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Abstract

In this paper we present an analysis of the demand for residential electricity of the U.S. mountain region. The objective is to develop two simulations analyzing how changes in electricity prices and warmer weather affect electricity consumption and greenhouse gas emissions. Electricity demand is modeled as a function of the price of electricity, real personal income, number of households, weather as a function of heating and cooling days, and the price of natural gas. A general-to-specific approach is used to develop congruent models. We are able to estimate an equilibrium correction model capturing long run electricity demand and short run or seasonal responses. We find that in the long-run, income elasticity is positive and inelastic, own-price elasticity is negative and inelastic, and cross-price elasticity is positive and inelastic. In the short-run, all price and income elasticities are perfectly inelastic and the only effects on demand for electricity are weather variables.

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1. Introduction

We analyze residential electricity demand for the Mountain Region of the U.S. The region has experienced significant economic and demographic growth since 1990. There have been structural changes as a result of population growth and electricity deregulation. In addition, there has been growing access to natural gas for residential consumers.

We have two goals in the paper. The first is to estimate an equilibrium correction model of electricity demand. This enables us to explain short run and long run dynamics simultaneously. The estimates are used to perform two simulations. The first examines the impact of a 10% increase in the electricity price on consumption and resulting greenhouse emissions. The second simulation addresses the effect of an ambient temperature increase of two degrees Fahrenheit on cooling needs, electricity consumption, and greenhouse gas emissions. The simulations use the price and weather elasticities to examine the effects on consumption and emissions projections in EIA's Annual Energy Outlook for 2011.

We develop a long-run model using cointegration techniques. Its properties include: white noise residuals, stable, consistent with economic intuition, explains previous results. The long-run relationship yields a negative and inelastic own price elasticity, positive income elasticity, and cross price elasticity with natural gas that is positive, but not linear homogenous. Next, we develop an error correction model incorporating the results of cointegration. The short-run relationship shows that weather effects are the main determinates of electricity demand.

Our paper is organized as follows. The next section presents a literature review of energy demand studies. Section three provides an overview of the formation of the general models used in energy demand. The fourth section provides an overview of the data used in the estimation of the model. The fifth section reviews the econometric issues and testing procedures used in cointegration and ECM, presenting and evaluating the results of the paper. Section six describes and reports the results from the simulations. The seventh section offers conclusions.

2. Literature Review

Electricity demand studies have been used for numerous reasons over the past four decades. Dahl (1993) suggests that the demand for energy and energy products have been studied more than any other good or factor. The importance of these studies hinges on extrapolating precise economic information such as price and income elasticities. These elasticities illustrate the impact of economic activity and energy prices on energy demand. This information can then be used to make difficult decisions in policy or even provide forecasts of future electricity demand, which would allow for planning. Erdogdu (2007) discusses how energy demand studies initially used two different approaches to modeling: the first being the "reduced form model" and the second being the "structural form model". Dahl defines it in more detail, starting with reduced form equations.

Reduced form modeling typically consists of double-log linear demand estimation in which energy demand is assumed to be a direct linear function of energy price and real income. Numerous studies have incorporated this technique due to the relative ease of the assumptions, application of econometric analysis, and availability of data (Dahl 1993, pgs. 24-55). It assumes the independent variables are exogenous. Understanding economic theory might suggest that this assumption is not accurate and that these variables are jointly determined. Therefore, this type of modeling might lead to biased estimates. To correct for this bias, researchers developed the structural form approach.

Structural form modeling allows for some variables to be endogenous. Given that some variables are endogenous, a system of equations must be estimated. This requires estimation of numerous indirect energy demand equations as functions of energy prices and demands and real income. Pindyck (1979) used the structural form model and gave a detailed treatment. The obvious difficulty of such models is the process by which data, variables, and equations must be assembled for estimation. This hurdle explains the prevalence of reduced form models in the literature. The above models have been used extensively and have taken on various forms to reduce bias and improve efficiency in the estimators. Simultaneous equations models, IV estimation, GMM estimation, fixed and random effects are examples of the various forms of modeling used. In order to produce unbiased estimates from these modeling techniques a strict assumption must hold, these models must assume that the data is stationary.

The assumption of stationary data for electricity price and demand series is often unrealistic. The use of non-stationary data forfeits any use of these previous techniques on statistical merit alone. Engle and Granger (1987) initially developed the technique of cointegration and error correction methods. This process allows for non-stationary data to become stationary through a process of integration and cointegration, verified through numerous tests. Once stationary, this data can be analyzed in the levels and differences to produce statistically unbiased models that are able to evaluate long-run or equilibrium elasticities as well as short-run elasticities. The analysis of cointegration was expanded to a system or multivariate framework by Johansen (1988) and explained by Hendry and Juselius (2000, 2001) in this journal.

Cointegration is becoming a more visible technique in electricity demand; see for example Erdogdu (2007), Holtedahl and Joutz (2004), and Joutz and Silk (1997). Cointegration analysis begins with a reduced form model and then tests for the existence of "structural" relationships.

Over the years numerous prices and income elasticities have been reported from electricity demand estimation (Dahl, 1993, 2002, 2011). Espey and Espey (2004) gathered price and income elasticities from 36 peer reviewed studies published between 1971 and 2000. These elasticities have covered different time periods and different parts of the world. In addition, the elasticities are estimated using various estimation techniques, most prominently, reduced form estimations, running OLS (Costello, 2006). They report that short-run price elasticities in the literature range from 0.076 to -2.01 and in the long-run they range from -0.07 to -2.5. They find short-run income elasticities ranging from 0.04 to 3.48 and long-run elasticities of 0.02 to 5.74. In addition, the average U.S. regional price and income elasticities are, in the short run, -0.64 and 0.50, respectively and in the long run, -0.74 and 0.75, respectively. These may be on the high side and possibly due to the limited use of cointegration when the surveys were conducted. The authors only report a single long-run price elasticity of -0.10, which falls into category of "other lag". What becomes apparent is that the reported variation in elasticities is large and the use of cointegration and error correction modeling is still evolving.

3. Formulation of a General Model

The most basic residential electricity consumption function is a static reduced form function, modeling electricity demand as a function of economic factors, X_t, and the stock of electrical equipment, K_t.

$$kWh_t = F\left(X_t, K_t\left(X_t\right)\right) \tag{1}$$

Short-run demand for electricity will fix the stock of electricity-using appliances and only allow demand to fluctuate as utilization of these fixed appliances fluctuates. Long-run demand for electricity allows for the stock of electricity-using appliances to fluctuate as well as the utilization rates. This allows for changes in relative prices and income.

The capital stock of energy-using appliances can be thought of as two unique types. The first represents demand for daily energy use such as lighting, refrigeration, cleaning and entertainment. The second represents the seasonal weather needs for the amount of air conditioning and heating required.

The general model for residential electricity demand will be formulated accordingly:

$$kWh/HH = f\,(P\ Elec/kWh,\ Income,\ P\ Natural\ Gas/Therm,\ Weather,\ Budget\ Share) \qquad (2)$$

where *kWh/HH* is the dependent variable and represents residential demand for electricity in kilowatt-hours per day. *P Elec/kWh* represents the price of electricity per kilowatt hour. Income represents real disposable income. The price of natural gas represents a substitute for electricity. Weather effects capture the heating and cooling degree days that drive electricity usage. Budget share takes into account the relative share of income spent on the consumption of electricity.

For this analysis, we assumed the demand for electricity is a normal good; therefore, the elasticity for the price of electricity is expected to be negative. The elasticity also is expected to be inelastic for both the long-run and short-run. Because it is assumed that the stock of electric appliances are fixed in the short-run, short-run elasticity should be more inelastic than the long-run elasticity. The elasticity for income is expected to be positive. and more inelastic in the short run than the long run. Since, the price of natural gas will proxy as a substitute, we would expect the sign to be positively related to demand for electricity, as the price of natural gas increases consumers should shift away from natural gas consumption, increasing demand for electricity. Price homogeneity can be tested. We understand that this interpretation may be confounded since natural gas is used in electricity generation. Therefore, the results might be ambiguous for natural gas. The weather variables are comprised of heating-degree and cooling-degree days. We assume that both should have a positive relation to electricity demand, as the days are warmer or cooler, increased usage of air conditioning or heating should result in higher demand for electricity. In the short-run, as the share of income used for electricity consumption increases, we expect to see decreased consumption of electricity.

4. Data: Sources and Description

We obtained the data from the Short Term Energy Outlook Tables (STEO) available from the website of the Energy Information Administration of the U.S. Department of Energy (2010). We specifically took data that applied to the mountain region and the residential sector of the U.S. We considered using state level data, but decided not to because our ultimate objective is to use the modeling in conjunction with the National Energy Modeling System (NEMS) which only reports data at the regional level. Table 1 provides the descriptive statistics. The sample is from January 1992 through January 2011.

Electricity demand is measured in million kilowatt-hours per day; we convert this to consumption per household per day. The quantity of electricity demanded in figure 1 shows a strong seasonal pattern with two spikes per year, in the summer and winter. There appears to be a general increase in electricity demand over the sample period. Total electricity grew by about 3.35% per annum and per household it grew a little more than one percent. The number of households, Figure 2, a reasonable proxy for customers grew from 64 million to 95 million, about 2.2% per annum. From 1992 to 2000, the seasonal summer and winter fluctuations are about the same for total consumption. On a per household basis through the summer peaks are increasing. From 2000 onward, the summer spikes increase absolutely and relatively and on a per household basis. Total consumption rose 4.25%, 5%, and 4.25% for June, July, and August respectively. Per household the growth rates were 2%, 2.7%, and 2% for the same months. The annual growth rates in January and February were only 0.4%. The growth and change in seasonal composition can be attributed to three main factors. First population growth and emigration into the Southwest (portion of the Mountain region) contributed to both effects. Second, there was greater penetration of air conditioning equipment into residences for this period. Third, natural gas access and hookups increased in the region. Natural gas is used predominantly in the winter months; about 45% of annual consumption occurs between December and February and usage in these months grew relative to overall natural gas consumption. EIA's Residential Energy Consumption Surveys over this period document these different effects.

Real personal income per household is measured in billions chained to 2005 dollars. The data is provided on a seasonally adjusted annual rate. In Figure 3 there is a strong trend up through 2000. Household income grew by over 25% to over $75,000 in the initial period. Then it declined for several years during the recession and mortgage crisis before increasing again. Household income was $85,000 by the end of 2007 and declined back to $80,000 by 2010.

Figure 4 provides a comparison of household electricity consumption and income. The two series are normalized to unity in 1992. Consumption grew about 20% over the 18 years while income rose by about 33%. Thus, the income elasticity will be less than unity.

The price of electricity is measured in cents per kilowatt-hour. In Figure 5, both nominal and real prices are given. The nominal prices were deflated[1] using the price index for personal consumption expenditures by major type of product, monthly (BEA, 2010). Nominal prices were relatively flat, 7.5 cents per kWh between 1991 to 2000. They increase steadily until 2010

[1] Prices were originally deflated using the general price index. Given the consistent result of positive own-price elasticity from this series, which does not hold up to any economic theory, a new deflator was used. The new deflator was the price index for personal consumption using the energy goods and services index.

when they are about 10 cents per kWh. In real terms prices were their highest 10 cents per kWh between 1992 through 1995, then they decline until 2000 and then start rising again and reaching about 9-9.5 cents per kWh in 2010. Consumers faced several real price "regimes" over the sample.

Figure 6 plots the real residential electricity and natural gas prices. Real monthly natural gas prices are measured in dollars per thousand cubic feet (tcf). The nominal prices are deflated in the same manner as real electricity prices using the price index for personal consumption expenditure from the Bureau of Economic Analysis. The patterns over time reveal interesting relative price movements. In the 1990s real natural gas prices were fairly flat, while electricity prices were falling. Starting in 2000 they rose from $6/tcf to nearly $14/tcf in 2006 then begin to decline. Electricity prices were rising during this same time but not as quickly. In 2008-10 electricity prices appear to rise relative natural gas prices.

Heating and cooling degree-days are computed as the number of days in a month the mean temperature falls below 65 °F and exceeds 72 °F, respectively. They are collected by NOAA and population weighted. We calculate the deviations from the 30-year averages of heating and cooling degree-days. This helps to capture strong weather effects. These series are plotted in Figure 7. There appear to be greater deviations in cooling degree days since 2000 and relatively more heating degree day needs prior to then. That said neither heating nor cooling degree-days show a trend. Heating degree-days display more variation then cooling degree-days, which is reasonable considering the states involved, are predominantly in higher elevation locations. Again, indicating a shift in weather patterns.

Figure 8 shows the monthly budget share households spend on electricity and natural gas consumption. Here we see changes in the share and seasonal patterns over time. These reflect the opportunities for fuel use, energy using appliances, heating and cooling needs and the changing demographics and income in the region. Between 1992 and 2000 the budget share dropped from highs of 2.75 percent in 1992 to highs of just below 2.00 percent in 2000. From 2000 onward, the downside of the budget share moves very little, but the upside of the budget share is much more volatile, hitting a low of 1.78 percent in 2002 and a high of 2.35 percent in 2007.

5. Econometric Issues and Hypothesis Tests

The general-to-specific approach is used as described by Hendry (1986) and Hendry and Juselius (2000, 2001). Campos, Ericsson, and Hendry (2005) describe general-to-specific modeling as "the practical embodiment of reduction." General-to-specific modeling attempts to uncover the local data generating process (DGP). Using theory and the existing empirical background, a general unrestricted model is constructed to approximate the local DGP. Using diagnostic tests, the unrestricted model is simplified to a "parsimonious congruent representation" that can be used for empirical analysis. The different structural, seasonal, and regime changes in consumption, relative prices, income, demographics all present challenges for modeling.

Specifically, Hotledahl and Joutz (2004) describe five steps to discover the parsimonious congruent representation. First, examine individual data to better understand the time series properties. Look for trends, patterns, and seasonal effects. Test for unit roots and seasonal unit roots, uncovering the order of integration. Second, form the Vector Autoregressive Regression (VAR) system. Test for the lag length of the system. Test for stability and the residual diagnostics. Third, determine if any cointegrating relationships are present. If they are found, the relationships need to be identified. Fourth, test for weak exogeneity and discover the appropriate cointegrating relationship. This allows for evaluation of the long-run or equilibrium relationships of the data. Finally, upon creation of the appropriate cointegrating relationship(s), a conditional error correction model of the endogenous variables can be specified. Through further tests of stability and residual diagnostics, a reduced form model is created and used for short-run economic hypothesis testing. This is the approach we will be following for our analysis.

5.1 Integration

Discovering the order of integration of each of the endogenous variable is the first step required. It is useful to determine the order of integration for the data because if multiple data are integrated of the same order, through cointegration, long-run or equilibrium relationships can be determined. Table 2 provides the 12th-order augmented Dickey-Fuller (1981) statistics for the variables: demand for electricity (ed), demand for electricity per household (edhh), real price of electricity (rpe), real price of natural gas (rpng), real personal income (rpi), and real personal income per household (rpihh).

All of the variables are in natural logarithms and tested in the levels, I(1), then they are first differenced and tested again, I(2). The deviation from unity of the estimated largest root appears in parentheses below each Dickey-Fuller statistic. This deviation should be approximately zero if the series has a unit root. The results from the tests are shown in Table 2. The first two rows test the null hypothesis that the series contains a unit root or is considered non-stationary. The second two rows test the null hypothesis that the first difference of the series contains a unit root or again, is considered non-stationary.

We find that for all the series in Table 2, the null hypothesis of a unit root fails to be rejected in the levels. Looking at all the series in the differences, we find that the null hypothesis of a unit root can be rejected. This implies that the first differences of the series are stationary, giving strong evidence that each of the series contain unit roots and are integrated of order 1, I(1).

Next, due to the obvious seasonal patterns observed in the series for electricity consumption, price of electricity, and price of natural gas, we follow Franses (1991), Franses and Hobijn (1997) and test for seasonal unit roots in monthly time series. The importance of this test determines whether the seasonal pattern is constant and is characterized as deterministic or if the seasonal pattern varies and should be characterized as stochastic. Deterministic seasonality can be modeled simply by applying seasonal dummy variables. Stochastic seasonal patterns require the use of seasonal differencing to be modeled. If seasonal differencing can be avoided, we can avoid the potential undesirable effects produced by differencing, such as the loss of information in the smoothed series.

We use the Franses and Hobijn auxiliary regression tests for seasonal unit roots. In Table 3, we provide the results. To test the null hypothesis that $\pi_1 = 0$ and $\pi_2 = 0$, a one-sided t-test is performed and the critical values are from t-tables based upon Monte Carlos replications from Frances (1990). To test the null hypothesis that $\pi_3 = \pi_4 = ... = \pi_{11} = \pi_{12} = 0$, the coefficients need to be tested as pairs because these pairs of complex units roots are conjugates, therefore seasonal unit roots are only present when $\pi_3 = \pi_4 = 0$, $\pi_5 = \pi_6 = 0$, and so on. When the null hypothesis $\pi_1 = 0$ cannot be reject it indicates the presence of a unit root similar to the Dickey-Fuller test done above. When the null hypothesis that pairs of π's are equal to zero cannot be rejected, it indicates that seasonal unit roots exist. Overall, the Franses and Hobijn tests indicate no sign of seasonal unit roots. However, electricity consumption appears to marginally exhibit signs of seasonal unit roots for the pairs 7 and 8, but these results are close to zero and as the test is performed for the joint test $\pi_3 = \pi_4 = ... = \pi_{11} = \pi_{12} = 0$, we can easily reject the null. Therefore, we will conclude that consumption does not show significant signs of seasonal unit roots. The other interesting result shows the rejection of the null $\pi_1 = 0$ for the real price of electricity, this might indicate the electricity price series shows no signs of a unit root. When compared to the critical value, this result is borderline significant and taking into account the results from the augmented Dickey-Fuller tests, we still will conclude that the real price of electricity is non-stationary of order 1. We conclude that modeling with seasonal dummy variables is appropriate and the model will not suffer from the loss of information by the differencing of seasonal data.

5.2 The VAR System

The VAR is specified as a four variable system with the sample period ranging from 1993(3) to 2010(12). The variables in the VAR include demand for electricity per household, price of electricity, real disposable income per household, and the price of natural gas. Prices are lagged one period due to the household response to pricing on electricity demand. The model also includes an intercept and centered seasonal dummies as exogenous variables. The lag length of the system is not known upfront, but through tests using the log-likelihood statistic, the AIC, and the SC, reducing the VAR to a reasonable length will increase the power of the Johansen procedure.

A 12th-order VAR was estimated first and tests on the lag length were conducted. Residual diagnostics suggested that there is no evidence of serial correlation of the residuals. Recursive analysis was performed on the system and it was found to be relatively stable. The residual density and histogram appeared normally distributed. The AIC suggested a sixth-order

VAR, whereas tests on the significance of each lag suggested a third-order VAR. Table 4 shows the lag length diagnostics for estimating VARs with lags three through six. Based upon the Schwartz criterion, we would find that a lag of three is the appropriate length of the VAR. While the AIC suggests that five lags is the appropriate length of the VAR. Based upon the maintained hypothesis, we cannot reject the null of the extra lags equal to zero when dropping from a six lags to five lags. We find that we can reject the null of the extra lags equal to zero when we drop from five lags to four lags. This suggests that a VAR with five lags is the appropriate length.

5.3 The Cointegration Analysis

Cointegration is the process by which two or more non-stationary variables integrated of the same order can be combined or cointegrated in a linear combination of lower order. These variables share common stochastic trend(s). When the variables are I(1), a stationary series is created which shows how these variables move together in long-run equilibrium. Cointegration is testable and is used to derive the error correction model.

The VAR has been identified above. Now using the Johansen Test, possible cointegrating vectors can be identified. Table 6 shows the results of the cointegration analysis. Using a lag length of five on the variables, edhh, rpe, rpihh, and rpng, a matrix of eigenvalues, Π is created using the Johansen procedure (1988). The test is designed to identify the rank of Π. The rank is identified as the number of linear independent rows or columns in the matrix. This matrix is pxp, but not necessarily full rank, thus giving three distinct cases for rank. Case 1, when $\text{rank}(\Pi) = p$, indicating the rank is full and all original variables are stationary, cointegration is not needed. For Case 2, $\text{rank}(\Pi) = 0$, indicating there are no cointegrating vectors among the variables, first differencing should be used. Finally, for case 3, $0 > \text{rank}(\Pi) =$

r < p, indicating r possible cointegrating vectors. Under case 3, rank(Π) is not full and can be specified as $\Pi = \alpha\beta'$, where α represents the (pxr) matrix of speed adjustment or feedback coefficients and β' is the (pxr) matrix of cointegrating vectors or long-run relationships. Here when p = 4, the possible values of r = 0, 1, 2, or 3. The first row of the table gives the null hypothesis tests that p – r = 0, 1, 2, or 3. In the first column, the null hypothesis states r = 0, which implies p – r = 4 indicating as in case 1, that there exist no cointegrating vectors. The λ_{max} and λ_{trace} test statistics indicate a clear presence of one cointegrating vector.

To find the implied cointegrating vector, the first column under edhh of the unrestricted standardized eigenvectors can be evaluated. The results are as follows:

$$edhh = -0.198\ rpe + 0.243\ rpihh + 0.050\ rpng \tag{3}$$

All coefficients have the expected signs. The numeric magnitudes follow reasonable estimates of long-run elasticities. They are consistent with previous studies.

The rest of Table 6 provides the results of additional tests for stationarity, weak exogeneity, and individual variable significance. The next test is a multivariate stationarity test. Similar to the augmented Dickey-Fuller test, this tests whether the variables are non-stationary. But here, the null hypothesis is that the variable is stationary, rejection of the null is easily done for all variables. This indicates the variables are non-stationary. This test is performed by setting all β's to zero but the variable of interest. This simply verifies previous results, only here, the test is multivariate and takes into account a larger information set. The final test is of variable significance. By setting each β to zero, significance can be established. The variables edhh, rpe, and rpihh are significant.

Tests of weak exogeneity identify whether a given α is zero. This is done to identify feedback of the cointegrating vector. If identified, weak exogeneity allows for simplification or reduction of the model and inference can be made the conditional model without loss of information. From Table 6, there is strong evidence of weak exogeneity among all variables except electricity consumption. This combined with previous information suggests we may interpret the cointegrating relation as electricity demand. A joint test of weak exogeneity, setting all α's associated with rpe, rpihh, and rpng to zero, gives $\chi^2(3) = 3.16$. Therefore, the model can be simplified and the corresponding cointegrating vector is:

$$edhh = -0.182\ rpe + 0.271\ rpihh + 0.0517\ rpng \tag{4}$$

Equation (4) is very similar to (3). The feedback coefficient for edhh is -0.74 when the restrictions for (4) are applied. This is a good indication that the results of this model are robust and a single equation will allow for inference without much loss of information.

Completing these tests, equation (4) identifies the cointegrating vector and long-run relationship. This indicates that the long-run elasticities are, for the price of electricity -0.182, for income 0.271, and for the price of natural gas 0.0517. These results fall within the bounds established by Espey and Espey's (2004) analysis.

5.4 The Error Correction Model

The cointegrated model represents the long-run or equilibrium model. The short-run relationship between the variables is modeled through a conditional vector equilibrium correction model (VEqCM). In the short-run, differences of variables can be employed to estimate short-run elasticities. More importantly, the VEqCM uses the deviations from the equilibrium relation or error correction term. This allows the model to express short-run electricity demand as a deviation from the long-run mean. The speed of adjustment gives the responsiveness back to the equilibrium or long-run.

To estimate the model, we differenced each of the four variables from the original VAR. Then we ran the VEqCM model using 4 lags:

$$\Delta edhh_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta edhh_{t-i} + \sum_{i=0}^{4} \delta_i \Delta x_{t-i} + \gamma ECM_{t-1} + \sum_{i=0}^{10} \mu_i s_{t-i} + \sum_{i=0}^{1} \phi_i W_{t-i} + \sum_{i=1,12} \eta_i Budshr_{t-i} + \varepsilon_t \quad (5)$$

where x_{t-i} represents the vector of differenced variables: rpe, rpihh, and rpng; ECM_{t-1} is the equilibrium correction term (equation (4)) from the cointegrating vector, lagged one period; s_{t-i} are centered seasonal dummies; W_{t-i} is a vector of weather variables: heating degree-days, cooling degree-days, deviations from heating degree-days, deviations from cooling degree-days, 30 year heating degree-day averages and 30 year cooling degree-day averages; $Budshr_{t-i}$ is the budget share spent on electricity consumption lagged 1 and 12 periods; ε_t is the error term. The original model has 26 estimated parameters.

We employ Autometrics with impulse indicator saturation and obtained the parsimonious model in Table 7. It also includes five dummies variables, found by Autometrics, which account for structural breaks or unseasonable weather in the sample. Table 7 also includes tests of normality, autocorrelation, and heteroscedasticity. These test statistics indicate the model is well specified and there are no problems with these issues.

The main drivers of short run electricity consumption are weather conditions as all four weather variables are highly significant. The second lag of electricity is positively related to electricity demand. The error correction term is negative and has a coefficient of -0.56, indicating that when electricity demand is above or below its long-run equilibrium level, consumption adjusts by just over one half within the first month. The interesting result from this model is that in the short-run, the elasticity of prices and income are perfectly inelastic. The budget share terms suggest that consumers respond negatively to large electricity budget shares in the previous month, but increase consumption from a year ago. This latter response may capture a trend effect.

Weather[2] is the dominant factor in short run electricity consumption. The sum of the heating degree-day coefficients show a positive effect from weather on consumption and as expected, cooling degree-days also shows a positive effect on consumption of electricity[3].

Finally, the stability of the model is tested by examining model and parameter consistency through recursive estimation. Figures 12 and 13 show the results from these tests. Figure 12 presents two graphs that test the model stability. The top figure is the one-step-ahead Chow test. The bottom figure is the n-step-ahead Chow test. The first test forecasts one period ahead while the second tests structural breaks through various break point Chow tests. The tests are normalized on the critical values at 5% and values greater than one indicate a rejection of the null hypothesis of no structural breaks. The model appears relatively stable. There appears to be only one rejection of the null hypothesis and given that there are 204 observations, a few rejections are expected. Therefore, this appears to be stable within reason. The n-step-ahead graph has no rejections. Figure 13 shows the OLS recursive coefficient estimates with the associated two standard error bounds plotted. These results also appear stable.

6. Simulations

We combine the long-run electricity consumption equation with projections from the EIA's National Energy Modeling System (NEMS) and Residential Energy Consumption Survey (RECS). Then, we examine the sensitivity of consumption to two scenarios. Aggregate energy

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[2] When model was run with only HD and CD or HDD and CDD, it was less stable and had problems of serial correlation. Also, the model was run with HD and CD squared to catch non-linear effects. Neither added to the model and they were dropped.

[3] When model was run with only HD and CD or HDD and CDD, coefficients on either pair were approximately equal to the sum of HD and HDD and CD and CDD, respectively.

spending and consumption patterns by households for the mountain region by usage for both electricity and natural gas are available from the RECS (2011).

In Figure 14 we show that the average growth per year for total households using any fuel is 2.3% from RECS for 1997, 2001, 2005, and 2009. The average growth per year of households using any fuel for air conditioning is 8.0%. The percent of households using fuel for air conditioning increased from 46.77% in 1997 to 72.15% in 2009. Since RECS reports electricity as the only fuel being used for air conditioning, these figures show how the housing boom of the 2000's has led to an increase in the percent of households using air conditioning and therefore an increase in electricity consumption for the average household in the mountain region.

The rest of the RECS figures confirm this result as total electricity consumption increased from 6 billion kWh in 1997 to 18 billion kWh in 2005. Total expenditure on electricity increased 72.4% from 4.46 billion dollars in 1997 to 7.60 billion dollars in 2005.

As reliance on electricity gets larger, due to increased use of air conditioning, appliances, lighting, and population growth, the potential economic policy questions of how price changes or weather changes might affect electricity consumption become potentially more important. Beyond this, questions of how these changes in consumption behavior might affect greenhouse gas emissions should be analyzed. We conduct two simulations, based on the congruent dynamic electricity demand model we have estimated.

To begin the simulation, we took data from the NEMS (2010)[4]. NEMS provides reference projections out to 2030. Table 8 provides summary statistics of the NEMS data and

[4] The simulations were performed using the Reference Case Model run for NEMS 2010. Aeo2010r1118a.xls. We obtained date from tables:

Table 3. Energy Prices by Sector and Source, (2008 dollars per million Btu, unless otherwise noted)
Table 4. Residential Sector Key Indicators and Consumption,(quadrillion Btu, unless otherwise noted)
Table 8. Energy Consumption by Sector and Source,(quadrillion Btu, unless otherwise noted)
Table 18. Energy Prices by Sector and Source,(2008 dollars per million Btu, unless otherwise noted)

projections. Residential consumption growth of electricity is projected to increase 27% between 2010 and 2030. Household growth is projected to be 40%. This indicates that NEMS projects residential electricity consumption per household to decrease by 9.5% over the next 20 years. This decrease could be attributed to a more efficient capital stock of electrical equipment and shell efficiency of homes.

In the first simulation, we assume a 10% increase in the price of electricity[5] due to an exogenous change, perhaps rationalizing the cost of consuming fossil fuels. Our model estimates own price elasticity to be approximately -0.2. Using these two pieces of information along with the NEMS projections we calculate the new consumption path for the residential sector. Table 9 provides these results. Over the next 20 years, NEMS originally projected consumption to increase by 27.2%. Simulating the price change, we see residential consumption now increases by 24.7%. Consumption per household now decreases by 11.4% instead of 9.6%.

To calculate the change in emissions, NEMS provides projections of the different fuels used in electricity consumption which allow us to calculate how the various fuels breakout by share of total consumption. NEMS also provides projections of carbon dioxide emissions by fuel type and power generation by fuel type in kilowatt-hours. Using this data we follow formula (6):

$$\begin{aligned}\Delta \text{Emissions} = \Delta &\text{Consumption of Elect.(kWh)} * \\ &[(\text{Share of Total Consumption})_{coal} * (\frac{\text{TonsCO2}}{\text{kWh}})_{coal} + \\ &(\text{Share of Total Consumption})_{NG} * (\frac{\text{TonsCO2}}{\text{kWh}})_{NG}]\end{aligned} \tag{6}$$

Table 28. Carbon Dioxide Emissions by Sector and Source,(million metric tons carbon dioxide equivalent, unless otherwise noted)
Table 117. Natural Gas Consumption by End-Use Sector and Census Division, (trillion cubic feet)

[5] Given that this is a partial equilibrium or demand driven model, we are implicitly assuming electricity production is perfectly elastic or that capacity will exist for any change in the production of electricity.

to calculate changes in emissions. We only use coal and natural gas in the calculation; there is a very small amount (less than 1%) of distillate fuel used in electricity generation. Coal and natural gas account for approximately 78% of the input share of electricity produced for consumption. This number holds steady throughout the 20 years of NEMS projections. But since we are interested in emissions, coal and natural gas account for over 99% of the emissions in electricity consumption, which again, holds throughout the 20 years of NEMS projections. Table 9 shows the baseline emissions projections and how these projections change based upon a 10% increase in price. The growth in emissions decreases from 11.78% to 9.54% or from 91.30 million metric tons of CO2 to 89.47 million metric tons of CO2 in 2030.

The second simulation addresses the effect of an increase in temperature on cooling needs, electricity consumption, and greenhouse gas emissions. We assume a two degree Fahrenheit increase in cooling degree-day needs. Assuming a base of 72 degrees this represents an increase in cooling degree-days of 2.77%.

Using estimates of cooling degree-day elasticities from our error correction model, suggest a 1% increase in cooling-degree days leads to a 3.9% monthly increase in the consumption of residential electricity. We calculate that the response to a two degree Fahrenheit warming on consumption of electricity is equal to 10%. Table 10 shows how residential electricity consumption increases from 27% to 40% based on these assumptions. Consumption per household in the reference case increases in 2020 and returns to 2010 levels in 2030 Thus the warming will effectively counteract the efficiency gains in the electrical stock projected in the reference case of the NEMS. Finally, emissions grow at 23%, approximately double the current projections.

7. Conclusion

We develop a dynamic model of residential electricity consumption for the Mountain region of the US capturing long run price and income effects and the short run seasonal effects. The VEqCM estimates for the long-run elasticities for own-price, cross-price, and income are consistent with theory, but appear more inelastic then most previous work. The short-run elasticities for prices and income are shown to be perfectly inelastic. Weather variables appear to be the major drivers of electricity demand in the short-run. This result appears to be reasonable for the geographic region, given the household type. The models created are statistically significant and stable.

These types of models are useful in policy analysis and decision making beyond just obtaining elasticity estimates. We study the effects of increasing residential electricity price increases and an increase in temperature in the US mountain region on electricity consumption and CO2 emissions. The simulations examine the possible effects from the reference case in EIA's NEMS projections in 2030. The first simulation was based on 10% increase in the price of electricity. Our results suggested that this would reduce consumption in 2030 by almost 2% and CO2 emissions by slightly more than 2%. The second simulation was based on warming of two degrees Fahrenheit. The temperature increase appears to offset the projected gains in efficiency of electricity consumption per household. Moreover, the growth in CO2 emission doubled from the NEMS reference case. These simulations showd how changes in prices or weather affect the consumption behavior of consumers, which in turn affect the emissions produced by electricity consumption.

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Table 1. Descriptive Statistics

Sample: Jan. 1992 - Jan. 2011 Variables each with 229 Observations				
	Mean	Std. Dev.	Min	Max
ED	203.91	53.29	117	360
EDHH	29.53	5.39	21.17	46.26
HH	6,844.10	839.00	5,268.00	8,002.00
EP	8.26	1.07	6.70	11.28
REP	10.79	2.15	6.64	14.35
NGP	8.45	2.94	4.54	16.79
RNGP	10.44	2.02	6.50	16.99
RPI	569.97	131.33	343.00	749.00
RPIHH	82,130.00	9,523.30	65,110.00	95,756.00
HD	413.38	323.68	2.00	1,054.00
CD	121.66	138.81	0.00	486.00
HDD	11.05	25.25	0.00	169.00
CDD	16.55	25.37	0.00	135.00
HD30AVG	436.34	329.76	19.00	951.00
CD30AVG	108.45	123.30	0.00	351.00
BUDSHR	1.65	0.30	1.19	2.73

Table 2. ADF(12) Statistics Testing for a Unit Root

	Variable[b,c]					
Null Order[a]	ed	edhh	rpe	rpng	rpi	rpihh
I(1)	-1.67	-0.80	-1.13	-2.71	-2.71	-1.96
	(-0.02)	(-0.03)	(-0.02)	(-0.09)	(0.002)	(-0.003)
I(2)	-10.70**	-10.92**	-9.06**	-11.60**	-3.61**	-4.33**
	(-5.46)	(-5.60)	(-1.10)	(-1.23)	(-4.61)	(-0.32)

[a] For a variable x, the ADF (1981) statistic, ADF(k) is the t ratio on π from the regression

$$\Delta x_t = \pi x_{t-1} + \sum_{i=1}^{k} \gamma \Delta x_{t-i} + \alpha_0 + \alpha_1 t + \sum_{i=2}^{12} \alpha_i s_{it} + e_t$$

where k is the number lags on the dependent variable; α_0 is the intercept; Π, $\{\gamma_t\}$, α_1 through α_{12} are coefficients; the $\{s_{it}\}$ are centered seasonal dummies; t is a trend; and e_t is an error term. For a given variable and null order of I(1), two values are reported --the 12th-order (k=12) ADF statistic and in parentheses the estimated coefficient on the lagged variable x_{t-1}--for variables in the levels. That coefficient should be 0 under the null hypothesis that x is I(1). For a given variable and null order of I(2), two values are reported for the first difference of the variables. A rejection implies that the first difference of the series is a stationary process.

[b] The sample for the ADF test was from 1993(3) - 2010(12) and all variables are in natural logarithms.

[c] The critical values for the t-tests at 5% are -3.43 and 1% are -4.00, * indicates rejection at the 5% level and ** indicates rejection at the 1% level

Table 3. Franses and Hobijn Auxiliary Regression Tests for Monthly Seasonal Unit Roots

	Variable[b,c]			
Null Hyp.[a]	ed	edhh	rpe	rpng
π_1=0[d]	-1.44	-2.43	-3.60**	-2.51
π_2=0	-4.25**	-4.29**	-3.64**	-4.16**
π_3,π_4=0	12.14**	12.22**	23.08**	20.99**
π_5,π_6=0	12.35**	12.39**	15.75**	24.56**
π_7,π_8=0	4.11	4.21	18.70**	14.91**
π_9,π_{10}=0	16.28**	16.37**	25.74**	21.29**
π_{11},π_{12}=0	8.42**	8.67**	24.72**	18.41**
$\pi_3,\ldots\ldots,\pi_{12}$=0	15.39**	15.64**	93.31**	59.60**

[a] The null hypothesis in this test is $(1\text{-}L^{12})y_t=\varepsilon_t$. The test is based on the expansion of the seasonal difference operator and assumes the presence of 12 roots on the unit circle as:

$$(1-\mathrm{L}^{12})=(1-\mathrm{L})(1+\mathrm{L})(1-\mathrm{iL})(1+\mathrm{iL})\left[1+(\sqrt{3}+i)\frac{L}{2}\right]\left[1-(\sqrt{3}+i)\frac{L}{2}\right]$$

This procedure requires testing the significance of the π_i's in the regression:

$$\varphi(\mathrm{L})\mathrm{y}_{8,\mathrm{t}}=\mu+\pi_1 y_{1,t-1}+\pi_2 y_{2,t-1}+\pi_3 y_{3,t-1}+\pi_4 y_{3,t-2}+\pi_5 y_{4,t-1}$$
$$+\pi_6 y_{4,t-2}+\pi_7 y_{5,t-1}+\pi_8 y_{5,t-2}+\pi_9 y_{6,t-1}+\pi_{10} y_{6,t-2}+\pi_{11} y_{7,t-1}+\pi_{12} y_{7,t-2}$$

Where

$$y_{1,t}=+(1+L)(1+L^2)(1+L^4+L^8)y_t,$$
$$y_{2,t}=-(1-L)(1+L^2)(1+L^4+L^8)y_t,$$
$$y_{3,t}=-(1-L^2)(1+L^4+L^8)y_t,$$
$$y_{4,t}=-(1-L^4)(1-\sqrt{3}L+L^2)(1+L^2+L^4)y_t,$$
$$y_{5,t}=-(1-L^4)(1+\sqrt{3}L+L^2)(1+L^2+L^4)y_t,$$
$$y_{6,t}=-(1-L^4)(1-L^2+L^4)(1-L+L^2)y_t,$$
$$y_{7,t}=-(1-L^4)(1-L^2+L^4)(1+L+L^2)y_t,$$
$$\mathrm{y}_{8,\mathrm{t}}=(1-\mathrm{L}^{12})y_t$$

[b] The sample for the Franses and Hobijn test was from 1993(1) - 2010(12) and all variables are in natural logarithms.

[c] * indicates rejection at the 5% level and ** indicates rejection at the 1% level

[d] Tests for π_1=0 and π_2=0 are one-sided t-tests, all other tests are F-tests, using critical values based on 25,000 Monte Carlo replications.

Table 4. F and Related Statistics for the Sequential Reduction
From Sixth-Order VAR to the Third-Order VAR

	Null hypothesis[a]				Maintained hypothesis[b]		
System	k	L	SC	AIC	VAR(6)	VAR(5)	VAR(4)
VAR(6)	144	2,214.91	-16.61	-18.826	-		
					-		
					-		
VAR(5)	128	2,199.37	-16.86	-18.831<	1.64		
					[0.06]		
					(16, 519)		
VAR(4)	112	2,156.85	-16.86	-18.59	3.22**	4.77**	
					[0.00]	[0.00]	
					(32, 669)	(16, 565)	
VAR(3)	96	2,133.04	-17.04<	-18.52	3.11**	3.80**	2.65**
					[0.00]	[0.00]	[0.00]
					(48, 699)	(32, 683)	(16, 578)

[a] The first five columns report the VAR with its order and, for each system, the number of unrestricted parameters k, the log-likelihood L, the Schwarz criterion, SC, and the Akaike information criterion, AIC.

[b] The three entries within a given block of numbers in the last three columns are the approximate F-statistic for testing the null hypothesis against the maintained hypothesis, the tail probability associated with that F-statistic in square brackets, and the respective degrees of freedom for the F-statistic.

Table 5

Unrestricted VAR Model with 5 Lags
Residual Diagnostics by Equation and System
Sample July 1992 - December 2009

edhh	Portmanteau(12):		15.6838
rpe	Portmanteau(12):		10.6129
rpng	Portmanteau(12):		3.39847
rpihh	Portmanteau(12):		9.86292
edhh	AR 1-12 test:	F(12,166)	2.7553 [0.0019]**
rpe	AR 1-12 test:	F(12,166)	1.0315 [0.4224]
rpng	AR 1-12 test:	F(12,166)	0.31058 [0.9868]
rpihh	AR 1-12 test:	F(12,166)	1.0700 [0.3886]
edhh	Normality test:	Chi^2(2)	1.1425 [0.5648]
rpe	Normality test:	Chi^2(2)	131.09 [0.0000]**
rpng	Normality test:	Chi^2(2)	56.339 [0.0000]**
rpihh	Normality test:	Chi^2(2)	3.3325 [0.1890]
edhh	ARCH 1-2 test:	F(2,174)	2.3661 [0.0969]
rpe	ARCH 1-2 test:	F(2,174)	10.014 [0.0001]**
rpng	ARCH 1-2 test:	F(2,174)	6.1560 [0.0026]**
rpihh	ARCH 1-2 test:	F(2,174)	1.3677 [0.2574]
edhh	hetero test:	F(40,137)	0.85868 [0.7063]
rpe	hetero test:	F(40,137)	0.80978 [0.7778]
rpng	hetero test:	F(40,137)	1.0404 [0.4199]
rpihh	hetero test:	F(40,137)	1.5927 [0.0258]*
Vector Portmanteau(12):		210 obs	132.819
Vector AR 1-12 test:		F(192,509)	1.0963 [0.2147]
Vector Normality test:		Chi^2(8)	235.75 [0.0000]**
Vector hetero test:		F(400,1272)	1.0872 [0.1463]

Table 6. Cointegration Analysis of the US Residential Mountain Region Electricity Data

Statistic	Null Hypothesis for Summary Test Statistics[a,b]			
	r = 0	r ≤ 1	r ≤ 2	r ≤ 3
Eigenvalue	0.288	0.059	0.322	0.019
λ_{max}	71.43**	12.72	6.87	3.95*
P-value	(0.00)	(0.49)	(0.51)	(0.05)
λ_{max} (adj.)	64.63**	11.51	6.22	3.57
P-value	(0.00)	(0.61)	(0.59)	(0.06)
λ_{trace}	94.98**	23.54	10.82	3.95*
P-value	(0.00)	(0.23)	(0.23)	(0.05)
λ_{trace} (adj.)	85.93**	21.30	9.79	3.57
P-value	(0.00)	(0.35)	(0.30)	(0.06)
	Standardized Eigenvectors β'			
Variable	edhh	rpe	rpng	rpihh
edhh	1.000	-0.330	-0.184	-1.333
rpe	0.198	1.000	4.160	-9.720
rpng	-0.050	-1.394	1.000	8.966
rpihh	-0.243	2.683	6.370	1.000
	Standardized Eigenvectors α			
Variable	edhh	rpe	rpng	rpihh
edhh	-0.729	0.008	0.003	0.000
rpe	-0.104	-0.030	-0.012	0.001
rpng	-0.151	0.061	-0.016	-0.001
rpihh	-0.003	-0.002	0.000	0.000
	Weak Exogeneity Test Statistics[c]			
Variable	edhh	rpe	rpng	rpihh
χ^2_1	57.73**	1.63	1.46	0.26
P-value	(0.00)	(0.20)	(0.23)	(0.61)
	Multivariate Statistic for Testing Stationarity			
Variable	edhh	rpe	rpng	rpihh
χ^2_3	53.24**	66.51**	64.27**	63.30**
P-value	(0.00)	(0.00)	(0.00)	(0.00)
	Statistic for Testing the Significance of a Given Variable			
Variable	edhh	rpe	rpng	rpihh
χ^2_1	58.31**	12.58**	1.02	5.18*
P-value	(0.00)	(0.00)	(0.31)	(0.02)

[a] The VAR includes five lags on each of the variables, an intercept, and monthly centered seasonal dummies. The estimation period is from 1992(7) - 2009(12).

[b] The statistics λ_{max} and λ_{trace} are Johansen's maximal eigenvalue and trace eigenvalue statistics for testing cointegration. The null hypothesis is in terms of the cointegration rank r and, for example, rejection of r = 0 is evidence in favor of at least one cointegrating vector. The statistics that include (adj.) are adjusted for degrees of freedom. The critical values are taken from Osterwald-Lenum (1992).

[c] The statistics for testing weak exogeneity, stationarity, and significance are evaluated under the assumption that r = 1. They are asymptotically distributed as χ^2_1, χ^2_3, and χ^2_1 respectively, if r actually is unity and if the associated null hypothesis is valid.

Table 7. Final Vector Error Correction Model

Sample Period: Jan. 1993 - Dec. 2009

Dependent Variable: Change in Log Consumption per Household per Day per Month

	Coefficient	Std.Error	t-value
Dedhh_2	0.108885	0.0358	3.04
CSeasonal_2	-0.064664	0.0080	-8.05
CSeasonal_5	0.092426	0.0091	10.20
CSeasonal_9	-0.097335	0.0110	-8.87
CSeasonal_10	-0.088398	0.0123	-7.22
CIa_1	-0.555831	0.0431	-12.90
CD	0.001218	0.0001	24.30
HD	0.000289	0.0000	7.78
HD_1	0.000116	0.0000	2.96
HD30AVG	0.000195	0.0000	4.27
HD30AVG_1	-0.000200	0.0000	-4.52
BUDSHR_1	-0.101968	0.0205	-4.97
BUDSHR_12	0.114535	0.0149	7.67
Constant	0.002124	0.0252	0.08
sigma	0.0285	RSS	0.148792158
R^2	0.9664	F(20,183) =	263 [0.000]**
log-likelihood	447.316	DW	1.81
no. of observations	204	no. of parameters	21
mean(Dedhh)	0.00033	var(Dedhh)	0.02169
AR 1-7 test:	F(7,176) =	1.6124	[0.1346]
ARCH 1-7 test:	F(7,169) =	1.0077	[0.4276]
Normality test:	Chi^2(2) =	2.5489	[0.2796]
Hetero test:	F(29,153) =	0.93146	[0.5713]
RESET test:	F(1,182) =	0.18454	[0.6680]

Table 8. NEMS Data and Projections

	Billion kWh				Millions		Residential
	Residential	Commercial	Industrial	Total	Population	Households	Household Kwh
2010	69.28	68.76	37.12	175.23	21.91	7.97	8,692.60
2020	77.07	85.48	42.52	205.2	26.07	9.48	8,129.75
2030	88.13	103.51	43.71	235.69	30.82	11.21	7,861.73
Growth	27.21%	50.54%	17.75%	34.50%	40.67%	40.65%	-9.56%
Annualized	1.21%	2.07%	0.82%	1.49%	1.72%	1.72%	-0.50%

Source: NEMS 2010 reference case

Table 9. Simulation # 1 - 10% Increase in Price

	Residential Consumption (Billion kWh)	Residential Consump. Per Household (kWh)	Simulated Residential Consumption	Simulated Residential Consumption/HH	Baseline Emissions (Million Metric Tons)	Simulated Emissions (Million Metric Tons)
2010	69.28	8,692.60	69.28	8,692.60	81.68	81.68
2020	77.07	8,129.75	75.53	7,967.15	85.53	83.82
2030	88.13	7,861.73	86.37	7,704.50	91.30	89.47
Growth	27.21%	-9.56%	24.66%	-11.37%	11.78%	9.54%
Annualized	1.21%	-0.50%	1.11%	-0.60%	0.56%	0.46%

Table 10. Simulation # 2 - Two degree Fahrenheit Increase in Cooling-Degree Day Needs

	Residential Consumption (Billion kWh)	Residential Consump. Per Household (kWh)	Simulated Residential Consumption	Simulated Residential Consumption/HH	Baseline Emissions (Million Metric Tons)	Simulated Emissions (Million Metric Tons)
2010	69.28	8,692.60	69.28	8,692.60	81.68	81.68
2020	77.07	8,129.75	84.78	8,942.72	85.53	94.08
2030	88.13	7,861.73	96.94	8,647.90	91.30	100.43
Growth	27.21%	-9.56%	39.93%	-0.51%	11.78%	22.96%
Annualized	1.21%	-0.50%	1.69%	-0.03%	0.56%	1.04%

Figure 1

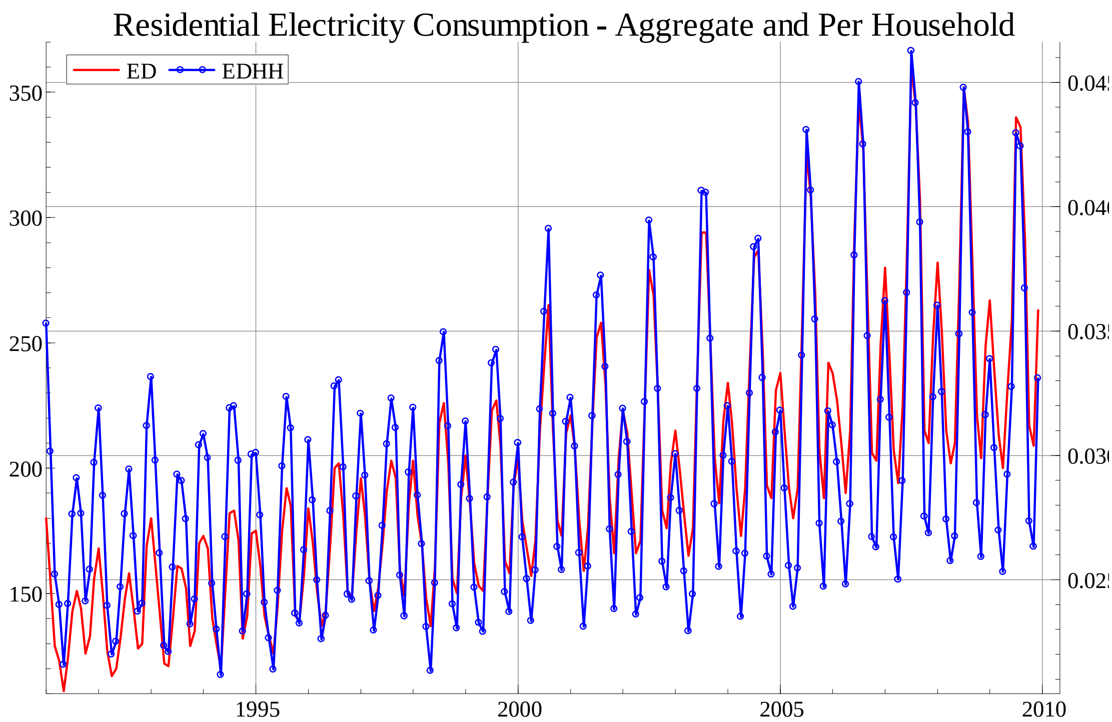


Figure 2

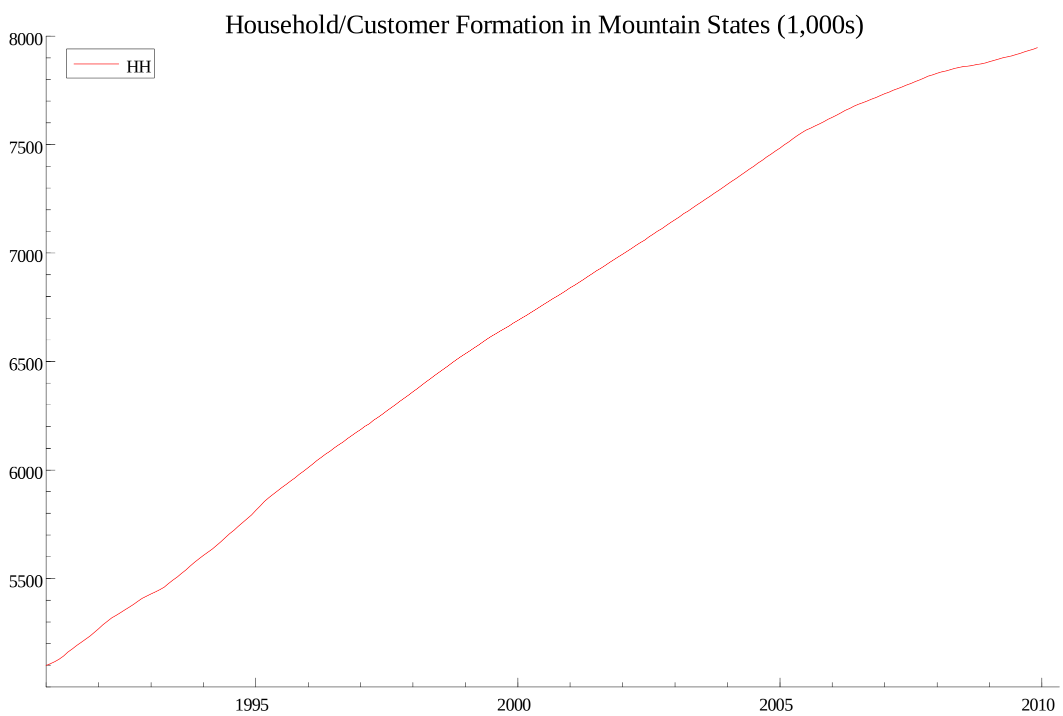


Figure 3

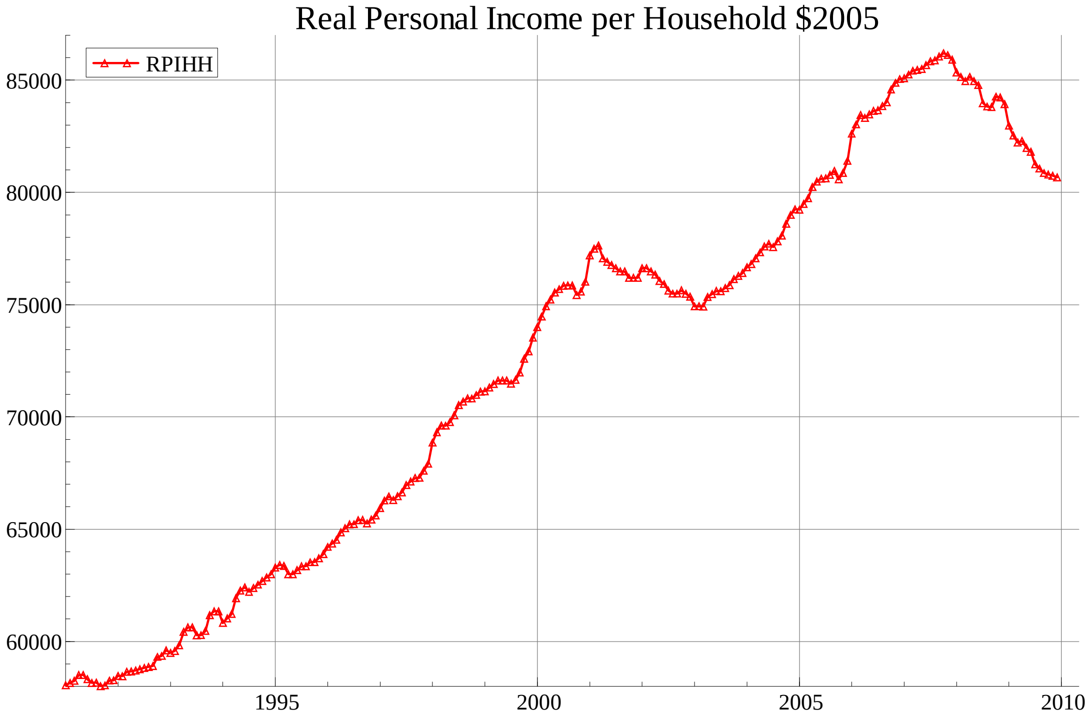


Figure 4

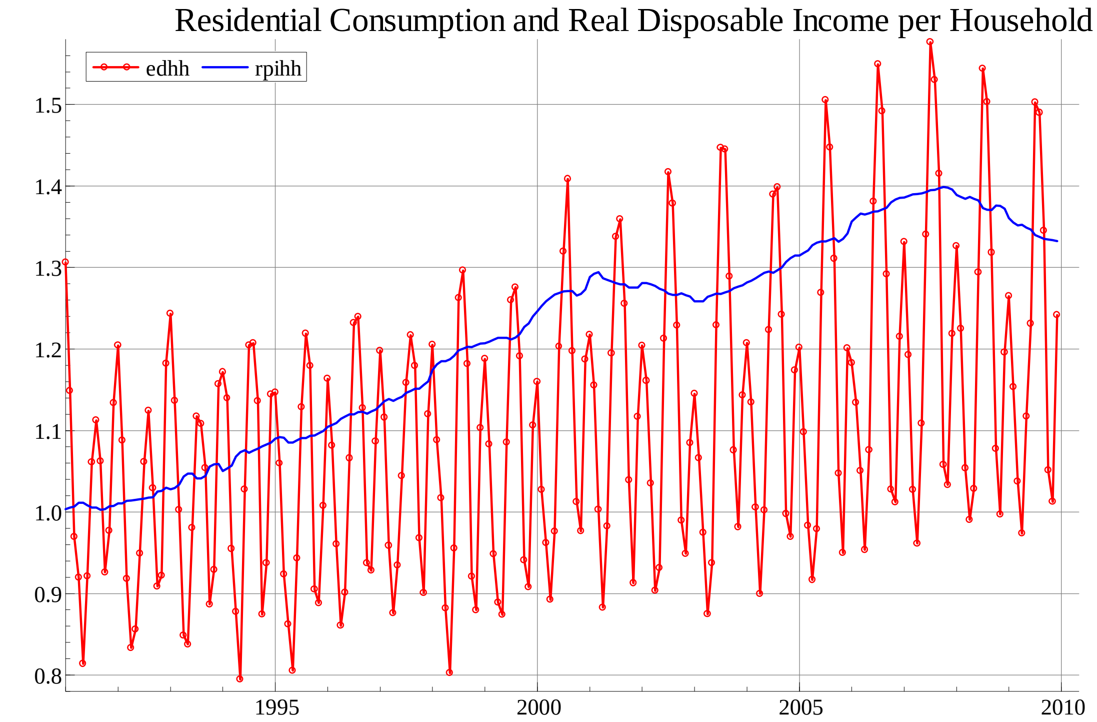
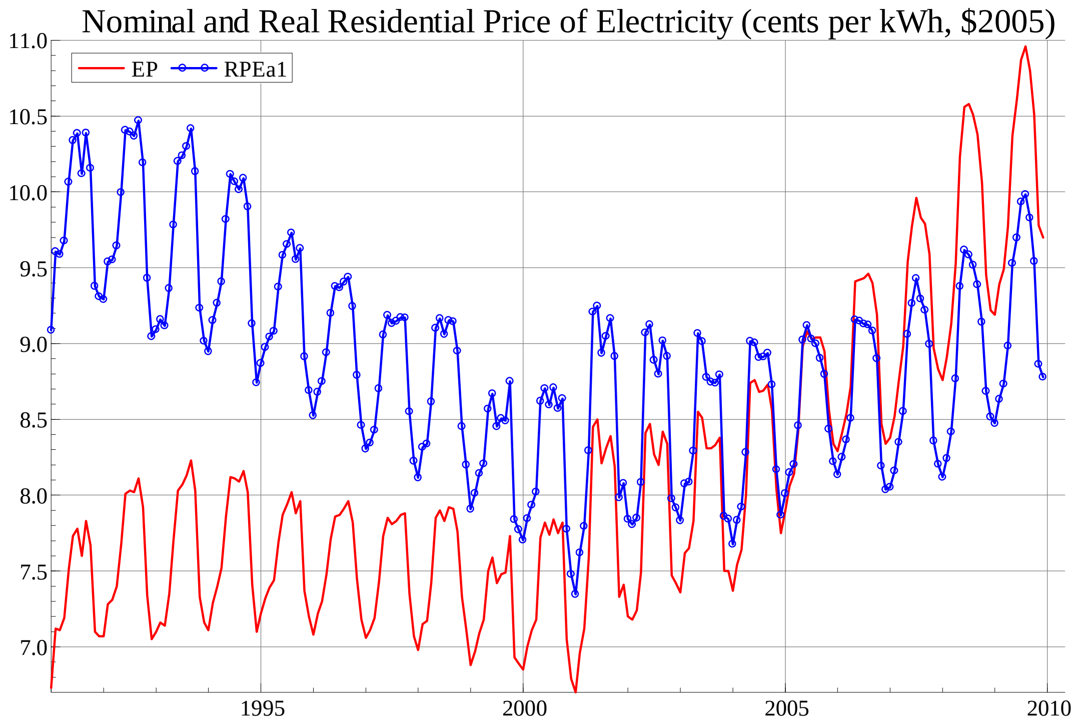


Figure 5



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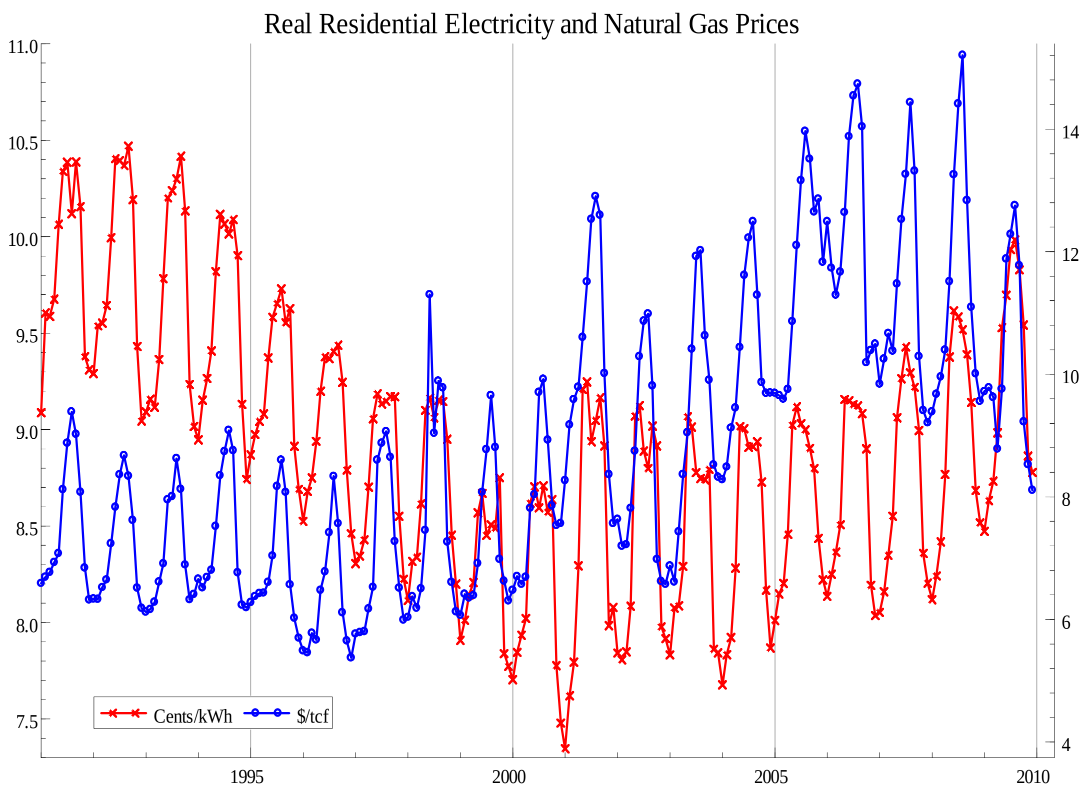

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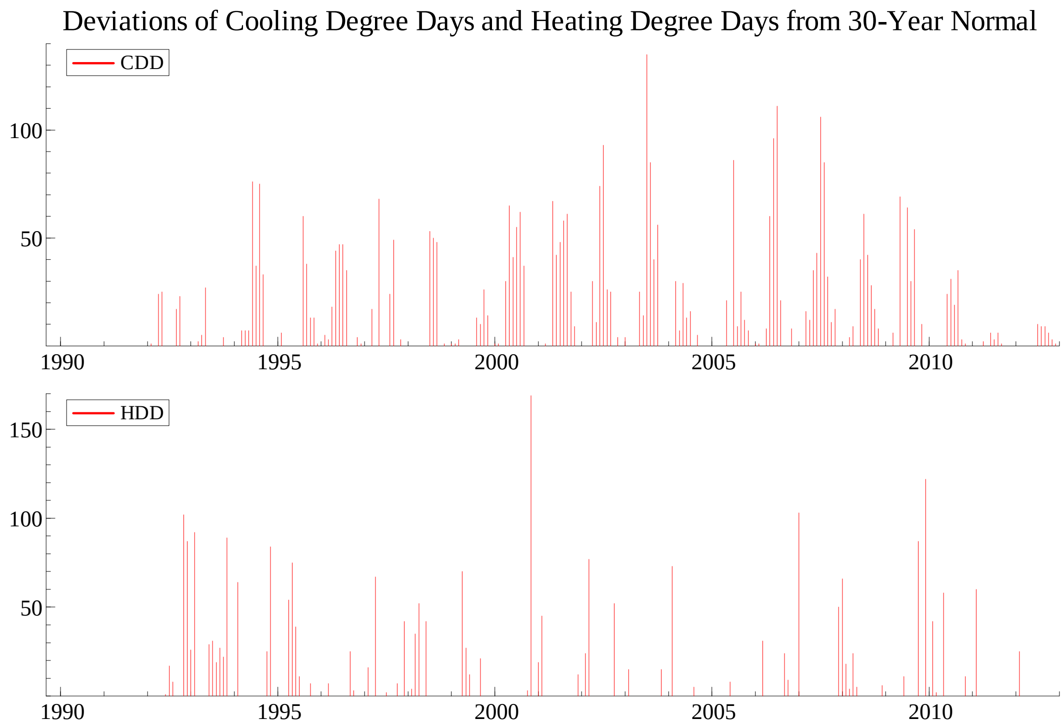

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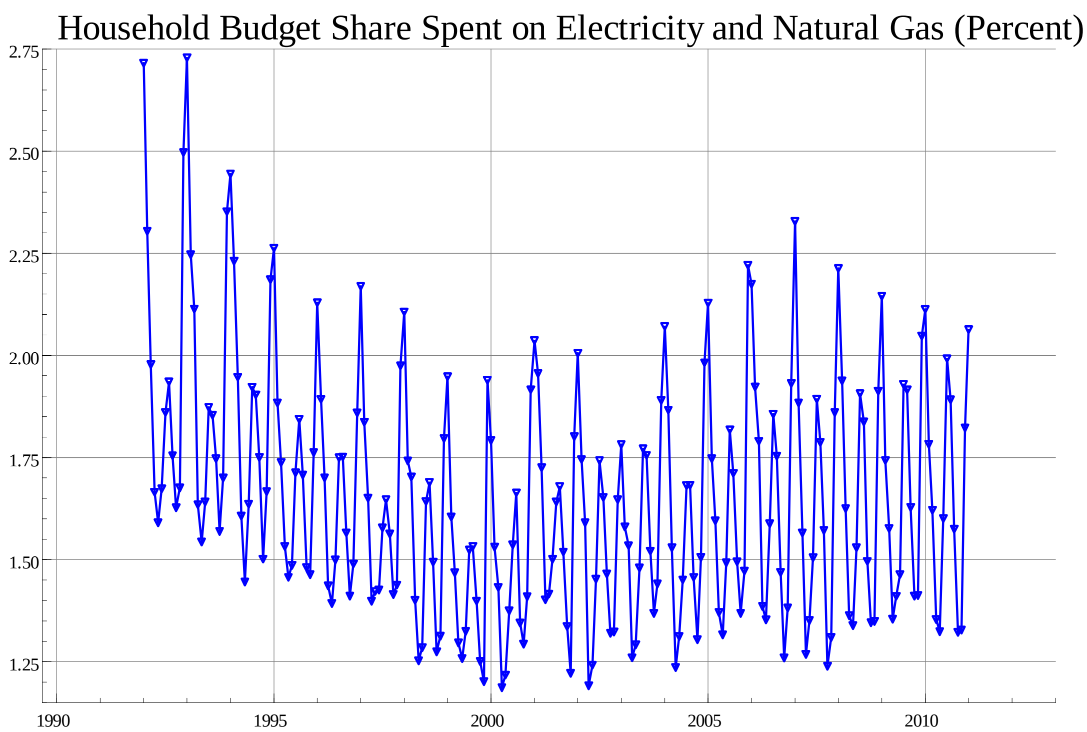

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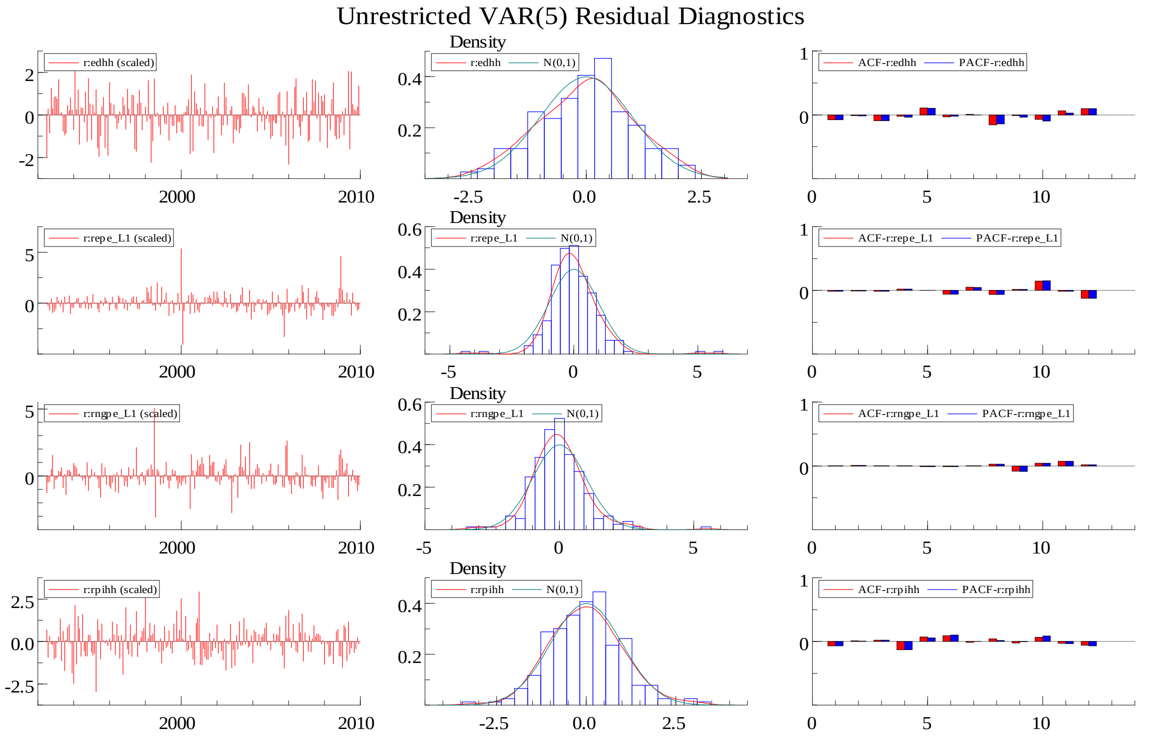

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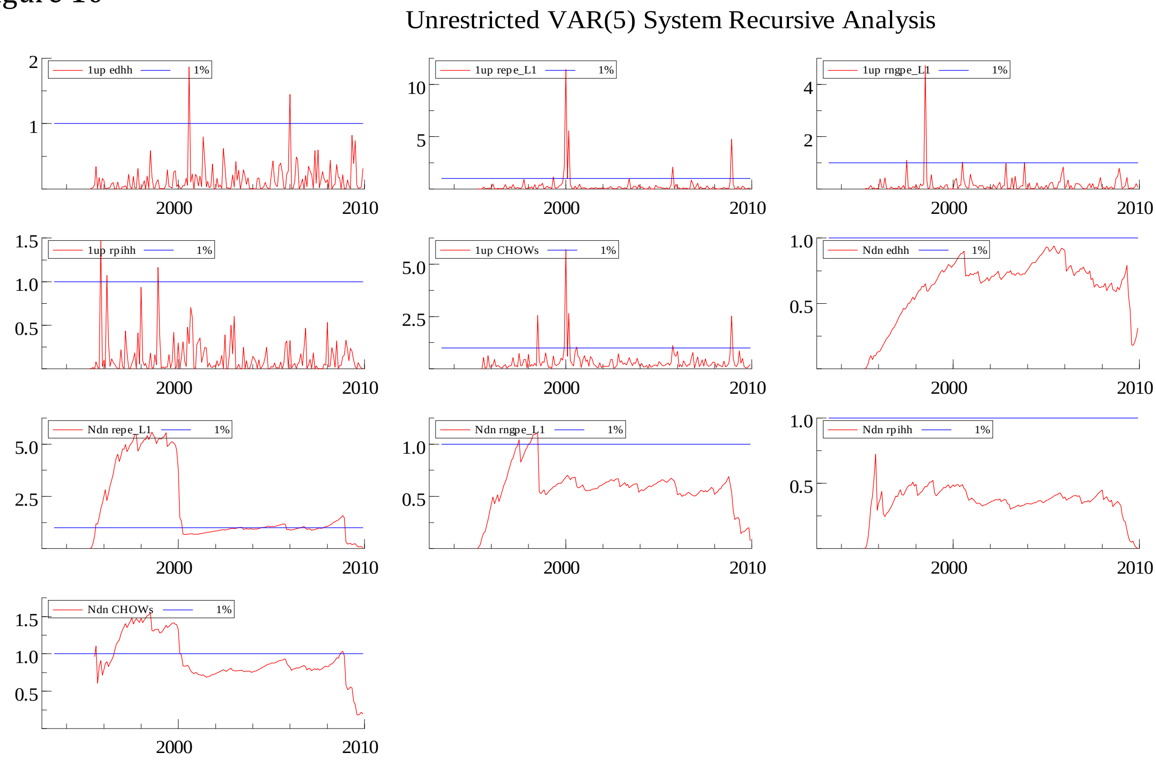
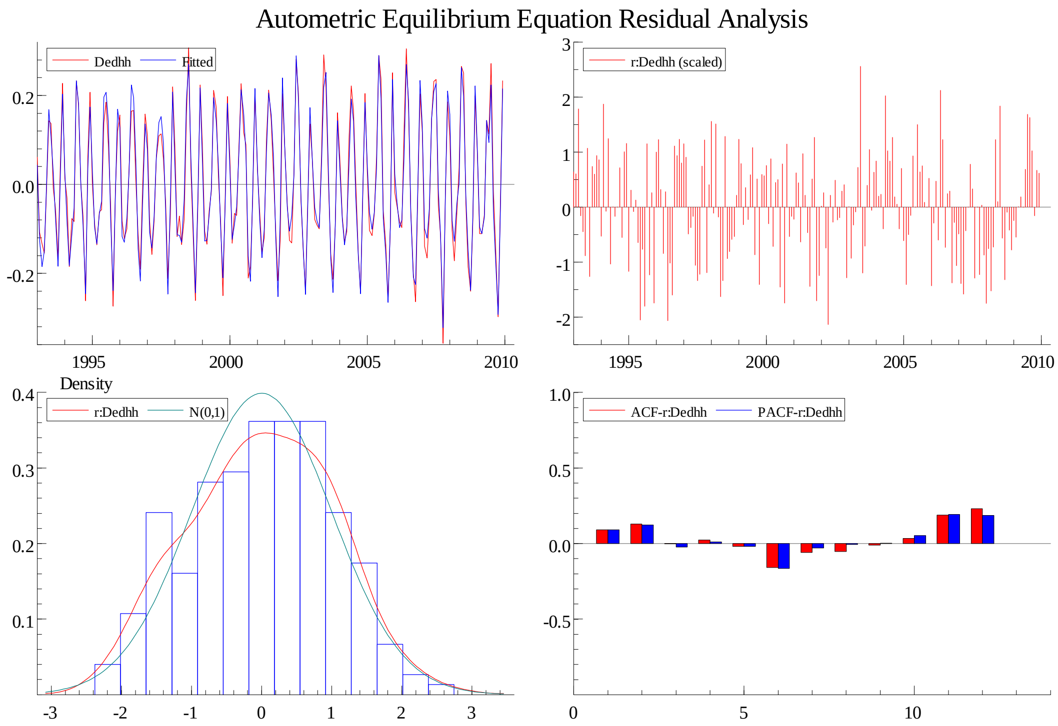


Figure 11



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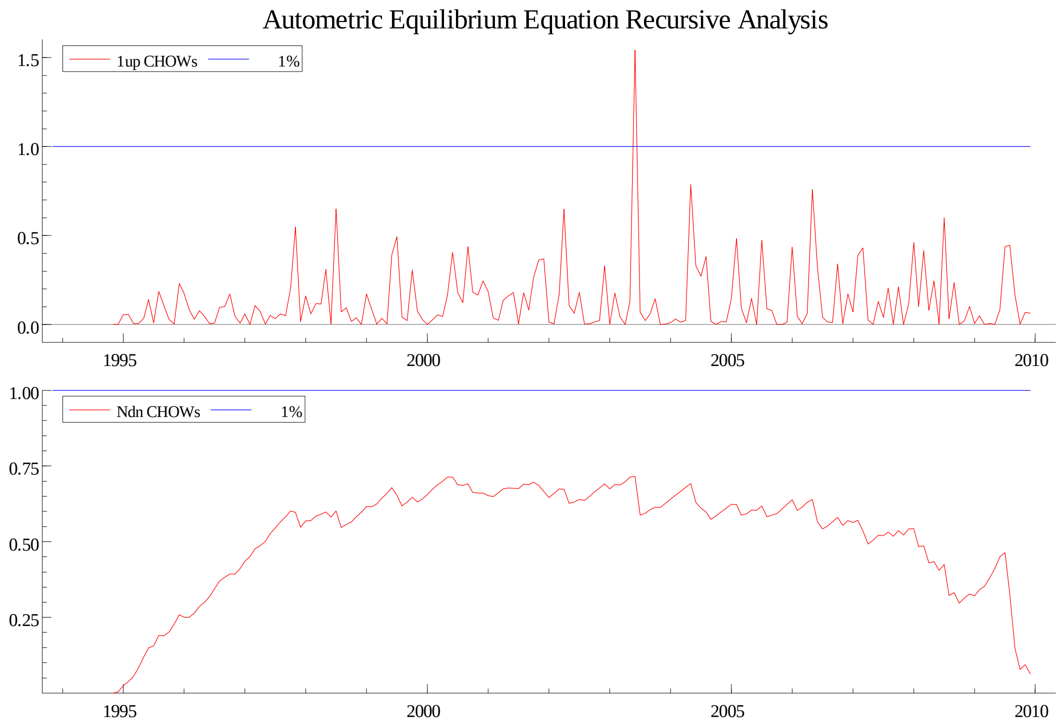
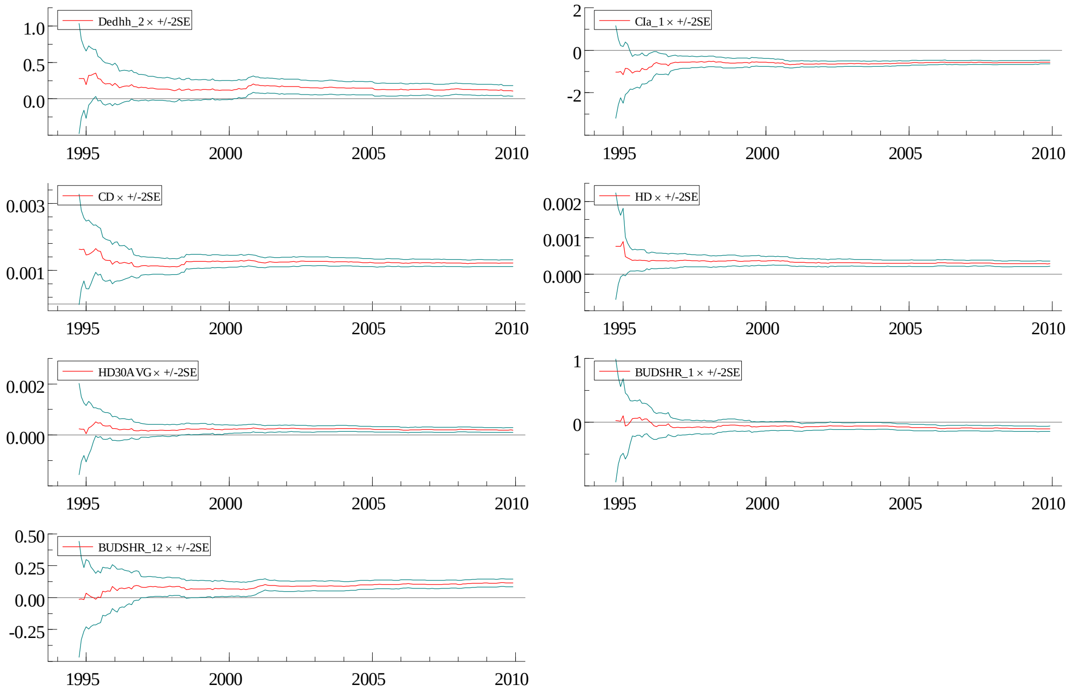


Figure 13

Autometrics Equilibrium Equation Recursive Beta



Figures 14 – 21. Use data from the Residential Energy Consumption Survey (RECS)

Figure 14

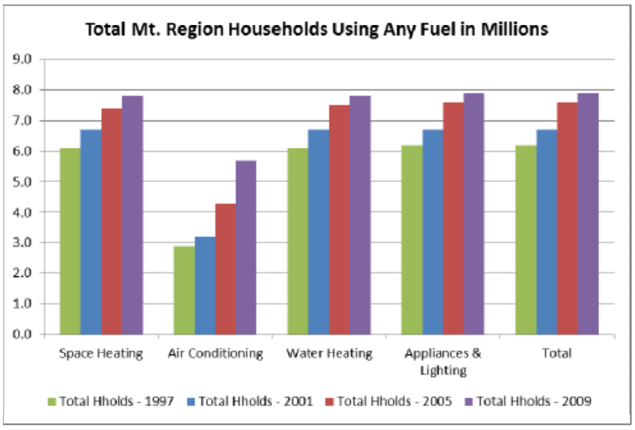


Figure 15

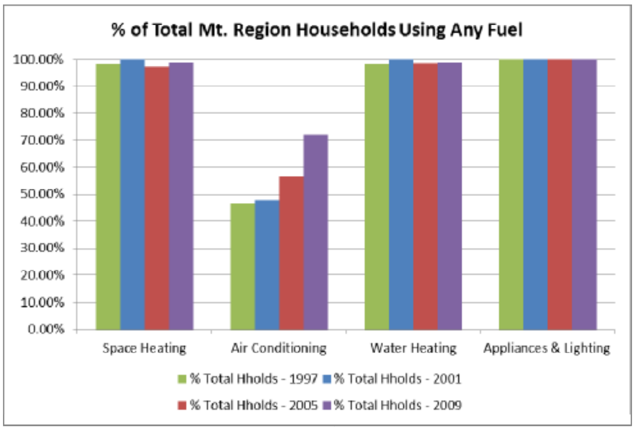


Figure 16

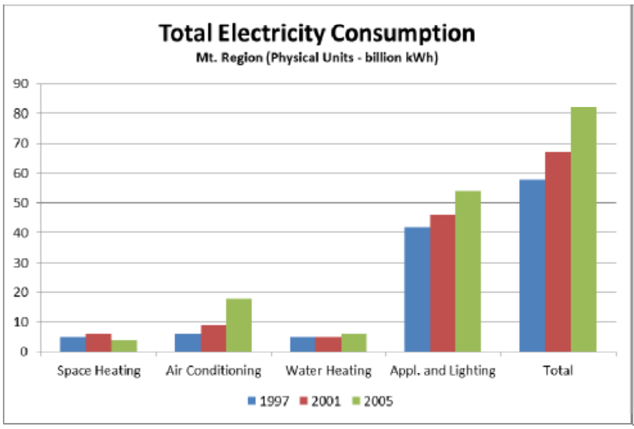


Figure 17

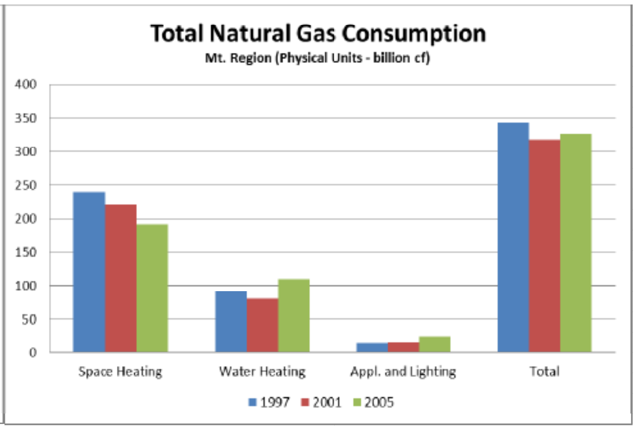


Figure 18

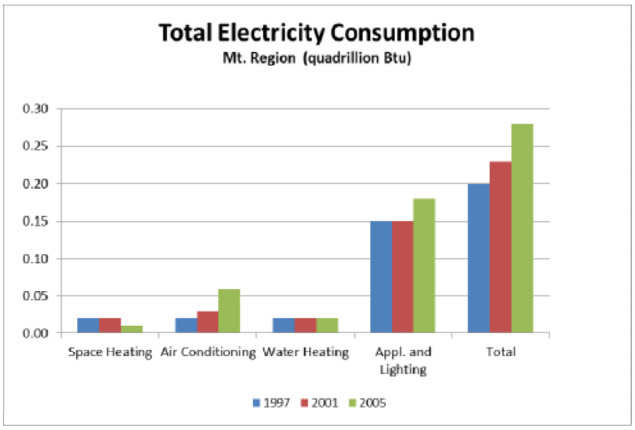


Figure 19

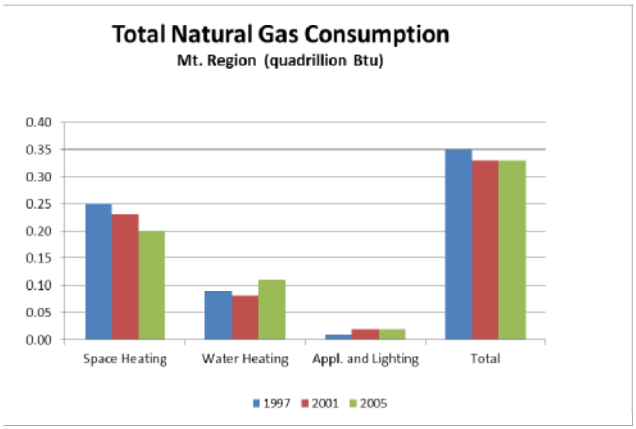


Figure 20

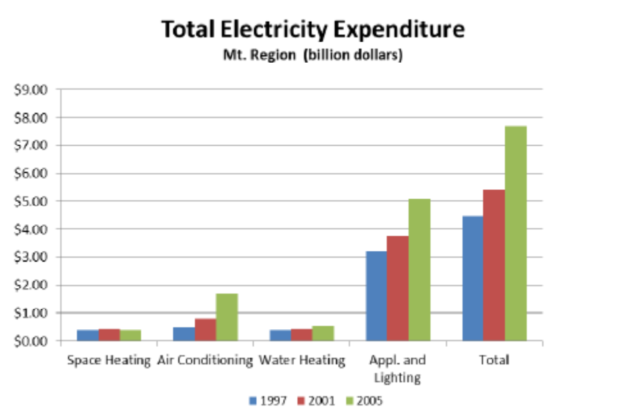


Figure 21