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Abstract

Previous studies provide strong evidence that energy demand elasticities vary across regions and states, arguing in favor of conducting energy demand studies at the smallest unit of observation for which good quality data are readily available, that is the utility level. We use monthly data from the residential sector of Xcel Energy's service territory in Colorado for the period January 1994 to September 2006. Based on a very general Autoregressive Distributed Lag model this paper uses a new approach to simulate the dynamic behavior of natural gas demand and obtain dynamic elasticities. Knowing consumers' response on a unit time basis enables one to answer a number of questions, such as, the length of time needed to reach demand stability. Responses to price and income were found to be much lower—even in the long run—than what has been commonly suggested in the literature. Interestingly, we find that the long run equilibrium is reached relatively quickly, around 18 months after a change in price or income has occurred, while the literature implies a much longer period for complete adjustments to take place.

Keywords: dynamic elasticities; ADL; natural gas demand; Colorado

JEL codes: C22; C51; Q41

1. Introduction

There has been a long-standing interest in modeling energy demand to estimate price and income elasticities. However, the vast majority of existing studies have focused on electricity, while natural gas has received much less attention. Table 1 presents a breakdown of the studies by product and by decade,[1] where the studies are categorized in a decade according to the most recent observation in the sample period studied. Clearly, there is a clustering of studies in the late 1970s and early 1980s probably as a result of the two oil price shocks. The table also shows how this research has been distributed with electricity receiving more than twice the attention of natural gas. Although the current decade has seen a decline in natural gas consumption per customer, new natural gas field discoveries are likely to lead to a much more important role for gas. In this paper, we analyze residential natural gas demand at the utility level in Colorado using monthly data spanning the period January 1994 to September 2006.

[insert table 1]

Previous studies have used a variety of models to estimate short-run, long-run or both types of elasticities However, we know of no study that explicitly quantifies the length of time needed for long-run adjustments to be completed or uses stochastic simulation to illustrate the adjustment process that takes place to reach the long run. While the dynamic adjustment path often can be computed manually using the estimated coefficients, such computations become very cumbersome as the number of lags increases. We aim to fill this gap in the natural gas demand literature by using dynamic elasticities,[2] which are elasticities at each point in time obtained by applying a permanent price (or income) shock to the model. The stochastic simulation shows how demand changes over time in response to this price change. Ultimately, the estimated monthly elasticities improve on earlier studies that consider at most two points to characterize the dynamic price-demand relationship, by allowing a time path of response of demand to a price change that is more flexible than the exponential path implied by a Koyck lag.

The significant body of research in this area has unfortunately provided a wide range of elasticity estimates. This has, in turn, created major difficulties for end users wishing to use elasticity estimates in energy models, whether at the national or at more disaggregated levels. This problem is further exacerbated by the fact that many studies fail to report the standard errors of their estimates, especially in the long-run (LR) case. This omission is most likely because, unlike their short-run counterparts, calculating the long-run estimates' standard errors is non

[1] It should be noted that included studies are limited to studies published in the English language. Also, the total number of studies is effectively less than what is reflected in Table 1 because some studies involve both products; electricity and natural gas. These studies typically apply the same model and methodology to both products.
[2] For a discussion of dynamic elasticities see Pindyck and Rubinfeld (1998).

trivial.[3] However, standard errors are essential for comparing the precision of estimates across studies. For example, Espey and Espey (2004) were not able to include the variance of the elasticity estimates in their meta-analysis on residential electricity price and income elasticities, because the standard errors were rarely reported in the 36 studies reviewed. The present work addresses this problem by reporting the standard error for each corresponding dynamic elasticity estimate along with the 95% confidence interval. This will make definitive conclusions about the precision of estimates possible and facilitate cross-study comparisons.

Another problem is that most of the abundant demand elasticity estimates in the literature, pertain to studies done in the 1970s and 1980s (see Table 1). However, a number of factors, including changes and shifts in energy use, more efficient appliances, and increased access to natural gas in rural areas (Bernstein and Griffin, 2006) could have changed the relationship between demand and its determinants. On one hand, some researchers suggest that there is evidence that demand may be becoming more elastic (Bernstein and Griffin, 2006), while on the other hand, some researchers such as Dahl (1993) and Espey and Espey (2004) found statistical evidence that demand has become more inelastic since the 1970s. Moreover, the supply constraints that previously existed for natural gas suggest that historical elasticities may not have much relevance in evaluating current and future natural gas demand (Dahl, 1993). Consequently, it is preferable to use a present-day set of elasticity estimates, rather than an adjusted set of dated estimates, especially given that the direction of such adjustment is ambiguous.

In particular, since very few studies have used data beyond 2000, the effect on demand of the change in price trends observed since 2000 has not been carefully analyzed. Only Joutz and Trost (2007) test for a change in residential natural gas price elasticity post 2000 using monthly data and find no evidence of a statistically significant change.

Previous studies provide strong evidence that the level of analysis has important implications for the accuracy of any demand elasticity estimates. The overwhelming majority of studies that have tested for geographical-based differences in elasticities have found that consumers in different regions respond differently to changes in the determinants of demand. This problem has to a large extent been ignored in the literature since there are just a few studies

[3] Although their application is quite involved, several methods for calculating the standard errors have been implemented, including bootstrapping, the delta, and the jackknife methods. For a discussion of these and other methods, see Efron (1981).

at the utility level compared to hundreds at the state or national level. Further, there is convincing evidence that demand models perform better when applied to data at a finer level of aggregation (Bohi, 1981). All of this argues in favor of conducting energy demand studies at the smallest unit of observation for which good quality time series data are readily available, that is the utility level. Therefore, the present study will focus on analyzing residential natural gas demand in Xcel Energy's service area in Colorado.[4]

The remainder of this paper is structured as follows. Section 2 reviews and compares existing residential natural gas elasticity estimates. The demand model employed is presented in section 3. In section 4 we introduce the data set followed by a description of the methodology used in section 5. Section 6 presents and discusses the results. Finally, section 7 contains concluding remarks and suggestions for future research in this field.

2. An overview of the existing elasticity estimates

More than a hundred studies on natural gas demand have been conducted since the 1940s, the majority of which are aimed at estimating demand elasticities. Unfortunately, these studies have produced such widely divergent estimates that the various surveys conducted to date have reported no firm consensus on price and income elasticities . For example, in a comprehensive review of energy demand studies, Bohi (1981) finds that the estimated demand elasticities vary considerably from one study to the next; some suggest that price is very important but others do not; some imply that income is the controlling factor while others imply that price is dominant; some indicate that interfuel substitution is important and others suggest it is not. Consequently, Bohi (1981) concludes that the many serious estimation problems produce divergent estimates making it very difficult for the researcher as well as the end-user to evaluate the reliability of, and compare between, the estimates.

In spite of the wide range of elasticity estimates, some surveys do report consensus values. However, without taking into consideration the individual standard errors one must be very careful with these values, which sometimes are calculated by taking the simple average of the available estimates. In his survey of 18 studies, Taylor (1977) concludes that the natural gas

[4] Xcel Energy is an electric and natural gas utility serving customers in eight different states. In the state of Colorado it serves 1.35 million electricity customers and 1.29 million natural gas customers. A list of the communities served can be found at the following link: http://www.xcelenergy.com/SiteCollectionDocuments/docs/5.26.2010FINALCO-CommunityServed.pdf

price elasticities are around -0.15 in the SR and more elastic than -1 in the LR. In general, LR estimates show a much wider variation than SR estimates. Bohi (1981) reviews 25 studies and concludes that consensus values for residential natural gas price elasticities are -0.1 (SR; range -0.03 to -0.4) and -0.5 (LR; range -0.17 to -1.0). Bohi and Zimmerman (1984) conclude a SR estimate of -0.2 and a LR estimate of -0.3 for the residential natural gas sector. In a recent meta-analysis on natural gas elasticities conducted by Dahl and Pechatnikov (2007) including a data set of around 400 observations on all consumer sectors, SR price elasticities were found to vary between 1.07 and -2.62, and the LR price elasticities were found to be even more disparate ranging between 53.73 and -115.

In comparing the own-price elasticities of household demand for electricity and natural gas, there is evidence that the short-run estimates in the natural gas market are lower than the electricity market (Bohi, 1981; Dahl, 1993; Labandeira et al., 2005). As Bohi (1981) explains this result is expected because gas is used primarily for space heating which is regarded as less of a luxury compared with many applications of electricity. Also, the estimated elasticities for natural gas are more uncertain than those for electricity possibly due to a combination of poor data and the confusing effects of disequilibrium markets that existed during the 1970s.

Research examining the cross-price elasticities between electricity and natural gas has generally found the cross-price elasticities to be small in magnitude and frequently not statistically significant. Typically, substitution between electricity and natural gas in the residential sector is limited to the following end uses: space heating, water heating, cooking, and clothes drying . For example, Garcia-Cerrutti (2000) in his study on residential energy demand in California counties notes that weak cross-price effects suggest that electricity and natural gas have largely independent uses and there is limited switching between them. Moreover, in some cases the estimated elasticities have negative signs which could be an indication that electricity and natural gas are treated as complements rather than substitutes. In his survey of electricity demand studies, Westley (1992) finds the means of the estimated cross-price elasticities with natural gas to be: 0.06 (SR) and 0.22 (LR) for the residential sector. Dahl (1993) finds that substitutability between natural gas and electricity increased with the more recent surveys with their average cross elasticities ranging between 0.53 and 0.65, whereas earlier they ranged between 0.10 and 0.20.

In looking at natural gas income elasticities, the studies surveyed by Bohi (1981) indicated that income is not important to gas demand. Similarly, Bohi and Zimmerman (1984) found that the income elasticities were largely insignificant especially in the residential and commercial sectors. In contrast, Joutz and Trost (2007) found significant but negative (usually associated with inferior goods) income elasticities. They argued that technology has improved over time as income has increased reducing the consumption of natural gas. They decided to exclude income from their final model and instead included a time trend to model the combined effect of income and technical change. For more on natural gas income elasticities see Dahl (1993) and Dahl and Pechatnikov (2007).

Although results in general have not been uniform, one can conclude that the majority of previous research finds natural gas demand to be negatively related to price—consistent with economic theory—but relatively inelastic to price changes. Furthermore, due to the more limited opportunities for substitution, the short-run price elasticity usually tends to be more inelastic than the long run with a few exceptions (see Choi, 2002; Yokohama et al., 2000; Danielsen, 1977). The latter are in violation of Le Châtelier's principle (for a formal proof, see Varian, 1992) and are usually dismissed by economists as being unreasonable. For example, the short-run response to higher prices is limited to decreasing the intensity of use of existing equipment. Alternatively, in the long run, consumers have the opportunity to respond to higher energy prices by purchasing equipment that is more efficient or even uses different (cheaper) energy sources. Even so, substitution between energy products in the residential sector is very limited and most often cross-price elasticities have been found to be statistically insignificant, as are income elasticities. Although a few economists have suggested some consensus values based on the limited number of studies they surveyed, it is clear that there is no general agreement on the magnitude of demand elasticities. Furthermore, these consensus values may not be reliable when the individual standard errors are not taken into consideration in determining the consensus elasticity values.

The role of technological change and its effect on energy demand has been investigated in several studies. Due to the unavailability of a time series reflecting technological change, most of these studies have used the time trend as a proxy. However, the time trend might capture any unobserved factors that change over time. Thus, one should be cautious when interpreting the estimated coefficient. Many of these studies have found the time trend to be insignificant and hence excluded it from their final specification (see for example Rushdi, 1986), while a few others such as Nan and Murry (1992) found that coefficient to be significant.

Previous studies[5] provide strong evidence that the level of analysis has important implications for the accuracy of elasticity estimates. The majority of studies that have investigated geographical-based differences in elasticities (e.g. Murray et al., 1978; Uri, 1975; Maddigan et al., 1983) did indeed find that elasticities vary between different areas. These differences are likely the result of variation in (1) the relative costs of substitutes and (2) the value of energy uses from one region to another. Prices of electricity and natural gas and hence the cost of substitutes vary throughout the country (Bernstein and Griffin, 2006). This could be the result of the availability of specific fuels or due to local energy policies. Many states, including Colorado for example, have programs to subsidize adoption of energy-efficient technologies, which also create geographic differences in the cost of a substitute to electricity and natural gas.

The second factor that gives rise to a significant degree of inter-regional heterogeneity is weather which affects space conditioning requirements (Uri, 1983). Locations where particular energy uses are very valuable, such as air conditioning in southern states or winter heating in northern states could have lower price elasticities than states with moderate weather, ceteris paribus. This is because air conditioning and heating are so valuable during periods of extreme weather that consumers are somewhat limited in their options to respond to price changes; the most evident option in the case of an own-price variation being an adjustment in the thermostat setting. Again, both of these driving factors, the cost of substitutes and value of energy uses, vary geographically, which suggests price elasticities probably differ across the country (Bernstein and Griffin, 2006).

One of the earliest studies to investigate regional differences in demand behavior was Fisher and Kaysen (1962) who conclude that “there are substantial differences in behavior in different regions of the country which must be taken into account in any explanation of demand.” Houthakker et al. (1974) estimated price elasticities for residential electricity and found that elasticities varied across states. They go on to say that an analysis based on nationwide time series, which had become the standard approach to demand analysis, cannot do justice to the regional variation and is unsatisfactory to that extent. Likewise, Maddala et al. (1997) estimated price elasticities in 49 U.S. states (excluding Hawaii) and found variation across states. Bernstein

[5] Studies surveyed in this section include electricity demand studies.

and Griffin (2006) examine the effects of different levels of data aggregation (national, regional, state, and utility) on the relationship between demand and price. They conclude that there are significant differences in the price-demand relationship between different regions and states especially in the residential sector. These results are in line with those of Chern and Just (1980) who also estimate demand at the national, regional, and state level, and conclude that price elasticities vary significantly among regions. Hence, they conclude that forecasts at the national level should not be used as the basis for making energy policies at the regional or state level.

Furthermore, in his study of 27 investor-owned utilities, Smith (1980) concludes that state-wide aggregates of elasticity may often be inapplicable to individual utilities. Also, Shin (1983) using data from seven Ohio utilities concludes, based on statistical testing, that there exist regional differences among consumers of each utility. Evidently, results from studies based on local data better reflect the particular characteristics of the localities under study (Snyder, 1979). In spite of these conclusions, most studies do not examine energy demand at the utility level (for exceptions see Murray et al., 1978; Smith, 1980; Shin, 1983; Joutz and Trost, 2007).

Of more immediate relevance to this paper, only two published studies estimate time-varying residential natural gas demand elasticities for Colorado (see Table 2).[6] Bernstein and Griffin's estimates are not significantly different from zero in the short run or in the long run. Maddala et al. (1997) obtain two different significant estimates for the SR, -0.101 and -0.312, using two different estimation methods. For the LR they do not report their standard errors, so we cannot evaluate the estimates or compare them to others. The divergence of results in the SR and the lack of reliable estimates in the LR (due to the omission of standard errors) suggest that additional work needs to be done in an effort to obtain more accurate elasticity estimates for Colorado.

[insert table 2]

3. Demand Model

The use of a static specification to model demand is not recommended because it is unclear whether such a model produces short-run elasticities, long-run elasticities, or something in between. In any case, only one set of elasticities can be estimated from such a model unlike the dynamic model. The latter model is based on the idea that the response of consumers to a

[6] Elasticity estimates from static models have not been included in Table 2.

change in income or prices is generally spread out over time in such a way that complete adjustment often takes years, and it is therefore useful to distinguish between short-run and long-run elasticities (Houthakker et al., 1974).

Typically, the short-run elasticity is less than the long-run elasticity (in absolute value) because of the time needed for complete adjustment (see Varian, 1992). Consequently, the short-run demand study is an examination of the factors that influence the levels of use of an existing stock of durable equipment, and the long-run demand study is an examination of the same factors in addition to the factors that influence the rate of change of that stock of equipment (Fisher and Kaysen, 1962). The use of energy in a given period depends on the use of a stock of energy-using equipment owned in that period, which is a function of economic and other conditions prevailing not only in the current year but also in preceding years (Westley, 1992). Further, consumers are limited in their ability to respond immediately to a change in one of the determinants of demand, and hence there exists a time dimension to consumption behavior (Bohi, 1981).

To capture these two different response types prior research distinguishes between SR and LR price elasticities. SR elasticities are estimated as the response to a price adjustment in the time period in which the adjustment occurs. LR elasticities are estimated as the total response to a price adjustment, i.e., the long run being defined in general as the time needed to achieve stability after a system shock has occurred (Donnelly, 1987). While estimating the SR response is relatively straightforward, estimating the LR response is more complicated and requires a more sophisticated model.

The most commonly used dynamic models are the partial adjustment and the distributed lag models. A major limitation of prior modeling approaches is they only consider at most two points (SR and LR) to characterize the dynamic price-demand relationship. In other words, only the SR and LR elasticities are estimated; other elasticities can be computed (although very few studies actually do that) but they are based on the specific adjustment path imposed by the model. This, unfortunately, ignores the intertemporal nature of the relationship and masks a number of important attributes, such as, how long does it take to reach demand stability after a price adjustment has occurred. Explicating the full temporal response represented by the dynamic elasticities requires generating the consumption response function to a permanent price change based on the estimated model.

Another limitation of these modeling approaches is that they impose restrictions on the relationship between demand and its determinants. For example, in the partial adjustment model all short-run to long-run elasticity ratios (that includes price, income, and other demand elasticities) are forced to be equal (Cuddington and Dagher, 2008). To avoid these restrictions, recent research (e.g. Fatai et al., 2003; Bentzen and Engsted, 2001) uses a more general model: the Auto Regressive Distributed Lag (ADL) model—which allows a full set of current and lagged variables to enter the equation—to model the dynamics of energy demand. The ADL $(m,n,p_1,p_2,\ldots)$[7] presented in Equation 1 is a very general and flexible dynamic model that is not subject to many of the restrictions on the dynamic relationship between demand and its determinants inherent in other models. It is easy to show that the ADL nests two of the most commonly used theory-based models, the Partial Adjustment Model and the Distributed Lag Model, as well as the newer Error Correction (EC) Model. See Baltagi (2008), Charemza and Deadman (1997), or Cuddington and Dagher (2008) for a complete derivation. This study builds on the ADL model and using a stochastic simulation approach we are able to obtain estimates of the dynamic elasticities.

$$Q_t = \alpha + \sum_{j=1}^{m} \beta_{0,j} Q_{t-j} + \sum_{k=0}^{n} \beta_{1,k} P_{t-k} + \sum_{l=0}^{p_q} \sum_{q=2}^{r} \beta_{q,l} V_{q,t-l} + \varepsilon_t \qquad \text{Equation 1}$$

where Q is the logarithm of the quantity of energy consumed, P is the logarithm of the real price of fuel studied, V is a vector of explanatory variables that includes the logarithm of real income, logarithms of real prices of related fuels and goods, and other relevant variables.[8] j, k, and l represent time lags and m, n, and p represent the number of lags for each of the corresponding variables.

Although there is no universal agreement as to what the determinants of natural gas demand are, the most commonly used ones in the literature include: own price, price of related products, as well as measures of income, demographics, weather, seasonal effects, and technological change . Based on both theoretical and empirical considerations, the demand for natural gas in the present study is posited to be a function of the following variables: real price of

[7] In the notation ADL (m,n,p,…) m refers to the number of lags of the first variable, n refers to the number of lags of the second variable and so on.
[8] The vector V includes price and non-price variables that have been theoretically and empirically found to be important determinants of the quantity of energy consumed. r-1 represents the number of variables in vector V.

natural gas (P_g), real price of electricity (P_e), real Colorado personal income (Y), heating degree days (HDD), and monthly dummies (M(i)).[9,10]

$$
\begin{aligned}
Q_{g,t} &= \alpha + \sum_{j=1}^{m} \beta_{0,j} Q_{g,t-j} + \sum_{k=1}^{n} \beta_{1,k} P_{g,t-k} + \sum_{l=1}^{p_2} \beta_{2,l} P_{e,t-l} + \sum_{l=0}^{p_3} \beta_{3,l} Y_{t-l} + \sum_{l=0}^{p_4} \beta_{4,l} HDD_{t-l} \\
&+ \beta_5 M1_t + \beta_6 M2_t + \beta_7 M3_t + \beta_8 M5_t + \beta_9 M6_t + \beta_{10} M7_t + \beta_{11} M8_t + \beta_{12} M9_t \qquad \text{Equation 2} \\
&+ \beta_{13} M10_t + \beta_{14} M11_t + \beta_{15} M12_t
\end{aligned}
$$

Nearly all studies so far have used the contemporaneous price variable in their demand equation. Although this raises concerns regarding the endogeneity of such a variable and whether single equation estimation by OLS would still be valid, these researchers have argued that in the case of gas, independent estimation of the single demand equation is justified. See Berndt and Watkins (1977) for a discussion of such arguments. In practice, however, the vast majority of energy users only learn of any price increase or decrease in any given month during the following month, when they receive their bill. Very few households invest the time and effort needed to track price changes as they are approved by the public utilities commission. It follows that, when using monthly data, the correct explanatory price variable to use would be the one-period lagged price variable (Joutz and Trost, 2007; Munley et al., 1990). In that case, the endogeneity issue becomes irrelevant.

4. Data

The ADL model of Equation 2 will be fitted to time-series monthly data at the utility level (Xcel Energy service area in Colorado), which provide more resolution than other more aggregated levels of data. A higher frequency of observations should allow greater resolution in determining the time response of the model in particular. Data for the period January 1994 to September 2006 (156 observations) were provided by Xcel Energy . If we had available similar data sets for the other states, we could have pooled the cross-sectional and time-series dimensions together and performed the analysis.[11]

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[9] A saturation/efficiency index developed by Itron for Xcel Energy was used in preliminary testing as a proxy for technological change but was not found to be helpful in explaining natural gas demand.
[10] The April dummy was randomly chosen to be omitted from the equation to avoid perfect multicollinearity.
[11] Data sets that have both cross-sectional and time series dimensions are being used more frequently in empirical research (Wooldridge, 2009). Such an analysis has several advantages and disadvantages that are worth

Following is a more detailed explanation of each of the variables that will be used in the regression. Figure 1 plots the complete time series data. Note that the variables that have been used in the following regressions have all been logged with the exception of heating degree days (HDD), due to the existence of several zero observations in the HDD time series. Also, the quantity and income variables have been normalized by the number of customers. All price and income series were deflated by the Colorado CPI.

Quantity

The dependent variable for natural gas use is the per household number of therms consumed during a month.

Price of Natural Gas

All Xcel Energy residential customers in Colorado face a single flat rate (R), and hence marginal and average prices are equal. As noted in the previous section, the price variable used is the one-period lagged price of natural gas. To be consistent with economic theory, the coefficient on the own price should be negative; as price rises demand for natural gas is expected to fall.

Price of Electricity

About three-fourths of Colorado households use natural gas as their primary energy source for home heating, one of the highest shares in the nation. Most of the remaining households—about one-fifth of Colorado households—rely on electricity for heating (EIA, 2007). Hence, electricity could be considered the single most important substitute for natural gas. Similarly to the above variable, the price variable used is the one-period lagged price of electricity. As can be seen from Figure 1, the electricity price series is unique in that it captures two price regimes; an increasing price regime in the first half of the study period and a decreasing price regime in the latter half of the study period. A priori, the coefficient on the price of a substitute is expected to be positive, and the coefficient on the price of a complement is expected to be negative. For example as the price of electricity rises, ceteris paribus, some

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mentioning here. Essentially, it would benefit from a richer data set with an increased variation across variables of interest such as price and income (Baltagi and Griffin, 2006). Moreover, more efficient estimates can be obtained due to reduced multicollinearity among variables and more degrees of freedom (Hsiao and Yanan, 2006). However, the major limitation is data collection or data availability which is the case in the present study. Another limitation is that the estimates will be less location specific. For example, some states will have different determinants of demand such as the use of a humidity index in states that suffer from high humidity.

consumers will switch away from electricity towards natural gas. Thus, the consumption of natural gas also rises.

Income

Colorado personal income, deemed an appropriate measure of income for a residential study, was converted from a quarterly to a monthly frequency using the quadratic match average conversion tool. Although, state and utility service area boundaries in Colorado do not exactly coincide, state variables are still appropriate in this analysis because the service area is spread across the whole state. Because energy is a normal good, increased consumption is closely linked to rising income (Uri, 1983), and thus the coefficient on income is expected to be positive. The two series, income and the number of consumers, are frequently found to be very highly correlated (in our case 0.98) such that the standard errors become enormous if they were both included as explanatory variables. This finding has been documented by various researchers including Uri (1975). To avoid this complication, we excluded the number of consumers as a regressor, but used it to transform the income and quantity variables into per-customer values.

Weather

Variations in weather effects are represented by regional heating degree days (HDD). One HDD is recorded for each degree that the mean daily temperature—the average of the day's minimum and maximum temperatures—is below the base level of $65°$ F. Weather is included because it directly affects the use of heating during the winter. A priori, the coefficient on the weather variable is expected to be positive; as it gets colder more energy is consumed.

Seasonality

In the present study, monthly binary variables will be used to account for the month-to-month variations in natural gas consumption that are not picked up by HDD, such as variations that are due to the influx of tourists during the skiing season.

[insert figure 1]

5. Methodology

Unit root testing on all variables was performed using the Augmented Dickey Fuller (ADF) test following the Dolado et al. (1990) approach. For more details on this procedure see Dolado et al. (1990) or Enders (1995). With the exception of natural gas per-customer consumption (Q_g), for which we could not reject the null hypothesis of a unit root, all other series were found to be stationary or I(0). However, further testing based on Dolado et al. (1990) and Dickey at al. (1986) showed that the source of the non-stationarity of the Q_g variable was the seasonality and not the existence of a unit root. Hence, the inclusion of the seasonal monthly dummies in the regression should be enough to address the existing non-stationarity.

To determine the best ADL model specification a grid search program,[12] implemented in Eviews and capable of handling hundreds of thousands of different lag specifications, was used. We consider up to 12 lags for Q_g, 6 lags for P_e, P_g, and Y, and 2 lags for HDD, which is expected to have a short-run influence only, and consequently not to affect demand several periods away. The best specification (most appropriate number of lags for each variable) is chosen based on the Schwarz Criterion (SC), which is known to be consistent so that as the sample size grows, SC tends to pick the true model if this model is among the choices (Kennedy, 2003). After selecting the regression specification with the optimal SC, we then perform residual diagnostics to make sure that we have spherical, normal residuals, rendering hypothesis testing valid.[13] The temporal stability of the model was investigated by checking for model as well as individual parameter stability using the recursive coefficient estimates and by examining the CUSUM plot. Given the low power of the CUSUM test (Kramer et al., 1988; Andrews, 1993), the Quandt Likelihood Ratio (QLR) test, also known as the Quandt-Andrews (QA) test, was also used. Since only lagged prices appear in the model due to the nature of the billing system, endogeneity does not pose a problem in our case. The sensitivity of all estimates to several key assumptions was assessed and the results were found to be robust. This analysis investigated the extent of the impact on the results due to changes in the frequency of the data, the sample period, and the lag selection methodology.

Based on the final selected ADL specification, the coefficient estimates from the ADL can be used to calculate the dynamic elasticities by applying a permanent 1% increase to the price (or income). Next, a stochastic simulation is carried out that compares consumption in both models (before and after the shock) and illustrates the dynamic effects of a permanent price (or income) increase on consumption. The output function provides information on how quantity changes over time in response to this change. In addition, confidence intervals are constructed

[12] See Cuddington and Dagher (2008) for the program code.
[13] It is important to recognize here that specifications with a large number of estimated parameters, reduce the degrees of freedom raising questions about the validity of theorems on the asymptotic distributions of test statistics.

around each of the dynamic elasticity estimates so that definitive conclusions about the precision of estimates of how consumers respond over the long run are possible.

6. Empirical Results and Discussion

The OLS estimates of the final preferred specification ADL(2,1,1,0,1) for the residential natural gas sector are presented in Table 3 ($\bar{R}^2 = 0.99$). Consistent with economic theory, the coefficient on the own price variable is negative and significant; as real price rises by 1%, quantity demanded in the following month will fall by 0.09%. The electricity cross-price elasticity is positive and significant indicating that consumers treat electricity and natural gas as substitutes; as the real price of electricity rises by 1%, the quantity of natural gas demanded will rise by 0.15%. Interestingly, quantity demanded appears to be more sensitive to changes in the price of electricity than to changes in the price of natural gas. However, further investigation reveals that the two coefficients are not statistically different from each other based on a Wald test. The estimated income elasticity is positive yet not significantly different from zero, reflecting the insensitivity of natural gas consumption at the residential level to changes in income. This result is consistent with natural gas being a necessity given that its predominant end-use is space heating (Berndt and Watkins, 1977). However, it could also be that the frequency conversion applied to this variable has made it difficult to accurately estimate its coefficient. The coefficient of HDD cannot be interpreted as an elasticity, rather it is the percentage change in consumption for one additional degree day. Thus, in the short-run an additional degree-day in a given month would raise consumption by 0.0013%. Looking at the standard error, one can see that this coefficient has been estimated with very high precision. The monthly dummies' coefficients suggest that consumption in October, November, December, and January is significantly higher than consumption in April, our base month, while consumption in May, June, and July is significantly lower than consumption in April. For the remaining months it is not statistically different from that of April. The percentage change in consumption due to a specific month, say January (β_j), can be calculated as $e^{\beta_j} - 1$ (Halvorsen and Palmquist, 1980).

[insert table 3]

Prior to this study, there exist only two sets of estimates for the residential natural gas price elasticity in Colorado (see Table 2); Bernstein and Griffin's (2006) estimates were insignificant both in the short and long run, while Maddala et al. (1997) obtain a range of two estimates, -0.101 and -0.312, in the SR. Our estimate is more inelastic in the SR, but cannot be compared to their LR values since their standard errors are missing. Although natural gas price elasticities are expected to be fairly inelastic because natural gas is consumed for basic services such as space and water heating, the present results provide clear evidence that the residential sector demand is much more inelastic than has been found in the literature at the national level. Some of the potential reasons behind the high inelasticity are detailed next.

Given the low energy expenditures per capita (rank 5 in lowest energy expenditures as of 2007 according to EIA) and the above average income per capita (rank 15 in personal income as of 2007 according to the BEA) relative to the rest of the states, one would expect Colorado consumers to be less responsive to price changes than consumers in most other states. Consistent with this hypothesis, Snyder (1979) found his own-price elasticity of electricity demand in Colorado to be relatively lower than his national estimates.

More recently, Kim (2004) examined whether combined-billed residential households of electricity and natural gas utilities (such as in this case) face information costs associated with determining the portion of their monthly energy bill attributed to natural gas consumption and the portion attributed to electricity consumption. He found electricity and natural gas demand to be more inelastic in such markets compared to separate-billed markets, an indication of the presence of information costs. This finding has important implications for both combined-bill utilities and their customers. Empirically, only one study (Snyder, 1979) compares Colorado price elasticity estimates to the national estimates using exactly the same model and estimation approach and finds them to be consistent with these expectations.

There is evidence from the electricity sector that monthly data produce more elastic estimates compared to annual (Espey and Espey, 2004), probably because the model would be able to pick up more subtle changes with monthly data than would be possible with annual data. The same reasoning should apply to the natural gas sector because the argument on which it rests is not sector specific, and hence the price inelasticity cannot be attributed to the use of monthly data. For the income elasticity the differences between annual and monthly data were not statistically different for either the SR or the LR cases (Espey and Espey, 2004).

Also consistent with our results, Bohi (1981) found that the price elasticities for electricity derived from disaggregate level data are smaller in absolute value than those derived from aggregate level data. Similarly, McClung (1988) concludes that elasticities estimated using microdata are uniformly and significantly smaller than those from the aggregate studies when using static models. Also, Espey and Espey (2004) in their meta-analysis of residential electricity studies conclude that the use of regional as opposed to aggregate U.S. data tends to produce less elastic SR price and LR income estimates.[14]

Moreover, a few researchers have pointed out the importance of the time period under study regarding its impact on the estimated elasticities. For example Dahl (1993) in her survey of energy demand studies notes that elasticities in recent studies after 1980 tend to be smaller in absolute value than those from earlier studies. Espey and Espey's (2004) meta-analysis results on residential electricity studies find that residential demand has grown more inelastic since the energy crises. They suggest that with time consumers are becoming less price elastic as electricity is becoming more of a necessity for both urban and rural customers. In addition, more and more electrical appliances such as air conditioners have become a part of daily life and consumers are increasingly relying on them. Similarly, as income rises and electricity becomes a smaller portion of total expenses, income elasticities are expected to decrease. Other factors contributing to the decreasing income elasticity are: (1) electrical appliances have saturated the residential market, (2) very few new appliances are being introduced to the market, and (3) replacement appliances are likely to be more energy efficient (Espey, 1998). All three noted factors, to a certain extent, apply to natural gas space and water heating equipment.

It is important to note here that the third point listed above has further implications than those related to the income elasticity. An energy-efficient improvement lowers the marginal cost of the end-use service leading to an increase in consumption, which in some cases can outweigh the initial reduction in consumption due to the efficiency improvement (EIA, 2003). This effect is known as the rebound effect. Khazzoom (1980) suggests that the price elasticity of energy demand be used as a proxy for the rebound effect. The above-reported price elasticities include the direct rebound effect during the time period considered since they are based on actual data. For a survey of studies on the rebound effect, see Greening et al. (2000) who conclude that the range of estimates for the size of the rebound effect is very low to moderate.

Figures 2a, 2b, and 2c trace the temporal path of the dynamic price and income elasticities obtained by shocking the system with a permanent price or income increase, where

[14] The cited analysis controls for the specification of electricity demand, the nature of the data, time and location of the study, and the estimation technique.

the two dashed lines represent the 95% confidence bands. One of the advantages of the dynamic elasticities graphs is that one can easily detect the complete estimated dynamics of the system in each and every period. From the generated graphs one can easily follow the elasticity path and determine how long it takes to get to the long run. The own-price elasticity, depicted in Figure 2a, starts at -0.091 (SE=0.026) and reaches -0.237 (SE=0.063) at the end of the period. Interestingly, the figure indicates that the system completely stabilizes around 18 months[15] after it has been shocked by a price change. The short run and long-run elasticities are identical to the ones reported in table 3 where the long-run price elasticity has been calculated in the traditional way. The cross-price elasticity, depicted in Figure 2b, starts at 0.153 (SE=0.056) and reaches 0.398 (SE=0.142) at the end of the period. Again, the long-run equilibrium is reached around 18 months after the price change is applied. As can be seen from Figure 2c, the income elasticity is not significantly different from zero.

[insert figures 2a, 2b, and 2c]

The results of the simulation imply a much shorter time period than expected for the long-run adjustments to complete. This is probably due to the limited month-to-month price variations in the data set during the period being studied. Changes of less than 1% might not be perceived by the consumer, and even if they are there is relatively little incentive to change the use or stock of energy-using equipment (Westley, 1992). Furthermore, consumers may have already adjusted their equipment stock to previous price shocks.

Analysts and policy-makers are always faced with the question of how to define the short run and the long run and consequently which set of elasticities to use. The use of dynamic elasticities eliminates this confusion by providing a clear picture of the adjustment path over time, and hence utilities and regulatory agencies will not have to restrict themselves to short-run or long-run changes. Knowing consumers' response over time enables one to answer a number of questions, such as, how long does it take to reach demand stability. In reviewing existing dynamic models, Bohi (1981) notes that dynamics cannot be adequately reflected in any model that strictly separates single-period from infinite-period adjustments especially when decisions are made continuously through all periods, and that it would be preferable to have a model that is

[15] Note that this observation is based on the examination of the third decimal number. The time to reach equilibrium is 12 months if one looks at the second decimal number instead.

capable of describing the path that adjustments might take over time. The dynamic elasticity approach is unique in that it fully captures the temporal nature of energy demand.

7. Conclusions and Implications

Based on the very general Autoregressive Distributed Lag model we estimate the residential natural gas demand elasticities at the utility level in Colorado using monthly data spanning the period January 1994 to September 2006. Price and income were found to be much more inelastic—even in the long run—than what has been commonly suggested in the literature, although most of the existing estimates are at the national level. Driving factors behind this demand insensitivity to changes in price and income include the following.

Natural gas demand in Colorado is expected to be less price elastic compared to other states due to the combination of low energy expenditures per capita and higher income per capita relative to the rest of the states. Also, there is evidence in the literature that data disaggregation produces lower (in absolute value) price elasticities (Bohi, 1981; McClung, 1988; Espey and Espey, 2004). Kim (2004) found that electricity and natural gas demand are more price inelastic in combined-billed markets, which is the case for Xcel Energy in Colorado. Hence, it is expected that price elasticity estimates for Xcel Energy in Colorado will be lower relatively to other states and to national estimates.

The present findings seem to be in agreement with the hypothesis that combined-billed markets are more price inelastic than individually-billed markets (Kim, 2004). Such a result has important policy implications for dual-product utilities, which have been on the rise driven by a growing preference among customers for energy suppliers that can provide more diversified energy services (Kim, 2004). First, this means that such utilities must be very careful when using "borrowed" price elasticity estimates and adjust the available estimates in accordance with the above findings. Second, it is clearly implied that for such utilities it will be harder to control consumption via price changes or by adding surcharges relative to single-product utilities.

Interestingly, we find that the long run equilibrium is reached relatively quickly around 18 months after the change, while the literature implies a minimum period of ten years for the long-run or complete adjustments to take place (Bohi, 1981). These results indicate that most of the adjustment to any price change takes place in the short run (changing the usage of existing equipment) rather than the long run where changes in the stock of equipment usually happen.

This could be because the vast majority of price changes in the data set during the period being studied are less than 1% from month to month. It has been suggested that such small changes might not be perceived by the consumer, and even if they are there is relatively little incentive to change the use or stock of energy-using equipment (Westley, 1992). Bigger price changes could be expected to induce more changes in the stock of durable equipment, which naturally take longer to accomplish. With more severe price changes, the consumers might react differently especially as electricity and natural gas expenditures become a more substantive portion of the consumer's budget.

Analysts and policy-makers are always faced with the question of how to define the short run and the long run and consequently which set of elasticities to use. The use of dynamic elasticities eliminates this confusion by providing a clear picture of the adjustment path over time, and hence utilities, regulatory agencies, and policymakers will not have to restrict themselves to the mere examination of short-run versus long-run changes. In practice, the proposed dynamic elasticity approach presented is expected to be a useful means of capturing adjustments over time and greatly simplifies the choice of elasticity to be employed in a particular analysis. In such a case, the end-user is no more restricted to a short-run versus a long-run analysis, as was the case previously.

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