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Price responsiveness of commercial demand for natural gas in the US

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Highlights

- The US commercial natural gas demand is price inelastic.
- Its own-price elasticity estimates vary by season and region.
- The size of these estimates has been declining over time.
- Deep decarbonization requires energy efficiency standards and DSM programs.
- Demand response programs efficiently allocate limited supply of natural gas.

Dear Professor Stanek,

Fully addressing the comments by three reviewers, our resubmission contains extensive revisions evidenced by the red-lined comparison file.

Due to its academic rigor and policy implication, our paper should be of significant interest to readers of *Energy*, as well as industry practitioners and policy analysts.

In closing, we thank the reviewers for their very helpful comments that have greatly improved our paper's content and exposition. With guarded optimism, we look forward to receiving *Energy*'s favourable decision of acceptance.

With best regards,

Raymond Li

CRediT Author Statement

Raymond Li: Conceptualization; Methodology; Software; Data Curation; Writing – Original Draft; Writing – Review & Editing **Chi-Keung Woo:** Conceptualization; Methodology; Writing – Original Draft; Project Administration; Writing – Review & Editing **Asher Tishler:** Conceptualization; Writing – Original Draft **Jay Zarnikau:** Conceptualization; Writing – Original Draft

Conflict of Interest Statement

The authors have no conflicts of interest with respect to the issues raised in this submission.

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Abstract

To estimate price responsiveness of commercial demand for natural gas in the US, we use five parametric specifications to conduct panel data analysis of a newly developed sample of 17,280 monthly observations for the lower 48 states in 1991-2020. We find that the US commercial natural gas demand is price inelastic, with statistically significant (p-value $\leq$ 0.05) static own-price elasticity estimates of -0.137 to -0.245, short-run -0.152 to -0.261 and long-run -0.281 to -0.463. These estimates vary by choice of a sample period, choice of a parametric specification, treatment of cross-section dependence, assumption of partial adjustment, and exclusion of fixed effects. Further, they vary by season and region and their size has been slowly declining over time. Finally, commercial natural gas shortage cost declines with the size of own-price elasticity estimates. The policy implications of these findings are: (a) price-induced conservation's likely limited effect on the US commercial natural gas demand justifies continuation of energy efficiency standards and demand-side-management programs for deep decarbonization; and (b) demand response programs such as real time pricing and reliability differentiation efficiently allocate limited supply of natural gas during a shortage among heterogenous end-users, thus reducing an economy's aggregate natural gas shortage cost.

1. Introduction

Natural gas demand's price elasticity estimates are necessary for various applications in an economy's quest for a clean and sustainable future. Examples of such applications include energy policy modelling (Hausman, 1975; Manne et al., 1979), resource planning (Logan et al., 2013; Abrell and Weigt, 2016; Holz et al., 2016; Çalcı et al., 2022), consumption projection (Huntington, 2007; Bianco et al., 2014; Dilaver et al., 2014), a carbon tax's effect on consumption (Xiang and Lawley, 2019), the size of price-induced consumption reduction (Rowland et al, 2017), an energy system's responses to price shocks (Brown et al., 2021), optimal pricing (Gong et al., 2016; Davis and Muehlegger, 2010), and welfare assessments of market liberalization (Lee et al., 2004) and shale gas's rapid growth (Hausman and Kellogg, 2015; Gillingham and Huang, 2019).

Table 1 summarizes own-price elasticity estimates for commercial natural gas demand.[1] The widely dispersed short- and long-run estimates offer little guidance for the above applications in connection to the US, the second largest country behind China in national energy consumption and CO_2 emissions. Underscoring this point is the use of own-price elasticity estimates to project consumption reduction due to the future trend of likely rising retail natural gas prices in the US.[2] Highly diverse elasticity estimates, however, can cause

[1] The US Department of Energy classifies 16 building types based on a commercial customer's line of business: office, retail, education, hotel, healthcare, restaurant, warehouse, and apartment rental (https://www.energycodes.gov/development/commercial/prototype_models).

[2] This trend is attributable to three reasons. The first reason is the technology path to deep decarbonization (Williams et al., 2012; Mahone et al., 2018). Natural gas is a bridge fuel for displacing coal and oil (Woo et al., 2018b; Gillingham and Huang, 2019). Further, electrification of energy-using durables (Williams et al., 2012; Mahone et al., 2018) requires large-scale development of emissions-free renewable resources that necessitates transmission expansion (Alagappan et al., 2011; Joskow, 2021) and natural gas-fired generation's flexible capacity for reliable grid integration (Zarnikau et al., 2019). The second reason is carbon trading that raises retail natural gas prices, which embody marginal costs of CO_2 emissions. It also increases electricity generation's demand for natural gas because natural gas has lower CO_2 emissions than coal. The third reason is the diminishing price effect of shale gas development due to environmental concerns about hydraulic fracturing (Sovacool, 2014) and projected growth of the US export of liquified natural gas (Arora and Cai, 2014; Çalcı et al., 2022).

large projection variations, magnifying the uncertainty in resource planning (e.g., pipeline capacity expansion to enhance an economy's natural gas supply infrastructure).

To obtain up-to-date estimates of the US commercial natural gas demand's price elasticities, we perform panel data analysis of a newly developed sample of 17,280 monthly observations in 1991-2020 for the lower 48 states that exclude Alaska and Hawaii. Presaging our key finding that the US commercial natural gas demand is price inelastic, Figure 1 portrays stagnant commercial natural gas consumption, albeit the 100% retail pass through (Woo et al., 2014b) of relatively low wholesale natural gas prices triggered by shale gas's explosive growth (Caporin and Fontini, 2017). Further, we propose using price elasticity estimates to calculate the cost of a natural gas shortage that may adversely affect an economy (Leahy et al., 2012; Alcaraz and Villalvazo, 2017), thereby demonstrating our paper's international relevance underscored by the recently reported global shortages.[3]

As its sample period is 1991-2020, our paper presents empirics unseen in natural gas demand studies published by the end of 2020:

- Our panel data exhibit highly significant (p-value < 0.01) cross-section dependence (CD) due to common shocks and interdependence of regression errors (Li et al., 2021). Erroneously ignoring the presence of CD tends to understate the US commercial natural gas demand's price responsiveness.
- The US commercial natural gas demand's statistically significant (p-value $\leq$ 0.05) static own-price elasticity estimates are -0.137 to -0.245, short-run -0.152 to -0.261 and long-run -0.281 to -0.463.

[3] https://www.worldoil.com/news/2021/6/25/natural-gas-prices-rally-as-global-shortages-abound

- The statistically significant factors affecting these elasticity estimates are the choice of a parametric specification, treatment of CD presence, assumption of partial adjustment, and exclusion of fixed effects.
- The US commercial natural gas demand's price responsiveness varies by season and region and has been slowly declining over time.
- A hypothetical one-day natural gas shortage that causes a 10% curtailment of the US commercial natural gas demand is expected to increase the commercial customer class's energy cost by less than 1%.

The rest of our paper proceeds as follows. Section 2 presents materials and methods. Section 3 reports empirics, the basis for Section 4: conclusions and policy implications.

2. Materials and methods

2.1 Literature review

To provide our paper's contextual background, we review nine selected studies of the US commercial natural gas demand.[4] Our review is intentionally brief, thanks to the available 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; Labanderia et al., 2017; Huntington et al., 2019).

Summarizing our selected studies, Table 2 yields the following remarks that shape our panel data analysis. First, the regional coverage of these studies spans from a single state to the lower 48 states. Second, these studies tend to use annual data, with the notable exception of Woo et al. (2018a) that uses monthly data. Third, all studies include prices for energy inputs other than natural gas to reflect inter-fuel substitution by commercial customers.

[4] Unintended to be exhaustive, the selected studies are found via a two-step process: (1) use scholar.google.com to find the initial list based on the keywords of "price elasticity", "commercial natural gas demand" and "United States"; and (2) narrow the initial list based on each study's citation by existing literature surveys and relevance to our paper.

Fourth, eight studies use the double-log specification and the remaining one the Generalized Leontief (GL) specification, notwithstanding that the linear, constant-elasticity-of-substitution (CES) and transcendental-logarithmic (TL) specifications are popular in energy demand analysis.[5] Fifth, the estimation methods range from OLS regression to iterated seemingly unrelated regressions. Sixth, all studies use average price data. Finally, the own-price elasticity estimates are diverse, ranging from -0.13 to -1.60.

2.2 Nonlinear pricing of commercial natural gas consumption in the US

A commercial 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., 2014a). Even if the per Mcf charge is linear, the presence of a fixed customer charge causes the customer's monthly average natural gas price (= total bill ÷ total usage) to decline with consumption. Should the per Mcf charge have a declining block structure, it would reinforce the negative relationship between the customer's monthly average price and consumption. This relationship exists, even though the customer may have zero own-price elasticity. Hence, using average price data may cause estimation bias in an analysis of the US commercial demand for natural gas.

Our panel data analysis uses the US Energy Information Administration's (EIA's) monthly average price data because absent disaggregate information at customer level, accurate marginal prices are impossible to obtain. Should the average price data be found endogenous, the resulting estimation bias could be remedied by instrumental variable (IV) estimation (Davidson and MacKinnon, 1993).

[5] Existing literature surveys show that the double-log and linear specifications are popular in energy demand analysis, chiefly because of their simple estimation and easy interpretation. The CES specification is easy to estimate and directly yields the elasticity of substitution (Woo et al., 2018b). Without restricting the elasticity of substitution to be a constant like the CES specification, the GL and TL specifications are flexible second-order approximations of an energy cost function for deriving energy demand/cost share equations that are readily estimable as seemingly unrelated regressions (Diewert, 1971; Caves and Christensen, 1980; Greene, 2003).

2.3 Five parametric specifications

This section derives our panel data analysis's five parametric specifications, chosen herein as alternative characterizations of the US commercial natural gas demand's data generating process (Davidson and MacKinnon, 1993). Our choice is also driven by these specifications' vastly different price elasticity formulae, a potential cause for the diverse price elasticity estimates reported in our literature review. However, if they all yield price elasticity estimates with size below one, we infer that the US commercial natural gas demand is deemed price inelastic.[6]

Our derivation of a parametric specification reflects that commercial natural gas demand is a derived input demand based on a commercial 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:

$$C \quad = \quad P_1 Y_1 + P_2 Y_2 + P_3 Y_3. \qquad (1)$$

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 $\boldsymbol{V}$ based on the transformation function $G(\boldsymbol{V}, Z, L, M, K)$.

Applying Shephard's Lemma to the energy cost function $C(\bullet)$ yields the natural gas demand function (Diewert, 1971):

[6] This inference reflects our primary interest in how the choice of a parametric specification may affect price elasticity estimates. It does not inform which specification can best characterize the commercial natural gas consumption's data generating process. As a contrasting example, Woo (1994) uses the Box-Cox function and log-likelihood ratio test to determine the choice between the linear and log-linear specifications.

$$\partial C(\bullet) / \partial P_1 \quad = \quad Y_1^* \quad = \quad H(P_1, P_2, P_3, Z). \tag{2}$$

As $H(\bullet)$ 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:

$$\varepsilon_1 \quad = \quad \partial \ln Y_1^* / \partial \ln P_1; \tag{3}$$

$$\varepsilon_j \quad = \quad \partial \ln Y_1^* / \partial \ln P_j \text{ for } j > 1. \tag{4}$$

Moreover, $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 0$ because $H(\bullet)$ is homogenous of degree zero in (P_1, P_2, P_3) (Varian, 1992). As $\varepsilon_1 \leq 0$ and $\varepsilon_2 + \varepsilon_3 \geq 0$, natural gas is a substitute for fuel oil/electricity.

Closely related to the cross-price elasticity ε_j is the elasticity of substitution σ_j between natural gas and energy type j (Blackorby and Russell, 1989):

$$\sigma_j \quad = \quad \varepsilon_j / S_j, \tag{5}$$

where S_j = cost share $j = P_j Y_j^* / (P_1 Y_1^* + P_2 Y_2^* + P_3 Y_3^*)$. When $\sigma_j = 0$, it indicates zero substitutability between natural gas and fuel oil/electricity. When σ_j is close to zero, it indicates limited substitutability. When $\sigma_j = \infty$, natural gas is a perfect substitute for fuel oil/electricity.

Suppose the parametric cost function is $C = e^{\beta_0} (P_1 / P_3)^{(1 + \beta_1)} (P_2 / P_3)^{\beta_2} Z^{\beta_Z} / (1 + \beta_1)$, which is unseen in existing non-residential studies of natural gas demand. 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 $(Y_1^* - Y_1)$:

$$\ln Y_1 \quad = \quad \beta_0 + \beta_1 \ln(P_1 / P_3) + \beta_2 \ln(P_2 / P_3) + \beta_Z \ln Z. \tag{6}$$

As Z is unobservable, estimating equation (6) assumes that $\ln Z$ is a linear function of employment X, cooling degree days CDD and heating degree days HDD.

Based on equation (3), the own-price elasticity is $\varepsilon_1 = \beta_1$. According to equation (4), the cross-price elasticities are $\varepsilon_2 = \beta_2$ and $\varepsilon_3 = -\beta_1 - \beta_2$, which are used to find σ_j via equation (5).

Suppose the parametric cost function is $C = \alpha_0 P_1 + 1/2\ \alpha_1 (P_1^2 / P_3) + \alpha_2 (P_1 P_2 / P_3) + \alpha_Z P_1 Z$, which is also unseen in existing non-residential studies of natural gas demand. Using equation (2), we derive the linear natural gas demand equation:

$$Y_1 = \alpha_0 + \alpha_1 (P_1 / P_3) + \alpha_2 (P_2 / P_3) + \alpha_Z Z. \quad (7)$$

Estimating equation (7) assumes that Z is a linear function of X, CDD and HDD.

Based on equation (3), the own-price elasticity is $\varepsilon_1 = \alpha_1 (P_1 / P_3) / Y_1$. According to equation (4), the cross-price elasticities are $\varepsilon_2 = \alpha_2 (P_2 / P_3) / Y_1$ and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

As ε_1 varies nonlinearly by price ratio and consumption level, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates based on the data used in the demand analysis. The same can be said about ε_2 and ε_3. Finally, the calculation process for (ε_1, ε_2, ε_3) applies to the specifications listed below.

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

$$\ln(Y_1 / Y_3) = \phi_0 + \phi_1 \ln(P_1/P_3), \quad (8)$$

where $\phi_1 = -1 \times \sigma$, where σ = identical elasticity of substitution among natural gas, fuel oil and electricity. The CES specification is restrictive in that σ does not vary by input energy type and energy price ratio. To account for possible dependence of $\ln(Y_1 / Y_3)$ on non-price factors, we assume ϕ_0 to be a linear function of X, CDD and HDD. The natural gas demand's own-price elasticity is:

$$\varepsilon_1 = \phi_1 (1 - S_1), \quad (9)$$

where $S_1 = P_1 Y_1 / C$ = natural gas cost share (Woo et al., 2018b).[7]

[7] Calculating ε_1 requires monthly data by state for commercial 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 commercial customer class does not consume fuel oil. We then use the EIA annual data to compute two annual natural cost shares: $AS_{max} = P_1 Y_1 / (P_1 Y_1 + P_3 Y_3)$ and $AS_{true} = P_1 Y_1 / (P_1 Y_1 + P_2 Y_2 + P_3 Y_3)$. Finally, we use $S_{max} (AS_{true} / AS_{max})$ to approximate S_1's monthly missing values.

For the GL cost function (Diewert, 1971; Woo et al., 2018a), the demand equation is:

$$Y_1 = b_{11} + b_{12} (P_2 / P_1)^{1/2} + b_{13} (P_3 / P_1)^{1/2} + b_{1Z} Z. \quad (10)$$

The own-price elasticity is:

$$\varepsilon_1 = - 1/2 [b_{12} (P_2 / P_1)^{1/2} + b_{13} (P_3 / P_1)^{1/2}] / Y_1. \quad (11)$$

The cross-price elasticities are $\varepsilon_2 = 1/2\ b_{12} (P_2 / P_1)^{1/2} / Y_1$ and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

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

$$S_1 = a_1 + a_{11} \ln(P_1/P_3) + a_{12} \ln(P_2/P_3) + a_{1Z} \ln Z. \quad (12)$$

The own-price elasticity is:

$$\varepsilon_1 = (a_{11} + S_1^2 - S_1) / S_1. \quad (13)$$

The cross-price elasticities are $\varepsilon_2 = (a_{12} + S_1 S_2) / S_1$ and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

2.4 Long-run elasticity

To obtain a long-run elasticity estimate, we use the 1-month lagged regressand as an additional regressor to characterize the parsimonious partial adjustment process often assumed by an energy demand study.[8] Let φ denote the lagged regressand's coefficient. As will be seen in Section 3 below, the significant estimate for φ is between 0.364 to 0.458. 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 - φ).

[8] The autoregressive distributed lag model is not used here because our preliminary exploration shows that the additional estimation sophistication does not lead to a better understanding of the US commercial natural gas demand's estimated price responsiveness.

2.5 Estimation of commercial shortage cost

A natural gas shortage with advance notice enables commercial customers to adjust their production activities.[9] The following steps estimate natural gas shortage cost as a percentage increase in the commercial customer class's energy cost:

(1) Assume a hypothetical one-day shortage that curtails D% of the commercial customer class's total natural gas demand per calendar day. If the shortage is expected to last N days, its total cost is the one-day estimate times N.

(2) Find the percentage price increase required to resolve the assumed shortage (Woo, 1994): $\Delta \ln P_1 = -(D / \varepsilon_1)$.

(3) Find the one-day shortage cost as a percentage of C:

$$SC = (\Delta C / C) \div 30 \text{ days}, \tag{14}$$

where $\Delta C = [\partial C / \partial P_1]\, \Delta P_1 = Y_1\, \Delta P_1$ based on Shephard's Lemma (Varian, 1992). As $(\Delta P_1 / P_1) = \Delta \ln P_1$, we find:

$$SC = (P_1\, Y_1 / C)\, (\Delta P_1 / P_1) \div 30 \text{ days} = -\, S_1 (D / \varepsilon_1) \div 30 \text{ days}. \tag{15}$$

The *SC* estimates based on equation (15) assume that when given advance notice, commercial customers can readily adjust/reschedule their production activities with negligible costs of lost production, idle labour, and material damage (Leahy et al., 2012; Woo et al., 2021).[10] This assumption makes sense because (a) the natural gas shortage implies fractional curtailment rather than total interruption of natural gas service; and (b) major

[9] 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/)

[10] The *SC* estimates based on equation (15) 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 K_{NG}, the grid's percentage capacity loss is L = 10% × (K_{NG} / K_T) where K_T = total generation capacity of the grid. As $(K_{NG} / K_T) < 1$, 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 \$$W$ per Mcf is likely small because W = (difference in per MWh fuel costs × MWh produced by replacement generation) ÷ total Mcf curtailed.

commercial end-uses of space heating, water heating and cooking can be partially met by electricity and fuel oil.

The following cases demonstrate that equation (15) 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 commercial energy cost.

(2) Suppose $S_1 > 0$. As a result, SC increases with natural gas's cost share S_1, the extent of D and the size of ε. If $S_1 = 30\%$, $D = 10\%$, and $\varepsilon = -0.1$, $SC = 30\% \div 30$ days $= 1\%$ of the commercial customer class's monthly energy cost.[11]

2.6 Data description

Our data sources are as follows. First, the EIA publishes the commercial customer class's monthly data for electricity and natural gas consumption and average prices P_1 and P_2 for each of the 50 states in the US. These data are based on each state's commercial energy sales and revenues reported by natural gas utilities and retail service providers. The EIA also publishes the class's monthly data for average retail fuel oil price P_3. However, it does not publish the class's monthly fuel oil consumption. While P_1, P_2 and P_3 are nominal prices, their conversion to real prices is unnecessary for our regression analysis because all specifications use price ratio data.

Second, the US Bureau of Labor Statistics (BLS) publishes the monthly data for commercial employment and civilian noninstitutional population. We use the monthly employment and population data to construct the data for X. We use the EIA's monthly data for natural gas and electricity consumption by state and the BLS's monthly data for population by state to derive the per capita data for Y_1 and Y_3.

[11] The dollar amount is ~$4 million per shortage day based on New England's commercial energy cost for the winter month of January in 2020.

Finally, 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).

Panel A of Table 3 presents the descriptive statistics of our panel data. It shows that all variables have wide ranges based on their minimum and maximum values. Further, the coefficients of variation (= standard deviation ÷ mean) indicate that the data for weather variables are more volatile than non-weather variables.

The second column of Panel B of Table 3 reports that Y_1 is weakly correlated with Y_3 (r = -0.044), suggesting limited substitutability between electricity and natural gas usage. Y_1 is negatively correlated with P_1 (r = -0.247) but less so with P_2 (r = -0.057) and P_3 (r = -0.122). It is negatively correlated with (P_1 / P_3) (r = -0.144) but its correlation with (P_2 / P_3) is very weak (r = 0.002). Finally, it is positively correlated with X (r = 0.115), negatively correlated with *CDD* (r = -0.458) and strongly correlated with *HDD* (r = 0.824).

The remaining columns report correlations for the other variables. As expected, P_1, P_2 and P_3 are positively correlated (r > 0.422) because wholesale spot prices for natural gas, fuel oil and electricity tend to move in tandem. The correlated price levels imply correlation (r = 0.471) between the energy price ratios. Because of their definitions, *CDD* and *HDD* are negatively correlated (r = -0.613).

While indicative, the correlations in Table 3 do not untangle the marginal effects of price ratios, employment, and weather on the US commercial natural gas demand, thus motivating our estimation strategy presented below.

2.7 Estimation strategy

As CD can introduce bias to the regression estimates (De Hoyos and Sarafidis, 2006), we adopt the dynamic common correlated effects (DCCE) panel estimator that accounts for CD presence (Chudik and Pesaran, 2015):

$$A_{kt} = \eta_k + \varphi A_{kt-1} + \beta_k B_{kt} + \sum_{m=0}^{M} \psi_{km} CA_{t-m} + \mu_{kt}, \quad (16)$$

where A is the dependent variable, B is a vector of explanatory variables, CA is a vector of cross-section averages, η_k is the state-specific fixed effect, μ_{kt} is the random error, k = 1 to 48 denotes an observation's state (= 1 for Alabama, …, 48 for Wyoming), and t denotes an observation's period (= 1 for Jan-1991, …, 360 for Dec-2020).[12] Using the popular double-log specification as an illustration, $A = \ln Y_1$ and $B' = (\ln(P_1/P_3), \ln(P_2/P_3), X, CDD, HDD)$.

We estimate equation (16) for each parametric specification. When φ is a positive fraction, it leads to the short- and long-run elasticity estimates. Under the restriction of $\varphi = 0$, equation (16) produces the static elasticity estimate. In this case, only current cross-section averages are included (i.e., $M = 0$) and the resulting estimator will resemble that of Pesaran (2006).[13] Under the assumption of CD absence, cross-section averages are not included ($\psi_{km} = 0$) and the mean group estimator (Pesaran and Smith, 1995) applies.

Our estimation strategy entails the following steps:

(1) Use the Pesaran (2020) test to detect CD in the data.

(2) Use the Pesaran (2007) panel unit root test that allows for CD to test for stationarity of the variables and avoid spurious regressions (Baltagi and Kao, 2001) in steps (3) and (4) below.

(3) Perform IV and non-IV estimation to estimate the coefficients of equation (16) for the four cases formed by (a) $\varphi = 0$ vs. $\varphi > 0$; and (b) $\psi_{km} \neq 0$ vs. $\psi_{km} = 0$. We use lagged price ratios in the prior three months as the instruments for the current month's price-ratio in IV estimation.

[12] Equation (16) does not use monthly dummies to account for the residual effects of seasonality uncaptured by monthly *CDD* and *HDD* because our preliminary exploration indicates that these monthly dummies have insignificant coefficient estimates.

[13] As the Pesaran (2006) estimator differs from the DCCE estimator, the resulting static own-price elasticity estimates may not always lie between the short-run and long-run estimates.

(4) Repeat step (3) for the remaining four specifications.

3. Empirics

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

Table 4 shows that the null hypotheses of cross-section independence and non-stationarity are decisively rejected (p-value < 0.01) for all variables, supporting our panel data analysis that accounts for CD presence *sans* the concern of spurious regressions.

3.2 General remarks

Three general remarks emerge from Table 5 that details our regression results. First, the regressions for all specifications resulted in adjusted R^2 values ≥ 0.87, indicating reasonable goodness of fit. Second, the null hypothesis of cross-section independence is decisively rejected (p-value < 0.01) for all specifications, implying that the estimates under CD absence are likely biased. Third, the Durbin-Wu-Hausman (Wooldridge, 2010) test results suggest that the current price ratio data are exogenous in ~70% of the models. Based on these remarks, our preferred regression results for each specification are those shaded in light green, all of which are based on CD presence and non-IV estimation.

3.3 Regression details

For the double-log specification, Panel A.1 of Table 5 reports that the US commercial natural gas demand has a static own-price elasticity estimate of -0.245. *HDD* has a significant effect on demand but not *X* and *CDD*. Panel A.2 reports that the short-run own-price elasticity estimate is -0.177. The long-run estimate is -0.298, thanks to lagged $\ln Y_1$'s 0.406 coefficient estimate. Panel A.3 reports relatively small estimates for the elasticity of substitution, suggesting limited substitutability between natural gas and fuel oil/electricity.

For the linear specification, Panels B.1 and B.2 show the positive but small coefficient estimates for *X*, *CDD* and *HDD*. The coefficient estimate for lagged Y_1 is 0.379 and statistically significant. The static own-price elasticity estimate is -0.240, the short-run estimate -0.226 and the long-run estimate -0.364. These estimates resemble those found under the double-log specification. Akin to Panel A.3, Panel B.3 conveys the message of limited substitutability.

For the CES specification, Panel C.1 and C.2 show that $\ln(Y_1 / Y_3)$ declines with $\ln(P_1 / P_3)$. The statistically significant coefficient estimates for *CDD* and *HDD* indicate the small impact of weather on the natural gas-electricity consumption ratio. The coefficient estimates for X are positive but insignificant. The coefficient estimate for lagged $\ln Y_1$ is 0.458 and statistically significant. The static own-price elasticity estimate is -0.137, the short-run estimate -0.152 and the long-run estimate -0.281. Hence, the CES specification generates smaller elasticity estimates than the double-log and linear specifications. Finally, Panel C.3 affirms limited substitutability between natural gas and electricity.

For the GL specification, Panel D.1 and D.2 report the statistically significant but small coefficient estimates for *CDD* and *HDD*. The coefficient estimate for X is insignificant. The coefficient estimate for lagged Y_1 is 0.364 and statistically significant. The static, short-run and long-run own-price elasticity estimate are -0.192, -0.206 and -0.324, respectively. These estimates are smaller than those found by Woo et al. (2018a), possibly due to our paper's longer sample period and modelling difference. Finally, Panel D.3 corroborates the message of Panels B.3 and C.3.

For the TL specification, Panel E.1 and E.2 report that the estimated effects of *CDD* and *HDD* are small but statistically significant. The positive coefficient estimates for X are small and insignificant. The coefficient estimate for lagged $\ln S_1$ is 0.436 and statistically significant. The static elasticity estimate is anomalously at 0.021. The short- and long-run estimates are -0.261 and -0.463, larger than those based on the other specifications. Finally, Panel E.3 reports the estimated elasticities of substitution that differ from those in Panels A.3 to D.3.

3.4 Seasonal pattern of own-price elasticity estimates

Panel F of Table 5 reports the seasonal own-price elasticity estimates. As expected, summer estimates are larger in size than winter elasticity estimates because natural gas is a major fuel for meeting commercial end-use requirement of space heating.

3.5 What moves the US natural gas demand's own-price elasticity estimates?

We use an OLS dummy variable regression to identify the statistically significant factors that move the US commercial natural gas demand's own-price elasticity estimates. After excluding the anomalously positive estimates, this regression's results in Table 6 yield the following remarks. First, 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. Second, the elasticity estimates based on non-TL specifications are numerically similar. Third, the use of IV estimation does not have a statistically significant effect on elasticity estimates. Fourth, the long-run elasticity estimates are larger in size than the static and short-run estimates. Finally, the highly significant and negative estimate for *CD* suggests that erroneously ignoring CD presence tends to shrink the size of elasticity estimates.

Importantly, all predicted price elasticities based on the OLS regression have size well below one. Hence, the US commercial natural gas demand is deemed price inelastic, irrespective of the modelling assumptions made in connection to the choice of a parametric specification, assumption of partial adjustment, treatment of CD, and use of IV estimation.

3.6 Time trend of own-price elasticity estimates

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 rolling-window's first period is Jan-1991 to Dec-2000 and last period Jan-2011 to Dec-2020. Figure 2 portrays the US commercial natural gas demand's declining price responsiveness over time, further confirmed by the OLS regression results shown in Table 7.

3.7 Commercial shortage costs

Table 8 reports *SC* estimates by specification and elasticity type under the assumption of a hypothetical one-day shortage that curtails *D* = 10% of commercial natural gas demand. We perform the *SC* calculations using the elasticity estimates based on CD presence and non-IV estimation. For comparison, we repeat the calculations using the elasticity estimates based on CD absence and non-IV estimation, showing that erroneously ignoring the statistically significant CD presence tends to overstate the size of *SC*. Nevertheless, the *SC* estimates in Table 8 are all less than 1% of the commercial customer class's energy cost.

3.8 Sensitivity checks

We choose the double-log specification with CD presence and non-IV estimation to perform several checks of the sensitivity of the US commercial natural gas demand's estimated price responsiveness. Our choice reflects the double-log specification's popularity evidenced by Table 2 and empirical plausibility portrayed by Table 5 and 6.

The first check repeats the panel data analysis with the fuel oil – electricity price ratio excluded. The resulting elasticity estimates becomes slightly smaller, with the static, short- and long-run own-price elasticity estimates respectively equal to -0.175, -0.133 and -0.225. Hence, excluding fuel oil as a regressor does not materially affect the own-price elasticity estimates.

The second check uses quarterly data instead of monthly data, thereby testing if reducing data frequency affects commercial 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. The resulting static price elasticity estimate is -0.199, short-run estimate -0.188, and long-run estimate -0.229. Thus, using less frequent data does not materially affect the price elasticity estimates reported in Panels A.1 and A.2 in Table 5.

The third check uses aggregate, instead of per capita, natural gas usage and employment data in the double-log demand regression. It finds that using aggregate data produces price elasticity estimates resemble those reported in Panels A.1 and A.2 of Table 5.

The fourth check uses price level instead of price ratio data. It finds that the static price elasticity estimate becomes -0.257, the short-run estimate -0.210, and the long-run estimate -0.339. Thus, using price level data does not materially alter the static estimate but moderately enlarges the short- and long-run estimates.

The fifth check implements the approach of Burke and Yang (2016). In the context of our panel data analysis, this approach is the double-log specification with the "between" estimator without state-specific fixed effects and CD presence. The resulting long-run own-price elasticity estimate is -1.153, close to the high-end estimates shown in Table 2. Hence, the between estimator yields much larger estimates than those reported in Table 5.

The final check investigates the US commercial natural gas demand's regional price responsiveness. This check's first investigation entails using regional data to re-estimate the double-log demand regressions. Table 9 shows that the Midwest, West, and South regions in Figure 3 have similar own-price elasticity estimates that are smaller in size than those of the Northeast region. As the Northeast region has higher natural gas prices than other regions, commercial natural gas demand in this region tends to be more price-sensitive because of more active inter-fuel substitution.

The final 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). Motivating this re-estimation is our conjecture that commercial customers who are more price responsive may be more likely to locate in a region with more stable and lower electricity prices made possible by the region's above-average *CS*. The first subsample contains states with below average *CS*, while the second subsample the remaining states. Table 9 indicates that the US commercial natural gas demand's price responsiveness does not depend on the relative abundance of coal-fired generation.

4. Conclusions and policy implications

Our paper's conclusions are as follows. First, accurate price elasticity estimates of natural gas demand are necessary for the various applications noted in Section 1. However, using extant studies to make reasonable price responsiveness assumptions is difficult, chiefly because of the large disparity in price elasticity estimates.

Second, a panel data analysis that uses monthly data by state over a long period is useful for estimating the US commercial natural gas demand's price responsiveness. Such an analysis, however, should recognize the effects of various factors listed in Section 3.5. That said, the key takeaway of our extensive empirics is the US commercial natural gas demand is price inelastic and its responsiveness has been slowly declining over time.

Finally, our own-price elasticity estimates match the mid estimates found by extant studies. They imply relatively small commercial energy cost's increases (< 1%) due to a hypothetical one-day shortage that curtails 10% of commercial natural gas demand.

Our conclusions have two policy implications. First, price-induced conservation is unlikely to materially reduce the US commercial class's future consumption of natural gas. Hence, the US path to deep decarbonization requires continuation of energy efficiency standards and DSM programs (Williams et al., 2012; Mahone et al., 2018).

Second, the aggregate cost of a natural gas shortage can be reduced by demand response programs like those enabled by smart metering for managing electricity shortage (Woo et al., 2014a). This is because natural gas shortage costs vary by price responsiveness and commercial customers are heterogenous (e.g., hospitals vs. warehouses) with diverse disaggregate price responsiveness (Newell and Pizer, 2005). As a result, real-time pricing incentivizes more price responsive commercial customers to reduce their demand so that undisrupted service can continue for less price responsive customers.

Lending further support to the second implication is reliability differentiation made possible by a natural gas retailer's demand subscription service (Woo, 1990; Woo et al., 2014a, 2019). This is because commercial customers with low shortage costs tend to subscribe relatively more non-firm service at discounted per Mcf charges, while commercial customers with high shortage costs tend to subscribe relatively more firm service at undiscounted per Mcf charges. When a natural gas shortage is eminent, non-firm service is curtailed before firm service (Chao and Wilson, 1987; Woo, 1990). The resulting allocation of limited supply is efficient, thus reducing an economy's aggregate natural gas shortage cost.

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Table 1. Own-price elasticity estimates of commercial demand for natural gas based on selected surveys

Study	Short run	Long run
Bohi and Zimmerman (1984)	-0.28 to -0.37	-1.86 to -2.37
Al-Sahlawi (1989)	-0.16 to -0.37	-1.06 to -2.26
Gillingham et al. (2009)	-0.14 to -0.29	-0.40 to -1.38

Note: Including additional surveys does not alter the table's main message that commercial demand for natural gas has highly diverse own-price elasticity estimates.

Table 2. Own-price elasticity estimates from selected studies of commercial demand for natural gas (NG) in the US

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		-0.161	-0.366
Liu (1983)	1967-1978	The US	Time series	Annual	Electricity, fuel oil	Double-log	OLS	-0.318 to -0.342		
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		-0.283	-1.428
Nan and Murry (1992)	1970 - 87	California	Time series	Annual	Electricity and petroleum products	Flexible double-log	Seemingly unrelated regressions		-0.570	-0.635
Denton et al. (2003)	CBECE Surveys for 1986 and 1992	The US	Cross section	Annual	Electricity	Double-log	Instrumental variable estimation			-0.63 to -1.62
Newell and Pizer (2005)	CBECE Surveys for 1986 and 1992	The US	Cross section	Annual	Electricity, fuel oil	Double-log	Discrete-continuous choice modelling			-1.39 to -1.60
Charles (2016)	2001- 2014	Lower 48 states	Panel	Monthly	Electricity	Double-log with and without partial adjustment	OLS with fixed effects	-0.137	-0.095	-0.232
Gautam and Paudel (2018)	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)		-0.117	-0.222
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	-0.468	-0.243	-0.641

Notes: (1) This table does not contain commercial natural gas demand studies outside the US because a scholar.google.com search does not yield recently published non-US studies relevant to our paper.
(2) CBECE Survey = Commercial Buildings Energy Consumption and Expenditure Survey conducted by the Department of Energy.
(3) Studies included herein have sample periods that end by 2016, suggesting potential insights to be gained from a large and recent sample of monthly data by state.
(4) Non-NG energy prices enter a commercial natural gas demand regression because of inter-fuel substitution.
(5) None of the panel data studies considers the impact of cross-section dependence on commercial natural gas demand’s empirical price responsiveness.

(6) 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 3. Monthly data used in our regression analysis; sample period = Jan-1991 to Dec-2020; geographic coverage = lower 48 states in the US, excluding Alaska and Hawaii; number of observations = 17,280

Panel A: Descriptive statistics

Variable	Definition	Mean	Standard deviation	Minimum	Maximum
Y_1	Per capita natural gas consumption (Mcf)	1.23	0.92	0.06	5.60
Y_3	Per capita electricity consumption (kWh)	437.42	115.30	92.86	1157.66
P_1	Natural gas price ($/Mcf)	8.21	3.00	1.76	22.07
P_2	Fuel oil price ($/gallon)	1.58	0.94	0.34	4.34
P_3	Electricity price ($/kWh)	0.086	0.026	0.037	0.212
P_1 / P_3	Natural gas – electricity price ratio	99.25	35.96	17.60	325.60
P_2 / P_3	Fuel oil – electricity price ratio	18.33	10.10	3.04	71.22
X	Per capita commercial employment	0.388	0.046	0.235	0.515
CDD	Cooling degree days	91.45	144.59	0	794
HDD	Heating degree days	434.99	422.46	0	2111

Panel B: Correlations

Variable	Y_1	Y_3	P_1	P_2	P_3	P_1 / P_3	P_2 / P_3	X	CDD	HDD
Y_1	1									
Y_3	-0.044	1								
P_1	-0.247	0.240	1							
P_2	-0.057	0.315	0.589	1						
P_3	-0.122	-0.140	0.422	0.462	1					
P_1 / P_3	-0.144	0.363	0.673	0.230	-0.335	1				
P_2 / P_3	0.002	0.438	0.471	0.878	0.025	0.471	1			
X	0.115	0.134	0.161	0.178	0.257	-0.033	0.086	1		
CDD	-0.458	0.369	0.120	0.029	0.002	0.093	0.011	-0.088	1	
HDD	0.824	-0.153	-0.142	-0.024	-0.039	-0.100	0.008	0.092	-0.613	1

Table 4. 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	543.63 (0.000)	-5.392 (0.000)
P_1 / P_3	433.94 (0.000)	-5.607 (0.000)
P_2 / P_3	607.98 (0.000)	-4.169 (0.000)
X	505.63 (0.000)	-2.471 (0.000)
CDD	569.54 (0.000)	-6.190 (0.000)
HDD	606.07 (0.000)	-6.190 (0.000)

Table 5. Regression results by specification; sample period: Jan-1991 to Dec-2020; statistically significant coefficient/elasticity estimates (p-value $\leq$ 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	0.13	0.13	0.18	0.18
Adjusted R^2	0.95	0.98	0.90	0.91
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.245**	**-0.186**	**-0.090**	-0.071
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	**0.166**	**0.140**	-0.027	-0.031
X = per capita industrial employment	0.357	0.255	0.532	0.518
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Static own-price elasticity	**-0.245**	**-0.186**	**-0.090**	-0.071
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	0.10	0.09	0.13	0.13
Adjusted R^2	0.97	0.97	0.95	0.95
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.177**	*0.025*	**-0.082**	-0.038
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	**0.099**	-0.022	-0.021	**-0.032**
X = per capita industrial employment	0.336	0.426	**1.043**	**0.886**
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Lagged $\ln Y_1$	**0.406**	**0.416**	**0.320**	**0.318**
Short-run own-price elasticity	**-0.177**	0.025	**-0.082**	-0.038
Long-run own-price elasticity	**-0.298**	***0.042***	**-0.121**	-0.056
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel A.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.079**	**0.078**	**0.131**
Natural gas - fuel oil	**0.166**	**0.099**	**0.167**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.95	0.98	0.91	0.91
(P_1 / P_3) = (natural gas price/electricity price)	**-0.0017**	**-0.0015**	**-0.0009**	-0.0008
(P_2 / P_3) = (fuel oil price / electricity price)	0.0043	**0.0042**	**-0.0026**	**-0.0026**
X = per capita industrial employment	0.0005	0.0006	-0.0002	0.0000
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Static own-price elasticity	**-0.240**	**-0.215**	**-0.126**	**-0.112**
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	0.00	0.00	0.00	0.00
Adjusted R^2	0.97	0.97	0.95	0.95
(P_1 / P_3) = (natural gas price/electricity price)	**-0.0016**	*0.0002*	**-0.0008**	-0.0005
(P_2 / P_3) = (fuel oil price / electricity price)	**0.0045**	-0.0005	**-0.0023**	**-0.0027**
X = per capita industrial employment	0.0006	0.0009	**0.0008**	0.0007
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Lagged Y_1	**0.379**	**0.381**	**0.310**	**0.308**
Short-run own-price elasticity	**-0.226**	***0.026***	**-0.111**	**-0.068**
Long-run own-price elasticity	**-0.364**	***0.042***	**-0.161**	**-0.098**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel B.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.135**	**0.114**	**0.184**
Natural gas - fuel oil	**0.106**	**0.112**	**0.180**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.17	0.17	0.24	0.24
Adjusted R^2	0.94	0.97	0.87	0.87
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.169**	-0.084	**-0.284**	**-0.281**
X = per capita industrial employment	0.837	0.714	**-3.314**	**-3.230**
CDD = cooling degree days	**0.000**	**0.000**	**-0.001**	**-0.001**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Static own-price elasticity	**-0.137**	**-0.068**	**-0.230**	**-0.227**
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	0.11	0.10	0.17	0.17
Adjusted R^2	0.97	0.97	0.94	0.94
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.188**	*0.036*	**-0.203**	**-0.167**
X = per capita industrial employment	0.232	0.141	**-1.297**	**-1.446**
CDD = cooling degree days	**-0.001**	**-0.001**	**-0.001**	**-0.001**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Lagged $\ln Y_1$	**0.458**	**0.467**	**0.377**	**0.376**
Short-run own-price elasticity	**-0.152**	***0.029***	**-0.164**	**-0.135**
Long-run own-price elasticity	**-0.281**	***0.054***	**-0.263**	**-0.217**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel C.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.169**	**0.188**	**0.347**
Natural gas – fuel oil	**0.169**	**0.188**	**0.347**

Note: The CES specification's regression coefficients for $\ln(P_1 / P_3)$ in Panels C.1 and C.2 are constant elasticities of substitution × -1, which are the same for the two fuel pairs.

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.96	0.98	0.91	0.91
$(P_2 / P_1)^{1/2}$ = (fuel oil price / natural gas price) $^{1/2}$	0.0000	0.0003	**-0.0002**	**-0.0002**
$(P_3 / P_1)^{1/2}$ = (electricity price / natural gas price) $^{1/2}$	**0.0001**	0.0000	**0.0001**	**0.0001**
X = per capita industrial employment	0.0004	0.0004	0.0000	0.0001
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Static own-price elasticity	**-0.192**	**-0.149**	**-0.103**	**-0.092**
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	0.00	0.00	0.00	0.00
Adjusted R^2	0.97	0.98	0.95	0.95
$(P_2 / P_1)^{1/2}$ = (fuel oil price / natural gas price) $^{1/2}$	0.0002	0.0000	**-0.0002**	**-0.0003**
$(P_3 / P_1)^{1/2}$ = (electricity price / natural gas price) $^{1/2}$	**0.0001**	0.0000	**0.0001**	**0.0001**
X = per capita industrial employment	0.0004	0.0004	**0.0009**	**0.0008**
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Lagged Y_1	**0.364**	**0.364**	**0.306**	**0.303**
Short-run own-price elasticity	**-0.206**	**-0.012**	**-0.093**	**-0.044**
Long-run own-price elasticity	**-0.324**	**-0.018**	**-0.134**	**-0.063**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel D.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.182**	**0.162**	**0.255**
Natural gas - fuel oil	**0.010**	**0.044**	**0.069**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.02	0.02	0.03	0.03
Adjusted R^2	0.95	0.97	0.89	0.89
$\ln(P_1 / P_3)$ = ln(natural gas price / electricity price)	**0.106**	**0.109**	**0.123**	**0.124**
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	-0.002	-0.003	**-0.028**	**-0.028**
X = per capita industrial employment	0.086	0.082	**-0.390**	**-0.377**
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.000**	**0.000**	**0.000**	**0.000**
Static own-price elasticity	***0.021***	***0.043***	***0.155***	***0.158***
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	0.02	0.02	0.02
Adjusted R^2	0.97	0.96	0.94	0.94
$\ln(P_1 / P_3)$ = ln(natural gas price / electricity price)	**0.070**	**0.028**	**0.082**	**0.075**
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	0.000	**0.023**	**-0.020**	**-0.018**
X = per capita industrial employment	0.008	0.013	**-0.152**	**-0.125**
CDD = cooling degree days	**0.000**	**0.000**	0.000	0.000
HDD = heating degree days	**0.000**	**0.000**	**0.000**	**0.000**
Lagged S_1	**0.436**	**0.480**	**0.360**	**0.369**
Short-run own-price elasticity	**-0.261**	**-0.589**	**-0.164**	**-0.220**
Long-run own-price elasticity	**-0.463**	**-1.132**	**-0.256**	**-0.348**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel E3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	***-0.051***	**0.220**	**0.390**
Natural gas - fuel oil	**0.031**	**0.041**	**0.073**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the cost share equations for these two energy types.

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	-0.245	-0.177	-0.298
(2) Linear	-0.240	-0.226	-0.364
(3) CES	-0.137	-0.152	-0.281
(4) GL	-0.192	-0.206	-0.324
(5) TL	*0.021*	-0.261	-0.463

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	-0.245	-0.177	-0.298
(2) Linear	-0.198	-0.186	-0.300
(3) CES	-0.135	-0.149	-0.276
(4) GL	-0.161	-0.174	-0.273
(5) TL	-0.125	-0.352	-0.625

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	-0.245	-0.177	-0.298
(2) Linear	-0.388	-0.365	-0.588
(3) CES	-0.153	-0.170	-0.313
(4) GL	-0.304	-0.326	-0.512
(5) TL	*0.424*	-0.026	-0.047

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	-0.245	-0.177	-0.298
(2) Linear	-0.267	-0.251	-0.404
(3) CES	-0.142	-0.158	-0.292
(4) GL	-0.214	-0.230	-0.361
(5) TL	*0.058*	-0.247	-0.439

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	-0.245	-0.177	-0.298
(2) Linear	-0.108	-0.102	-0.164
(3) CES	-0.119	-0.132	-0.243
(4) GL	-0.089	-0.096	-0.150
(5) TL	-0.273	-0.418	-0.741

Notes: (1) While the double-log specification's elasticity estimates do not vary monthly, the same cannot be said for the other specifications.
(2) As expected, summer estimates are larger in size than winter elasticity estimates because commercial usage of natural gas is mainly for space heating.

Table 6. OLS dummy variable regression whose regressand is the US commercial natural gas demand's own-price elasticity estimate

Variable	Estimate	Standard error	*p*-value
Adjusted R^2	0.467		
RMSE	0.129		
Intercept	-0.312	0.071	0.000
F_1 = 1 if double-log specification, 0 otherwise	0.275	0.089	0.004
F_2 = 1 if linear specification, 0 otherwise	0.239	0.089	0.011
F_3 = 1 if CES specification, 0 otherwise	0.224	0.092	0.020
F_4 = 1 if GL specification, 0 otherwise	0.306	0.098	0.003
IV = 1 if IV estimation, 0 otherwise	0.001	0.043	0.978
ST = 1 if static, 0 otherwise	-0.042	0.030	0.170
LR = 1 if long-run, 0 otherwise	-0.109	0.050	0.036
CD = 1 if CD presence is correctly accounted, 0 otherwise	-0.126	0.043	0.006

Note: The sample size is 50 observations = (5 specifications × 3 elasticity types × 2 CD treatments ×2 estimation methods) – 10 observations with anomalously positive elasticity estimates.

Table 7. Own-price elasticity estimate = Intercept + b ID + error; sample size = 241 observations for each elasticity type

Panel A: Static elasticity

Variable	Estimate	Standard error	p-value
Regressand's mean			
Adjusted R^2	0.830		
RMSE	0.024		
Intercept	-0.310	0.003	0.000
ID	0.001	0.00002	0.000

Panel B: Short-run elasticity

Variable	Estimate	Standard error	p-value
Regressand's mean			
Adjusted R^2	0.820		
RMSE	0.026		
Intercept	-0.286	0.003	0.000
ID	0.001	0.00002	0.000

Panel C: Long-run elasticity

Variable	Estimate	Standard error	p-value
Regressand's mean			
Adjusted R^2	0.840		
RMSE	0.036		
Intercept	-0.401	0.005	0.000
ID	0.001	0.00003	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 1991 – 2000. The last observation (ID = 241) is based on the last 10-year period of 2011 – 2020.
(3) The small but highly significant b estimate for ID in each panel's last row is positive, indicating that the US commercial natural gas's price responsiveness has been slowing decreasing over time.

Table 8. Natural gas shortage cost (*SC* = percentage increase in industrial energy cost) for 2020 by elasticity type and specification for a hypothetical one-day shortage that causes curtailment for 10% of commercial natural gas demand; anomalous estimates in *italic*

Panel A. CD presence and non-IV estimation

Parametric specification	Static		Short run		Long run	
	ε_1	*SC*	ε_1	*SC*	ε_1	*SC*
Double-log	-0.245	0.2%	-0.177	0.3%	-0.298	0.2%
Linear	-0.240	0.2%	-0.226	0.2%	-0.364	0.1%
CES	-0.137	0.4%	-0.152	0.4%	-0.281	0.2%
GL	-0.192	0.3%	-0.206	0.3%	-0.324	0.2%
TL	*0.021*	*-2.5%*	-0.261	0.2%	-0.463	0.1%

Panel B. CD absence and non-IV estimation

Parametric specification	Static		Short run		Long run	
	ε_1	*SC*	ε_1	*SC*	ε_1	*SC*
Double-log	-0.090	0.6%	-0.082	0.6%	-0.121	0.4%
Linear	-0.126	0.4%	-0.111	0.5%	-0.161	0.3%
CES	-0.230	0.2%	-0.164	0.3%	-0.263	0.2%
GL	-0.103	0.5%	-0.093	0.6%	-0.134	0.4%
TL	*0.155*	*-0.3%*	-0.164	0.3%	-0.256	0.2%

Notes: (1) The *SC* calculation entails two steps: (1) calculate the disaggregate *SC* number for each 2020 observation in the panel; and (2) calculate the simple average of all disaggregate *SC* numbers.
(2) Accounting for CD presence tends to shrink *SC* estimates that are mostly below 1% of commercial energy cost. Hence, the 1% ceiling is an empirically plausible *SC* assumption for the purpose of resource planning.

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
Northeast	-0.502	-0.249	-0.512
Midwest	-0.219	-0.139	-0.209
South	-0.187	-0.159	-0.280
West	-0.247	-0.160	-0.296
States with below average coal shares of total generation	-0.232	-0.188	-0.297
States with above average coal shares of total generation	-0.262	-0.163	-0.294

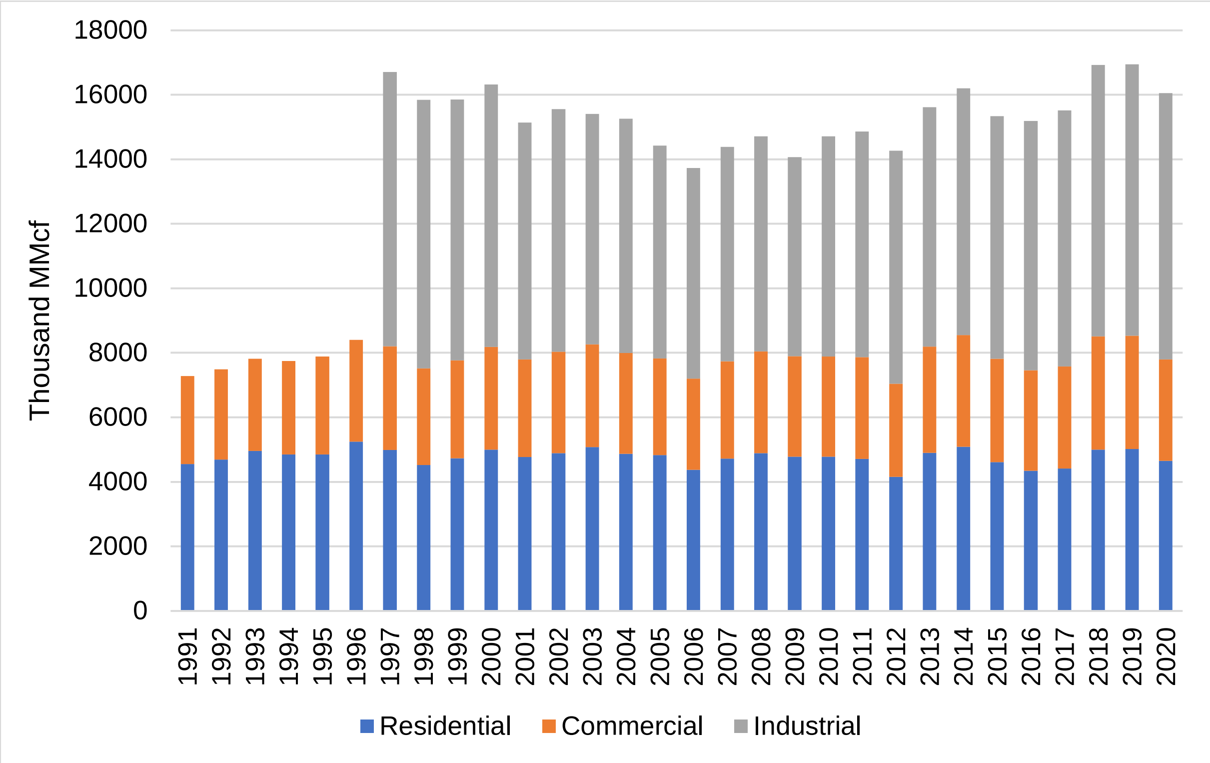
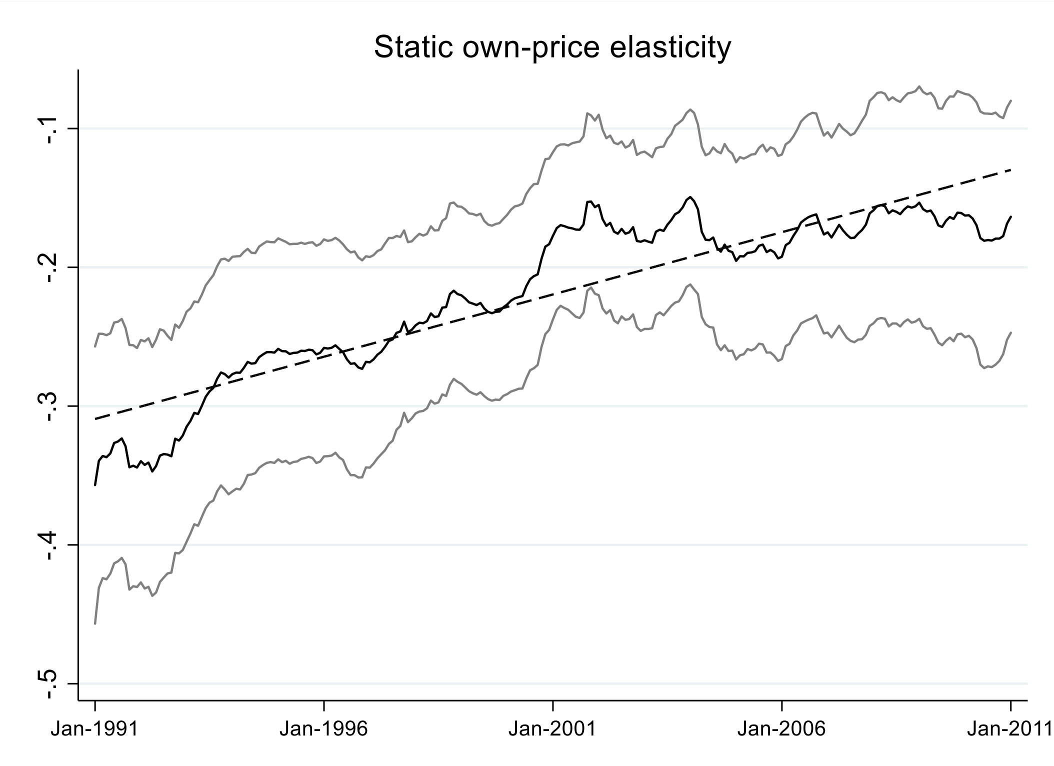
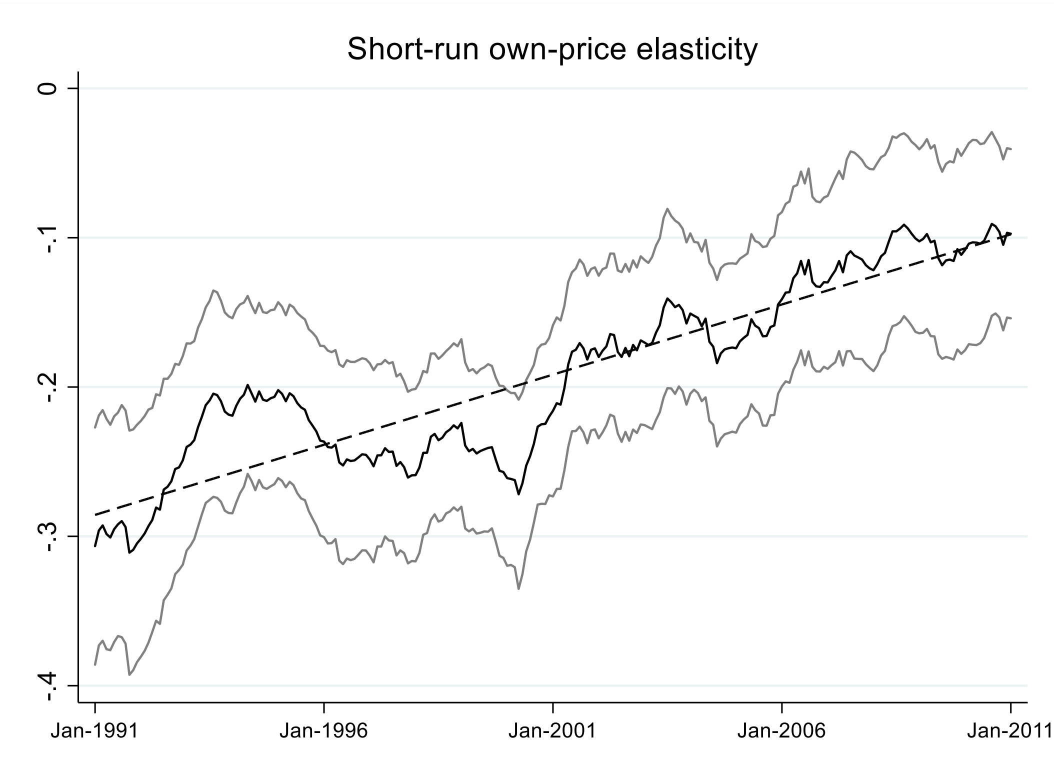


Figure 1. US annual natural gas consumption by end-use customer class in 1991-2020, recognizing that annual industrial consumption data are unavailable for years prior to 1997 (Data source: US Energy Information Agency).


Static own-price elasticity
-.1
-.2
-.3
-.4
-.5
Jan-1991
Jan-1996
Jan-2001
Jan-2006
Jan-2011


Short-run own-price elasticity
0
-.1
-.2
-.3
-.4
Jan-1991
Jan-1996
Jan-2001
Jan-2006
Jan-2011

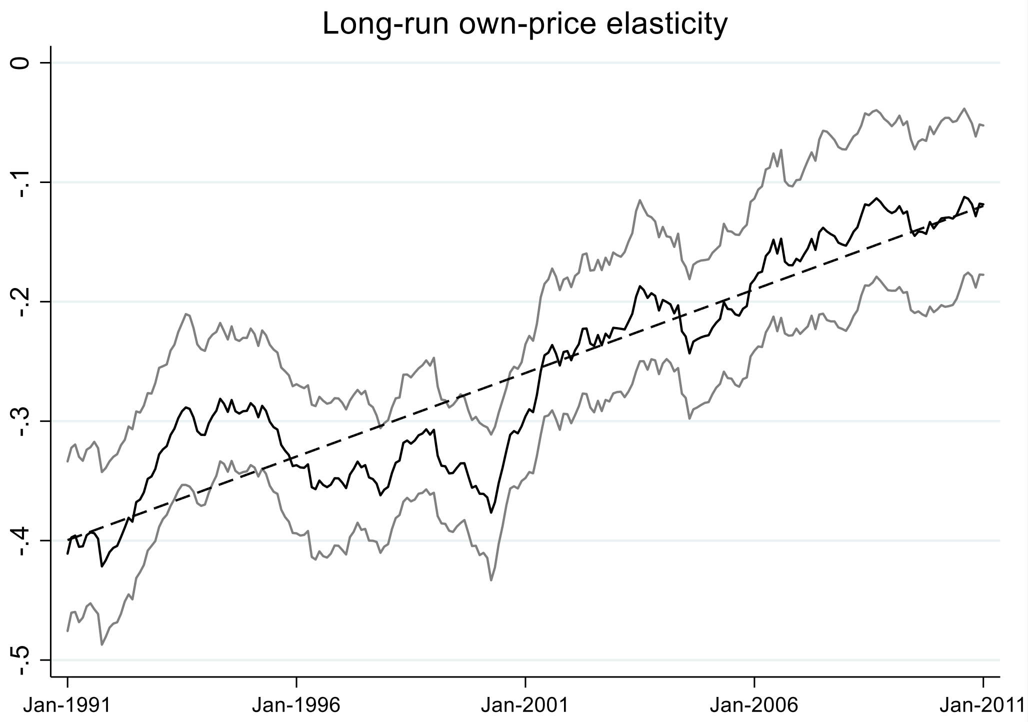


Figure 2. Own-prices elasticity estimates from a rolling-window analysis that uses the double-log specification with CD presence and non-IV estimation. The horizontal axis shows the starting period of each rolling-window. The middle solid black line portrays an elasticity estimate. The lower and upper solid grey lines form the estimate's 95% confidence interval. The dashed line is the estimate's linear time trend.

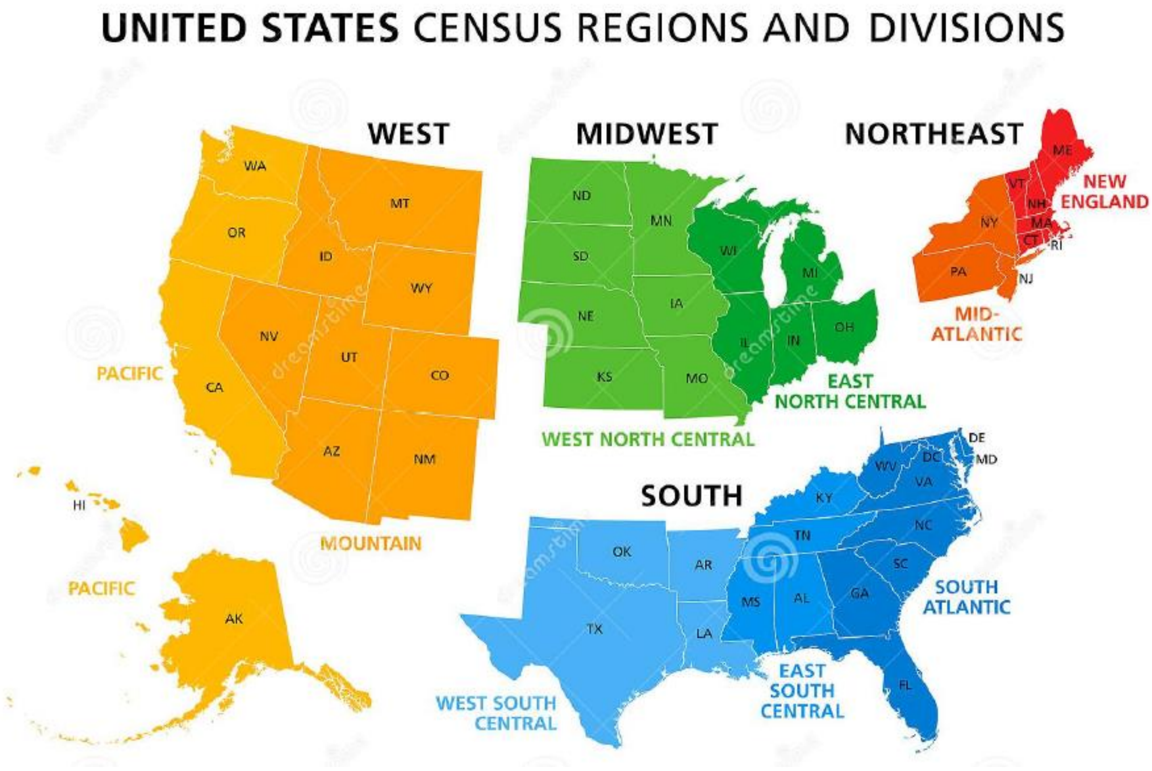


Figure 3. Census regions in the US

Price responsiveness of commercial demand for natural gas in the US

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Abstract

To estimate price responsiveness of commercial demand for natural gas in the US, ~~our panel data analysis uses~~we use five parametric specifications ~~and~~to conduct panel data analysis of a newly developed sample of 17,280 monthly ~~data~~observations for the lower 48 states in 1991-2020~~, finding (1) the~~. We find that the US commercial natural gas demand is price inelastic, with statistically significant (p-value ≤ 0.05) static own-price elasticity estimates ~~are~~of -0.137 to -0.245, short-run -0.152 to -0.261 and long-run -0.281 to -0.463~~; (2) these~~. These estimates ~~varies~~vary by choice of a sample period, choice of a parametric specification, treatment of cross-section dependence ~~(CD),~~, assumption of partial adjustment, and exclusion of fixed effects~~; (3) these elasticity estimates~~. Further, they vary by season and region and their ~~small~~ size has been slowly declining over time~~; (4) erroneously ignoring the highly significant (p-value < 0.01) CD shrinks empirical price responsiveness; (5) excluding the fixed effects magnifies empirical price responsiveness; and (6)~~. Finally, commercial natural gas shortage ~~costs decline~~cost declines with the size of own-price elasticity estimates. The policy implications of these findings are: (a) price-induced conservation's ~~foreword looking~~likely limited effect on the US commercial natural gas demand ~~is likely negligible, justifying~~justifies continuation of ~~standards for~~ energy efficiency ~~and CO_2 emissions~~ standards and demand-side-management programs for deep decarbonization; and (b) demand response programs such as real time pricing and reliability differentiation efficiently allocate limited supply of natural gas during a shortage among heterogenous end-users, thus reducing an economy's aggregate natural gas shortage cost ~~may use real time pricing or reliability differentiation~~.

1. Introduction

~~Commercial~~Natural gas demand's price elasticity estimates are necessary for various applications in an economy's quest for a clean and sustainable future. Examples of such applications include energy policy modelling (Hausman, 1975; Manne et al., 1979), resource planning (Logan et al., 2013; Abrell and Weigt, 2016; Holz et al., 2016; Çalcı et al., 2022), consumption ~~of natural gas has been stagnant in~~projection (Huntington, 2007; Bianco et al., 2014; Dilaver et al., 2014), a carbon tax's effect on consumption (Xiang and Lawley, 2019), the ~~US, as evidenced by Figure 1 that shows annual usage levels by customer class~~size of price-induced consumption reduction (Rowland et al, 2017), an energy system's responses to price shocks (Brown et al., 2021), optimal pricing (Gong et al., 2016; Davis and Muehlegger, 2010), and welfare assessments of market liberalization (Lee et al., 2004) and shale gas's rapid growth (Hausman and Kellogg, 2015; Gillingham and Huang, 2019).

Table 1 summarizes own-price elasticity estimates for commercial natural gas demand.[1] The widely dispersed short- and long-run estimates offer little guidance for the above applications in connection to the US, the second largest country behind China in national energy consumption and CO_2 emissions. Underscoring this point is the use of own-price elasticity estimates to project consumption reduction due to the future trend of likely rising retail natural gas prices in the US.[2] Highly diverse elasticity estimates, however, can cause

[1] The US Department of Energy classifies 16 building types based on a commercial customer's line of business: office, retail, education, hotel, healthcare, restaurant, warehouse, and apartment rental (https://www.energycodes.gov/development/commercial/prototype_models).

[2] This trend is attributable to three reasons. The first reason is the technology path to deep decarbonization (Williams et al., 2012; Mahone et al., 2018). Natural gas is a bridge fuel for displacing coal and oil (Woo et al., 2018b; Gillingham and Huang, 2019). Further, electrification of energy-using durables (Williams et al., 2012; Mahone et al., 2018) requires large-scale development of emissions-free renewable resources that necessitates transmission expansion (Alagappan et al., 2011; Joskow, 2021) and natural gas-fired generation's flexible capacity for reliable grid integration (Zarnikau et al., 2019). The second reason is carbon trading that raises retail natural gas prices, which embody marginal costs of CO_2 emissions. It also increases electricity generation's demand for natural gas because natural gas has lower CO_2 emissions than coal. The third reason is the diminishing price effect of shale gas development due to environmental concerns about hydraulic fracturing

large projection variations, magnifying the uncertainty in resource planning (e.g., pipeline capacity expansion to enhance an economy's natural gas supply infrastructure).

To obtain up-to-date estimates of the US commercial natural gas demand's price elasticities, we perform panel data analysis of a newly developed sample of 17,280 monthly observations in 1991-2020~~.~~[3] ~~Figure 1 hints~~ for the lower 48 states that exclude Alaska and Hawaii. Presaging our key finding that the US commercial natural gas demand is price inelastic ~~because~~, Figure 1 portrays stagnant commercial natural gas consumption, albeit the 100% retail pass through (Woo et al., 2014b) of relatively low wholesale natural gas prices ~~that are fully passed through to retail natural gas prices (Woo et al., 2014b) are relatively low in recent years due to~~ triggered by shale gas's explosive growth (Caporin and Fontini, 2017). Further, we propose using price elasticity estimates to calculate the cost of a natural gas shortage that may adversely affect an economy (Leahy et al., 2012; Alcaraz and Villalvazo, 2017), thereby demonstrating our paper's international relevance underscored by the recently reported global shortages.[4]

~~This paper estimates the US commercial natural gas demand's price responsiveness because accurate price elasticity estimates are necessary for various applications in energy policy development.[5] Internationally relevant based on the recently reported global~~

(Sovacool, 2014) and projected growth of the US export of liquified natural gas (Arora and Cai, 2014; Çalcı et al., 2022).

~~[3] The US Department of Energy classifies 16 building types based on a commercial customer's line of business: office, retail, education, hotel, healthcare, restaurant, warehouse, and apartment rental (https://www.energycodes.gov/development/commercial/prototype_models).~~

[4] https://www.worldoil.com/news/2021/6/25/natural-gas-prices-rally-as-global-shortages-abound

~~[5] Examples of such applications include energy policy modelling (Hausman, 1975; Manne et al., 1979), resource planning (Logan et al., 2013; Abrell and Weigt, 2016; Holz et al., 2016; Çalcı et al., 2022), consumption projection (Huntington, 2007; Bianco et al., 2014; Dilaver et al., 2014), carbon tax's estimated effect of demand reduction (Xiang and Lawley, 2019), the size of price-induced demand reduction (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's rapid growth (Hausman and Kellogg, 2015; Gillingham and Huang, 2019)~~

~~shortages,[6] it also estimates the cost of natural gas shortage that adversely affects an economy (Leahy et al., 2012; Alcaraz and Villalvazo, 2017).~~

~~Table 1 reports highly diverse own-price elasticity estimates available from three selected surveys. In response, we perform a comprehensive analysis of 17,280 monthly observations of average prices and total usage levels available from the US Energy Information Administration (EIA) for the lower 48 states in 1991-2020.~~

~~Our paper is original, thanks to its seven salient features unseen in extant studies. First, it uses five parametric specifications and a large~~ As its sample period is 1991-2020, our paper presents empirics unseen in natural gas demand studies published by the end of 2020:

- Our panel ~~to estimate the US commercial natural gas demand's static, short-run, and long-run own-price elasticities. Second, it documents the~~data exhibit highly significant ~~presence~~ (p-value < 0.01) ~~of~~ cross-section dependence (CD) due to common shocks and interdependence of regression errors (Li et al., 2021). ~~Third, it documents erroneously ignoring CD presence shrinks own-price elasticity estimates. Fourth, it detects seasonality of price responsiveness. Fifth, it presents regional own-price elasticity estimates, updating those found ~35 years ago. Sixth, its rolling-window approach documents the declining trend of price responsiveness. Seventh, it uses own-price elasticity estimates to calculate natural gas shortage costs, thus illustrating the usefulness of demand response (DR) programs for managing natural gas shortage~~Erroneously ignoring the presence of CD tends to understate the US commercial natural gas demand's price responsiveness.

~~Our scientific innovation comprises seven contributions to the literature of energy demand analysis. The first six contributions are our newly developed empirics and the last our methodology:~~

[6] ~~https://www.worldoil.com/news/2021/6/25/natural-gas-prices-rally-as-global-shortages-abound~~

- The US commercial natural gas demand's statistically significant (p-value ≤ 0.05) static own-price elasticity estimates are -0.137 to -0.245, short-run -0.152 to -0.261 and long-run -0.281 to -0.463.
- ~~Statistically~~The statistically significant factors affecting these elasticity estimates are the choice of a parametric specification, treatment of CD presence, ~~and~~ assumption of partial adjustment, and exclusion of fixed effects.

~~(1) Erroneously ignoring the highly significant presence of CD shrinks empirical~~The US commercial natural gas demand's price responsiveness~~.~~

~~(2) The "between" estimator magnifies empirical price responsiveness.~~

- ~~Price responsiveness~~ varies by season and region and has been slowly declining over time.

~~(3)~~ A hypothetical one-day natural gas shortage that causes a 10% curtailment of ~~commercial demand increases~~the US commercial natural gas demand is expected to increase the commercial customer class's energy cost by less than 1%.

- ~~Subject to data availability, this paper's approach is applicable to the industrial 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 presents materials and methods. Section 3 reports empirics, the basis for Section 4: conclusions and policy implications.

2. Materials and methods

2.1 ~~Expected trend of rising retail natural gas prices in the US~~

~~There are three reasons for the expected trend of rising retail natural gas prices in the US for the coming years. The first reason is the technology path to deep decarbonization (Williams et al., 2012; Mahone et al., 2018). Natural gas is a bridge fuel for displacing coal and oil (Woo et al., 2018b; Gillingham and Huang, 2019). Further, electrification of energy-~~

~~using durables (Williams et al., 2012; Mahone et al., 2018) requires large-scale development of emissions-free renewable resources (Alagappan, et al., 2011) that necessitates reliable grid integration using natural gas-fired generation's flexible capacity (Zarnikau et al., 2019).~~

~~The second reason is carbon trading enabled by a cap-and-trade program for CO_2 emissions permits.[7] Carbon trading raises retail natural gas prices that embody marginal costs of CO_2 emissions. It also increases electricity generation's demand for natural gas because natural gas has lower CO_2 emissions than coal. However, Figure 2 shows that this expected demand increase driven by rising natural-gas-fired generation is moderated by the EIA's projected expansion of emissions-free renewable resources.~~

~~The third reason is related to shale gas's explosive growth (Caporin and Fontini, 2017), whose price reduction effect will likely diminish because of environmental concerns about hydraulic fracturing (Sovacool, 2014) and projected growth of the US export of liquified natural gas (Arora and Cai, 2014; Çalcı et al., 2022).~~

~~2.2 Nonlinear pricing of commercial natural gas consumption in the US~~

~~A commercial 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., 2014a). Even if the per Mcf charge is linear, the presence of a fixed customer charge causes the customer's monthly average natural gas price (= total bill ÷ total usage) to be endogenously declining with consumption. Should the per Mcf charge have an inclining block structure, the observed positive correlation between the average price data and usage data misinforms commercial natural gas demand's price responsiveness.~~

~~[7] Woo et al. (2017) describe California's program that causes power laundering by hydro generators in the Pacific Northwest.~~

~~Our panel data analysis uses the EIA's monthly average price data because absent disaggregate information at customer level, accurate marginal prices are impossible to obtain. Should average price data be found endogenous, the ensuing estimation bias could be corrected by instrumental variable (IV) estimation (Davidson and MacKinnon, 1993).~~

~~2.3~~ Literature review

To provide our paper's contextual background, we review ~~a sample of~~ nine selected studies of the US commercial natural gas demand.[8] Our review is intentionally brief, thanks to the available 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; Labanderia et al., 2017; Huntington et al., 2019).

~~Table 2 summarizes~~Summarizing our selected studies~~. Emerged from,~~ Table 2 ~~are~~yields the following remarks that shape our panel data analysis. First, the regional coverage of these studies spans from a single state to the lower 48 states. Second, these studies tend to use annual data, with the notable exception of Woo et al. (2018a) that ~~use~~uses monthly data. Third, all studies ~~use non-~~include prices for energy inputs other than natural~~-~~ gas ~~energy prices~~ to reflect inter-fuel substitution by commercial customers. Fourth, eight studies use the double-log specification and the remaining one ~~uses~~ the Generalized Leontief (GL) specification, notwithstanding that the linear, constant-elasticity-of-substitution (CES) and ~~Translog~~transcendental-logarithmic (TL) specifications are popular in energy demand analysis.[9] Fifth, the estimation methods range from OLS regression to iterated seemingly

[8] Unintended to be exhaustive, the selected studies are found via a two-step process: (1) use scholar.google.com to find the initial list based on the keywords of "price elasticity", "commercial natural gas demand" and "United States"; and (2) narrow the initial list ~~by considering~~based on each study's citation by existing literature surveys and relevance to our paper.

[9] Existing literature surveys show that the double-log and linear specifications are popular in energy demand analysis, chiefly because of their simple estimation and easy interpretation. The CES specification is easy to estimate and directly yields the elasticity of substitution (Woo et al., 2018b). Without restricting the elasticity of substitution to be a constant like the CES specification, the GL and TL specifications are flexible second-order approximations of an energy cost function for deriving energy demand/cost share equations that are readily estimable as seemingly unrelated regressions (Diewert, 1971; Caves and Christensen, 1980; Greene, 2003).

unrelated regressions. Sixth, all studies use average price data. Finally, the own-price elasticity estimates are diverse, ranging from -0.13 to -1.60.

2.2 Nonlinear pricing of commercial natural gas consumption in the US

A commercial 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., 2014a). Even if the per Mcf charge is linear, the presence of a fixed customer charge causes the customer's monthly average natural gas price (= total bill ÷ total usage) to

~~2.4 Knowledge gaps~~

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

- ~~**KG1**: None of the studies examines the time trend of price responsiveness.~~
- ~~**KG2**: None of the studies investigates seasonality of price responsiveness.~~
- ~~**KG3**: None of the studies considers the effect of data frequency on price elasticity estimates.~~

~~**KG4**: Little is known about how price elasticity estimates vary by~~ decline with consumption. Should the per Mcf charge have a declining block structure, it would reinforce the negative relationship between the customer's monthly average price and consumption. This relationship exists, even though the customer may have zero own-price elasticity. Hence, using average price data may cause estimation bias in an analysis of the US commercial demand for natural gas.

Our panel data analysis uses the US Energy Information Administration's (EIA's) monthly average price data because absent disaggregate information at customer level, accurate marginal prices are impossible to obtain. Should the average price data be found endogenous, the resulting estimation bias could be remedied by instrumental variable (IV) estimation (Davidson and MacKinnon, 1993).

2.3 Five parametric specifications

This section derives our panel data analysis's five parametric specifications, chosen herein as alternative characterizations of the US commercial natural gas demand's data generating process (Davidson and MacKinnon, 1993). Our choice is also driven by these specifications' vastly different price elasticity formulae, a potential cause for the diverse price elasticity estimates reported in our literature review. However, if they all yield price elasticity estimates with size below one, we infer that the US commercial natural gas demand is deemed price inelastic.[10]

- Our derivation of a parametric specification~~.~~
- ~~**KG5**: None of the studies estimates the impact of CD on price elasticity estimates.~~
- ~~**KG6**: There is a lack of recent estimates of regional price responsiveness, as the study by Lin et al. (1987) is ~35 years old.~~
- ~~**KG7**: None of the studies quantifies natural gas shortage cost.~~

~~2.5 Five parametric specifications~~

~~Commercial~~ reflects that commercial natural gas demand is a derived input demand based on a commercial customer's problem of two-stage cost minimization ~~problem~~ (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:

$$C = P_1 Y_1 + P_2 Y_2 + P_3 Y_3. \qquad (1)$$

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),

[10] This inference reflects our primary interest in how the choice of a parametric specification may affect price elasticity estimates. It does not inform which specification can best characterize the commercial natural gas consumption's data generating process. As a contrasting example, Woo (1994) uses the Box-Cox function and log-likelihood ratio test to determine the choice between the linear and log-linear specifications.

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 $\boldsymbol{V}$ based on the transformation function $G(\boldsymbol{V}, Z, L, M, K)$. ~~For brevity, we omit the detailed derivation of the customer's natural gas demand's parametric specification (Li and Woo, 2021).~~

Applying Shephard's Lemma to the energy cost function $C(\bullet)$ yields the natural gas demand function (Diewert, 1971):

$$\partial C(\bullet) / \partial P_1 \quad = \quad Y_1^* \quad = \quad H(P_1, P_2, P_3, Z). \tag{2}$$

As $H(\bullet)$ 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:

$$\varepsilon_1 \quad = \quad \partial \ln Y_1^* / \partial \ln P_1; \tag{3}$$

$$\varepsilon_j \quad = \quad \partial \ln Y_1^* / \partial \ln P_j \text{ for } j > 1. \tag{4}$$

Moreover, $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 0$ because $H(\bullet)$ is homogenous of degree zero in (P_1, P_2, P_3) (Varian, 1992). As $\varepsilon_1 \leq 0$ and $\varepsilon_2 + \varepsilon_3 \geq 0$, natural gas is a substitute for fuel oil/electricity.

Closely related to the cross-price elasticity ε_j is the elasticity of substitution σ_j between natural gas and energy type j (Blackorby and Russell, 1989):

$$\sigma_j \quad = \quad \varepsilon_j / S_j, \tag{5}$$

where S_j = cost share $j = P_j Y_j^* / (P_1 Y_1^* + P_2 Y_2^* + P_3 Y_3^*)$. When $\sigma_j = 0$, it indicates zero substitutability between natural gas and fuel oil/electricity. When σ_j is close to zero, it indicates limited substitutability. When $\sigma_j = \infty$, natural gas is a perfect substitute for fuel oil/electricity.

Suppose the parametric cost function is $C = e^{\beta_0} (P_1 / P_3)^{(1 + \beta_1)} (P_2 / P_3)^{\beta_2} Z^{\beta_Z} / (1 + \beta_1)$, which is unseen in existing non-residential studies of natural gas demand. Using equation (2) and taking natural log, we derive the double-log natural gas demand equation ~~is:~~corresponding to Y_1's recorded value *sans* the additive random error of $(Y_1^* - Y_1)$:

$$\ln Y_1 = \beta_0 + \beta_1 \ln(P_1 / P_3) + \beta_2 \ln(P_2 / P_3) + \beta_Z \ln Z. \qquad (\cancel{2}6)$$

As Z is unobservable, estimating equation (~~2~~6) assumes that $\ln Z$ is a linear function of employment X, cooling degree days CDD and heating degree days HDD. ~~The own-price elasticity is $\varepsilon = \beta_1$.~~

~~The linear demand equation is:~~

Based on equation (3), the own-price elasticity is $\varepsilon_1 = \beta_1$. According to equation (4), the cross-price elasticities are $\varepsilon_2 = \beta_2$ and $\varepsilon_3 = -\beta_1 - \beta_2$, which are used to find σ_j via equation (5).

Suppose the parametric cost function is $C = \alpha_0 P_1 + 1/2\ \alpha_1 (P_1^2 / P_3) + \alpha_2 (P_1 P_2 / P_3) + \alpha_Z P_1 Z$, which is also unseen in existing non-residential studies of natural gas demand. Using equation (2), we derive the linear natural gas demand equation:

$$Y_1 = \alpha_0 + \alpha_1 (P_1 / P_3) + \alpha_2 (P_2 / P_3) + \alpha_Z Z. \qquad (\cancel{3}7)$$

Estimating equation (~~3~~7) assumes that Z is a linear function of X, CDD and HDD. ~~The own-price elasticity is:~~

$$\cancel{\varepsilon = \alpha_1 (P_1 / P_3) / Y_1. \qquad (4)}$$

Based on equation (3), the own-price elasticity is $\varepsilon_1 = \alpha_1 (P_1 / P_3) / Y_1$. According to equation (4), the cross-price elasticities are $\varepsilon_2 = \alpha_2 (P_2 / P_3) / Y_1$ and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

As ε_1 varies nonlinearly by price ratio and consumption level, its average value for the entire US is the arithmetic mean of our panel's month- and state-specific estimates based on the data used in the demand analysis. ~~This~~ The same can be said about ε_2 and ε_3. Finally, the calculation ~~of ε~~process for $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ applies to the ~~remaining~~ specifications listed below.

~~Under~~For the CES cost specification~~,~~ (Woo et al., 2018b), the ~~natural gas – electricity consumption ratio~~ equation to be estimated is:

$$\ln(Y_1 / Y_3) = \phi_0 + \phi_1 \ln(P_1/P_3), \qquad \cancel{(5}(8)$$

where $\phi_1 = -1 \times \sigma$, where σ = identical elasticity of substitution among natural gas, fuel oil and electricity. The CES specification is restrictive in that σ does not vary by input energy type and energy price ratio. To account for possible dependence of $\ln(Y_1 / Y_3)$ on non-price factors, we assume ϕ_0 to be a linear function of X, CDD and HDD. The ~~CES~~natural gas demand's own-price elasticity is:

$$\varepsilon_1 = \phi_1 (1 - \cancel{S),}\ \cancel{(6}S_1), \qquad (9)$$

where ~~S~~$S_1 = P_1 Y_1 / C$ = natural gas cost share (Woo et al., 2018b).[11]

~~The~~For the GL cost function (Diewert, 1971; Woo et al., 2018a), the demand equation is:

$$Y_1 = b_{11} + b_{12} (P_2 / P_1)^{1/2} + b_{13} (P_3 / P_1)^{1/2} + b_{1Z} Z. \qquad (10)$$

The own-price elasticity is:

$$\cancel{(7}\varepsilon_1 = - 1/2 \, [b_{12} (P_2 / P_1)^{1/2} + b_{13} (P_3 / P_1)^{1/2}] / Y_1. \qquad (11)$$

The cross-price elasticities are $\varepsilon_2 = 1/2 \, b_{12} (P_2 / P_1)^{1/2} / Y_1$ and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

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

$$S_1 = a_1 + a_{11} \ln(P_1/P_3) + a_{12} \ln(P_2/P_3) + a_{1Z} \ln Z. \qquad (12)$$

[11] Calculating ε_1 requires monthly data by state for commercial 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 commercial customer class does not consume fuel oil. We then use the EIA annual data to compute two annual natural cost shares: $AS_{max} = P_1 Y_1 / (P_1 Y_1 + P_3 Y_3)$ and $AS_{true} = P_1 Y_1 / (P_1 Y_1 + P_2 Y_2 + P_3 Y_3)$. Finally, we use $S_{max} (AS_{true} / AS_{max})$ to approximate S_1's monthly missing values.

The own-price elasticity is:

~~$\varepsilon = -1/2\,[b_{12}(P_2/P_1)^{1/2} + b_{13}(P_3/P_1)^{1/2}]/Y_1.$ (8)~~

$\varepsilon_1 = (a_{11} + S_1^2 - S_1)/S_1.$ (13)

The ~~TL's natural gas cost share equation is:~~

~~$S = a_1 + a_{11}\ln(P_1/P_3) +$~~ cross-price elasticities are $\varepsilon_2 = (a_{12}$ ~~$\ln(P_2/P_3) + a_{1Z}\ln Z.$ (9)~~

~~The own-price elasticity is:~~

~~$\varepsilon = (a_{11}$ +~~ + $S_1 S_2$ ~~$- S) / S.$ (10)~~$) / S_1$

and $\varepsilon_3 = -\varepsilon_1 - \varepsilon_2$.

2.~~6~~4 Long-run elasticity

To obtain a long-run elasticity estimate, we use the 1-month lagged regressand as an additional regressor to characterize the parsimonious partial adjustment process often assumed by an energy demand study.[12] Let φ denote the lagged regressand's coefficient. As will be seen in Section 3 below, the significant estimate for φ is between 0.364 to 0.458. 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 - φ).

2.~~7~~5 Estimation of commercial shortage cost

[12] The autoregressive distributed lag ~~(ADRL)~~ model is not used here because our preliminary exploration shows that the additional estimation sophistication does not lead to a better understanding of the US commercial natural gas demand's ~~empirical~~estimated price responsiveness.

A natural gas shortage with advance notice enables commercial customers to adjust their production activities.[13] The following steps estimate natural gas shortage cost as a percentage increase in the commercial customer class's energy cost:

(1) Assume a hypothetical one-day ~~natural gas~~ shortage that curtails D% of the commercial customer class's total natural gas demand per calendar day. If the shortage is expected to last N days, its total cost is the one-day estimate times N.

(2) Find the ~~virtual~~percentage price ~~$VP_1 = (1 + \Delta \ln P_1)$ that resolves~~increase required to resolve the assumed shortage~~, where~~ (Woo, 1994): $\Delta \ln P_1 = -(D / \varepsilon_1$~~) (Woo, 1994~~).

(3) Find the one-day shortage cost as a percentage of C:

$$SC = (\Delta C / C) \div 30 \text{ days}, \qquad (\cancel{11}14)$$

where $\Delta C = [\partial C / \partial P_1]\, \Delta P_1 = Y_1\, \Delta P_1$ based on Shephard's Lemma (Varian, 1992). As $(\Delta P_1 / P_1) = \Delta \ln P_1$, we find:

$$SC = (P_1 Y_1 / C)\,(\Delta P_1 / P_1) \div 30 \text{ days} = -\,\cancel{S}S_1\,(D / \cancel{\varepsilon)}\varepsilon_1) \div 30 \text{ days}. \qquad (\cancel{12}15)$$

The SC estimates based on equation (~~12~~15) assume that when given advance notice, commercial customers can readily adjust/reschedule their production activities with negligible costs of lost production, idle labour, and material damage (Leahy et al., 2012; Woo et al., 2021).[14] This assumption makes sense because (a) the natural gas shortage implies

[13] 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/)

[14] The SC estimates based on equation (~~12~~15) 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 K_{NG}, the grid's percentage capacity loss is L = 10% × (K_{NG} / K_T) where K_T = total generation capacity of the grid. As (K_{NG} / K_T) < 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 $\$W$ per Mcf is likely small because W = (difference in per MWh fuel costs × MWh produced by replacement generation) ÷ total Mcf curtailed.

fractional curtailment rather than ~~complete disruption~~total interruption of natural gas service; and (b) major commercial end-uses of space heating, water heating and cooking can be partially met by electricity ~~using durables~~and fuel oil.

The following cases demonstrate that equation (~~12~~15) is economically meaningful:

(1) Suppose ~~S~~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 commercial energy cost.

(2) Suppose ~~S~~S_1 > 0. As a result, SC increases with natural gas's cost share ~~S~~S_1, the extent of D and the size of ε. If ~~S~~S_1 = 30%, D = 10%, and ε = -0.1, SC = 30% ÷ 30 days ~~per month~~ = 1% of the commercial customer class's monthly energy cost.[15]

[15] The dollar amount is ~$4 million per shortage day based on New England's commercial energy cost for the winter month of January in 2020.

2.~~8~~6 Data description

Our data sources are as follows. First, the EIA publishes the commercial customer class's monthly data for electricity and natural gas consumption and average prices P_1 and P_2 for each of the 50 states in the US. These data are based on each state's commercial energy sales and revenues reported by natural gas utilities and retail service providers. The EIA also publishes the class's monthly data for average retail fuel oil price P_3. However, it does not publish the class's monthly fuel oil consumption. While P_1, P_2 and P_3 are nominal prices, their conversion to real prices is unnecessary for our regression analysis because all specifications use price ratio data.

Second, the US Bureau of Labor Statistics (BLS) publishes the monthly data for commercial employment and civilian noninstitutional population. We use the monthly employment and population data to construct the data for X. We use the EIA's monthly data for natural gas and electricity consumption by state and the BLS's monthly data for population by state to derive the per capita data for Y_1 and Y_3.

Finally, 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).

Panel A of Table 3 presents the descriptive statistics of our panel data. It shows that all variables have wide ranges based on their minimum and maximum values. Further, the coefficients of variation (= standard deviation ÷ mean) indicate that the data for weather variables are more volatile than non-weather variables.

The ~~last~~second column of Panel B of Table 3 reports that Y_1 is ~~only~~ weakly correlated with Y_3 (r = -0.044), suggesting limited substitutability between electricity and natural gas usage. Y_1 is negatively correlated with P_1 (r = -0.247) but less so with P_2 (r = -0.057) and P_3 (r = -0.122). It is ~~also~~ negatively correlated with (P_1 / P_3) (r = -0.144) but its correlation with

(P_2 / P_3) is very weak (r = 0.002). Finally, it is positively correlated with X (r = 0.115), negatively correlated with CDD (r = -0.458) and strongly correlated with HDD (r = 0.824).

~~While informative, the correlation coefficients~~The remaining columns report correlations for the other variables. As expected, P_1, P_2 and P_3 are positively correlated (r > 0.422) because wholesale spot prices for natural gas, fuel oil and electricity tend to move in tandem. The correlated price levels imply correlation (r = 0.471) between the energy price ratios. Because of their definitions, CDD and HDD are negatively correlated (r = -0.613).

While indicative, the correlations in Table 3 do not untangle the marginal effects of price ratios, employment, and weather on the US commercial natural gas demand, thus motivating our estimation strategy presented below.

2.~~9~~7 Estimation strategy

As CD can introduce bias to the regression estimates (De Hoyos and Sarafidis, 2006), we adopt the dynamic common correlated effects (DCCE) panel estimator that accounts for CD presence (Chudik and Pesaran, 2015):

$$A_{kt} = \eta_k + \varphi A_{kt-1} + \beta_k B_{kt} + \sum_{m=0}^{M} \psi_{km} CA_{t-m} + \mu_{kt},$$

(~~13~~16)

where A is the dependent variable, B is a vector of explanatory variables, CA is a vector of cross-section averages, η_k is the state-specific fixed effect, μ_{kt} is the random error, k = 1 to 48 denotes an observation's state (= 1 for Alabama, …, 48 for Wyoming), and t denotes an observation's period (= 1 for Jan-1991, …, 360 for Dec-2020).[16] Using the popular double-log specification as an illustration, $A = \ln Y_1$ and B' = (ln(P_1/ P_3), ln(P_2/P_3), X, CDD, HDD).

[16] Equation (16) does not use monthly dummies to account for the residual effects of seasonality uncaptured by monthly CDD and HDD because our preliminary exploration indicates that these monthly dummies have insignificant coefficient estimates.

We estimate equation (~~13~~16) for each parametric specification. When φ is a positive fraction, it leads to the short- and long-run elasticity estimates. Under the restriction of $\varphi = 0$, equation (~~13~~16) produces the static elasticity estimate. In this case, only current cross-section averages are included (i.e., $M = 0$) and the resulting estimator will resemble that of Pesaran (2006).[17] Under the assumption of CD absence, cross-section averages are not included ($\psi_{km} = 0$) and the mean group estimator (Pesaran and Smith, 1995) applies.

Our estimation strategy entails the following steps:

(1) Use the Pesaran (2020) test to detect CD in the data.

(2) Use the Pesaran (2007) panel unit root test that allows for CD to test for stationarity of the variables and avoid spurious regressions (Baltagi and Kao, 2001) in steps (3) and (4) below.

(3) Perform IV and non-IV estimation to estimate the coefficients of equation (~~13~~16) for the four cases formed by (a) $\varphi = 0$ vs. $\varphi > 0$; and (b) $\psi_{km} \neq 0$ vs. $\psi_{km} = 0$. We use lagged price ratios in the prior three months as the instruments for the current month's price-ratio in IV estimation.

~~(4) Perform the Durbin-Wu-Hausman test (Wooldridge, 2010) to test for endogeneity of the price ratios, thereby determining if IV estimation is necessary to obtain unbiased elasticity estimates.~~

~~(5)~~(4) Repeat ~~steps~~step (3) ~~and (4)~~ for the remaining four specifications.

3. Empirics

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

[17] As the Pesaran (2006) estimator differs from the DCCE estimator, the resulting static own-price elasticity estimates may not always lie between the short-run and long-run estimates.

Table 4 shows that the null hypotheses of cross-section independence and non-stationarity are decisively rejected (p-value < 0.01) for all variables, supporting our panel data analysis that accounts for CD presence *sans* the concern of spurious regressions.

3.2 General remarks

Three general remarks emerge from Table 5 that details our regression results. First, the regressions for all specifications resulted in adjusted R^2 values ≥ 0.87, indicating reasonable goodness of fit. Second, the null hypothesis of cross-section independence is decisively rejected (p-value < 0.01) for all specifications, implying that the estimates ~~with~~under CD absence ~~may be~~are likely biased. Third, the Durbin-Wu-Hausman (Wooldridge, 2010) test results suggest that the current price ratio data are exogenous~~, except for~~ in ~70% of the ~~case of CES specification with CD absence. Thanks to~~models. Based on these remarks, our preferred regression results for each specification are those shaded in light green, all of which are based on CD presence and non-IV estimation.

3.3 Regression details

For the double-log specification, Panel A.1 of Table 5 reports that the US commercial natural gas demand has a static own-price elasticity estimate of -0.245. *HDD* has a significant effect on demand but not *X* and *CDD*. Panel A.2 reports that the short-run own-price elasticity estimate is -0.177. The long-run estimate is -0.298, thanks to lagged lnY_1's 0.406 coefficient estimate. Panel A.3 reports relatively small estimates for the elasticity of substitution, suggesting limited substitutability between natural gas and fuel oil/electricity.

For the linear specification, Panels B.1 and B.2 show the positive but small coefficient estimates for ~~employment~~*X*, *CDD*~~, *HDD*~~ and *HDD*. The coefficient estimate for lagged Y_1 is 0.379 and statistically significant. The static own-price elasticity estimate is -0.240, the short-run estimate -0.226 and the long-run estimate -0.364. These estimates resemble those found under the double-log specification. Akin to Panel A.3, Panel B.3 conveys the message of limited substitutability.

For the CES specification, Panel C.1 and C.2 show that $\ln(Y_1 / Y_3)$ declines with $\ln(P_1 / P_3$~~) under the CES specification.~~). The statistically significant coefficient estimates for *CDD* and *HDD* indicate the small impact of weather on the natural gas-electricity consumption ratio. The coefficient estimates for *X* are positive but insignificant. The coefficient estimate for lagged $\ln Y_1$ is 0.458 and statistically significant. The static own-price elasticity estimate is -0.137, the short-run estimate -0.152 and the long-run estimate

-0.281. Hence, the CES specification generates smaller elasticity estimates than the double-log and linear specifications. Finally, Panel C.3 affirms limited substitutability between natural gas and electricity.

For the GL specification, Panel D.1 and D.2 report the ~~GL specification's coefficient estimates. Though~~ statistically significant~~, the~~ but small coefficient estimates for *CDD* and *HDD* ~~are very small~~. The coefficient estimate for *X* is insignificant. The coefficient estimate for lagged Y_1 is 0.364 and statistically significant. The static, short-run and long-run own-price elasticity estimate are -0.192, -0.206 and -0.324, respectively. These estimates are smaller than those found by Woo et al. (2018a), possibly due to our paper's longer sample period and modelling difference. Finally, Panel D.3 corroborates the message of Panels B.3 and C.3.

For the TL specification, Panel E.1 and E.2 report that the estimated effects of *CDD* and *HDD* are small but statistically significant. The positive coefficient estimates for *X* are small and insignificant. The coefficient estimate for lagged $\ln S_1$ is 0.436 and statistically significant. The static elasticity estimate is anomalously at 0.021. The short- and long-run estimates are -0.261 and -0.463, larger than those based on the other specifications. Finally, Panel E.3 reports the estimated elasticities of substitution that differ from those in Panels A.3 to D.3.

3.4 Seasonal pattern of own-price elasticity estimates

~~Addressing **KG2**,~~ Panel F of Table 5 reports the seasonal own-price elasticity estimates. As expected, summer estimates are larger in size than winter elasticity estimates because natural ~~gas's main~~gas is a major fuel for meeting commercial end-use ~~is~~requirement of space heating.

3.5 What moves ~~empirical price responsiveness~~the US natural gas demand's own-price elasticity estimates?

~~Motivated by **KG4** and **KG5**, we~~We use an OLS dummy variable regression to ~~delineate what moves~~identify the statistically significant factors that move the US commercial natural gas demand's ~~empirical~~ own-price ~~responsiveness.~~elasticity estimates. After excluding the anomalously positive ~~own-price elasticity~~ estimates, this regression's results in Table 6 yield the following remarks. First, 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. Second, the elasticity estimates based on non-TL specifications are numerically similar. Third, the use of IV estimation does not have a statistically significant effect on elasticity estimates. Fourth, the long-run elasticity estimates are larger in size than the static and short-run estimates. Finally, the highly significant and negative estimate for *CD* suggests that erroneously ignoring CD presence tends to shrink ~~empirical price responsiveness.~~the size of elasticity estimates.

Importantly, all predicted price elasticities based on the OLS regression have size well below one. Hence, the US commercial natural gas demand is deemed price inelastic, irrespective of the modelling assumptions made in connection to the choice of a parametric specification, assumption of partial adjustment, treatment of CD, and use of IV estimation.

3.6 Time trend of own-price elasticity estimates

~~Motivated by **KG1**, we~~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 rolling-window's first period is Jan-1991 to Dec-2000 and last period Jan-2011 to Dec-2020. Figure ~~3~~2 portrays the US commercial natural gas demand's declining price responsiveness over time, ~~as~~further confirmed by the OLS regression results shown in Table 7.

3.7 Commercial shortage costs

~~Motivated by **KG7**,~~ Table 8 reports *SC* estimates by specification and elasticity type under the assumption of a hypothetical one-day shortage that curtails *D* = 10% of commercial natural gas demand. We perform the *SC* calculations using the elasticity estimates based on CD presence and non-IV estimation. For comparison, we repeat the calculations using the elasticity estimates based on CD absence and non-IV estimation~~. Table 8 shows~~, showing that erroneously ignoring the statistically significant CD presence tends to overstate the size of *SC*. ~~That said~~Nevertheless, the *SC* estimates in Table 8 are all less than 1% of the commercial customer class's energy cost.

3.8 Sensitivity checks

We choose the double-log specification with CD presence and non-IV estimation to perform several ~~sensitivity~~ checks of the sensitivity of the US commercial ~~demands' empirical~~natural gas demand's estimated price responsiveness. Our choice reflects the double-log specification's popularity evidenced by Table 2 and empirical plausibility portrayed by Table 5 and 6.

The first check repeats the panel data analysis with the fuel oil – electricity price ratio excluded. The resulting elasticity estimates becomes slightly smaller, with the static, short- and long-run own-price elasticity estimates respectively equal to -0.175, -0.133 and -0.225. Hence, excluding fuel oil as a regressor does not materially affect the own-price elasticity estimates.

~~Motivated by **KG3**, the~~The second check uses quarterly data instead of monthly data, thereby testing if ~~a longer decision period~~reducing data frequency affects commercial natural gas demand's price elasticity estimates. It ~~does not~~cannot use annual data because the DCCE estimator requires more time series observations than what the annual data can provide. The resulting static price elasticity estimate is -0.199, short-run estimate -0.188, and long-run estimate -0.229. Thus, using ~~a longer decision period~~less frequent data does not materially affect the price elasticity estimates reported in Panels A.1 and A.2 in Table 5.

The third check uses aggregate, instead of per capita, natural gas usage and employment data in the double-log demand regression. ~~This check's finding is~~It finds that using aggregate data produces price elasticity estimates~~ that~~ resemble those reported in Panels A.1 and A.2 of Table 5.

The fourth check uses price level instead of price ratio data. ~~Its finding is~~It finds that the static price elasticity estimate becomes -0.257, the short-run estimate -0.210, and the long-run estimate -0.339. Thus, ~~the use of~~using price level data does not materially alter the static estimate but moderately enlarges the short- and long-run estimates.

The fifth check implements the approach of Burke and Yang (2016). In the context of our panel data analysis, this approach is the double-log specification with the "between" estimator without state-specific fixed effects and CD presence. The resulting long-run own-price elasticity estimate is -1.153, close to the high-end estimates shown in Table 2. Hence, the between estimator yields much larger estimates than those reported in Table 5.

~~Motivated by **KG6**, the~~ The final check investigates the US commercial natural gas demand's regional price responsiveness~~:~~

~~Re~~. This check's first investigation entails using regional data to re-estimate the double-log demand regressions ~~using regional data.~~. Table 9 shows that the Midwest, West, and South regions in Figure ~~4~~3 have similar own-price elasticity estimates that are smaller in size than those of the Northeast region. As the Northeast region has higher natural gas prices than other regions, commercial natural gas demand in this region ~~is~~tends to be more price-sensitive because of more active inter-fuel substitution.

~~Re-estimate~~The final 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). Motivating this re-estimation is our conjecture that commercial customers who are more price responsive may be more likely to locate in a region with more stable and lower electricity prices made possible by the region's above-average *CS*. The first subsample contains states with below average *CS*, while the second subsample the remaining states. Table 9 indicates that the US commercial natural gas demand's price responsiveness ~~is unaffected by~~does not depend on the relative abundance of coal-fired generation.

4. Conclusions and policy implications

~~4.1 Conclusions~~

Our paper's ~~main~~ conclusions are as follows. First, accurate price elasticity estimates of natural gas demand are necessary for the ~~important~~various applications noted in Section 1. However, ~~making~~using extant studies to make reasonable price responsiveness assumptions ~~based on extant studies~~ is difficult, chiefly because of the large disparity in price elasticity estimates.

Second, a panel data analysis that uses monthly data by state over a long period is useful for estimating ~~price responsiveness of~~the US commercial natural gas ~~demand in the US~~demand's price responsiveness. Such an analysis, however, should recognize the effects of various factors listed in Section 3.5. That said~~.~~, the key takeaway of our extensive empirics is ~~that~~ the US commercial natural gas ~~demand's~~demand is price inelastic and its responsiveness ~~is relatively low and~~has been slowly declining over time.

Finally, our own-price elasticity estimates match the mid estimates found by extant studies. They imply relatively small commercial energy cost's increases (< 1%) due to a hypothetical one-day shortage that ~~curtails10~~curtails 10% of commercial natural gas demand.

~~4.2 Policy implications~~

~~Emerged from our~~Our conclusions ~~are the following~~have two policy implications. First, ~~declining price responsiveness means that~~ price-induced conservation is unlikely to ~~substantially~~materially reduce the US commercial ~~natural gas~~class's future consumption ~~in the US.~~of natural gas. Hence, the US path to deep decarbonization requires continuation of ~~EE and CO_2 emissions~~energy efficiency standards and DSM programs (Williams et al., 2012; Mahone et al., 2018).

Second, ~~our empirics highlight that~~ the aggregate cost of a natural gas shortage can be reduced by demand response programs like those enabled by smart metering for managing electricity shortage (Woo et al., 2014a). This is because natural gas shortage costs vary by price responsiveness~~. As~~ and commercial customers are heterogenous (e.g., hospitals vs. warehouses) with diverse disaggregate price responsiveness (Newell and Pizer, 2005~~), an economy's aggregate shortage cost can be reduced by DR programs like those enabled by smart metering for management of electricity shortage. Real-time pricing~~). As a result, real-time pricing incentivizes more price responsive commercial customers ~~with relatively low~~

~~shortage cost~~ to reduce their demand so that undisrupted service can continue for less price responsive customers~~ with relatively high shortage cost (Woo et al., 2014a).~~.

~~A corollary of~~Lending further support to the second implication is reliability differentiation made possible by ~~forward contracts for firm and non-firm services~~ a natural gas retailer's demand subscription service (Woo, 1990; Woo et al., 2014a, 2019). This is because commercial customers with ~~relatively~~ low shortage costs tend to ~~contract~~subscribe relatively more non-firm service at discounted per Mcf charges, while commercial customers with ~~relatively~~ high shortage costs tend to ~~contract~~subscribe relatively more firm service at undiscounted per Mcf charges. When a natural gas shortage is eminent, non-firm service ~~customers are~~is curtailed before firm service ~~customers.~~(Chao and Wilson, 1987; Woo, 1990). The resulting allocation of ~~the~~ limited supply ~~of natural gas is almost as~~is efficient~~ as real-time pricing (Chao and Wilson, 1987),~~, thus reducing an economy's aggregate natural gas shortage cost.

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Table 1. Own-price elasticity estimates of commercial demand for natural gas based on selected surveys

Study	Short run	Long run
Bohi and Zimmerman (1984)	-0.28 to -0.37	-1.86 to -2.37
Al-Sahlawi (1989)	-0.16 to -0.37	-1.06 to -2.26
Gillingham et al. (2009)	-0.14 to -0.29	-0.40 to -1.38

Note: Including additional surveys does not alter the table's main message that commercial demand for natural gas has highly diverse own-price elasticity estimates.

Table 2. Own-price elasticity estimates from selected studies of commercial demand for natural gas (NG) in the US

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		-0.161	-0.366
Liu (1983)	1967-1978	The US	Time series	Annual	Electricity, fuel oil	Double-log	OLS	-0.318 to -0.342		
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		-0.283	-1.428
Nan and Murry (1992)	1970 - 87	California	Time series	Annual	Electricity and petroleum products	Flexible double-log	Seemingly unrelated regressions		-0.570	-0.635
Denton et al. (2003)	CBECE Surveys for 1986 and 1992	The US	Cross section	Annual	Electricity	Double-log	Instrumental variable estimation			-0.63 to -1.62
Newell and Pizer (2005)	CBECE Surveys for 1986 and 1992	The US	Cross section	Annual	Electricity, fuel oil	Double-log	Discrete-continuous choice modelling			-1.39 to -1.60
Charles (2016)	2001- 2014	Lower 48 states	Panel	Monthly	Electricity	Double-log with and without partial adjustment	OLS with fixed effects	-0.137	-0.095	-0.232
Gautam and Paudel (2018)	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)		-0.117	-0.222
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	-0.468	-0.243	-0.641

Notes: (1) This table does not contain commercial natural gas demand studies outside the US because a scholar.google.com search does not yield recently published non-US studies relevant to our paper. ~~Moreover, the selected studies reinforce Table 1's main message that natural gas demand has highly diverse own-price elasticity estimates.~~

(2) CBECE Survey = Commercial Buildings Energy Consumption and Expenditure Survey conducted by the Department of Energy.

(3) Studies included herein have sample periods that end by 2016, suggesting potential insights to be gained from a large and recent sample of monthly data by state.

(4) Non-NG energy prices enter a commercial natural gas demand regression because of inter-fuel substitution.

(5) None of the panel data studies considers the impact of cross-section dependence on commercial natural gas demand's empirical price responsiveness.

(6) 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 3. ~~Descriptive statistics for the monthly~~Monthly data used in our regression analysis; sample period = Jan-1991 to Dec-2020~~ for the~~; geographic coverage = lower 48 states in the US, excluding Alaska and Hawaii; number of observations = 17,280

Panel A: Descriptive statistics

Variable ~~(Source)~~	Definition	Mean	Standard deviation	Minimum	Maximum
Y_1 ~~(EIA and BLS)~~	Per capita natural gas consumption (Mcf)	1.23	0.92	0.06	5.60
Y_3 ~~(EIA and BLS)~~	Per capita electricity consumption (kWh)	437.42	115.30	92.86	1157.66
P_1 ~~(EIA)~~	Natural gas price ($/Mcf)	8.21	3.00	1.76	22.07
P_2 ~~(EIA)~~	Fuel oil price ($/gallon)	1.58	0.94	0.34	4.34
P_3 ~~(EIA)~~	Electricity price ($/kWh)	0.086	0.026	0.037	0.212
P_1 / P_3	Natural gas – electricity price ratio	99.25	35.96	17.60	325.60
P_2 / P_3	Fuel oil – electricity price ratio	18.33	10.10	3.04	71.22
X ~~(BLS)~~	Per capita ~~industrial~~commercial employment	0.388	0.046	0.235	0.515
CDD ~~(NOAA)~~	Cooling degree days	91.45	144.59	0	794
HDD ~~(NOAA)~~	Heating degree days	434.99	422.46	0	2111

~~Notes: (1) EIA is the US Energy Information Administration, BLS the US Bureau of Labor Statistics, 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).~~Panel B: Correlations

Variable	Y_1	Y_3	P_1	P_2	P_3	P_1 / P_3	P_2 / P_3	X	*CDD*	*HDD*
Y_1	1									
Y_3	-0.044	1								
P_1	-0.247	0.240	1							
P_2	-0.057	0.315	0.589	1						
P_3	-0.122	-0.140	0.422	0.462	1					
P_1 / P_3	-0.144	0.363	0.673	0.230	-0.335	1				
P_2 / P_3	0.002	0.438	0.471	0.878	0.025	0.471	1			
X	0.115	0.134	0.161	0.178	0.257	-0.033	0.086	1		
CDD	-0.458	0.369	0.120	0.029	0.002	0.093	0.011	-0.088	1	
HDD	0.824	-0.153	-0.142	-0.024	-0.039	-0.100	0.008	0.092	-0.613	1

Table 4. 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	543.63 (0.000)	-5.392 (0.000)
P_1 / P_3	433.94 (0.000)	-5.607 (0.000)
P_2 / P_3	607.98 (0.000)	-4.169 (0.000)
X	505.63 (0.000)	-2.471 (0.000)
CDD	569.54 (0.000)	-6.190 (0.000)
HDD	606.07 (0.000)	-6.190 (0.000)

Table 5. Regression results by specification; sample period: Jan-~~2001~~1991 to Dec-2020; 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	0.13	0.13	0.18	0.18
Adjusted R^2	0.95	0.98	0.90	0.91
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.245**	**-0.186**	**-0.090**	-0.071
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	**0.166**	**0.140**	-0.027	-0.031
X = per capita industrial employment	0.357	0.255	0.532	0.518
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Static own-price elasticity	**-0.245**	**-0.186**	**-0.090**	-0.071
p-value for testing H_0: CD is absent	-	-	0.000	0.000
~~p-value for testing H_0: natural gas price ratio data are exogeneous~~	~~0.908~~		~~0.759~~	

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	0.10	0.09	0.13	0.13
Adjusted R^2	0.97	0.97	0.95	0.95
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.177**	*0.025*	**-0.082**	-0.038
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	**0.099**	-0.022	-0.021	**-0.032**
X = per capita industrial employment	0.336	0.426	**1.043**	**0.886**
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Lagged $\ln Y_1$	**0.406**	**0.416**	**0.320**	**0.318**
Short-run own-price elasticity	**-0.177**	0.025	**-0.082**	-0.038
Long-run own-price elasticity	**-0.298**	***0.042***	**-0.121**	-0.056
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel A.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.~~186~~079**	**0.~~794~~078**	**0.131**
Natural gas - fuel oil	**0.166**	**0.099**	**0.167**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.95	0.98	0.91	0.91
(P_1 / P_3) = (natural gas price/electricity price)	**-0.0017**	**-0.0015**	**-0.0009**	-0.0008
(P_2 / P_3) = (fuel oil price / electricity price)	0.0043	**0.0042**	**-0.0026**	**-0.0026**
X = per capita industrial employment	0.0005	0.0006	-0.0002	0.0000
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Static own-price elasticity	**-0.240**	**-0.215**	**-0.126**	**-0.112**
p-value for testing H_0: CD is absent	-	-	0.000	0.000
~~p-value for testing H_0: natural gas price ratio data are exogeneous~~	~~0.357~~		~~0.327~~	

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.97	0.97	0.95	0.95
(P_1 / P_3) = (natural gas price/electricity price)	**-0.0016**	*0.0002*	**-0.0008**	-0.0005
(P_2 / P_3) = (fuel oil price / electricity price)	**0.0045**	-0.0005	**-0.0023**	**-0.0027**
X = per capita industrial employment	0.0006	0.0009	**0.0008**	0.0007
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Lagged Y_1	**0.379**	**0.381**	**0.310**	**0.308**
Short-run own-price elasticity	**-0.226**	***0.026***	**-0.111**	**-0.068**
Long-run own-price elasticity	**-0.364**	***0.042***	**-0.161**	**-0.098**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel B.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.~~140~~135**	**0.~~793~~114**	**0.184**
Natural gas - fuel oil	**0.106**	**0.112**	**0.180**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.17	0.17	0.24	0.24
Adjusted R^2	0.94	0.97	0.87	0.87
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.169**	-0.084	**-0.284**	**-0.281**
X = per capita industrial employment	0.837	0.714	**-3.314**	**-3.230**
CDD = cooling degree days	**0.000**	**0.000**	**-0.001**	**-0.001**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Static own-price elasticity	**-0.137**	**-0.068**	**-0.230**	**-0.227**
p-value for testing H_0: CD is absent	-	-	0.000	0.000
~~*p*-value for testing H_0: natural gas price ratio data are exogeneous~~	~~0.959~~		~~0.001~~	

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	0.11	0.10	0.17	0.17
Adjusted R^2	0.97	0.97	0.94	0.94
$\ln(P_1 / P_3)$ = ln(natural gas price/electricity price)	**-0.188**	*0.036*	**-0.203**	**-0.167**
X = per capita industrial employment	0.232	0.141	**-1.297**	**-1.446**
CDD = cooling degree days	**-0.001**	**-0.001**	**-0.001**	**-0.001**
HDD = heating degree days	**0.001**	**0.001**	**0.001**	**0.001**
Lagged $\ln Y_1$	**0.458**	**0.467**	**0.377**	**0.376**
Short-run own-price elasticity	**-0.152**	***0.029***	**-0.164**	**-0.135**
Long-run own-price elasticity	**-0.281**	***0.054***	**-0.263**	**-0.217**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel C.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.~~811~~169**	**0.~~000~~188**	**0.347**
Natural gas – fuel oil	**0.169**	**0.188**	**0.347**

Note: The CES specification's regression coefficients for $\ln(P_1 / P_3)$ in Panels C.1 and C.2 are constant elasticities of substitution × -1, which are the same for the two fuel pairs.

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.96	0.98	0.91	0.91
$(P_2 / P_1)^{1/2}$ = (fuel oil price / natural gas price) $^{1/2}$	0.~~0001~~0000	0.~~0000~~0003	**-0.~~0001~~0002**	**-0.~~0001~~0002**
$(P_3 / P_1)^{1/2}$ = (electricity price / natural gas price) $^{1/2}$	**0.~~0000~~0001**	0.~~0003~~0000	**~~-~~0.~~0002~~0001**	**~~-~~0.~~0002~~0001**
X = per capita industrial employment	0.0004	0.~~0006~~0004	0.0000	0.0001
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Static own-price elasticity	**-0.192**	**-0.149**	**-0.103**	**-0.~~094~~092**
p-value for testing H_0: CD is absent	-	-	0.000	0.000
~~*p*-value for testing H_0: natural gas price ratio data are exogeneous~~	~~0.131~~		~~0.295~~	

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	0.00	0.00	0.00	0.00
Adjusted R^2	0.97	0.98	0.95	0.95
$(P_2 / P_1)^{1/2}$ = (fuel oil price / natural gas price) $^{1/2}$	0.~~0001~~0002	~~-~~0.~~0001~~0000	**-0.~~0001~~0002**	**-0.~~0001~~0003**
$(P_3 / P_1)^{1/2}$ = (electricity price / natural gas price) $^{1/2}$	**0.~~0002~~0001**	0.~~0013~~0000	**~~-~~0.~~0002~~0001**	**~~-~~0.~~0002~~0001**
X = per capita industrial employment	0.0004	0.~~0001~~0004	**0.0009**	**0.~~0007~~0008**
CDD = cooling degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
HDD = heating degree days	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Lagged Y_1	**0.364**	**0.~~363~~364**	**0.306**	**0.~~304~~303**
Short-run own-price elasticity	**-0.206**	**-0.~~113~~012**	**-0.093**	**-0.~~055~~044**
Long-run own-price elasticity	**-0.324**	**-0.~~177~~018**	**-0.134**	**-0.~~080~~063**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel D.3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	**0.~~156~~182**	**0.~~610~~162**	**0.255**
Natural gas - fuel oil	**0.010**	**0.044**	**0.069**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the demand equations for these two energy types.

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	0.02	0.02	0.03	0.03
Adjusted R^2	0.95	0.97	0.89	0.89
$\ln(P_1 / P_3)$ = ln(natural gas price / electricity price)	**0.106**	**0.109**	**0.123**	**0.124**
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	-0.002	-0.003	**-0.028**	**-0.028**
X = per capita industrial employment	0.086	0.082	**-0.390**	**-0.377**
CDD = cooling degree days	0.000	0.000	**0.000**	**0.000**
HDD = heating degree days	**0.000**	**0.000**	**0.000**	**0.000**
Static own-price elasticity	***0.021***	***0.043***	***0.155***	***0.158***
p-value for testing H_0: CD is absent	-	-	0.000	0.000
~~p-value for testing H_0: natural gas price ratio data are exogeneous~~	~~0.566~~		~~0.435~~	

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	0.02	0.02	0.02
Adjusted R^2	0.97	0.96	0.94	0.94
$\ln(P_1 / P_3)$ = ln(natural gas price / electricity price)	**0.070**	**0.028**	**0.082**	**0.075**
$\ln(P_2 / P_3)$ = ln(fuel oil price / electricity price)	0.000	**0.023**	**-0.020**	**-0.018**
X = per capita industrial employment	0.008	0.013	**-0.152**	**-0.125**
CDD = cooling degree days	**0.000**	**0.000**	0.000	0.000
HDD = heating degree days	**0.000**	**0.000**	**0.000**	**0.000**
Lagged ~~$\ln Y_{-1}$~~ S_{-1}	**0.436**	**0.480**	**0.360**	**0.369**
Short-run own-price elasticity	**-0.261**	**-0.589**	**-0.164**	**-0.220**
Long-run own-price elasticity	**-0.463**	**-1.132**	**-0.256**	**-0.348**
p-value for testing H_0: CD is absent	-	-	0.000	0.000

Panel E3: Elasticity of inter-fuel substitution based on the preferred results shaded in light green

Fuel pair	Static	Short-run	Long-run
Natural gas - electricity	***-0.~~530~~051***	**0.~~856~~220**	**0.390**
Natural gas - fuel oil	**0.031**	**0.041**	**0.073**

Note: We cannot derive the elasticity of substitution between fuel oil and electricity because our regression analysis does not estimate the cost share equations for these two energy types.

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	-0.245	-0.177	-0.298
(2) Linear	-0.240	-0.226	-0.364
(3) CES	-0.137	-0.152	-0.281
(4) GL	-0.192	-0.206	-0.324
(5) TL	*0.021*	-0.261	-0.463

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	-0.245	-0.177	-0.298
(2) Linear	-0.198	-0.186	-0.300
(3) CES	-0.135	-0.149	-0.276
(4) GL	-0.161	-0.174	-0.273
(5) TL	-0.125	-0.352	-0.625

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	-0.245	-0.177	-0.298
(2) Linear	-0.388	-0.365	-0.588
(3) CES	-0.153	-0.170	-0.313
(4) GL	-0.304	-0.326	-0.512
(5) TL	*0.424*	-0.026	-0.047

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	-0.245	-0.177	-0.298
(2) Linear	-0.267	-0.251	-0.404
(3) CES	-0.142	-0.158	-0.292
(4) GL	-0.214	-0.230	-0.361
(5) TL	*0.058*	-0.247	-0.439

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	-0.245	-0.177	-0.298
(2) Linear	-0.108	-0.102	-0.164
(3) CES	-0.119	-0.132	-0.243
(4) GL	-0.089	-0.096	-0.150
(5) TL	-0.273	-0.418	-0.741

Notes: (1) While the double-log specification's elasticity estimates do not vary monthly, the same cannot be said for the other specifications.
(2) As expected, summer estimates are larger in size than winter elasticity estimates because commercial usage of natural gas is mainly for space heating.

Table 6. OLS dummy variable regression whose regressand is the US commercial natural gas demand's own-price elasticity estimate

Variable	Estimate	Standard error	p-value
Adjusted R^2	0.~~452~~467		
RMSE	0.129		
Intercept	-0.~~325~~312	0.~~074~~071	0.000
F_1 = 1 if double-log specification, 0 otherwise	0.~~320~~275	0.~~102~~089	0.~~003~~004
F_2 = 1 if linear specification, 0 otherwise	0.~~245~~239	0.~~093~~089	0.011
F_3 = 1 if CES specification, 0 otherwise	0.~~230~~224	0.~~095~~092	0.020
F_4 = 1 if GL specification, 0 otherwise	0.~~284~~306	0.~~097~~098	0.~~005~~003
IV = 1 if IV estimation, 0 otherwise	0.~~011~~001	0.~~040~~043	0.~~782~~978
ST = 1 if static, 0 otherwise	-0.~~049~~042	0.030	0.~~109~~170
LR = 1 if long-run, 0 otherwise	-0.~~106~~109	0.~~049~~050	0.~~037~~036
CD = 1 if CD presence is correctly accounted, 0 otherwise	-0.~~114~~126	0.~~040~~043	0.~~007~~006

Note: The sample size is ~~52~~50 observations = (5 specifications × 3 elasticity types × 2 CD treatments ×2 estimation methods) – ~~8~~10 observations with anomalously positive elasticity estimates.

Table 7. Own-price elasticity estimate = Intercept + *b* *ID* + error; sample size = 241 observations for each elasticity type

Panel A: Static elasticity

Variable	Estimate	Standard error	*p*-value
Regressand's mean			
Adjusted R^2	0.830		
RMSE	0.024		
Intercept	-0.310	0.003	0.000
ID	0.001	0.00002	0.000

Panel B: Short-run elasticity

Variable	Estimate	Standard error	*p*-value
Regressand's mean			
Adjusted R^2	0.820		
RMSE	0.026		
Intercept	-0.286	0.003	0.000
ID	0.001	0.00002	0.000

Panel C: Long-run elasticity

Variable	Estimate	Standard error	*p*-value
Regressand's mean			
Adjusted R^2	0.840		
RMSE	0.036		
Intercept	-0.401	0.005	0.000
ID	0.001	0.00003	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 1991 – 2000. The last observation (*ID* = 241) is based on the last 10-year period of 2011 – 2020.

(3) The small but highly significant *b* estimate for *ID* in each panel's last row is positive, indicating that the US commercial natural gas's price responsiveness has been slowing decreasing over time.

Table 8. Natural gas shortage cost (*SC* = percentage increase in industrial energy cost) for 2020 by elasticity type and specification for a hypothetical one-day shortage that causes curtailment for 10% of commercial natural gas demand; anomalous estimates in *italic*

Panel A. CD presence and non-IV estimation

Parametric specification	Static		Short run		Long run	
	ε_1	*SC*	ε_1	*SC*	ε_1	*SC*
Double-log	-0.245	0.2%	-0.177	0.3%	-0.298	0.2%
Linear	-0.240	0.2%	-0.226	0.2%	-0.364	0.1%
CES	-0.137	0.4%	-0.152	0.4%	-0.281	0.2%
GL	-0.192	0.3%	-0.206	0.3%	-0.324	0.2%
TL	*0.021*	*-2.5%*	-0.261	0.2%	-0.463	0.1%

Panel B. CD absence and non-IV estimation

Parametric specification	Static		Short run		Long run	
	ε_1	*SC*	ε_1	*SC*	ε_1	*SC*
Double-log	-0.090	0.6%	-0.082	0.6%	-0.121	0.4%
Linear	-0.126	0.4%	-0.111	0.5%	-0.161	0.3%
CES	-0.230	0.2%	-0.164	0.3%	-0.263	0.2%
GL	-0.103	0.5%	-0.093	0.6%	-0.134	0.4%
TL	*0.155*	*-0.3%*	-0.164	0.3%	-0.256	0.2%

Notes: (1) The *SC* calculation entails two steps: (1) calculate the disaggregate *SC* number for each 2020 observation in the panel; and (2) calculate the simple average of all disaggregate *SC* numbers.

(2) Accounting for CD presence tends to shrink *SC* estimates that are mostly below 1% of commercial energy cost. Hence, the 1% ceiling is an empirically plausible *SC* assumption for the purpose of resource planning.

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
Northeast	-0.502	-0.249	-0.512
Midwest	-0.219	-0.139	-0.209
South	-0.187	-0.159	-0.280
West	-0.247	-0.160	-0.296
States with below average coal shares of total generation	-0.232	-0.188	-0.297
States with above average coal shares of total generation	-0.262	-0.163	-0.294

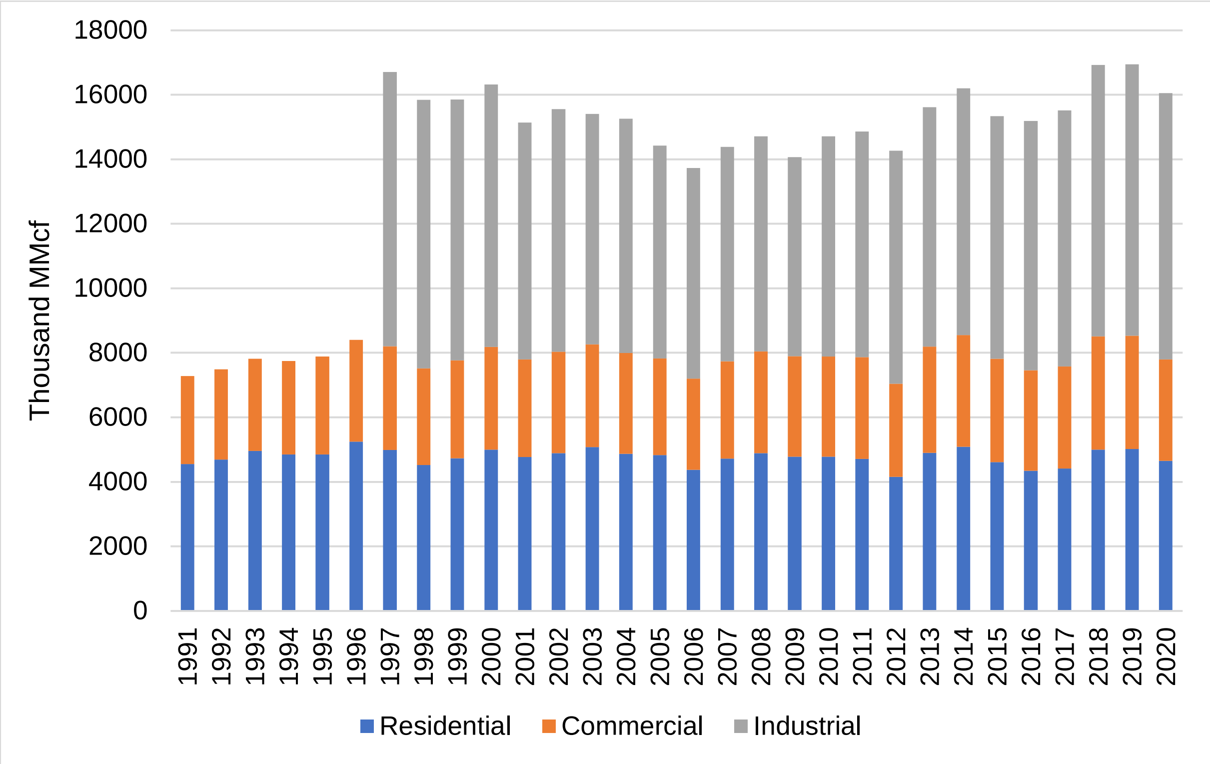
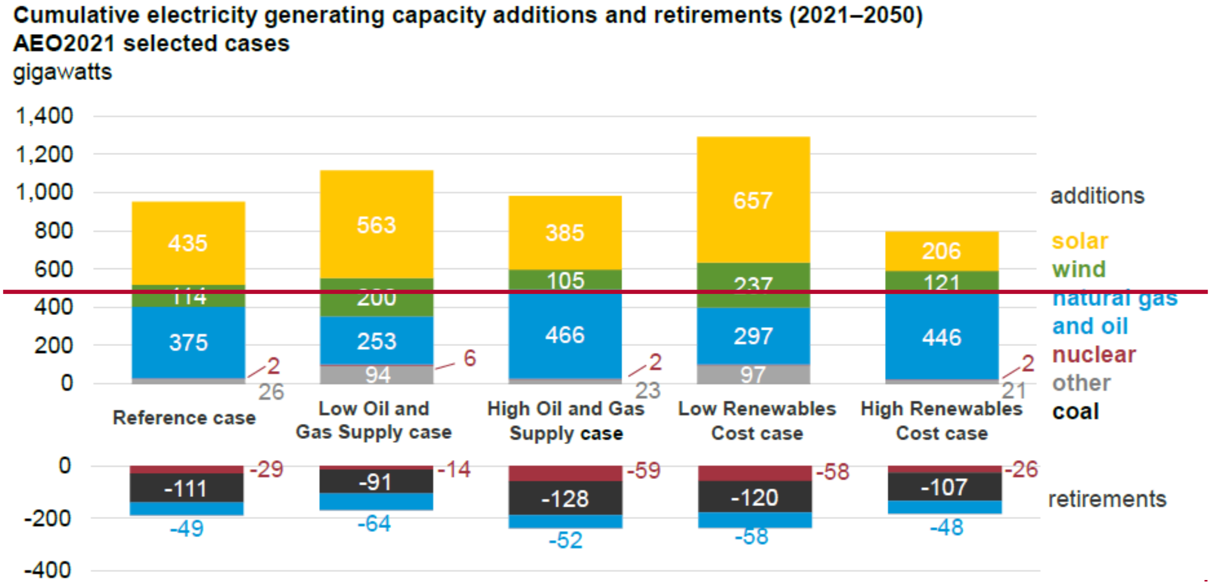
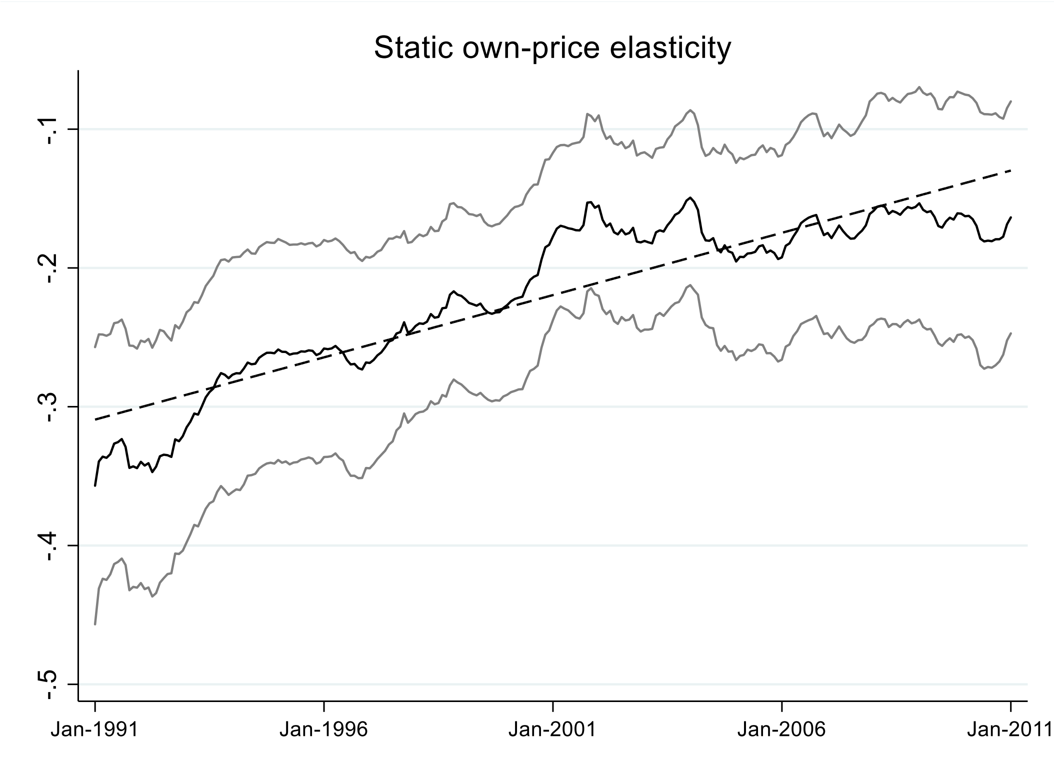
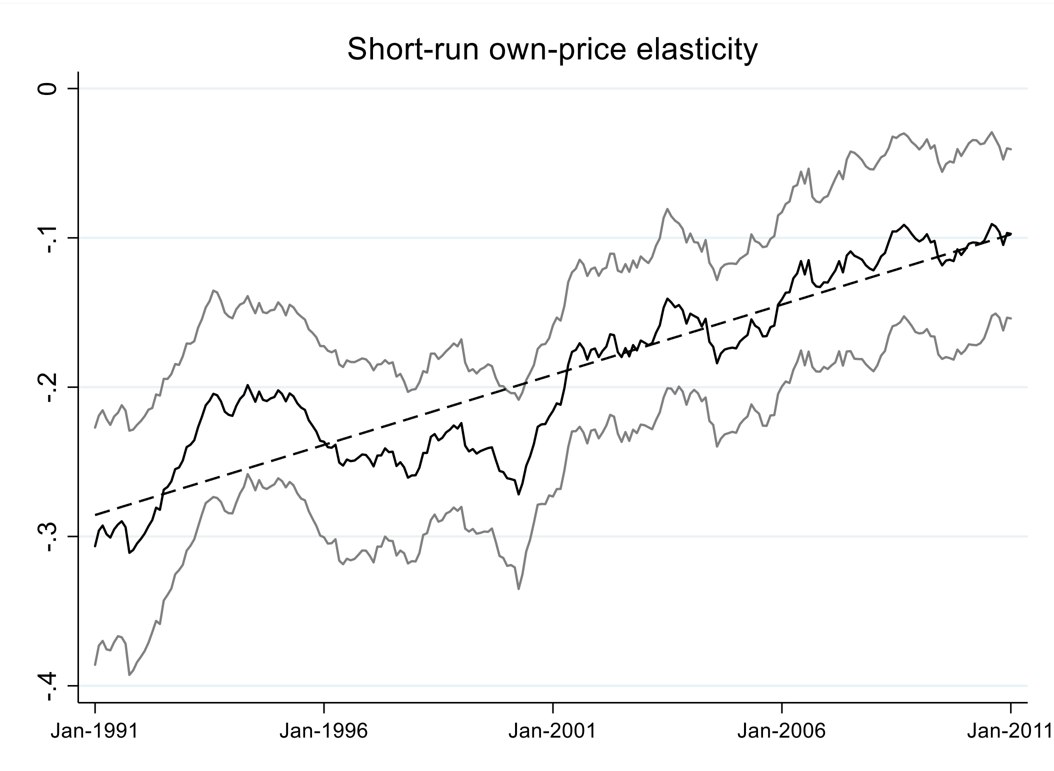


Figure 1. US annual natural gas consumption by end-use customer class in 1991-2020, recognizing that annual industrial consumption data are unavailable for years prior to 1997 (Data source: US Energy Information Agency).



~~Figure 2. Projected capacity expansion of electricity generation in the US (Source: https://www.eia.gov/pressroom/presentations/AEO2021_Release_Presentation.pdf)~~


Static own-price elasticity
-.1
-.2
-.3
-.4
-.5
Jan-1991
Jan-1996
Jan-2001
Jan-2006
Jan-2011


Short-run own-price elasticity
0
-.1
-.2
-.3
-.4
Jan-1991
Jan-1996
Jan-2001
Jan-2006
Jan-2011

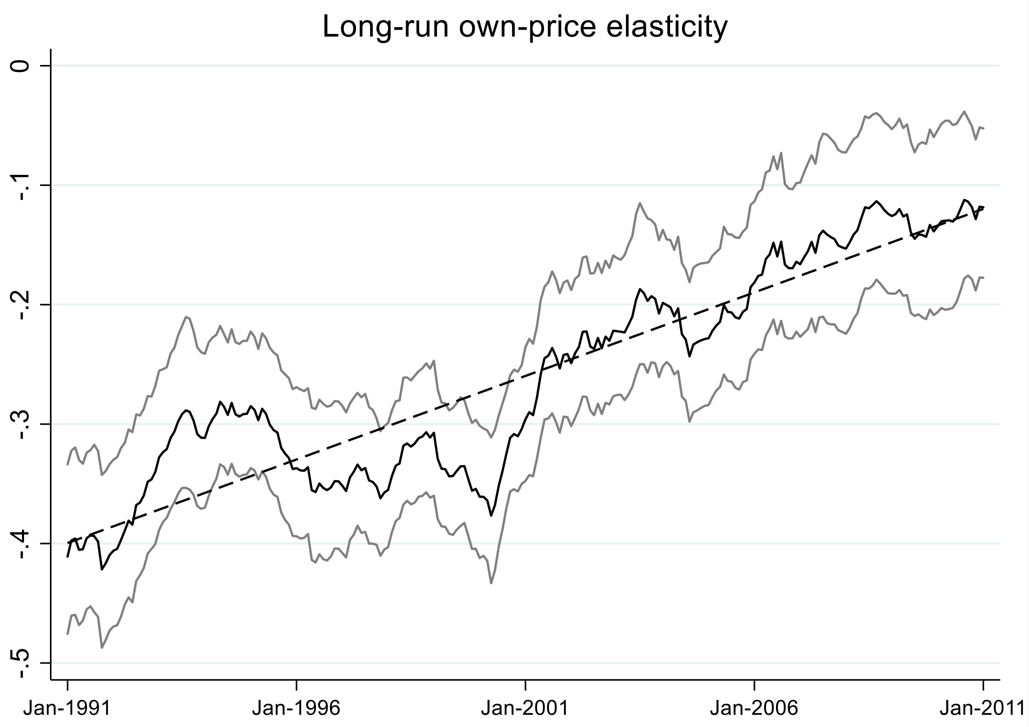


Figure 2. Own-prices elasticity estimates from a rolling-window analysis that uses the double-log specification with CD presence and non-IV estimation. The horizontal axis shows the starting period of each rolling-window. The middle solid black line portrays an elasticity estimate. The lower and upper solid grey lines form the estimate's 95% confidence interval. The dashed line is the estimate's linear time trend.

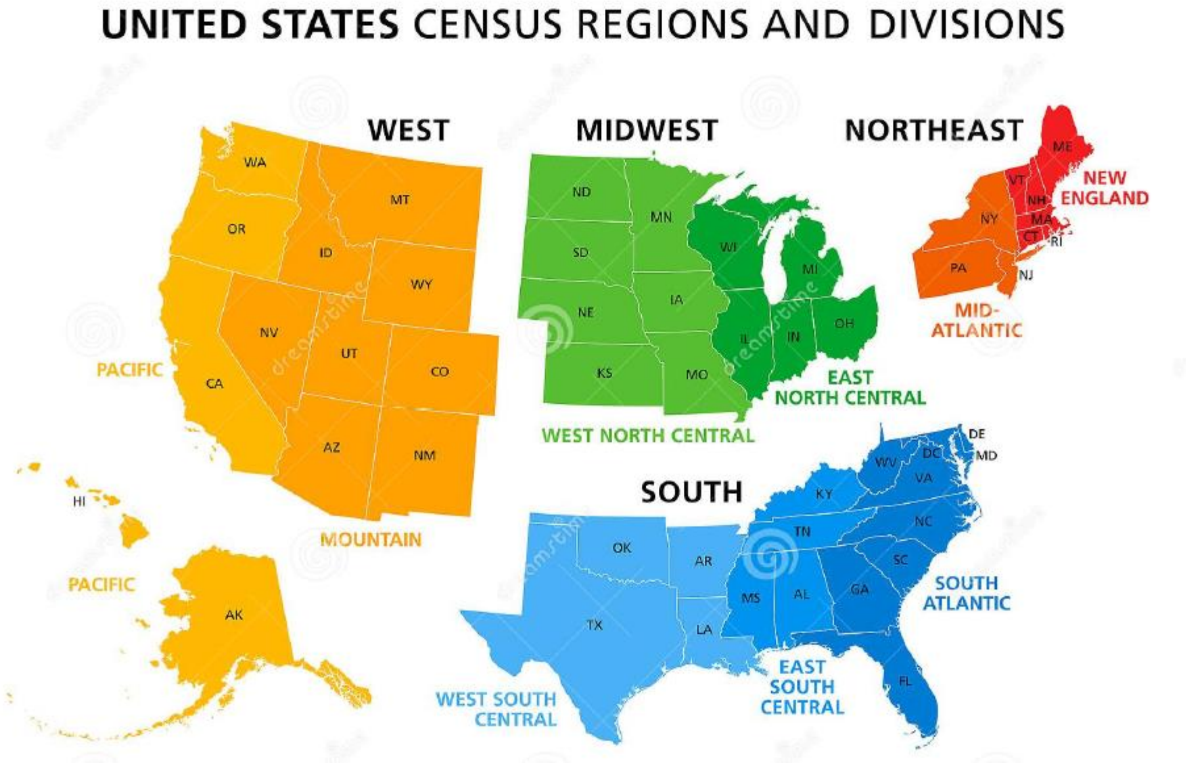


Figure 43. Census regions in the US

Responses to Reviewer 1

Comment 1. The knowledge gaps are not appropriate and exaggerated. The authors cannot review the entire related literatures, 'contribution' may be more appropriate.

Response 1. Thanks to this insightful comment, we have removed the offending materials.

Comment 2. The author does not show the data source, such as the price from spot or future market, the correlation of natural gas and oil price, and so on.

Response 2. We have extensively revised Section 2.6: Data description to show the data sources.

Comment 3. The substitutability between natural gas, fuel oil and electricity is not considered. These fuels are used in the same sectors? What is the elasticity of substitution among these fuels?

Response 3.1. The completely rewritten Section 2.3 explains our estimation of the elasticities of substitution.

Response 3.2. We have expanded Table 5 to report the estimated elasticities of substitution between natural gas and fuel oil/electricity.

Comment 4. The equation (4), the own-price elasticity is consumption divided by consumption? The own-price elasticity is equal to changes in demand divided by price.

Response 4. Our resubmission's Section 2.3 derives the regression equations and clearly state the related own- and cross-price elasticity formulae.

Comment 5. The derivation is weird without some citation.

Response 5. Our resubmission's Section 2.3 details the derivation with relevant citations.

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Responses to Reviewer 2

Comment 1. This paper estimates the elasticities of commercial natural gas demand. This study has some innovations comparing with the existing studies. However, the motivations of this studies are not clear. Why do you do this research? Why introduce your so-called innovations into your work?

Response 1. Fully concurring with this insightful comment, we have extensively revised the paper's introduction to explain why we do this research and why we introduce our innovations.

Comment 2. I think this paper should be re-organized. The introduction and literature review should be the first two parts of a paper.

Response 2. We have done so as instructed.

Comment 3. I don't think "uses five parametric specifications" is an innovation. You should explain why do you select these methods. What are the advantages?

Response 3.1. We have removed our misguided claim.

Response 3.2. Footnote 5 explains the advantages of these specifications.

Response 3.3. The first paragraph of our resubmission's rewritten Section 2.3 explains why we consider these specifications.

Comment 4. How can you back up the seventh contribution in Page 4? The general use in other countries should be supported by your findings or careful derivation.

Response 4. Our resubmission has removed our unsubstantiated claim.

Comment 5. The data sources should be explained clearly.

Response 5. We have extensively revised Section 2.6: Data description to show the data sources and construction.

Responses to Reviewer 3

Comment 1. The study focuses on estimating price responsiveness of commercial demand for natural gas, which belongs to social economic topics just within the USA.

Response 1. Our resubmission's introduction now states why our study internationally relevant, not just a social economic topic within the US.

Comment 2. Thus, the reviewer recommends to submit it to ENERGY POLICY journal.

Response 2. We select Energy for the following reasons:

- Energy is a top journal that appreciates state-of-art techniques and a large data sample. Hence, it is more appropriate than Energy Policy.
- Energy has published papers related to estimating energy demand price elasticities in the presence of cross-section dependence, an important econometric issue that is less relevant for a policy-focused journal such as Energy Policy.
- Whether our paper is appropriate for Energy is a decision to be made by Energy's subject editor. Absent this decision, submitting our paper to another journal like Energy Policy seems unwarranted.