herein because of their adoption by the studies listed in Table 2. Further, they yield vastly different formulae for calculating own-price elasticities, a potential cause for the diverse elasticity estimates in Tables 1 and 2.

We begin by stating the double-log demand equation:[[15]](#footnote-16)

ln*Y*1 = **0+ **1ln(*P*1 / *P*3) + **2ln(*P*2 / *P*3) + *Z*ln*Z*, (1)

where *Y*1 = monthly per capita industrial consumption of natural gas, *P*1 = monthly average natural gas price ($/Mcf), *P*2 = monthly average fuel oil price ($/gallon) and *P*3 = monthly average electricity price ($/kWh). Since the monthly intermediate output *Z* is unobservable, we assume that ln*Z* in equation (1) is a linear function of monthly per capita industrial employment *X*, monthly cooling degree days (*CDD*) and monthly heating degree days (*HDD*). The own-price elasticity is **1 = **1, which does not vary by consumption level and across time and states.

The linear demand equation is:

*Y*1 = **1+ **11 (*P*1 / *P*3) + **12 (*P*2 / *P*3) + *ZZ.* (2)

The own-price elasticity is **1 = **11 (*P*1 / *P*3) / *Y*1. Since **1 depends on the price ratio and the natural gas usage level, it varies by consumption level and across time and states. Hence, the average value of **1 for the entire US is the Mcf-weighted average of our panel’s month- and state-specific estimates. Finally, we again assume that *Z* is a linear function of *X*, *CDD* and *HDD*.

For the CES specification (Woo et al., 2017c, 2018c), the equation to be estimated is:

ln(*Y*1/ *Y*3) = **0 + **1ln(*P*1/*P*3). (3)

In addition, we assume that **0 is a linear function of *X*, *CDD* and *HDD*. The own-price elasticity given is **1 = **1(1 – *S*1), where *S*1 = *P*1 *Y*1/ (*P*1 *Y*1 + *P*2 *Y*2+ *P*3 *Y*3) = natural gas cost share. As **1 varies by consumption level and over time and states, its average value for the entire US is the Mcf-weighted average of our panel’s month- and state-specific estimates.

The computation of **1 under the CES specification 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 by customer class are available. Hence, we generate fuel oil’s monthly cost shares in three steps: (1) use the EIA monthly industrial data to compute *S*1max = *P*1 *Y*1 / (*P*1 *Y*1 + *P*3 *Y*3) under the assumption that a state’s industrial customer class does not consume fuel oil; (2) use the EIA annual data to compute two annual natural gas cost shares: *AS*1max = *P*1 *Y*1 / (*P*1 *Y*1 + *P*3 *Y*3) and *AS*1true = *P*1 *Y*1 / (*P*1 *Y*1 + *P*2 *Y*2 + *P*3 *Y*3); and (3) use *S*1max (*AS*true / *AS*max) to approximate the monthly missing *S*1 values.

For the GL specification (Diewert, 1971; Woo et al., 2018b), the industrial natural gas demand function is:

*Y*1 = *b*11 + *b*12 (*P*2 / *P*1)1/2 + *b*13 (*P*3 / *P*1)1/2 + *b*1*Z* *Z*. (4)

Estimating equation (4) assumes that *Z* is a linear function of *X*, *CDD* and *HDD*. The own-price elasticity is **1 = -1/2 [*b*12 (*P*2 / *P*1)1/2 +*b*13 (*P*3 / *P*1)1/2 ] / *Y*1, which varies by consumption level and over time and states. Hence, the average value of **1 for the entire US is the Mcf-weighted average of our panel’s month- and state-specific estimates.

For the TL specification (Greene 2003, Chapter 14), the natural gas cost share equation is:

*S*1 = *a*1 + *a*11 ln(*P*1/*P*3) + *a*12 ln(*P*2/*P*3) + *a*1*Z* ln*Z*. (5)

Estimating equation (5) assumes that ln*Z* is a linear function of *X*, *CDD* and *HDD* and the data for *S*1 are approximated values used by the CES specification’s own-price elasticity calculation. The own-price elasticity is **1 = (*a*11 + *S*12 – *S*1) / *S*1 that varies by consumption level and across time and states. Hence, its average value for the entire US is the Mcf-weighted average of our panel’s month- and state-specific estimates.

2.6 Long-run elasticity

The models described above ignore the dependence of a current month’s consumption on the prior month’s consumption, reflecting the industrial sector’s difficulties in abruptly changing production processes and equipment in response to changes in relative prices. To address this, we include the 1-month lagged regressand as an additional regressor to characterize the partial adjustment process, as similarly done by six of the seven US studies in Table 2 that entail dynamic modelling.[[16]](#footnote-17)

Let ** denote the lagged regressand’s coefficient. The results presented in the next section reveal that the statistically significant (*p*-value ≤ 0.05) estimate for ** is between 0.491 to 0.519.[[17]](#footnote-18) After estimating specification *j*’s short-run elasticity (SRE)*,* we obtain the long-run elasticity LRE = SRE / (1 - **).

Whether the assumption of partial adjustment is reasonable is an empirical issue best settled by statistical results. Our estimated regressions reported in Section 3 have relatively high adjusted *R*2 values and coefficient estimates that are mostly significant with expected signs. Hence, the assumption is deemed reasonable in characterizing the data generating process of the US industrial demand for natural gas.

2.7 Estimation of industrial shortage cost

Consider a natural gas shortage with advance notice.[[18]](#footnote-19) Even if the shortage is relatively mild (e.g., amount short = 10% of industrial demand), it can cause industrial customers to incur incremental costs. Measured by the increase in energy costs (Woo et al., 2021), such shortage costs are likely small because the advance notice enables industrial customers to adjust/reschedule their production activities with negligible costs of lost production, idle labour, and material damage (Leahy et al., 2012).[[19]](#footnote-20)

We use the following steps to estimate natural gas shortage cost as a percentage increase in industrial energy cost:

1. Assume a hypothetical one-day natural gas shortage that causes curtailment of *D*% of the industrial customer class’s total demand.[[20]](#footnote-21)
2. Find the percentage price increase required to resolve the assumed shortage (Woo, 1994): ln*P*1 = -(*D* / **1).
3. Find the one-day shortage cost as a percentage of *C*(⚫):

*SC* = [*C*(⚫) / *C*(⚫)] ÷ 30 days, (7)

where *C*(⚫) = [∂*C*(⚫) / ∂*P*1] *P*1 = *Y*1 *P*1 based on Shephard’s Lemma (Diewert, 1971). As (*P*1 / *P*1) = ln*P*1,

*SC* = [*P*1 *Y*1 / *C*(⚫)] (*P*1 / *P*1) ÷ 30 days = - *S*1 (*D* / **1) ÷ 30 days. (8)

Equation (8) is remarkably simple and uses the same data for estimating natural gas demand’s own-price elasticity. Hence, it is readily applicable to any customer class (e.g., commercial customers or all customers) in any region (e.g., a single country like China or several countries in Europe or Asia). As the assumed curtailment is relatively small (*D* = 10%) and has advance notice, the *SC* estimate based on equation (8) does not consider an industrial customer’s likely small costs for such items as idle labour and material damage.

The following cases demonstrate that equation (8) is economically meaningful:

1. Suppose *S*1 = 0 because of zero natural gas consumption. As a result, the value of *SC* is zero and natural gas shortage has no impact on industrial energy cost.
2. Suppose *S*1 > 0. As a result, *SC* increases with natural gas’s cost share *S*1, the extent of shortage *D* and the size of **1. For example, *S*1 = 30%, *D* = 10%, and **1 = -0.1 implies *SC* = 30% ÷ 30 days per month = 1% of monthly energy cost.[[21]](#footnote-22)

To illustrate *SC*’s dependence on parametric specification and elasticity type, we employ here the natural gas’s cost share in 2019 and the static, short-run, and long-run own-price elasticity estimates by specification. This illustration demonstrates that for a given specification, the static *SC* is between the short- and long-run *SC*. When the specification yields elasticity estimates that are large in absolute value, it leads to relatively small *SC* values.

2.8 Data description

Our data sources are as follows:

* The EIA publishes the industrial customer class’s monthly data for electricity and natural gas consumption levels and average prices for each of the 50 states in the US. These data are based on each state’s industrial energy sales and revenues reported by utilities and retail service providers. The EIA also publishes the industrial customer class’s monthly average fuel oil prices though not consumption levels.
* The US Bureau of Labor Statistics (BLS) publishes the monthly data for industrial employment and civilian noninstitutional population. We use the monthly employment and population data to construct the data for *X*.
* We use the EIA and BLS data to derive the per capita data for *Y*1 and *Y*3. Further, *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.
* The US National Oceanic and Atmospheric Administration publishes the monthly data for CDD = monthly sum of max(daily average temperature - 65°F, 0) and HDD = monthly sum of max(65°F - daily average temperature, 0).

Table 3 provides descriptive statistics for the variables employed in our panel data. All variables listed in this table exhibit substantial variability, as is evident by their minimal and maximal values. Based on the coefficient of variation (= standard deviation / mean), the data for non-weather variables are less volatile than weather variables.

The final column of Table 3 reports that *Y*1 is positively correlated with *Y*3 (*r* = 0.509), suggesting that electricity and natural gas usage tend to move in tandem. It is negatively correlated with *P*1 (*r* = -0.273) but less so with *P*2 (*r* = -0.027) and *P*3 (*r* = -0.226). It is negatively correlated with (*P*1 / *P*3) (*r* = -0.087) but positively correlated with (*P*2 / *P*3) (*r* = 0.117). While it is positively correlated with *X* (*r* = 0.286), its correlation with *CDD* and *HDD* is very weak (|*r*| < 0.10). In summary, the correlation coefficients in Table 2 do not untangle the marginal effects of price ratios, employment, and weather on the US industrial natural gas demand, enhancing our estimation strategy presented below.

2.9 Estimation strategy

We employ the double-log specification with partial adjustment to illustrate our estimation strategy:

ln*Y*1*kt* = **1ln(*P*1*kt* / *P*3*kt*) + **2ln(*P*2*kt* / *P*3*kt*) + *XXkt*+ *CDDCDDkt* + *HDDHDDkt* +

** ln*Y*1*kt*-1 + *k* + *yt* + *kt*, (9)

where *k* = state-specific fixed effects, *yt* = month-specific fixed effects, and*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 (9) under the restriction of ** = 0 produces the static elasticity estimate. When the ** estimate is statistically significant, the short- and long-run elasticity estimates are those explained in Section 2.5.

Following an insightful reviewer’s suggestion, we use 11 monthly dummies (i.e., *D*1*m* = 1 if *m* = January, 0 otherwise; …; *D*11*m* = 1 if *m* = November, 0 otherwise) as regressors in equation (9) to account for *yt*, the residual demand effect of seasonality uncaptured by the monthly weather variables of *CDD* and *HDD*. The same is done for the other four specifications. Our initial analysis reveals that these monthly dummies have insignificant (*p*-values > 0.05) coefficient estimates for all five specifications, chiefly because the monthly weather variables have already captured the bulk of seasonality’s demand effects. Hence, the rest of our paper restricts *yt* = 0, yielding coefficient estimates that are numerically close to those obtained *sans* this restriction.[[22]](#footnote-23)

We use the dynamic common correlated effects (DCCE) panel estimator that accounts for cross-section dependence to estimate equation (9).[[23]](#footnote-24) Chudik and Pesaran (2015) show that the DCCE estimator yields consistent estimates when current and lagged cross-section averages of the dependent and explanatory variables are included in the dynamic panel regression. Under the restriction of ** = 0, only current cross-section averages are included and the resulting estimator will resemble that of Pesaran (2006).[[24]](#footnote-25) Under the assumption of CD absence, cross-section averages are not included and equation (9) is estimated using the mean group estimator (Pesaran and Smith, 1995).

Our multistep estimation strategy is as follows:

1. Determine the statistical significance of CD by the Pesaran (2020) test.
2. Ensure stationarity of the variables and avoid spurious regressions (Baltagi and Kao, 2001) in steps (3) and (4) below by applying the Pesaran (2007) panel unit root test that accounts for CD.
3. Perform IV and non-IV estimation to estimate the coefficients of equation (9) for the following four cases: (a) ** = 0 vs. ** > 0; and (b) CD presence vs. CD absence.[[25]](#footnote-26)
4. Repeat step (3) for the remaining four specifications.

**3. Empirics**

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

Table 4 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 the presence of CD without the concern of spurious regressions.

3.2 Regression details

Table 5 contains our preferred regression results based on the presence of CD detected in Table 4 and non-IV estimation based on the Durbin-Wu-Hausman test results of exogenous price ratio data. All specifications have adjusted *R*2 values ≥ 0.72, indicating a reasonable goodness of fit.

We now turn our attention to regression details. For the double-log specification, Panel A of Table 5 reports that the US industrial natural gas demand has a static own-price elasticity estimate of -0.062 and increases with employment, *CDD* and *HDD*. The short-run own price elasticity estimate is -0.056, smaller in absolute value than its long-run counterpart of -0.116 due to the coefficient estimate of 0.519 for lagged ln*Y*1. Parenthetically, the double-log specification’s static elasticity estimate corroborates the -0.069 estimate in Woo et al. (2018a), but our short-run and long-run elasticity estimates differ.[[26]](#footnote-27)

For the linear specification, Panel B shows the positive coefficient estimates for employment, *CDD*, *HDD* and lagged *Y*1. The static own-price elasticity estimate is -0.039, close to the one under the double-log specification. While still in comparable magnitudes, the linear specification generates estimates that are smaller (in absolute value) than those from the double-log specification. The short- and long-run estimates are -0.035 and -0.069, smaller (in absolute value) than those found by Woo et al. (2018b).

For the CES specification, Panel C shows that ln(*Y*1 / *Y*3) declines with ln(*P*1 / *P*3). The estimated coefficient for employment is positive, but statistically insignificant. The static own-price elasticity estimate is -0.040, and the short- and long-run estimate are -0.029 and -0.060. These estimates are numerically close to those obtained from the linear specification.

For the GL specification, Panel D reports that the coefficient estimates for employment is positive and statistically significant. The estimates for the coefficients on the *CDD* and *HDD* variables are close to zero. The static own-price elasticity estimate is -0.048, the short-run estimate -0.038 and the long-run estimate -0.077, smaller in absolute value than those based on the double-log, but similar to those found by the linear and CES specifications.

For the TL specification, Panel E reports that the estimated effect of employment on natural gas cost share is positive though insignificant. The estimated effect of increased *HDD* is positive, while coefficient on *CDD* is negative. The static own-price elasticity estimate is -0.027, while the short- and long-run estimates are -0.125 and -0.179. These elasticity estimates are larger in absolute value than those estimated using the other specifications.

In summary, the own-price elasticity estimates in Table 5 are moderately diverse. While matching the estimates in Table 2 that are low in absolute value, they are less supportive of the EIA’s short-run elasticity assumption of -0.269.

3.3 Factors affecting the US industrial demand’s own-price elasticity estimates

We use a simple OLS dummy variable regression to delineate factors that moves the US industrial natural gas demand’s own-price elasticity estimates. Table 6 contains this regression’s results that have the following interpretations:

* The positive and statistically significant coefficient estimates for *Fj* for *j* = 1 to 4 indicate that the TL specification tends to magnify the size of own-price elasticity estimates in comparison to the other specifications.
* The estimate for *IV* indicates that IV estimation leads to larger elasticity estimates (in absolute value), although this effect may not be significant.
* The coefficient estimate for *LR* suggests that the long-run elasticity estimates are larger in absolute value than the static and short-run elasticity estimates.
* The highly significant (*p*-value < 0.01) positive coefficient estimate for *CD* suggests that erroneously ignoring cross-section dependence tends to inflate the empirical price responsiveness of industrial natural gas demand in the US.

When taken together, the preceding interpretations suggest similarity of elasticity estimates based on the double-log, linear, CES and GL specifications, thus lending support to the empirical plausibility of these specifications.

Finally, all predicted own-price elasticities generated by Table 6’s coefficient estimates are between -1 and 0. Hence, the US industrial natural demand is deemed price inelastic, irrespective the modelling decisions in connection to the choice of a parametric specification, treatment of CD, assumption of partial adjustment, and estimation method (IV vs. non-IV).

3.4 Time trend of own-price elasticity estimates

Motivated by KG1, we use a rolling-window approach to find elasticity estimates by 10-year period under the double-log specification with CD presence and non-IV estimation. The first period of the rolling-window is Jan-2001 to Dec-2010, and the last period is Jan-2010 to Dec-2019. Figure 3 portrays the US industrial natural gas demand’s small but rising price responsiveness over time, which is further confirmed by the OLS regression results shown in Table 7.

3.5 Industrial customer class’s natural gas shortage costs

Motivated by KG5, we calculate *SC* estimates by specification and elasticity type under the assumption of a hypothetical one-day shortage that curtails 10% of industrial natural gas demand. The elasticity estimates used are those based on CD presence and non-IV estimation. To provide a contrast, we repeat the *SC* calculation using the elasticity estimates based on CD absence and non-IV estimation.

Table 8 shows that erroneously ignoring the statistically significant CD presence understates the size of *SC*. That said, the *SC* estimates in Table 8 are in the main relatively small, less than 4% of the industrial customer class’s daily energy cost.

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’ estimated price responsiveness. Our choice reflects the double-log specification’s popularity evidenced by Table 2 and empirical plausibility portrayed by Table 5.

The first check repeats the panel data analysis after excluding the regressor of fuel oil – electricity price ratio. Its finding is that the static own-price elasticity estimate becomes -0.055, short-run -0.048 and long-run -0.107. These estimates are only slightly smaller than those obtained under the original specification. Hence, excluding fuel oil from our panel data analysis does not materially affect the own-price elasticity estimates.

Motivated by KG2, the second check uses quarterly data instead of monthly data, thereby testing if a longer decision period affects industrial natural gas 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 -0.060, the short-run estimate -0.070, and the long-run estimate -0.103. Thus, reducing data frequency does not materially affect price elasticity estimates reported in Panel A of Table 5.

The third check uses aggregate, instead of per capita, energy usage and employment data for estimating the double-log demand regression. Its finding is that using aggregate data does not alter the price elasticity estimates reported in Panel A of Table 5.

The fourth check uses price level data instead of price ratio data. Its finding is that the static price elasticity estimate becomes -0.074, the short-run estimate -0.063, and the long-run estimate -0.120. Thus, allowing the US industrial natural gas demand to depend on price levels instead of price ratios does not materially alter the size of price elasticity estimates.

The fifth check implements the approach of Burke and Yang (2016), a panel data analysis based on the double-log specification with the “between” estimator *sans* CD presence and fixed effects. The resulting long-run own-price elasticity estimate is -1.106, numerically close to the estimate of -1.21 found by Burke and Yang (2016).

The sixth check estimates an ARDL variant of equation (19), with the number of lags determined by the Akaike Information Criterion. The ARDL(1,1) estimates of the short- and long-run own-price elasticities are -0.070 and -0.098, numerically close to the estimates produced by the more parsimonious partial adjustment model reported in Panel A of Table 5. Robustness checks involving 2 to 6 lags further reveal that the elasticity estimates are insensitive to the lag order of the ARDL model.

Motivated by KG4, the seventh check investigates regional price responsiveness. This check’s first investigation entails re-estimating the double-log demand regressions for each of the four US census regions. Table 9 shows that the Midwest, West and South regions have similar own-price elasticity estimates that are smaller than those of the Northeast region. As the Northeast region has higher natural gas prices than other regions, industrial natural gas demand in this region is likely more price-sensitive because of inter-fuel substitution by industrial customers.

The seventh check’s second investigation entails re-estimating 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 9 indicates that industrial customers who are less able to respond to energy price shocks are likely in states with low and stable electricity prices enabled by relative abundance of coal-fired generation which tends to have more-stable fuel costs.

**4. Conclusions and policy implications**

Our paper has the following conclusions. First, accurate price elasticity estimates are necessary for the applications stated in Section 1. However, it is difficult to make reasonable elasticity assumptions based on the wide range of natural gas price elasticity estimates presently appearing in the academic literature, as is similarly the case for electricity demand (Fisher et al., 1992; Orans, 2008). As a result, the assumption should be based on a natural gas demand analysis of a large and recent sample for the region/country of interest.

Second, a panel data analysis that uses monthly data by state over a long period is useful for estimating price responsiveness of industrial natural gas 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, partial adjustment, treatment of CD, time trend, and region. That said, the key takeaway of our extensive empirics is that US industrial natural gas demand is, in the main, price inelastic and exhibits slowly rising price responsiveness over time.

Finally, our own-price elasticity estimates are between -0.03 to -0.18, matching the low estimates (in absolute value) found by antecedent studies. Yet the values that we obtained are smaller in absolute value than the EIA’s short-run estimate and the long-run estimate based on the between estimator used by Burke and Yang (2016). Further, they lead to the relatively small increase in industrial energy cost due to a hypothetical one-day shortage that causes curtailment of 10% of industrial natural gas demand.

Our conclusions have three policy implications. First, price-induced reduction of industrial natural gas demand can be material though relatively small (up to 2% for a 10% price increase). Second, deep decarbonization may require continuation of energy efficiency standards and demand-side-management programs (EPA, 2008), as increases in natural gas prices (through carbon taxes or the market effects mentioned earlier) may alone be insufficient to induce large changes in demand. Third, as the electric grid in the U.S. reduces its emissions of greenhouse gasses and electrification emerges as a viable strategy to address climate change, rising prices of natural gas might not alone lead to the greater electrification of the industrial sector.

Our empirics document how natural gas shortage costs vary by price responsiveness. As heterogenous industrial customers (e.g., chemical manufacturing vs. food processing) likely have diverse price responsiveness, an economy’s aggregate natural gas shortage cost can be reduced by demand response and real-time price rationing strategies that resemble those used by the electricity sector (DOE, 2006; Horowitz and Woo, 2006; FERC, 2008-2020; EPRI, 2021). Moreover, this diversity of industrial energy consumers with a large range of price elasticities of demand and outage costs provides opportunities to improve price-based rationing of natural gas during shortages and the design of quantity rationing schemes using demand subscription service principles (Woo et al., 2014a)

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**Appendix 1. Derivation of parametric specifications**

This appendix derives our panel data analysis’s five parametric specifications, reflecting that industrial natural gas demand is an input demand based on an industrial customer’s problem of two-stage cost minimization (Woo et al., 2021).

In Stage 1, the customer procures natural gas *Y*1 (Mcf) at price *P*1 ($/Mcf), fuel oil *Y*2 (gallon) at *P*2 ($/gallon) and electricity *Y*3 (kWh) at price *P*3 ($/kWh) to minimize its monthly energy cost for producing intermediate output *Z*:

*C* = *P*1 *Y*1 + *P*2 *Y*2 + *P*3 *Y*3. (A.1)

Let (*Y*1\*, *Y*2\*, *Y*2\*) denote the least-cost energy usage levels that solve the Stage 1 problem. The resulting energy cost function is *C*(*P*1, *P*2, *P*3, *Z*) = *P*1 *Y*1\* + *P*2 *Y*2\* + *P*3 *Y*3\*, which 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). In Stage 2, the customer chooses the least-cost mix of *Z* and non-energy inputs such as labour (*L*), material (*M*) and capital (*K*) to produce output vector ***V*** based on the transformation function *G*(***V***, *Z*, *L*, *M*, *K*).

Applying Shephard’s Lemma to the energy cost function *C*(⚫) yields the natural gas demand function (Diewert, 1971; Varian, 1992):

∂*C*(⚫) / ∂*P*1 = *Y*1\* = *H*(*P*1, *P*2, *P*3, *Z*). (A.2)

As *H*(⚫) is homogenous of degree zero in (*P*1, *P*2, *P*3,), it moves with energy price ratios (*P*1 / *P*3) and (*P*2 / *P*3) (Varian, 1992).

The natural gas demand function’s respective own- and cross-price elasticities are:

*e*1 = ∂ln*Y*1\* / ∂ln*P*1; (A.3)

*ej* = ∂ln*Y*1\* / ∂ln*Pj* for *j* > 1. (A.4)

Moreover, *e*1+ *e*2 + *e*3 = 0 because *H*(⚫) is homogenous of degree zero in (*P*1, *P*2, *P*3,) (Varian, 1992). As *e*1≤ 0 and *e*2 + *e*3 ≥ 0, natural gas is a substitute for fuel oil/electricity.

Suppose the parametric cost function is *C* = *e*0 (*P*1 / *P*3)(1 + **1) (*P*2 / *P*3)*2ZZ* / (1 + **1), which is unseen in the studies listed in Table 2. Using equation (2) and taking natural log, we derive the double-log natural gas demand equation corresponding to *Y*1’s recorded value *sans* the additive random error of (*Y*1\* - *Y*1):

ln*Y*1 = **0+ **1ln(*P*1 / *P*3) + **2ln(*P*2 / *P*3) + *Z*ln*Z*. (A.5)

Suppose the parametric cost function is *C* = **0 *P*1+ 1/2 **1 (*P*12/ *P*3) + **2 (*P*1*P*2 / *P*3) + *ZP*1 *Z*,which is also unseen in the studies listed in Table 2. Using equation (A.2), we derive the linear natural gas demand equation:

*Y*1 = **0+ **1 (*P*1 / *P*3) + **2 (*P*2 / *P*3) + *ZZ.* (A.6)

For the CES cost specification (Woo et al., 2017c, 2018c), the equation to be estimated is:

ln(*Y*1/ *Y*3) = **0 + **1ln(*P*1/*P*3). (A.7)

Based on Woo et al. (2018b), the natural gas demand equation under the GL cost function is:

*Y*1 = *b*11 + *b*12 (*P*2 / *P*1)1/2 + *b*13 (*P*3 / *P*1)1/2 + *b*1*Z* *Z*. (A.8)

According to Greene (2003, Chapter 14), the natural gas cost share equation under the TL cost function is:

*S*1 = *a*1 + *a*11 ln(*P*1/*P*3) + *a*12 ln(*P*2/*P*3) + *a*1*Z* ln*Z*. (A.9)

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Table 1. Industrial natural gas demand’s own-price elasticity estimates based on selected surveys

|  |  |  |
| --- | --- | --- |
| Study | Short run | Long run |
| Bohi and Zimmerman (1984) | -0.61 to -0.63 | -2.40 to -2.54 |
| Al-Sahlawi (1989) | -0.08 to -0.634 | -0.120 to -2.533 |
| Gillingham et al. (2009) | -0.51 to -0.62 | -0.89 to -2.92 |

Note: Including additional surveys does not alter this table’s main message that industrial natural gas demand has highly diverse own-price elasticity estimates.

Table 2. Own-price elasticity estimates from selected studies of industrial natural gas (NG) demand

Panel A: Eleven US studies

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Study | Sample period | Regional  coverage | Data type | Data frequency | Non-NG energy prices | Parametric specification | Estimation method | Static | Short run | Long run |
| Beierlein et al. (1981) | 1967-1977 | Nine Northeast states | Panel | Annual | Electricity, fuel oil | Double-log with partial adjustment | Error components - seemingly unrelated regressions |  | -0.618 | -2.537 |
| Gowdy (1983) | 1960-1978 | Manufacturing industries in New York | Time series by industry | Annual | Electricity, fuel oil | Double-log with and without partial adjustment | Three-stage least squares |  | -0.120 to -1.490 | -0.156 to -3.820 |
| Liu (1983) | 1967-1978 | The US | Time series | Annual | Electricity, fuel oil | Double-log | OLS | -0.242 |  |  |
| Duffus and Chern (1984) | 1967-1977 | The US primary metals industry | Panel based on survey data | Annual | Electricity, coal, fuel oil | Generalized fuel choice model with and without partial adjustment | Seemingly unrelated regressions | -0.733 | -0.675 | -2.125 |
| Lin et al. (1987) | 1967-1983 | Nine regions of the US | Panel | Annual | Electricity, fuel oil | Double-log with partial adjustment | Error components - seemingly unrelated regressions |  | -0.255 | -1.803 |
| Beltramo (1989) | 1974-1981 | The US manufacturing industries | Panel | Annual | Fuel oil | NG share equation | Generalized nonlinear least squares | -0.050 to -0.373 |  |  |
| Huntington (2007) | 1958-2003 | The US | Time series | Annual | Electricity, coal, oil products | Linear annual growth equation | Autoregressive distributed lag regression |  | -0.179 to -0.244 | -0.533 to -0.668 |
| Jones (2014) | 1960-2011 | The US | Time series | Annual | Electricity, coal, fuel oil biomass, | Dynamic linear logit | Maximum likelihood |  | -0.086 to -0.088 | -0.468 to -0.516 |
| Suh (2016) | 1970-2010 | The US | Time series | Annual | Electricity, coal, fuel oil, biomass | Differential fuel allocation model | Iterated seemingly unrelated regression | -0.048 |  |  |
| Charles (2016) | 2001- 2014 | Lower 48 states | Panel | Monthly | Electricity | Double-log with and without partial adjustment | OLS with fixed effects | -0.0684 | -0.0264 | -0.106 |
| Gautam and Paudel (2018b) | 1997-2011 | Nine Northeast states | Panel | Annual | Electricity, fuel oil | Double-log with autoregressive distributed lag | Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) |  |  | -0.285 |
| Woo et al. (2018a) | 2001-2016 | Lower 48 states | Panel | Monthly | Electricity, fuel oil | Generalized Leontief (GL) system of energy intensities with and without partial adjustment | Iterated seemingly unrelated regressions | -0.287 | -0.0686 | -0.4937 |

Panel B: Seven non-US studies

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Study | Sample period | Regional  coverage | Data type | Data frequency | Non-NG prices | Parametric specification | Estimation method | Static | Short-run | Long-run |
| Estrada and Fugleberg (1989) | 1960-1983 | France and Germany | Time series | Annual | Electricity, coal, fuel oil | TL | Generalized least squares | -0.30 to  -0.84 |  |  |
| Erdogu (2010) | 1988-2005 | Turkey | Time series | Quarterly | None | Double-log with partial adjustment | OLS |  | -0.78 | -7.81 |
| Khan (2015) | 1978-2011 | Pakistan | Time series |  | Coal and oil product prices | Double-log with partial adjustment | OLS |  | -0.12 | -0.27 |
| Burke and Yang (2016) | 1978-2011 | 44 countries | Panel | Annual | Gasoline as a proxy of oil substitutes | Double-log | OLS and instrumental variable estimation |  |  | -0.37 to  -1.21 |
| Peñasco et al. (2017) | 1995-2010 | Spanish manufacturing sector | Panel | Annual | None | Double-log | Augmented Mean Group Estimator |  |  | -0.442 to -0.478 |
| Lim (2019) | 1998-2018 | Korea | Time series | Monthly | None | Double-log | Kalman filter method |  | 0.0 to -0.02 |  |
| Agnolucci and De Lipsisa (2020) | 1990 - 2014 | UK | Panel for 8 subsectors | Annual | Electricity, coal, fuel oil | System of log[fuel share / (1 – fuel share)] regressions | Vector error correction model |  |  | -0.62 to  -2.40 |

Notes: (1) Most of the studies included herein have sample periods that end by 2016 and use annual data, suggesting the potential insights to be gained from a large and recent panel of monthly data.

(2) Non-NG energy prices enter an industrial natural gas demand equation because of inter-fuel substitution.

(3) The specification of Agnolucci and De Lipsisa (2020) based on fuel shares resembles those derived from the CES specification by Woo et al. (2017b).

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

(5) None of the panel data studies considers the impact of cross-section dependence on industrial natural gas demand’s price elasticity estimates.

(6) This table classifies 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 3. Descriptive statistics for the panel of monthly industrial data in Jan-2001 to Dec-2019 for the lower 48 states; number of observations = 10,944

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Definition | Mean | Standard deviation | Minimum | Maximum | Correlation with *Y*1 |
| *Y*1 | Per capita natural gas consumption (Mcf) | 2.800 | 3.426 | 0.020 | 28.332 | 1.0 |
| *Y*3 | Per capita electricity consumption (kWh) | 448.26 | 306.57 | 51.78 | 2177.51 | 0.509 |
| *P*1 | Natural gas price ($/Mcf) | 7.280 | 2.650 | 1.710 | 22.750 | -0.273 |
| *P*2 | Fuel oil price ($/gallon) | 2.080 | 0.819 | 0.507 | 4.335 | -0.027 |
| *P*3 | Electricity price ($/kWh) | 0.067 | 0.024 | 0.027 | 0.182 | -0.226 |
| *P*1 / *P*3 | Natural gas – electricity price ratio | 116.92 | 51.11 | 19.19 | 434.03 | -0.087 |
| *P*2 / *P*3 | Fuel oil – electricity price ratio | 32.69 | 13.96 | 6.49 | 98.13 | 0.117 |
| *X* | Per capita employment | 0.093 | 0.023 | 0.042 | 0.173 | 0.286 |
| *CDD* | Cooling degree days | 94.48 | 147.07 | 0 | 761 | 0.095 |
| *HDD* | Heating degree days | 431.62 | 423.97 | 0 | 1919 | -0.005 |

Table 4. Test statistics for cross-section independence and non-stationarity data; *p*-values in ( )

|  |  |  |
| --- | --- | --- |
| Variable | H0: cross-section independence | H0: Non-stationary data |
| *Y*1 | 142.16  (0.000) | -3.480  (0.000) |
| *P*1 / *P*3 | 328.20  (0.000) | -4.607  (0.000) |
| *P*2 / *P*3 | 445.39  (0.000) | -3.479  (0.000) |
| *X* | 401.98  (0.000) | -2.093  (0.010) |
| *CDD* | 454.32  (0.000) | -6.145  (0.000) |
| *HDD* | 480.78  (0.000) | -6.184  (0.000) |

Table 5. Preferred regression results based on CD presence and non-IV estimation with fixed effects for states; sample period: Jan-2001 to Dec-2019; statistically significant coefficient/elasticity estimates (*p*-value ≤ 0.05) in **bold**

Panel A: Double-log specification

|  |  |  |
| --- | --- | --- |
| Variable | Without partial adjustment | With partial adjustment |
| RMSE | 0.14 | 0.11 |
| Adjusted *R*2 | 0.72 | 0.83 |
| ln(*P*1 / *P*3) = ln(natural gas price/electricity price) | **-0.062** | **-0.056** |
| ln(*P*2 / *P*3) = ln(fuel oil price / electricity price) | **0.109** | **0.082** |
| *X* = per capita employment | **7.215** | 3.425 |
| *CDD* = cooling degree days (in thousands) | 0.020 | 0.064 |
| *HDD* =heating degree days (in thousands) | **0.245** | **0.194** |
| Lagged ln*Y*1 | **-** | **0.519** |
| Static own-price elasticity | **-0.062** | **-** |
| Short-run own-price elasticity | **-** | **-0.056** |
| Long-run own-price elasticity | **-** | **-0.116** |

Panel B: Linear specification

|  |  |  |
| --- | --- | --- |
| Variable | Without partial adjustment | With partial adjustment |
| RMSE | 0.00 | 0.00 |
| Adjusted *R*2 | 0.80 | 0.90 |
| (*P*1 / *P*3) = (natural gas price/electricity price) | -0.0001 | **-0.0001** |
| (*P*2 / *P*3) = (fuel oil price / electricity price) | **0.0014** | **0.0008** |
| *X* = per capita employment | **0.0142** | **0.0082** |
| *CDD* = cooling degree days (in thousands) | 0.0002 | 0.0002 |
| *HDD* =heating degree days (in thousands) | **0.0006** | **0.0004** |
| Lagged *Y*1 | **-** | **0.491** |
| Static own-price elasticity | **-0.039** | **-** |
| Short-run own-price elasticity | **-** | **-0.035** |
| Long-run own-price elasticity | **-** | **-0.069** |

Panel C: CES specification

|  |  |  |
| --- | --- | --- |
| Variable | Without partial adjustment | With partial adjustment |
| RMSE | 0.16 | 0.12 |
| Adjusted *R*2 | 0.74 | 0.85 |
| ln(*P*1 / *P*3) = ln(natural gas price/electricity price) | **-0.070** | **-0.052** |
| *X* = per capita employment | 2.423 | 1.048 |
| *CDD* = cooling degree days (in thousands) | **-0.188** | -0.057 |
| *HDD* =heating degree days (in thousands) | **0.156** | **0.166** |
| Lagged ln(*Y*1/ *Y*3) | **-** | **0.507** |
| Static own-price elasticity | **-0.040** | **-** |
| Short-run own-price elasticity | **-** | **-0.029** |
| Long-run own-price elasticity | **-** | **-0.060** |

Panel D: GL specification

|  |  |  |
| --- | --- | --- |
| Variable | Without partial adjustment | With partial adjustment |
| RMSE | 0.00 | 0.00 |
| Adjusted *R*2 | 0.80 | 0.90 |
| (*P*2 / *P*1)1/2  = (fuel oil price / natural gas price) 1/2 | **0.0011** | **0.0006** |
| (*P*3 / *P*1)1/2  = (electricity price / natural gas price) 1/2 | -0.0003 | -0.0001 |
| *X* = per capita employment | **0.0186** | **0.0090** |
| *CDD* = cooling degree days (in thousands) | 0.0001 | 0.0002 |
| *HDD* =heating degree days (in thousands) | **0.0006** | **0.0004** |
| Lagged *Y*1 | **-** | **0.511** |
| Static own-price elasticity | **-0.048** | **-** |
| Short-run own-price elasticity | **-** | **-0.038** |
| Long-run own-price elasticity | **-** | **-0.077** |

Panel E: TL specification

|  |  |  |
| --- | --- | --- |
| Variable | Without partial adjustment | With partial adjustment |
| RMSE | 0.03 | 0.02 |
| Adjusted *R*2 | 0.89 | 0.93 |
| ln(*P*1 / *P*3) = ln(natural gas price/electricity price) | **0.189** | **0.155** |
| ln(*P*2 / *P*3) = ln(fuel oil price / electricity price) | -0.009 | -0.008 |
| *X* = per capita employment | 0.465 | 0.492 |
| *CDD* = cooling degree days (in thousands) | **-0.038** | -0.011 |
| *HDD* =heating degree days (in thousands) | **0.036** | **0.034** |
| Lagged *S*1 | **-** | **0.298** |
| Static own-price elasticity | **-0.027** | **-** |
| Short-run own-price elasticity | **-** | **-0.125** |
| Long-run own-price elasticity | **-** | **-0.179** |

Table 6. 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 | 0.461 |  |  |
| RMSE | 0.135 |  |  |
| Intercept | -0.350 | 0.073 | 0.000 |
| *F*1 = 1 if double-log specification, 0 otherwise | 0.226 | 0.081 | 0.007 |
| *F*2 = 1 if linear specification, 0 otherwise | 0.253 | 0.080 | 0.003 |
| *F*3 = 1 if CES specification, 0 otherwise | 0.278 | 0.081 | 0.001 |
| *F*4 = 1 if GL specification, 0 otherwise | 0.253 | 0.081 | 0.003 |
| *IV* = 1 if IV estimation, 0 otherwise | -0.059 | 0.035 | 0.096 |
| *SR* = 1 if short-run, 0 otherwise | 0.000 | 0.033 | 0.990 |
| *LR* = 1 if long-run, 0 otherwise | -0.109 | 0.049 | 0.032 |
| *CD* = 1 if CD present, 0 otherwise | 0.124 | 0.035 | 0.001 |

Table 7. 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 | -0.048 |  |  |
| Adjusted *R*2 | 0.059 |  |  |
| RMSE | 0.011 |  |  |
| Intercept | -0.043 | 0.003 | 0.000 |
| *ID* | -0.00009 | 0.00004 | 0.044 |

Panel B: Short-run elasticity

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Estimate | Standard error | *p*-value |
| Regressand’s mean | -0.055 |  |  |
| Adjusted *R*2 | 0.383 |  |  |
| RMSE | 0.016 |  |  |
| Intercept | -0.034 | 0.004 | 0.000 |
| *ID* | -0.00039 | 0.00005 | 0.000 |

Panel C: Long-run elasticity

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Estimate | Standard error | *p*-value |
| Regressand’s mean | -0.084 |  |  |
| Adjusted *R*2 | 0.413 |  |  |
| RMSE | 0.024 |  |  |
| Intercept | -0.049 | 0.005 | 0.000 |
| *ID* | -0.00062 | 0.00007 | 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 2010 – 2019.

(3) The small but highly significant *b* estimate for ID in each panel’s last row is negative, indicating that the US industrial natural gas demand’s price responsiveness has been slowing increasing over time.

Table 8. Natural gas shortage cost (*SC* = percentage increase in industrial energy cost) for 2019 by elasticity type and specification for a one-day shortage that causes curtailment of 10% of industrial natural gas demand

Panel A. CD presence and non-IV estimation

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Parametric specification | Static | | Short run | | Long run | |
| *e*1 | *SC* | *e*1 | *SC* | *e*1 | *SC* |
| Double-log | -0.062 | 1.7% | -0.056 | 1.9% | -0.116 | 0.9% |
| Linear | -0.039 | 2.7% | -0.035 | 3.0% | -0.069 | 1.5% |
| CES | -0.040 | 2.6% | -0.029 | 3.6% | -0.060 | 1.7% |
| GL | -0.048 | 2.2% | -0.038 | 2.7% | -0.077 | 1.4% |
| TL | -0.027 | 3.9% | -0.125 | 0.8% | -0.179 | 0.6% |

Panel B. CD absence and non-IV estimation

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Parametric specification | Static | | Short run | | Long run | |
| *e*1 | *SC* | *e*1 | *SC* | *e*1 | *SC* |
| Double-log | -0.202 | 0.5% | -0.110 | 0.9% | -0.242 | 0.4% |
| Linear | -0.175 | 0.6% | -0.078 | 1.3% | -0.171 | 0.6% |
| CES | -0.141 | 0.7% | -0.070 | 1.5% | -0.154 | 0.7% |
| GL | -0.187 | 0.6% | -0.085 | 1.2% | -0.185 | 0.6% |
| TL | -0.151 | 0.7% | -0.275 | 0.4% | -0.437 | 0.2% |

Note: The *SC* calculation entails two steps: (1) calculate the disaggregate *SC* number for each 2019 observation in the panel; and (2) calculate the simple average of all disaggregate *SC* numbers.

Table 9. Regional own-price elasticity estimates for the lower 48 states based on the double-log specification with CD presence and non-IV estimation

|  |  |  |  |
| --- | --- | --- | --- |
| Region definition | Static elasticity | Short-run elasticity | Long-run elasticity |
| States in the Northeast census region | -0.156 | -0.124 | -0.246 |
| States in the Midwest census region | -0.050 | -0.051 | -0.106 |
| States in the South census region | -0.064 | -0.063 | -0.146 |
| States in the West census region | -0.079 | -0.027 | 0.063 |
| States with below average coal shares of total generation | -0.091 | -0.067 | -0.135 |
| States with above average coal shares of total generation | -0.049 | -0.045 | -0.093 |

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



Figure 2. Annual box plots of monthly average industrial natural gas prices across the lower 48 states







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 horizontal axis shows the starting period of each rolling-window. 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.

1. Section 2.2 lists the reasons for this trend. [↑](#footnote-ref-2)
2. As detailed in Section 2.6 below, the industrial customer class’s natural gas shortage cost is measured by the effect of a shortage on the class’s total cost of procuring natural gas, fuel oil and electricity to produce final outputs. [↑](#footnote-ref-3)
3. A case in point is New England’s winter natural gas shortage (<https://jbartlett.org/2020/12/new-england-again-warned-about-shortage-of-natural-gas-pipelines/>). [↑](#footnote-ref-4)
4. <https://www.worldoil.com/news/2021/6/25/natural-gas-prices-rally-as-global-shortages-abound> [↑](#footnote-ref-5)
5. Our sample period excludes year 2020 because of missing monthly data for some states and Covid-19’s impact on the US energy consumption. [↑](#footnote-ref-6)
6. See Section 2.5 that details these specifications. [↑](#footnote-ref-7)
7. A static price elasticity is estimated by a demand regression that ignores the relationship between current and past consumption. Short-run and long-run price elasticity are estimated from a demand regression that accounts for this relationship. [↑](#footnote-ref-8)
8. Cross-section dependence in an energy demand analysis that uses panel data captures common shocks (e.g., federal government policies and regional weather patterns) attributable to interdependence of the key regressors and/or regression errors (Li et al., 2021). [↑](#footnote-ref-9)
9. <https://www.eia.gov/energyexplained/natural-gas/use-of-natural-gas.php> [↑](#footnote-ref-10)
10. In the simple case of a single output and two inputs, input substitution is a movement along the production function’s isoquant (Varian, 1992). [↑](#footnote-ref-11)
11. For the simple case in the last footnote, the effect of rising output on input usage is given by the production function’s expansion path (Varian, 1992). [↑](#footnote-ref-12)
12. The various natural gas growth scenarios in the U.S. Department of Energy’s Annual Energy Outlook 2021 are available at <https://www.eia.gov/outlooks/aeo/pdf/03%20AEO2021%20Natural%20gas.pdf> [↑](#footnote-ref-13)
13. A graphical description of the US renewable capacity expansion is the EIA’s Annual Energy Outlook 2021 press release available at https://www.eia.gov/pressroom/presentations/AEO2021\_Release\_Presentation.pdf. [↑](#footnote-ref-14)
14. Our choice of studies which assess natural gas price elasticity estimates is as follows. We employ Google Scholar to identify an initial set of papers based on the keywords “price elasticity”, “industrial natural gas demand” and “United States”. The final list includes studies that are the most relevant to our paper. [↑](#footnote-ref-15)
15. For brevity we exclude the additive random error, which is a common procedure in the energy demand literature. [↑](#footnote-ref-16)
16. We did not use autoregressive distributed lag (ADRL) modelling since preliminary exploration shows that ADRL does not improve our understanding of the price response of the US demand for industrial natural gas. [↑](#footnote-ref-17)
17. The implication of this finding is that after experiencing a demand shock, an industrial customer achieves its equilibrium mix of electricity and natural gas usage within three months. [↑](#footnote-ref-18)
18. An example is New England’s winter natural gas shortage caused by pipeline capacity constraint (https://jbartlett.org/2020/12/new-england-again-warned-about-shortage-of-natural-gas-pipelines/) [↑](#footnote-ref-19)
19. The resulting shortage cost estimates do not consider a natural gas shortage’s adverse impact on electricity generation (Leahy et al., 2012). We reason that this impact is likely small because an electric grid in the US typically has a large fleet of heterogenous generation plants to maintain an operating reserve margin of 5% to 7% of daily peak MW demand (Woo et al., 2019). While a 10% natural gas shortage may shut down 10% of the grid’s natural-gas-fired generation capacity *KNG*, the grid’s percentage capacity loss is *L* = 10% × (*KNG* / *KT*) where *KT* = total generation capacity of the grid. As (*KNG* / *KT*) < 1, *L* is below 10%, which can be resolved by the grid’s operating reserve and electricity DR programs. Admittedly, the natural gas shortage can alter the grid’s least-cost dispatch, the ensuing incremental cost of $*l* per Mcf is likely small because *l* = (difference in per MWh fuel costs × MWh produced by replacement generation) ÷ total Mcf curtailed. [↑](#footnote-ref-20)
20. If the actual natural gas shortage lasts multiple days, the total cost estimate is the one-day estimate times the number of shortage days. [↑](#footnote-ref-21)
21. The dollar amount is ~$7 million per shortage day based on New England’s industrial energy cost for the winter month of January in 2019. [↑](#footnote-ref-22)
22. We also decide not to include additional regressors formed by the monthly and yearly dummies because these regressors are all insignificant. Further, they cause severe multicollinearity that renders our regression results unmeaningful with many insignificant coefficient estimates. [↑](#footnote-ref-23)
23. This estimator generates standard errors for gauging the statistical significance of the coefficient estimates while accommodating heteroscedasticity and autocorrelation. [↑](#footnote-ref-24)
24. 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. (2018a). [↑](#footnote-ref-25)
25. We use the lagged price ratios in the prior three months as instruments for the current month’s price-ratio. The lagged price ratios are highly correlated with the current price ratio (*r* = 0.86 to 0.94). As the lagged price ratios in month *t* are determined by average prices in months *t*-1, *t*-2 and *t*-3, they are pre-determined variables for month *t*. While a state’s natural gas sale in month *t* can be serially correlated with those in the prior months, its variation in month *t* cannot causally alter the average prices already recorded in the prior months. In short, the price ratios in the three prior months are suitable instruments because of their high correlations with and causal independence of the current month’s energy price ratio. [↑](#footnote-ref-26)
26. This difference in elasticity estimates may be attributable to the differences in data, parametric specifications, and estimation methods. [↑](#footnote-ref-27)