


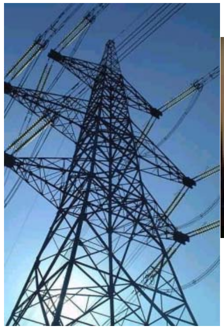

Forecasting and Energy Demand Analysis: Issues and Trends in Energy Regulation

Michigan State University, Institute of Public Utilities, Forecasting Workshop for Regulators, Charleston, South Carolina.

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Introduction -- Topics

Introduction

1 Introduction: What Are Forecasts and Why Do We Need Them?

Introduction - Definitions

Economic Forecasting

The Science of Explaining Tomorrow Why the Predictions You Made Yesterday Didn't Come True Today

Introduction - Definitions

Utility Forecasting

The Art of Explaining to Regulators Why the Predictions You Are Making Are Better Than the Other Side's and Lead to Fair, Just, and Reasonable Rates.

Introduction - Definitions

What is a forecast?

Informal definition: Projection or development of conclusions regarding likely outcomes that have not yet occurred.

Common elements:

(1) Uncertainty about the future.

(2) Typically uses some combination of empiricism and judgment.

(3) Expected future usually based on observed past.

Introduction – Use of Forecasts in Regulation

The terminology between "forecasts" and standard empirical analysis often gets cluttered since both use historic data to make inferences about likely outcomes either yesterday ("backcast"), today, or in the future.

Common uses of forecasts in the regulatory process can be generalized into:

(1) Ratemaking purposes: forecasts can be used to establish test year information.

(2) Resource planning purposes: supply and demand-side resources needs over time. Most IRP principles recognize that the first step is development of a reliable forecast.

(3) Other special purposes: truing up data, benchmarking and performance goals, normalization (i.e., weather, other factors), estimating the impact of certain "events" or actions on utility outcomes(i.e., recession, implementation of efficiency, new customer, departing customer, reactions to rate design, etc).

Rates, Test Years, and Regulation

The "regulatory compact," as a general term, gives utilities the opportunity to earn a fair rate of return of and on their investments and prudently-incurred costs. In return, they are expected to provide safe, reliable, and economic service.

The first part of the compact defines the concept of the rate case, while the second part defines what utilities are expected to do between rate cases for those returns.

Determining "costs" and "value" have been considerable academic and applied challenge since the early days of regulation.

Unfortunately, the real world falls short of the ideals of economic theory since legal standards define this as a reasonable process.

Test Years and Test Periods

The "test year" is a basic concept used throughout utility regulation to define the time frame within which rates are set. Some differentiate the "test period" as a more refined version of this concept that takes the "known and measurable" adjustments into account. Can often be used with terms such as "rate period" and "rate year."

Selection of the test year and its corresponding test period adjustments can be controversial.

Criticisms is that these conditions have passed and are not likely to be reflective of future operating conditions. The more dated the test year, the more challenged and controversial, the ratemaking process.

Rejoinder is that there is legal and policy obligation to base test years on known and measureable information.

Historic versus Projected Test Years

The potential "staleness" of historic test years has led some states to adopt forecasted test years which is a projection of the anticipated outlook in some upcoming year.

A forecasted test year can suffer from a problem similar to a historic test year since the forecast can become more speculative the further removed it is from the current period.

Can lead to a process that includes considerable debate, judgment, and in some instances compromises.

Current, there are an estimated 31 states that use strict historic test years, 4 states that use strict forecasted test years, and 15 states that allow utilities to choose between forecasted or historic.

2 Forecasting methods

Forecasting Methods -- Common Types

Variety of different forecasting types can arise in the regulatory process. These can be generalized into the following types each with their own strengths and weaknesses.

Structural/stochastic approaches (econometrics)

Astructural/stochastic approaches (time series)

Structural/deterministic

Combination of Forecasts

Forecasted Inputs/Third Party Forecasts

Forecasting Methods – Structural/Stochastic (econometrics)

"Stochastic" since these approaches are based on statistical estimation principles.

Common econometric models, typically focused on demand modeling, that can take a variety of functional forms.

Most common approach is a log-linear model that posit that energy demand (kWh, KW, Dth) is a function of prices, income, weather, and other factors.

Long historic that dates to the early 1970s on this more aggregate approach.

Most common approach used by utilities in regulatory filings of all types. Input data comes from internal historic information.

Forecasted input data (like income) typically comes from third-party sources.

Forecasting Methods – “Astructural”/stochastic (time series)

These approaches tend to be agnostic about the functional form and relationships/factors influencing demand.

Since these factors are based upon approximations of theory, and data can be unreliable and not representative of the true relationships (i.e., price), only a time series can produce least-biased output.

Autoregressive (“AR”), moving average (“MA”), integrated (“I”), approaches are used and combined (AR, MA, ARMA, ARIMA).

Variations not uncommon on relatively smooth moving trends like customer forecasts. However, can be used to model energy use and energy use per customer as well.

Forecasting Methods – Structural/Deterministic

"Deterministic" entails that models have no randomly distributed-properties. In other words, they are not statistically estimated but based upon a pre-defined (axiomatic) set of relationships. Can be very "black-box" in nature.

Basic ***class cost of service model*** can be thought of as a "deterministic" model of costs since it is based upon a set of assumed relationships (i.e., functional relationships and cost allocation factors).

Multi-areas dispatch models: based on a linear or non-linear optimization model.

Valuation modeling: income, market, and cost approach used in some states for rate base.

Cost-effectiveness modeling: mathematical relationships on "costs" and "benefits" that rise to differing stakeholders: utility, participant, non-participant, all ratepayers, society.

Forecasting Methods – Combination of Forecasts

Based upon the conclusion that any two unbiased forecasts can be combined to produce an equally unbiased forecast with increased performance.

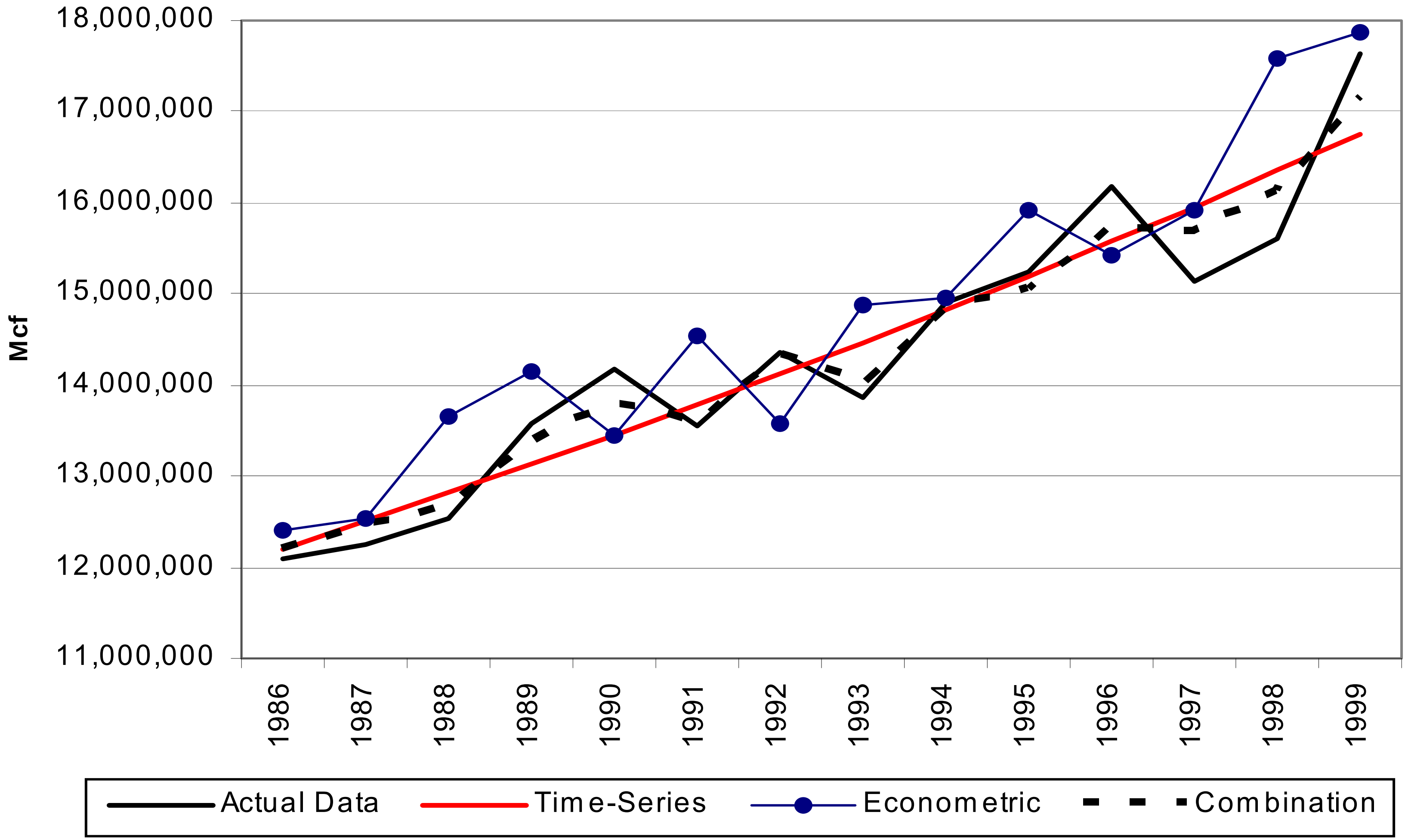
Useful method when you have two models with offsetting performance issues. The “derivatives” approach to forecasting.

Keys: (1) any two unbiased forecast (2) how forecasts are combined or weighted. Does require some subjectivity.

Despite usefulness, not commonly used. Cannot be used in all situations, depends on the models and their purpose. Combining can, in some instances, take two unbiased forecasts/estimates to create a biased forecast/estimate. (i.e., valuation modeling)

Forecasting Methods – Combination of Forecasts: Example

Comparison of actual and predicted demand model(s) – structural, time series, combination



Forecasting Methods – Forecasted Inputs/ Third Party Forecasts

Generalized term for using forecasts and inputs from a third party. These parties develop and maintain their own proprietary modeling data and methodologies and sell the results to utilities or regulatory commissions.

Utilities often subscribe to these forecasts particularly economic outlooks.

The origins for many of these companies are common, but players and names have changed with mergers and acquisitions in this business.

Global Insight commonly used source for forecasted information.

Many states will use their own independent forecasting sources for certain types of information (Indiana Utility Forecasting Group, Florida Legislative Research).

Forecasting Method – Relative Advantages

Models	Data Requirements	Technical Requirements	Parsimony	Robustness	Gamemanship
Structural/Stochastic	Moderate	High	Moderate-Low	Moderate-Low	Moderate-High
Astructural/Stochastic	Low	Moderate	High	Moderate	Moderate-Low
Structural/Deterministic	High	Moderate-High	Low	Moderate-Low	High
Combination	Low-Moderate	Low	High	Moderate-Low	High
Third-Party Forecasts	Low	Low	High	NA	High

Forecasting – Data, Inputs, and Assumptions

Any empirical model is a function of its data, input and assumption. The common adage of "garbage in, garbage out" is very true in forecasting and empirical modeling generally.

Common data problems:

- Unique and not publicly available series.
- Calculation errors.
- Transformation/standardization errors.
- Missing values
- Outliers

Forecasting – Best Practices

What Makes a "Good" Forecast?

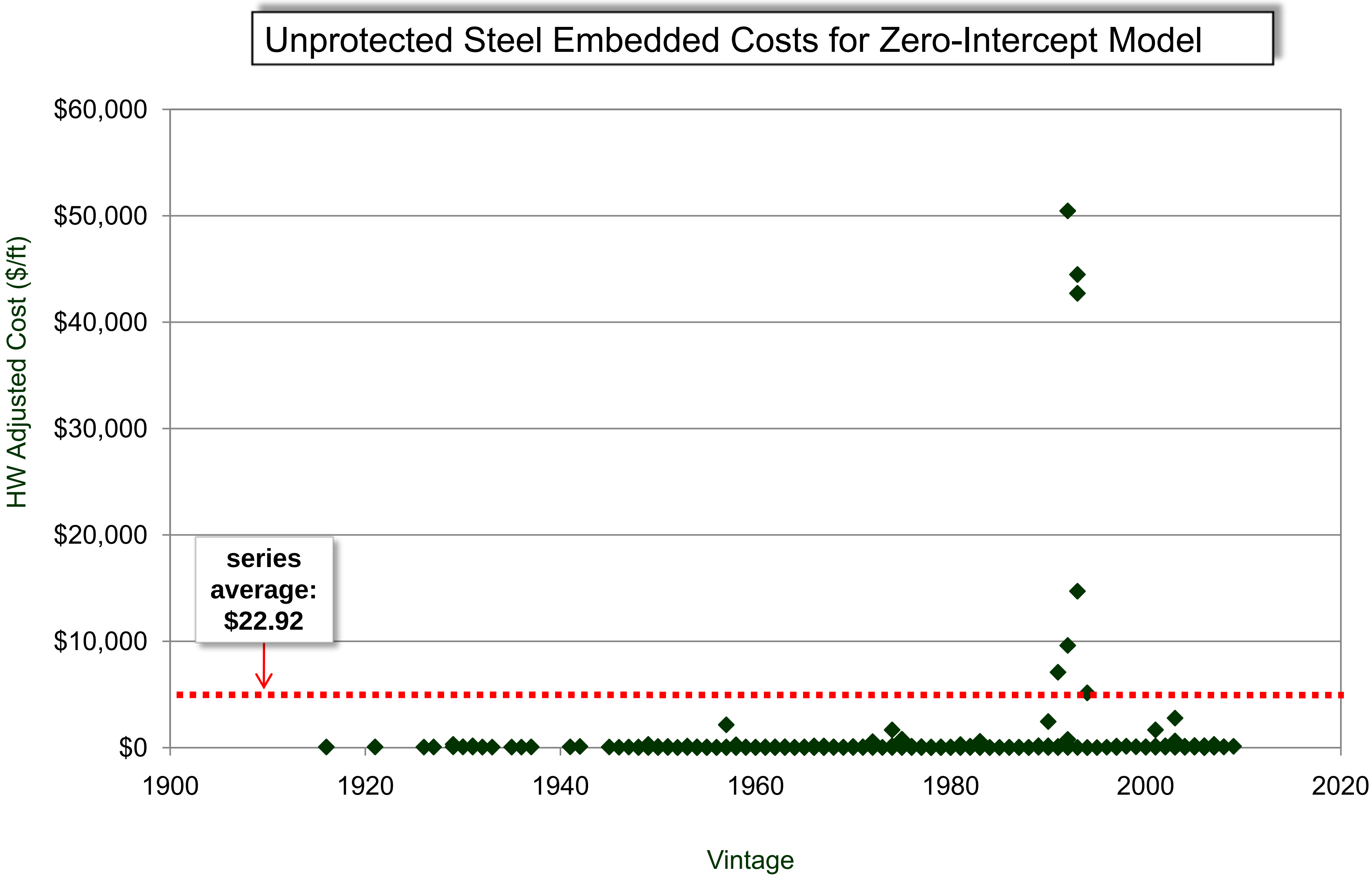
(1) Data, inputs and assumptions

(2) Parsimony and consistency

(3) Robustness

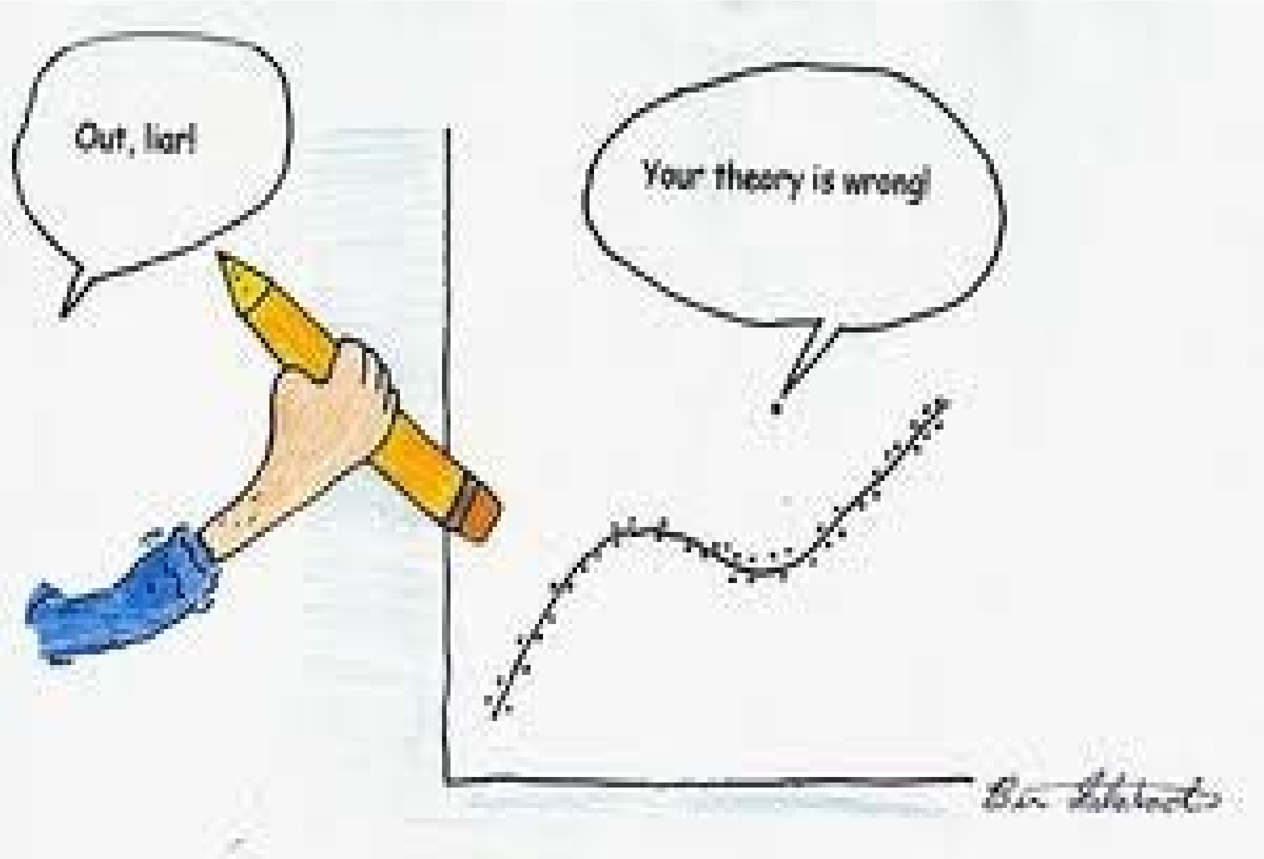
(4) Predictability and replication

Forecasting – Best Practices – Data and Assumptions (Outliers)



Forecasting – Best Practices – Data and Assumptions (Outliers)

Understanding the difference between true outliers and "different" observation is important. Tests such as Grubbs Test and other objective measures should be facilitated.



Forecasting – Best Practices – Parsimony & Consistency

Parsimony: the simplest and most frugal route of statistical explanation available. Commonly-facilitated goal for science, math, and statistics.

Does not mean "dumbing-down" the analysis.

Does mean that analytic complication for the sake of analytic complication is a waste of computational effort, regulatory resources, and at worst, a potential sign of empirical gamesmanship.

Forecasting – Best Practices – Parsimony & Consistency

Consistency: analyses that follow academic literature, utility, and/or regulatory practice.

Utility regulation is an area rich with a long history of combining the best of theory and practice. New analytic innovations that offer better insights or enhanced predictability should be welcomed, but weighed against the dollars/issues at stake.

Forecasting – Best Practices - Robustness

Model, forecast, or empirical approach can be said to be robust if changes in one or two inputs or assumptions do not lead to wild swings in the results.

Does not mean that predicted output cannot be variable or even volatile (i.e., wholesale power prices, energy commodity prices).

Robustness can be subjective in evaluating "large" changes in order of magnitude but can be less subjective in evaluating changes in direction or sign (i.e., results that move from positive to negative and vice versa).

Forecasting – Best Practices – Predictability and Replication

The are a variety of measures that examine overall empirical "goodness-of-fit." Commonly used summary statistic is referred to as "R-squared" which is also called the "coefficient of determination," or the square of the "correlation coefficient."

R-square, however, is not the only measure, and can actually be an inappropriate measure in comparing models of different composition since often adding regressors can inflate R^2 values. Also – **"correlation is not causation."**

Make sure variable signs are significant and of the correct signs

Replication: from a regulatory perspective, it is imperative that forecasts and models be replicated. It is simply bad regulatory practice to accept forecasts at face value without additional checks.

Avoid taking results from deterministic models that cannot be replicated. Black box results also create bad precedent.

Common forecasting adjustments (usage)

3

Demand Modeling

Factors Affecting Demand

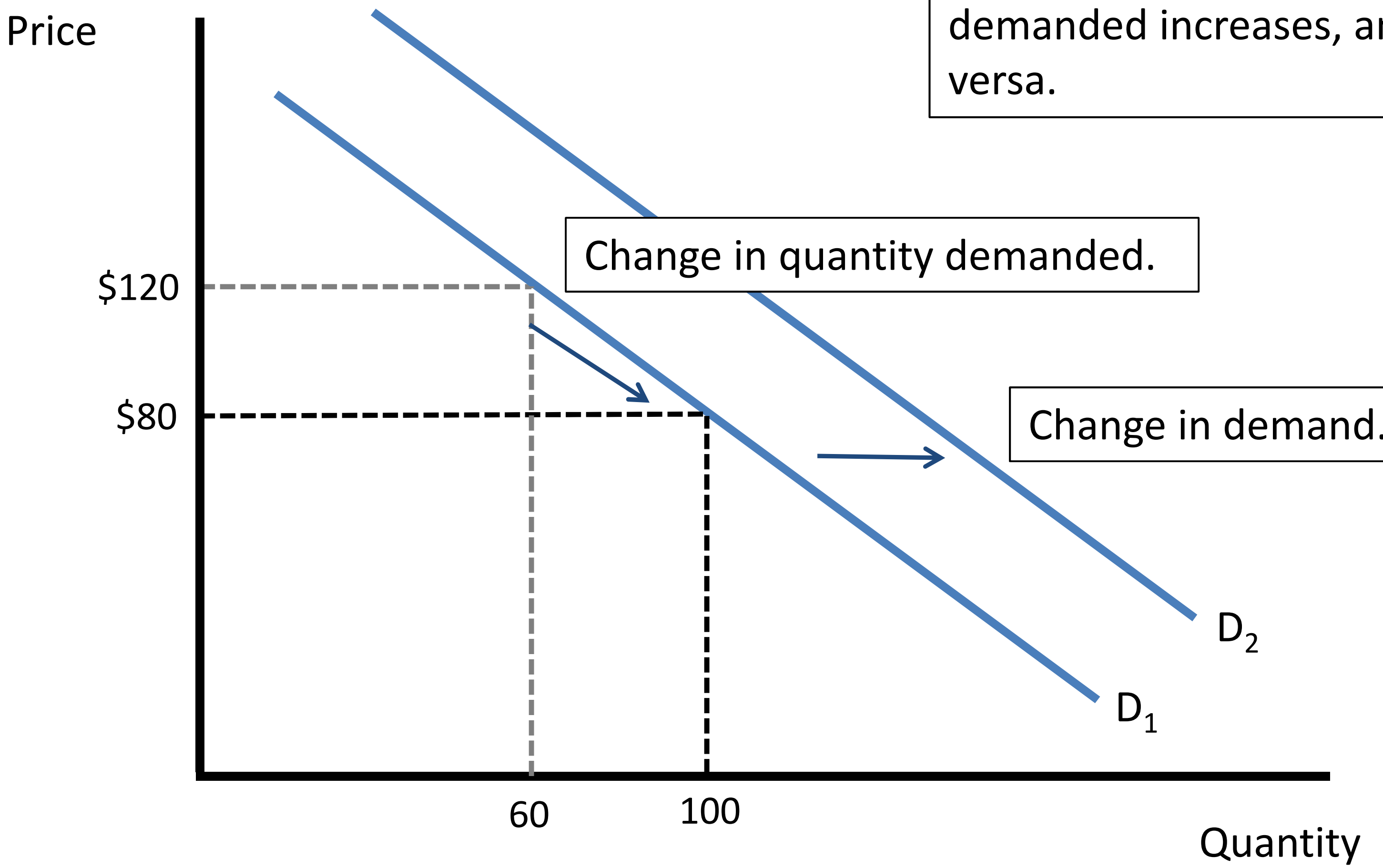
Factors influencing energy demand (gas, electric) are similar to other goods and services and include:

- The price of the good itself
- The price of complements and substitutes
- Income
- Weather
- Tastes of preferences
- Consumer expectations about future prices and income

Additional factors include technological innovation, demand-side management programs, legislation, etc.

Demand Basics: Difference Between Changes in Demand and Quantity Demanded

As price decreases, quantity demanded increases, and vice versa.



Factors of Particular Importance: Price Elasticity

$$\text{Price elasticity of demand} = \frac{\text{percentage change in quantity demanded}}{\text{percentage change in price}} = \xi$$

Elasticity	Value	Terminology	Definition	Total Revenue Impact (P*Q) for Percent Increase in Price
$\xi =$	< -1	Elastic	percentage change in quantity demanded is greater than percentage change in price.	Revenues Fall
$\xi =$	1	Unit Elastic	percentage change in quantity demanded is equal to the percentage change in price	Constant
$\xi =$	> -1	Inelastic	percentage change in quantity demanded is less than percentage change in price.	Revenues Increase

Factors of Particular Importance: Income Elasticity

Price elasticity of demand = $\dfrac{\text{percentage change in quantity demanded}}{\text{percentage change in income}} = \eta$

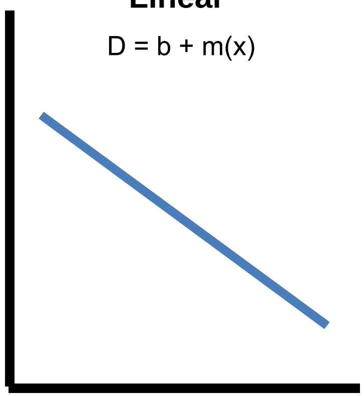
Elasticity	Value	Terminology	Definition
η	>1	Elastic	percentage change in quantity demanded is greater than percentage change in income
η	1	Unit Elastic	percentage change in quantity demanded is equal to the percentage change in income
η	< 1	Inelastic	percentage change in quantity demanded is less than percentage change in income

Functional Forms

In practice, demand curves can take many different shapes

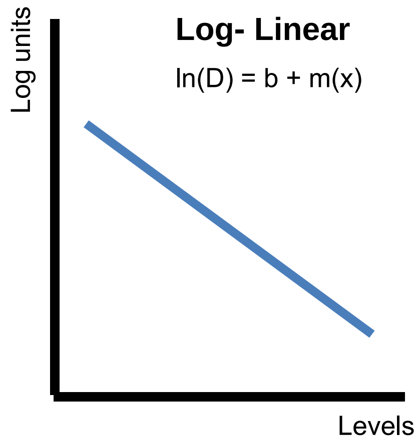
Linear

$D = b + m(x)$



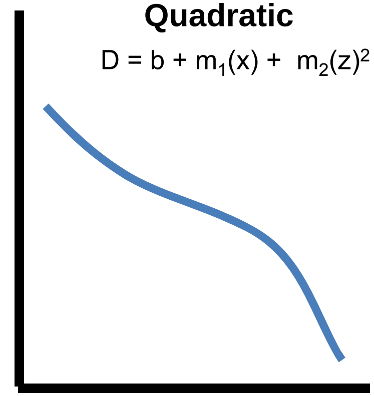
Log- Linear

$\ln(D) = b + m(x)$



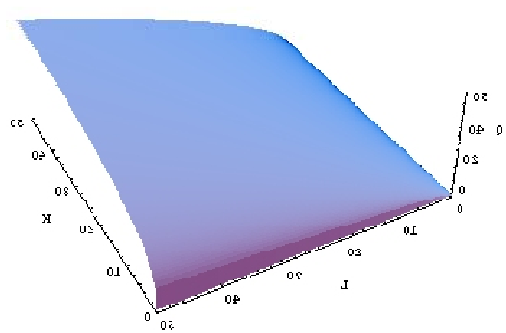
Quadratic

$D = b + m_1(x) + m_2(z)^2$



Cobb-Douglas

$D = AX^{m1}Z^{m2}$



Functional Forms – Translog Function

General forms (log linear, log-log):

$$D = b + m(x)$$

$$\log(D) = b + m(\log(x))$$

More specific form:

$$\log D = \beta_0 + \beta_1 P + \beta_2 Y + \beta_3 W + \beta_4 X$$

$$\log D = \beta_0 + \beta_1 \log P + \beta_2 \log Y + \beta_3 \log W + \beta_4 \log X$$

Where:
D = Natural gas demand
P = Price of natural gas
Y = Income
W = Weather
X = Other structural variables influencing demand
B = Estimated parameters.

Functional Forms – Translog Function

General form:

$$\ln(D_t) = \beta_0 + \sum_{i}^{N} \beta_i X_i + \sum_{i}^{N}\sum_{j}^{N} \beta_{ij} X_{it} X_{ij} + \varepsilon$$

More specific form:

$\log D = \beta_0 + \beta_1 \log P + \beta_{11}(\log P)^2 + \beta_{12}(\log P)(\log Y) + \beta_{13}(\log P)(\log W) + \beta_{14}(\log P)(\log X) + \beta_2 \log Y + \beta_{22}(\log Y)^2 + \beta_{23}(\log Y)(\log W) + \beta_{24}(\log Y)(\log X) + \beta_3 \log W + \beta_{33}(\log W)^2 + \beta_{34}(\log W)(\log X) + \beta_4 \log X + \beta_{44}(\log X)^2$

Where P = prices, Y = income, W = weather, and X = other structural variables.

Demand Modeling Forms: Advantages/Disadvantages

Approach	Strengths	Weaknesses
Log-linear / double-log	1. Relatively easy to specify and estimate.	1. Constant elasticity assumption often unrealistic and not justifiable.
	2. Estimated coefficients are directly interpretable as short-run elasticities, and long-run elasticities are easy to calculate.	2. Sometimes problems of consistency with the underlying economic theory.
	3. Estimated standard errors provide measure of the variability of the estimated elasticities.	3. Appropriate only when one has reason to believe that the variables enter multiplicatively into the equation.

Demand Modeling Forms: Advantages/Disadvantages

Approach	Strengths	Weaknesses
Translog	1. Imposes a minimum of restrictions on demand behavior and is very flexible.	1. Sometimes lack degrees of freedom due to the large number of regressions.
	2. Firmly based in economic theory.	2. Only well-behaved for a limited range of relative prices.
	3. Particular demand characteristics are testable (e.g., separability, homotheticity, etc.).	3. Estimated elasticities are not directly interpretable.
	4. Allows the analysis of substitutional relations.	4. More comlicated estimation techniques are required.
		5. Static formulations dominate.

Demand Modeling Forms: Advantages/Disadvantages

Approach	Strengths	Weaknesses
Qualitative Choice	1. Appropriate when dependent variable comprises a finite set of discrete alternatives.	1. Inefficient estimates in the case of zeros (logit, probit).
	2. Relatively easy to estimate.	2. Theoretically not based on assumptions of utility maximization (logit).
	3. Flexible specification.	3. Relies on rich and reliable data sets.
	4. Tobit models allow for observations to equal zero.	

Demand Modeling Forms: Advantages/Disadvantages

Approach	Strengths	Weaknesses
Pooled time series / cross-section	1. Pooling enables greater efficiency of the estimates.	1. Only makes sense if the cross-sectional parameters are constant over time.
		2. Difficult specification.

Lag Structures

Prices and Income are often subjected to various different lag structures in the demand modeling/forecasting process.

The use of lags recognizes that it takes time for the full impact of either changes in price or income to materialize on energy demand.

Lags also allow for the estimation of short run and longer run elasticities.

Challenge is determining the most appropriate lag structure.

Two common approaches: (1) finite distributed lags and (2) infinite distributed lag.

Literature Review

One of the pioneers of demand modeling was Hendrick S. Houthakker. His work in energy demand modeling, developed in the early 1950s, was the basis for his broader work in overall demand modeling.

Les Taylor, a former student and colleague of Houthakker completed the first formal surveys of the literature in the Bell Journal (1975, electricity only), and later, more broadly, for energy demand (1977) in a general manuscript.

One of the more comprehensive surveys of energy demand modeling was prepared by Douglas R. Bohi for the Electric Power Research Institute(EPRI) in 1982 with a special emphasis on price and income elasticities.

Literature Review – Good Survey Articles on Demand Modeling

A general primer on the role of natural gas demand forecasting and how it relates to overall LDC planning can be found in:

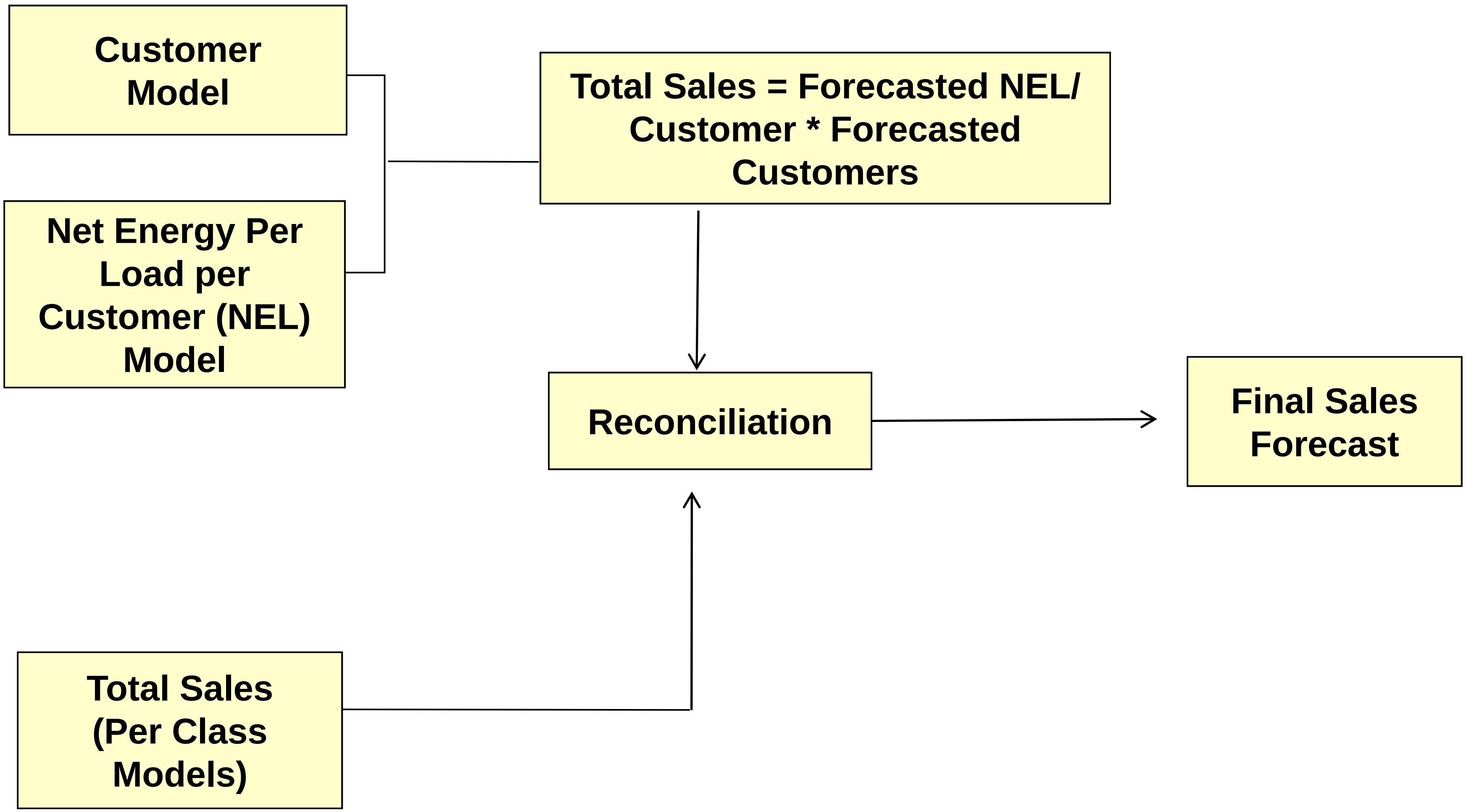
> **Charles Goldman, et al (1993). *Primer on Gas Integrated Resource Planning.* Berkeley, California: Lawrence Berkeley Laboratories.**

More recent survey specific to residential energy demand provided by Reinhard Madlener

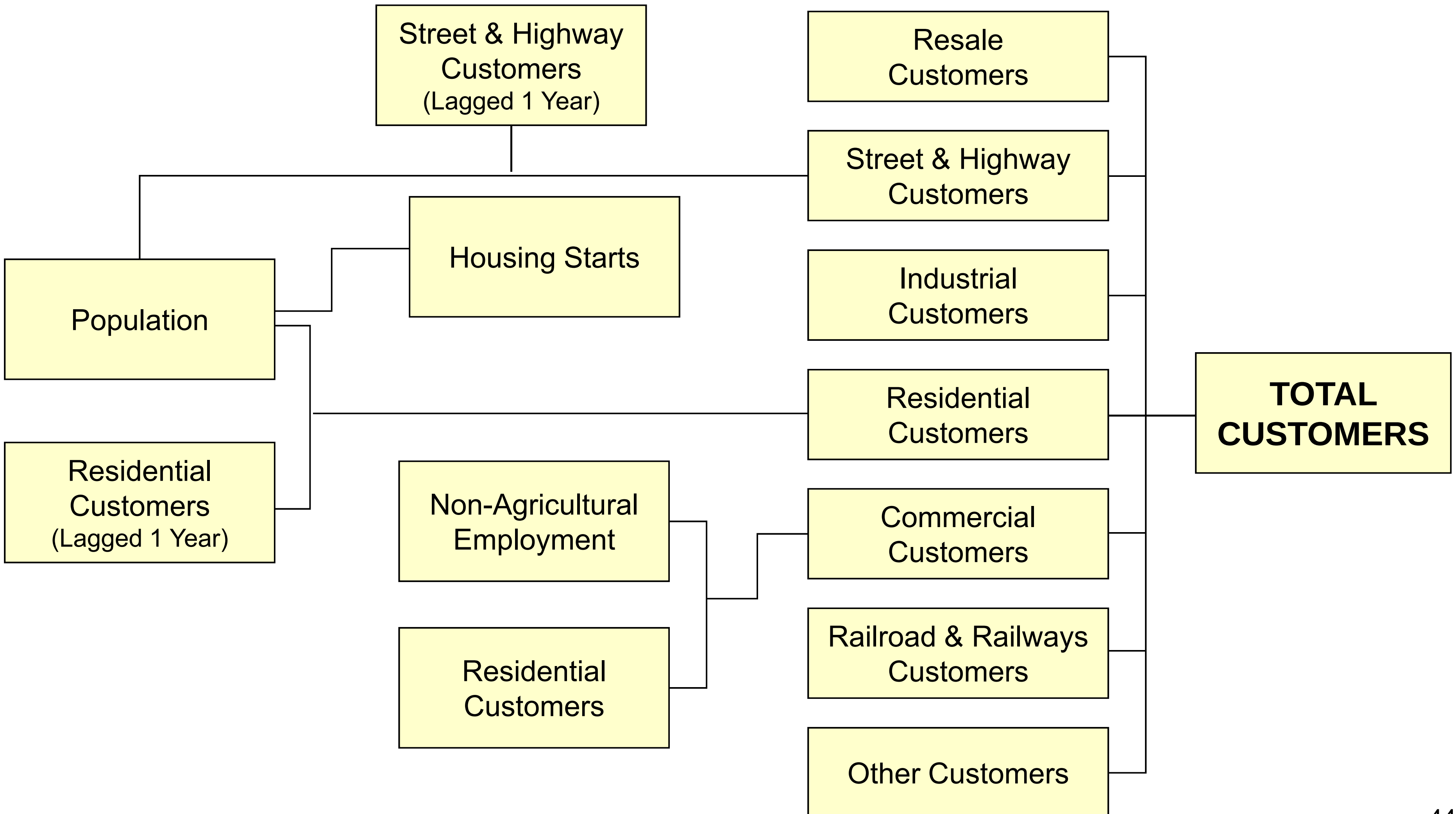
> **See Reinhard Madlener. (1996) Econometric Analysis of Residential Energy Demand: A Survey. *Journal of Energy Literature.* 2:3-32.**

Madlener focuses on incorporating different functional forms, such as those previously mentioned, into energy demand modeling.

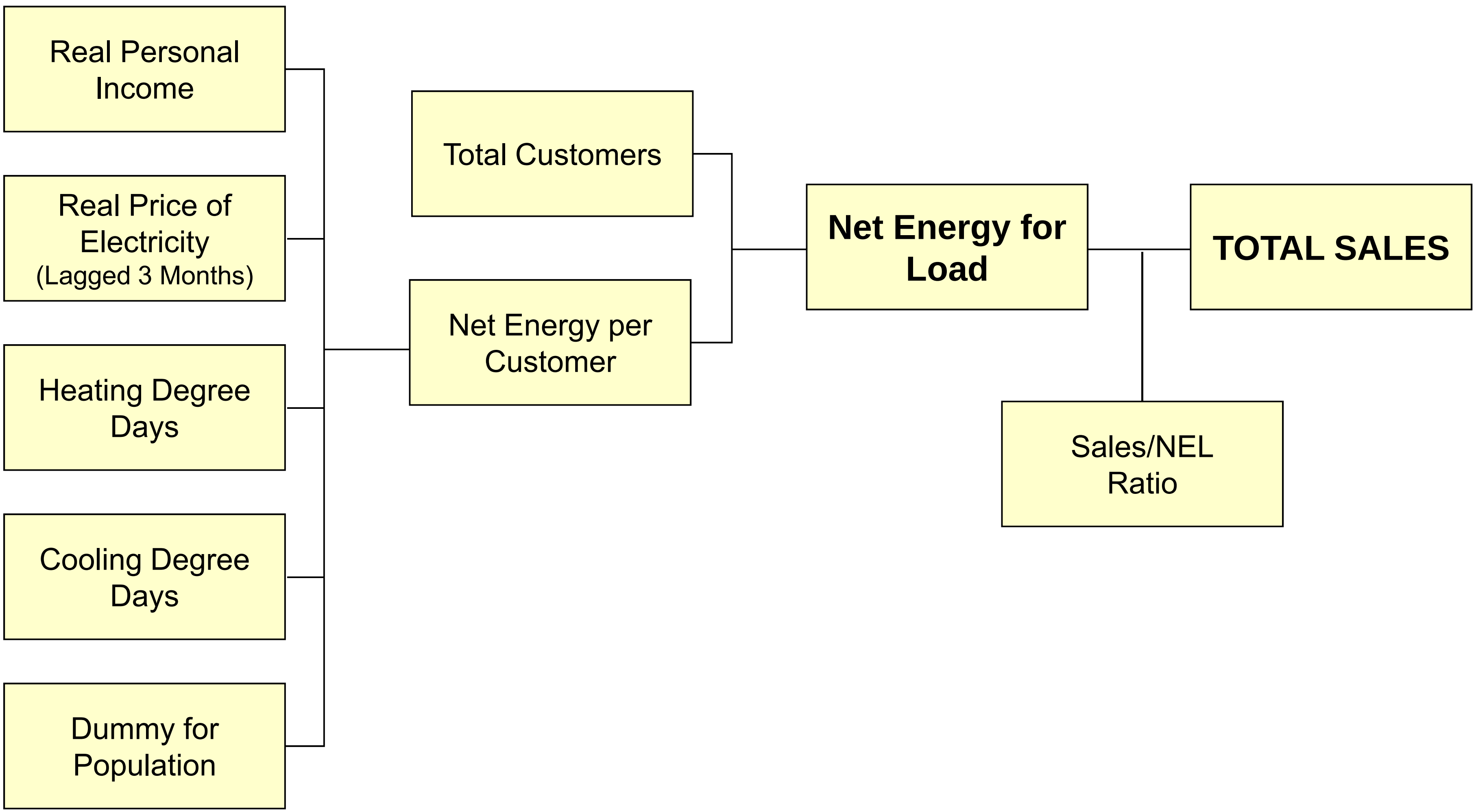
Forecasting as a Process – Electricity Example



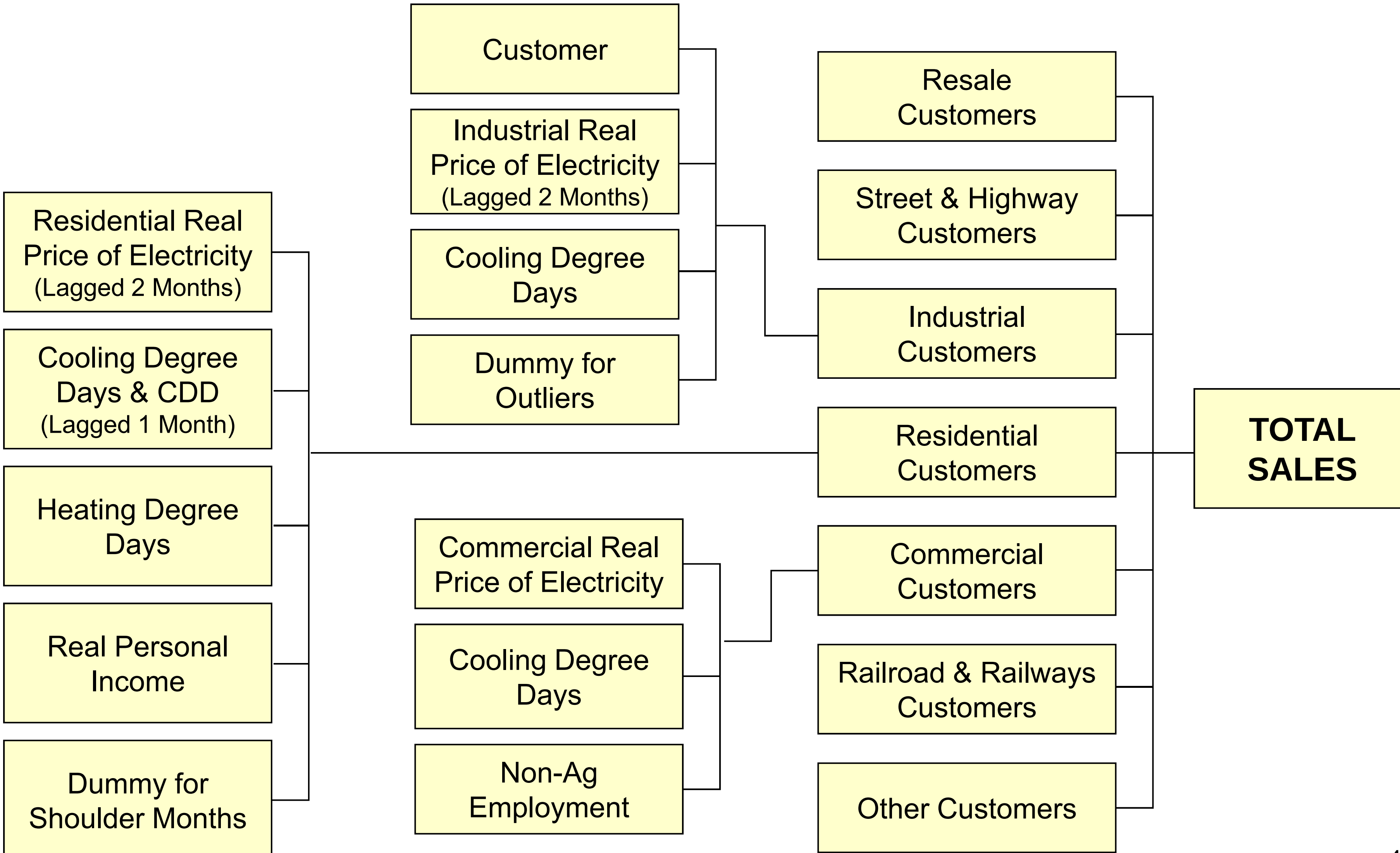
Forecasting as a Process – Total Customer Forecast (Electricity)



Forecasting as a Process – Sales Forecast (Electricity)



Forecasting as a Process – Secondary Sales Forecast (Electricity)



Electricity Usage Modeling (Residential MWh)

The output to the left is basic electricity demand model.

Variables are listed in the left hand column, coefficients, standard errors, t statistics, and probabilities are provided in the middle portion of the table.

Model run on total class energy use basis (not use per customer), includes variables on weather (HDD, CDD), and seasonality.

Summary statistics are at the bottom for the regression performance.

Basic Residential Electricity Model

Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample: 2001M01 2007M12
Included observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	77062.56	24661.34	3.125	0.003
PRICE_PER_MWH	495.833	134.0178	3.700	0.000
CDDS	58.59974	31.01987	1.889	0.063
HDDS	4.181725	29.24739	0.143	0.887
MONTHS=FEBRUARY	-25202.24	7050.043	-3.575	0.001
MONTHS=MARCH	-42121.5	11193.91	-3.763	0.000
MONTHS=APRIL	-45071.31	15814.16	-2.850	0.006
MONTHS=MAY	-53866.27	19103.64	-2.820	0.006
MONTHS=JUNE	-16903.37	22715.95	-0.744	0.459
MONTHS=JULY	-10293.86	23610.49	-0.436	0.664
MONTHS=AUGUST	-9595.14	22257.27	-0.431	0.668
MONTHS=SEPTEMBER	418.0799	19289.94	0.022	0.983
MONTHS=OCTOBER	-23797.64	15892.66	-1.497	0.139
MONTHS=NOVEMBER	-39172.22	9222.773	-4.247	0.000
MONTHS=DECEMBER	-18086.45	5929.047	-3.050	0.003

R-squared	0.870725	Mean dependent var	123874
Adjusted R-squared	0.844496	S.D. dependent var	27188.7
S.E. of regression	10721.62	Akaike info criterion	21.5583
Sum squared resid	7.93E+09	Schwarz criterion	21.9924
Log likelihood	-890.4505	Hannan-Quinn criter.	21.7328
F-statistic	33.19624	Durbin-Watson stat	0.99864
Prob(F-statistic)	0		

Electricity Usage Modelign – Surveying the Landscape of Typical Output

First Model

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Prob(F-statistic)	0		

Constant reflecting base use

Higher R^2 and Adj-R^2 values tend to indicate model fit, but should be used with caution.

Parsimony is an important aspect of model building, the Adj-R^2 balances both goodness of fit and the principle of parsimony.

Probability values (P-Values) reflect the significance of each variable. They are related to t-Statistics. The higher the t-statistic, the lower the p-value.

Akaike Info Criterion ("AIC") and Schwarz Info Criterion ("SIC") are also good measures of parsimony (lower is better).

Electricity Usage Modeling – Examining Initial Statistical Output

This is the first model run. Two initial results stand out from the output.

Heating degree days have very low statistical significance, other variables have relatively strong statistics.

From diagnostics perspective, the Durbin-Watson test statistic is about 0.99 indicating the possibility of autocorrelation.

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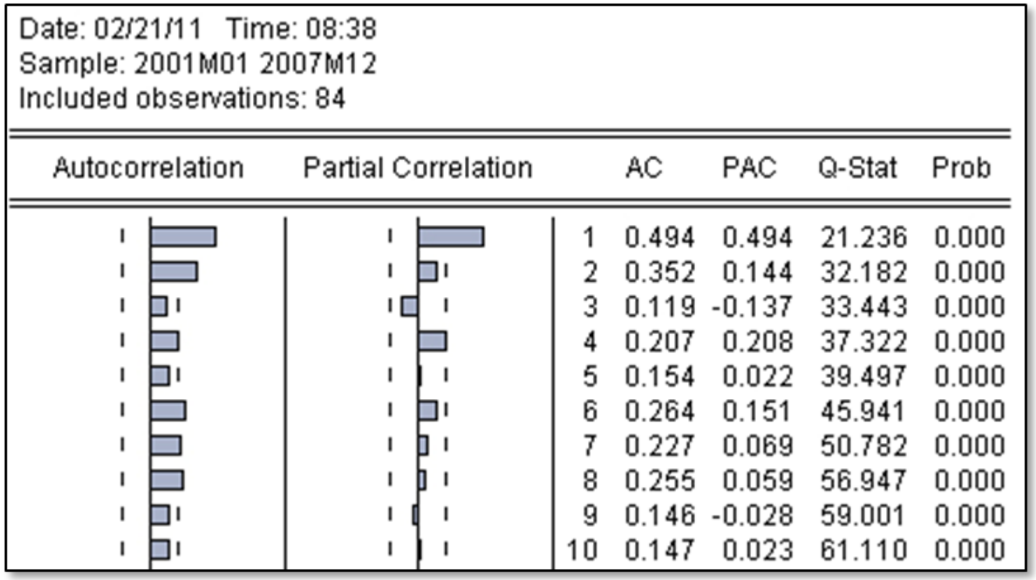
Sum squared resid	7.93E+09	Schwarz criterion	21.9924
Log likelihood	-890.4505	Hannan-Quinn criter.	21.7328
F-statistic	33.19624	Durbin-Watson stat	0.99864
Prob(F-statistic)	0		

Electricity Usage Analysis – Serial Correlation

The Durbin-Watson test statistic is based on the null hypothesis that autocorrelation does not exist (serially independent).

A test-statistic of 2 is the "sweet spot", a statistic of 1 or less indicates that a strong presence of autocorrelation may exist.

A correlogram at right shows statistically significant partial autocorrelation indicating that an AR(1) term may be necessary to capture mean reversion.



Date: 02/21/11 Time: 08:38
Sample: 2001M01 2007M12
Included observations: 84

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.494	0.494	21.236	0.000
		2	0.352	0.144	32.182	0.000
		3	0.119	-0.137	33.443	0.000
		4	0.207	0.208	37.322	0.000
		5	0.154	0.022	39.497	0.000
		6	0.264	0.151	45.941	0.000
		7	0.227	0.069	50.782	0.000
		8	0.255	0.059	56.947	0.000
		9	0.146	-0.028	59.001	0.000
		10	0.147	0.023	61.110	0.000

Electricity Usage Modeling– Reviewing the Corrected Output

The AR (1) adjustment appears to be correcting the AT problem.

However, two important explanatory variables (Price and weather) are not statistically significant.

This is likely due to collinearity with the monthly dummy variables. Prices and CDDs are highly seasonal.

Trimming the seasonal variables may improve performance.

Second Model

Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample (adjusted): 2001M02 2007M12
Included observations: 83 after adjustments
Convergence achieved after 12 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	149214.00	16835.870	8.863	0.000
PRICE_PER_MWH	-147.13	149.056	-0.987	0.327
CDDS	26.46	22.663	1.168	0.247
MONTHS=APRIL	-37825.03	5889.203	-6.423	0.000
MONTHS=AUGUST	11752.20	13334.930	0.881	0.381
MONTHS=DECEMBER	-17771.64	3654.395	-4.863	0.000
MONTHS=FEBRUARY	-24034.76	3466.476	-6.933	0.000
MONTHS=JULY	12929.77	14709.440	0.879	0.383
MONTHS=JUNE	5632.00	13813.830	0.408	0.685
MONTHS=MARCH	-41404.49	4553.503	-9.093	0.000
MONTHS=MAY	-36011.90	9774.505	-3.684	0.001
MONTHS=NOVEMBER	-34003.97	4893.835	-6.948	0.000
MONTHS=OCTOBER	-14052.58	6142.966	-2.288	0.025
MONTHS=SEPTEMBER	12342.97	9581.288	1.288	0.202
AR(1)	0.74	0.084	8.708	0.000

R-squared	0.920754	Mean dependent var	123867
Adjusted R-squared	0.904439	S.D. dependent var	27354
S.E. of regression	8455.912	Akaike info criterion	21.085
Sum squared resid	4.86E+09	Schwarz criterion	21.522
Log likelihood	-860.0371	Hannan-Quinn criter.	21.261
F-statistic	56.43495	Durbin-Watson stat	2.2384
Prob(F-statistic)	0		

Inverted AR Roots	0.74

Electricity Usage Modeling – Moving to Parsimony

Reduced ("more parsimonious") model shows some improvement since all the relevant variables are statistically significant, autocorrelation has been corrected although some model performance statistics are not as attractive.

Second Model

Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample (adjusted): 2001M02 2007M12
Included observations: 83 after adjustments
Convergence achieved after 12 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R-squared	0.920754	Mean dependent var		123867
Adjusted R-squared	0.904439	S.D. dependent var		27354
S.E. of regression	8455.912	Akaike info criterion		21.085
Sum squared resid	4.86E+09	Schwarz criterion		21.522
Log likelihood	-860.0371	Hannan-Quinn criter.		21.261
F-statistic	56.43495	Durbin-Watson stat		2.2384
Prob(F-statistic)	0			
Inverted AR Roots	0.74			

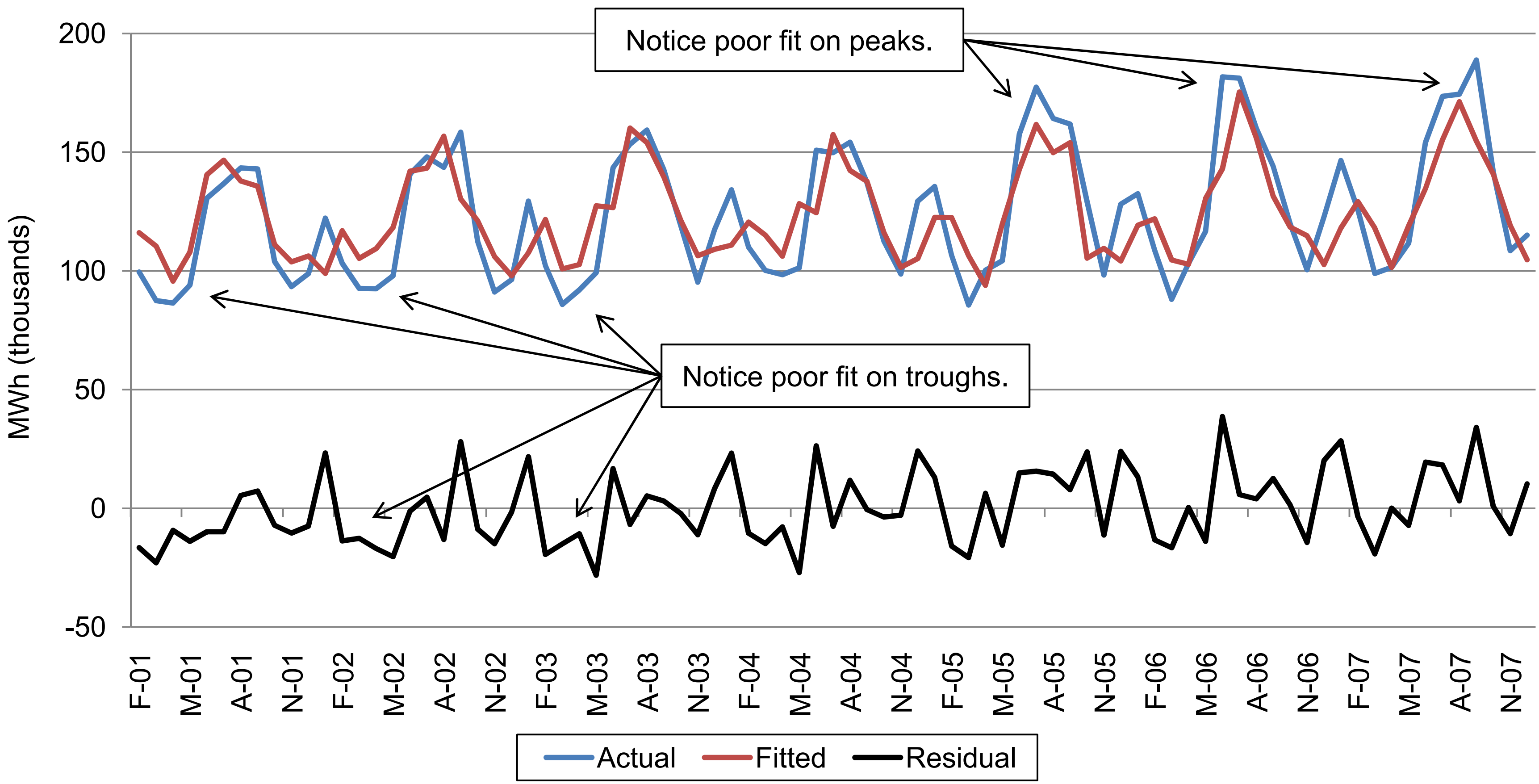
Third Model

Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample (adjusted): 2001M02 2007M12
Included observations: 83 after adjustments
Convergence achieved after 114 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	170991.50	26376.850	6.483	0.000
PRICE_PER_MWH	-591.94	228.062	-2.596	0.011
CDDS	98.62	14.892	6.622	0.000
AR(1)	0.63	0.106	5.935	0.000
R-squared	0.677899	Mean dependent var		123867
Adjusted R-squared	0.665667	S.D. dependent var		27353.9
S.E. of regression	15816.45	Akaike info criterion		22.2225
Sum squared resid	1.98E+10	Schwarz criterion		22.3391
Log likelihood	-918.233	Hannan-Quinn criter.		22.2693
F-statistic	55.42159	Durbin-Watson stat		1.91957
Prob(F-statistic)	0			
Inverted AR Roots	0.63			

Electricity Usage Modeling – Plotting the Fit

Occular analysis: fitted to actual values. Model is not completely capturing seasonal effects and that these effects are increasing and decreasing through time. A multiplicative seasonal adjustment may fix this problem.



Electricity Usage Modeling – Trend and Seasonality Adjustments

Use of multiplicative seasonal and trend variable improves overall performance.

Third Model

Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample (adjusted): 2001M02 2007M12
Included observations: 83 after adjustments
Convergence achieved after 114 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	170991.50	26376.850	6.483	0.000
PRICE_PER_MWH	-591.94	228.062	-2.596	0.011
CDDS	98.62	14.892	6.622	0.000
AR(1)	0.63	0.106	5.935	0.000

R-squared	0.677899	Mean dependent var	123867
Adjusted R-squared	0.665667	S.D. dependent var	27353.9
S.E. of regression	15816.45	Akaike info criterion	22.2225
Sum squared resid	1.98E+10	Schwarz criterion	22.3391
Log likelihood	-918.233	Hannan-Quinn criter.	22.2693
F-statistic	55.42159	Durbin-Watson stat	1.91957
Prob(F-statistic)	0		
Inverted AR Roots	0.63		

Final Model

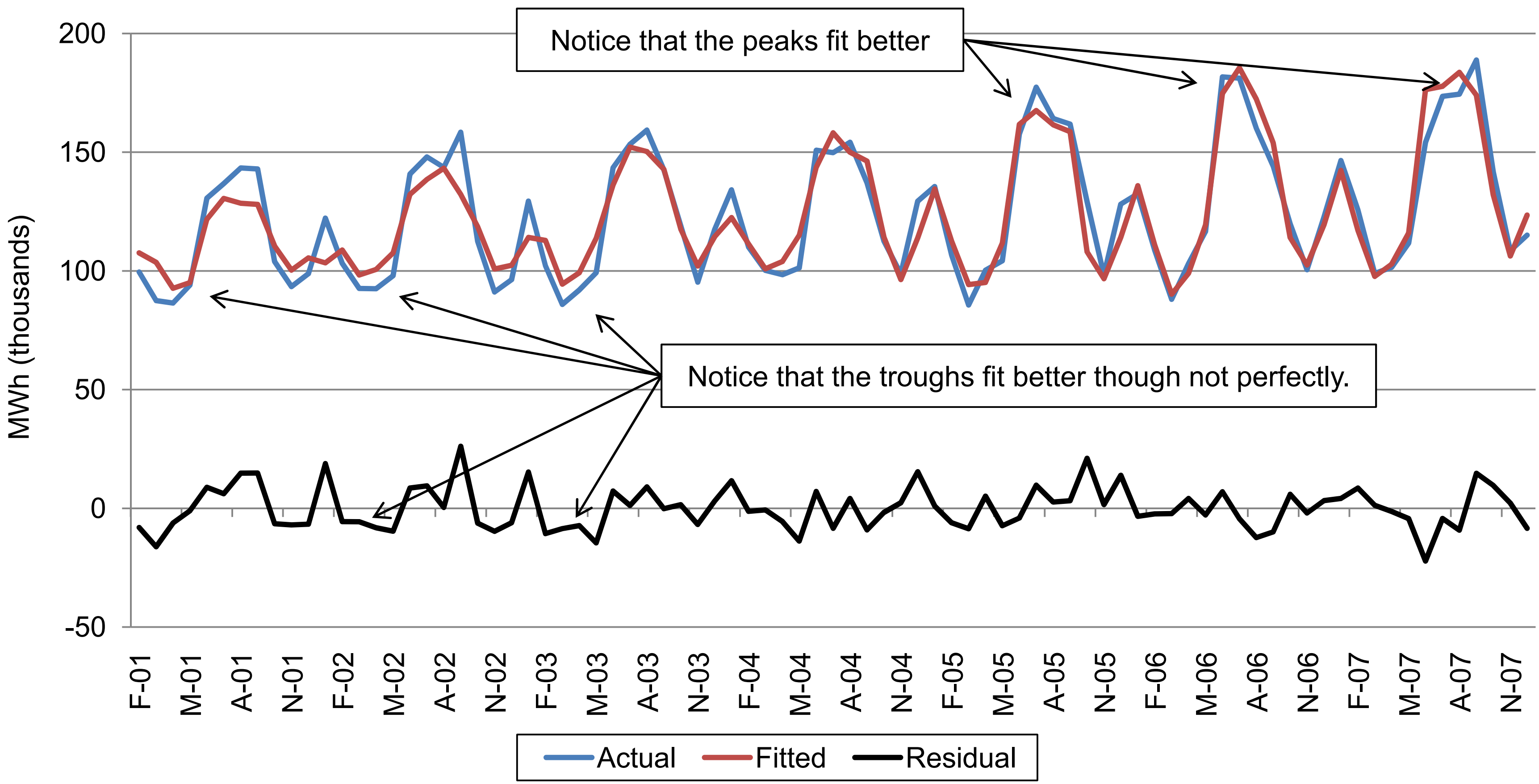
Dependent Variable: RESIDENTIAL_MWH
Method: Least Squares
Sample (adjusted): 2001M02 2007M12
Included observations: 83 after adjustments
Convergence achieved after 16 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	144558.20	15032.280	9.617	0.000
PRICE_PER_MWH	-436.20	143.209	-3.046	0.003
CDDS	41.53	8.962	4.634	0.000
TREND	-1255.98	193.778	-6.482	0.000
TREND*SA	1691.87	163.115	10.372	0.000
AR(1)	0.41	0.109	3.782	0.000

R-squared	0.888704	Mean dependent var	123867
Adjusted R-squared	0.881477	S.D. dependent var	27354
S.E. of regression	9417.18	Akaike info criterion	21.208
Sum squared resid	6.83E+09	Schwarz criterion	21.383
Log likelihood	-874.1321	Hannan-Quinn criter.	21.278
F-statistic	122.97	Durbin-Watson stat	1.7732
Prob(F-statistic)	0		
Inverted AR Roots	0.41		

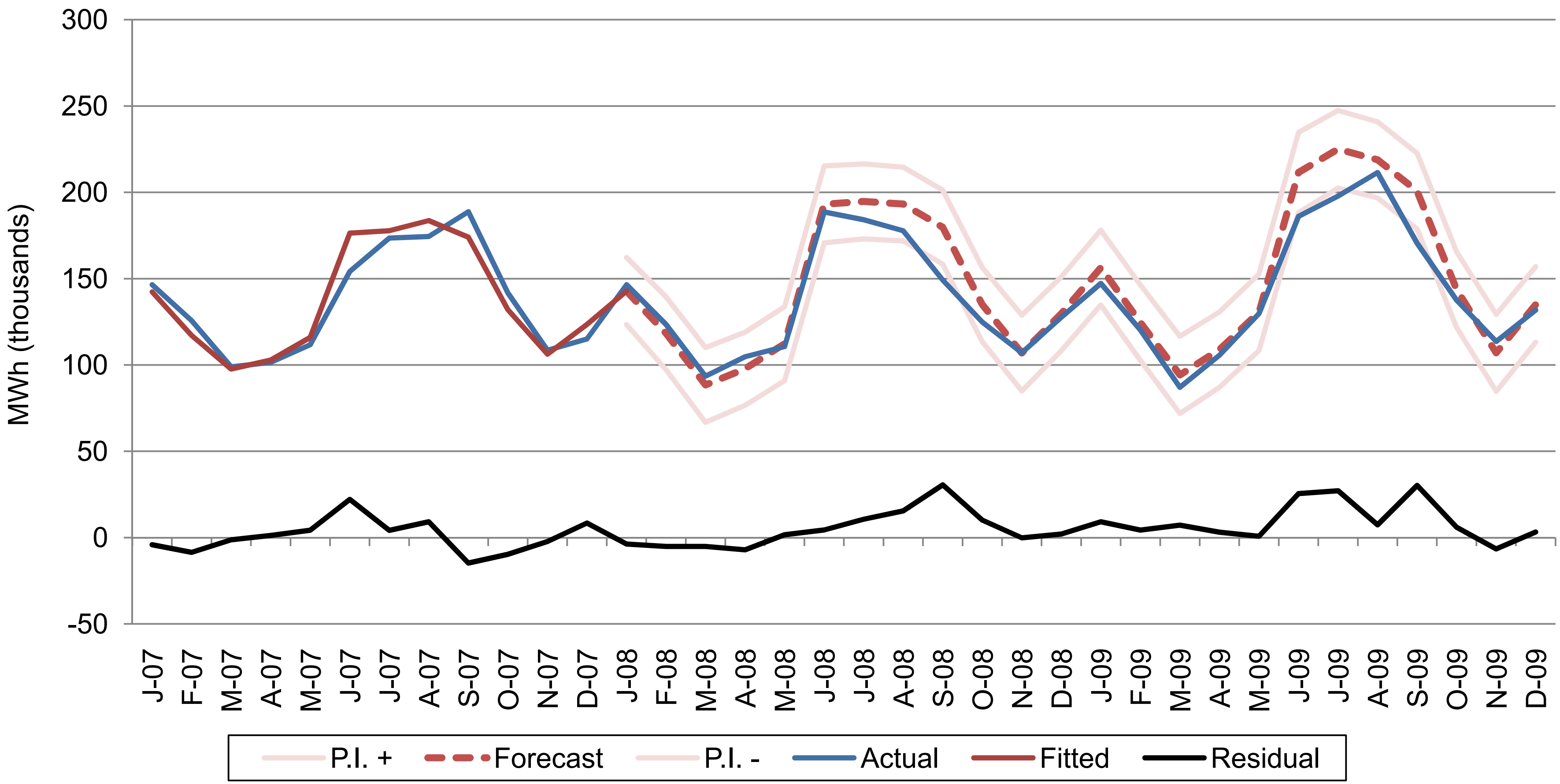
Electricity Usage Analysis (Residential) -- Final Model Fit

The new adjustment seems to work better. Peaks and troughs fit better.



Electricity Usage Modeling – Backcast Approach

A backcast is fitted by holding out data from January 2008 through December 2009, and plotting model results on the know data. The light pink lines are two standard deviation prediction intervals.



Electricity Demand Modeling: Sometimes it is just trial and error.

Demand Analysis: Natural Gas Demand Models (Residential)

Natural gas demand model (residential) relatively straightforward and is a function of lagged prices, income, weather and customers.

Constant reflecting base use (double log model)

Lagged price impacts (elasticities): short run v. long run

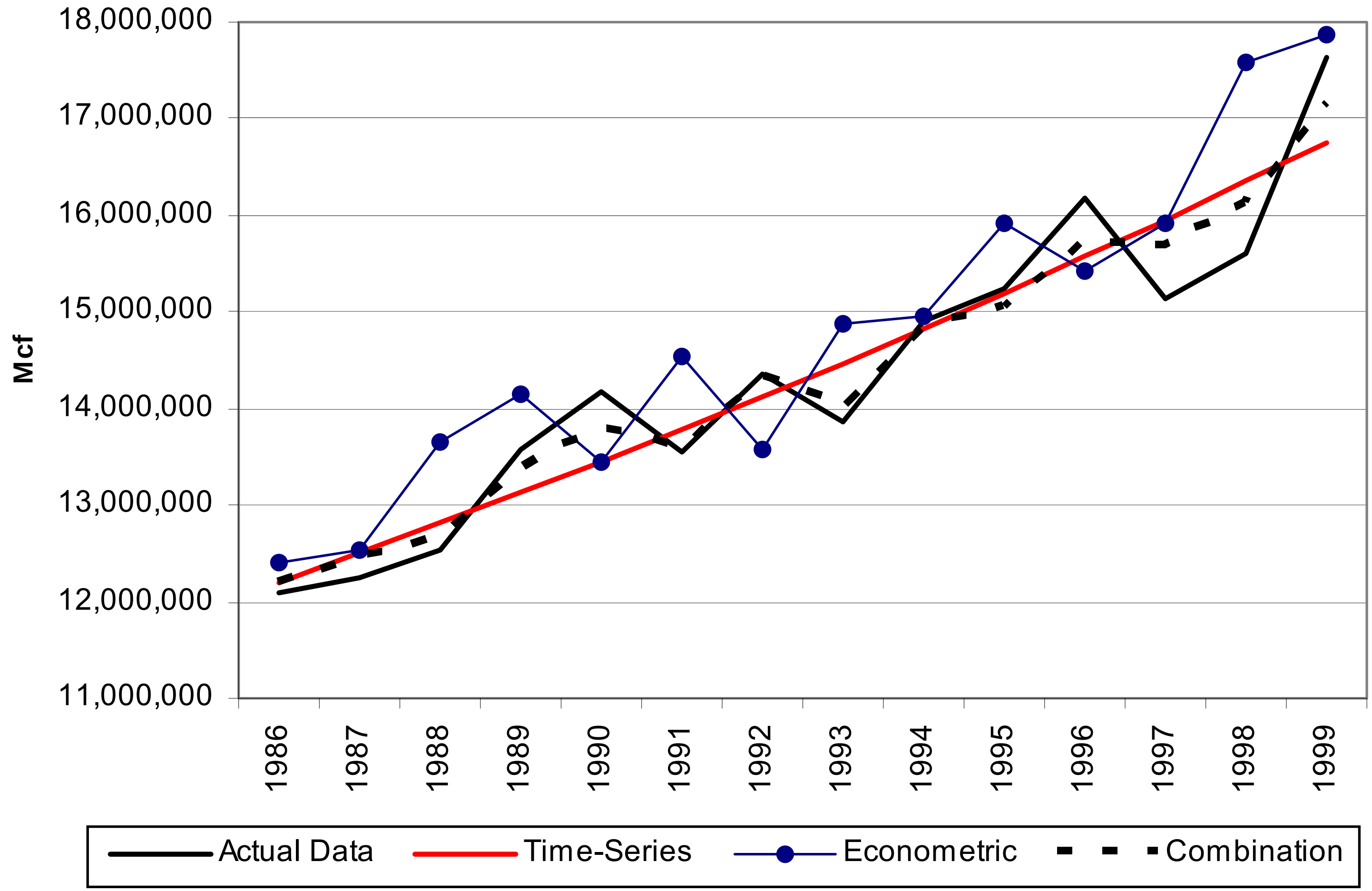
Income (elasticity)

Weather and customer impacts

Variable	Coefficient	Standard Error	t-Statistic
Intercept	-5.8853	2.8533	-2.06
Polynomial Price Terms			
Current Period Price	-0.2042	0.1078	-1.89
Lagged Price (t-1)	-0.1021	0.0539	-1.89
Income (PCI)	1.4991	0.5170	2.90
Heating Degree Days	0.5574	0.0922	6.05
Customers	0.1946	0.2685	0.72
Adjusted R^2	0.982		

Demand Analysis: Natural Gas Demand Models (Residential)

Comparison of actual and predicted demand model(s) – structural, time series, combination



Demand Analysis: Natural Gas Demand Models (Commercial)

Natural gas demand model (commercial) set up in fashion similar to residential.

Constant reflecting base use (double log model)

Lagged price impacts (elasticities): short run v. long run

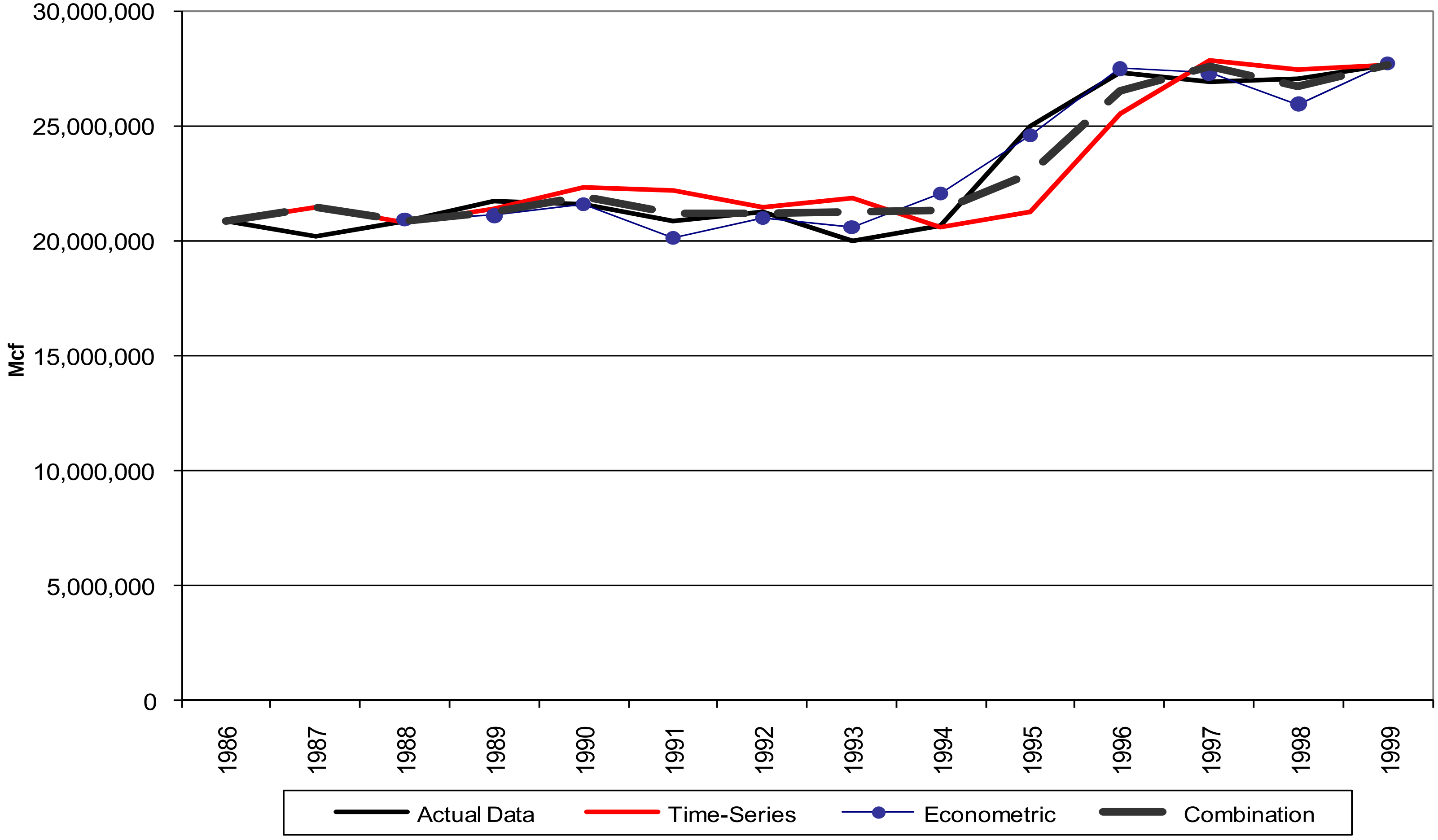
Income (elasticity)

Weather and customer impacts

Variable	Coefficient	Standard Error	t-Statistic
Intercept	41.8978	20.8635	2.01
Polynomial Price Terms			
Current Period Price	-0.8042	0.3504	-2.29
Lagged Price (t-1)	-0.5361	0.2336	-2.29
Lagged Price (t-2)	-0.2681	0.1168	-2.29
Income (PCI)	0.1453	1.3608	0.11
Heating Degree Days	0.0172	0.2551	0.07
Customers	-2.6406	2.5185	-1.05
Adjusted R^2	0.9122		

Demand Analysis: Natural Gas Demand Models (Commercial)

Comparison of actual and predicted demand model(s) – structural, time series, combination



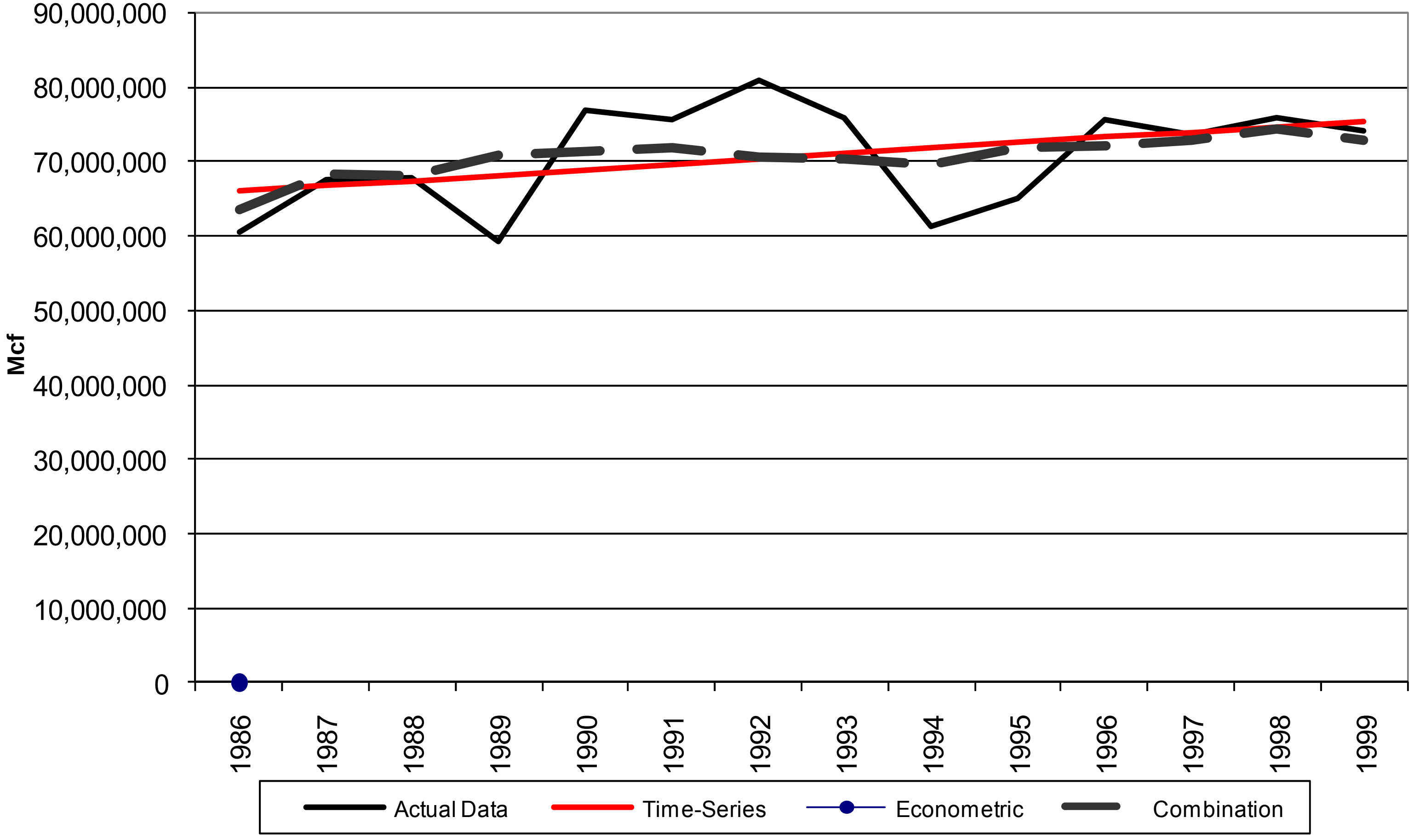
Demand Analysis: Natural Gas Demand Models (Industrial)

Industrial demand models notoriously difficult to estimate (as group).

Variable	Coefficient	Standard Error	t-Statistic
Intercept	17.1259	1.4676	11.67
Price	-0.1178	0.2669	-0.44
Income (Manufacturing GSP)	0.1901	0.1878	1.01
Customers	-0.1665	0.1696	-0.98
Adjusted R^2	0.251		

Demand Analysis: Natural Gas Demand Models (Industrial)

Comparison of actual and predicted demand model(s) – structural, time series, combination



4

Common forecasting adjustments (usage)

Common Forecasting Adjustments: Demand/Billing Determinants

Demand or billing unit data is often changed or modified in the ratemaking and/or planning process in order to account for a variety of anticipated changes that may be the result of policy or other factors.

Common adjustments include:

- *Weather normalization*
- *Income/economic adjustments*
- *“Unusual” events (ice-storms, hurricanes, catastrophes)*
- *Price change, stimulation or repression*
- *Energy efficiency*

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

Weather normalization adjustment is not the same as a weather normalization clause tracker.

Weather normalization, in context of “forecasting,” is process to standardize billing units for “normal” weather.

Weather normalization clause is an ongoing tracker to adjustment monthly bills for “normal” weather-related/influenced use.

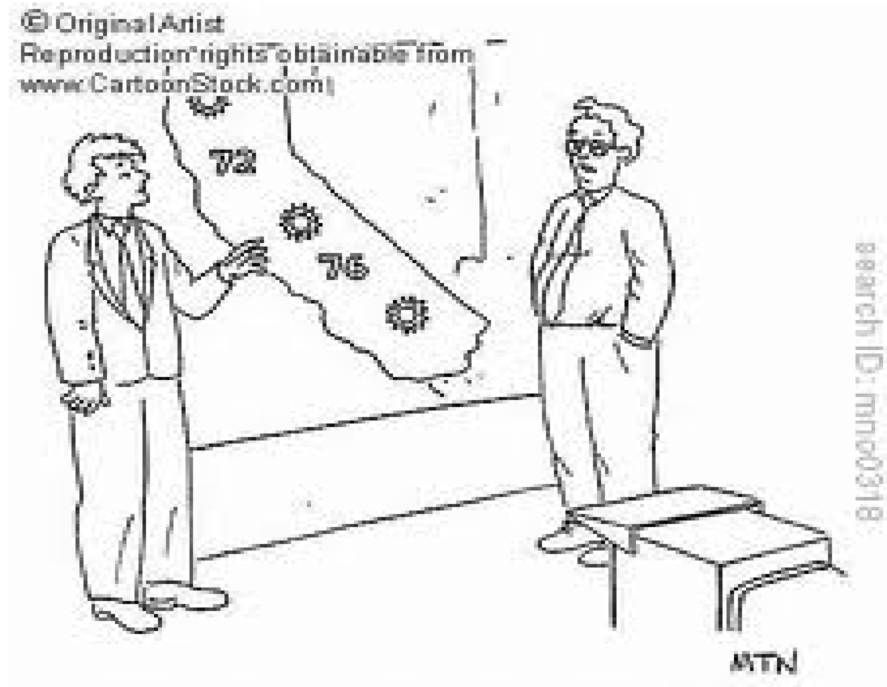
Normalization moves billing determinants to the “average” or “typical” use level. So if period in question has colder than normal weather, and greater than average HDDs, billing determinants will be adjusted downwards, and vice versa.

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

Why is "normal" weather an issue?

Global warming/climate change debate.

Until recently (roughly last 2 years), a warmer-than-average winter weather cycle that was particularly evident in the mid-west and western U.S..



"The weather never changes here. You're fired."

Many utilities believed that the standard definition of "normal" was not picking up this trend.

Many utilities took the position that defining shorter periods were better predictors.

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

Weather normalization adjustments can range from the very simple to the very complicated.

The empirical/analytic challenge is developing a set of weather-related parameters that define (in unbiased fashion) the relationship between weather and energy use.

As a general rule, the results from a load forecast can be used to establish these parameters, although often that is not the case.

Most often, the debate does not focus on the estimation of weather parameters as it does in defining the "normal" period for establishing "normal" weather.

This becomes a policy debate as much as it does an empirical debate.

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

Policy questions on defining "normal" weather:

Distinction needs to be made between "cycle" and "trend."

- *What adjustment are we really making? Is this a forecast or a normalization process?*
- *Regardless, should the ratemaking process be based on cycles or trends?*
- *What is the best time period to set for normal weather if a change is determined to be appropriate? (5 years, 10 years, etc.)*
- *Should any changes in revenue recovery risk be identified in the ratemaking process?*

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

Company	Number of Months Covered by Clause	Mechanism Type	Customer Classes	Number of Years (Normal)
Alabama				
Alagasco	12	1	Residential, Small Commercial and Small Industrial	n.a.
Arkansas				
Arkansas Western Gas	6	1	Residential, Commercial	30
CenterPoint Energy	6	2	Residential, Small Commercial	30
Arkansas Oklahoma Gas	6	1	Residential, Small Business	30
Georgia				
Atmos Energy	12	1	Residential, Commercial	n.a.
Indiana				
Indiana Gas	7	1	Residential, General	30
Southern Indiana Gas & Electric	7	1	Residential, General	30
Citizens Gas & Coke Utility / Westfield Gas	7	1	Residential, Small General	30
Nine small gas distribution companies	7	1	Residential, General	30
Kansas				
Atmos Energy	12	1	All	30
Aquila	12	2	All	30
Kansas Gas Service Company	12	2	Residential, General	30
Kentucky				
Atmos Energy	7	1	Residential, Commercial, Public	30
Columbia Gas	5	1	Residential, Small General	30
Delta Natural Gas	5	1	Residential, Small General	30
Louisville Gas and Electric	6	1	Residential, Commercial	30
Louisiana				
Atmos – Louisiana Gas Service	4	1	Residential, Commercial	n.a.
Atmos – Trans Louisiana Gas	4	1	Residential, Commercial	n.a.
Maryland				
Columbia Gas	5	1	All	30

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

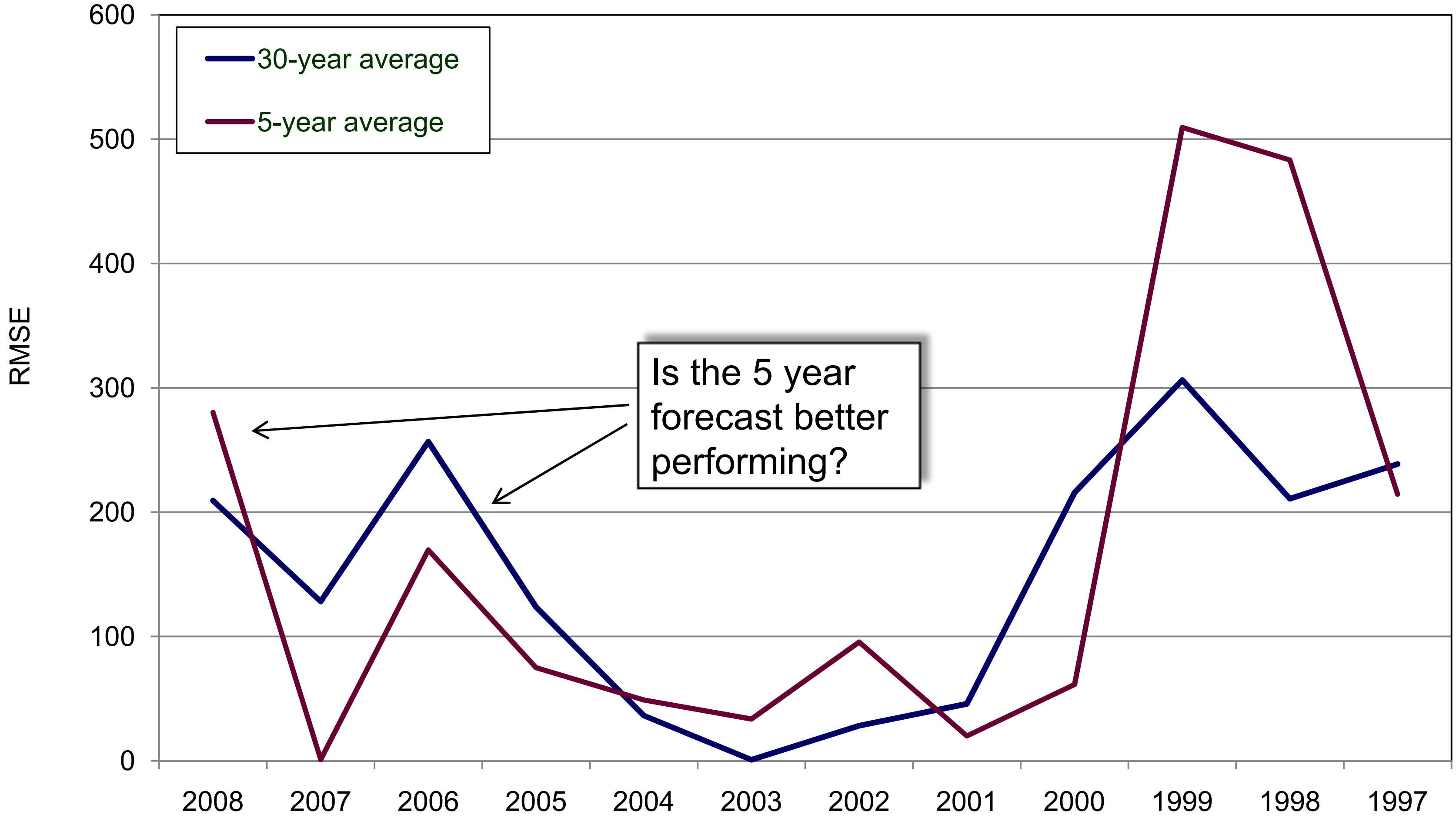
Company	Number of Months Covered by Clause	Mechanism Type	Customer Classes	Number of Years (Normal)
Mississippi				
Atmos Energy	6	1	Residential, General	30
Centerpoint	n.a.	n.a.	n.a.	n.a.
North Dakota				
Montana-Dakota Utilities	7	1	Residential, General	30
New Jersey				
Elizabethtown Gas	8	2	Residential, General	20
New Jersey Natural Gas	8	2	Residential, General, Economic Dev.	20
South Jersey	8	2	Residential, General	20
New York				
Consolidated Edison	7	1	All	30
KeySpan Energy Delivery	7	1	Residential, Firm Transport	30
National Fuel Gas Distribution	7	1	Residential, General, Small Cogen	30
New York State Electric & Gas	8	1	All	30
Niagara Mohawk	8	1	Residential, Small and Large General, Transportation	30
Orange & Rockland Utilities	8	1	Residential, General, Firm Transportation	30
Rochester Gas & Electric	8	1	Residential, General, Firm Transportation	30
Oklahoma				
Arkansas Oklahoma Gas	6	2	Residential, Small Business	10
Oklahoma Natural Gas	8	1	Residential, Commercial, Industrial	30
Oregon				
NW Natural	6	2	Residential, Commercial	25
Pennsylvania				
Philadelphia Gas Works	8	2	General, Municipal, Public Housing	30
Rhode Island				
Narragansett Electric	6	1	All	n.a.
South Carolina				
Piedmont Natural Gas	5	2	Residential, Commercial	30
South Carolina Electric & Gas	6	1	Residential, Small and Medium General	n.a.

Common Forecasting Adjustments: Demand/Billing Determinants – Weather

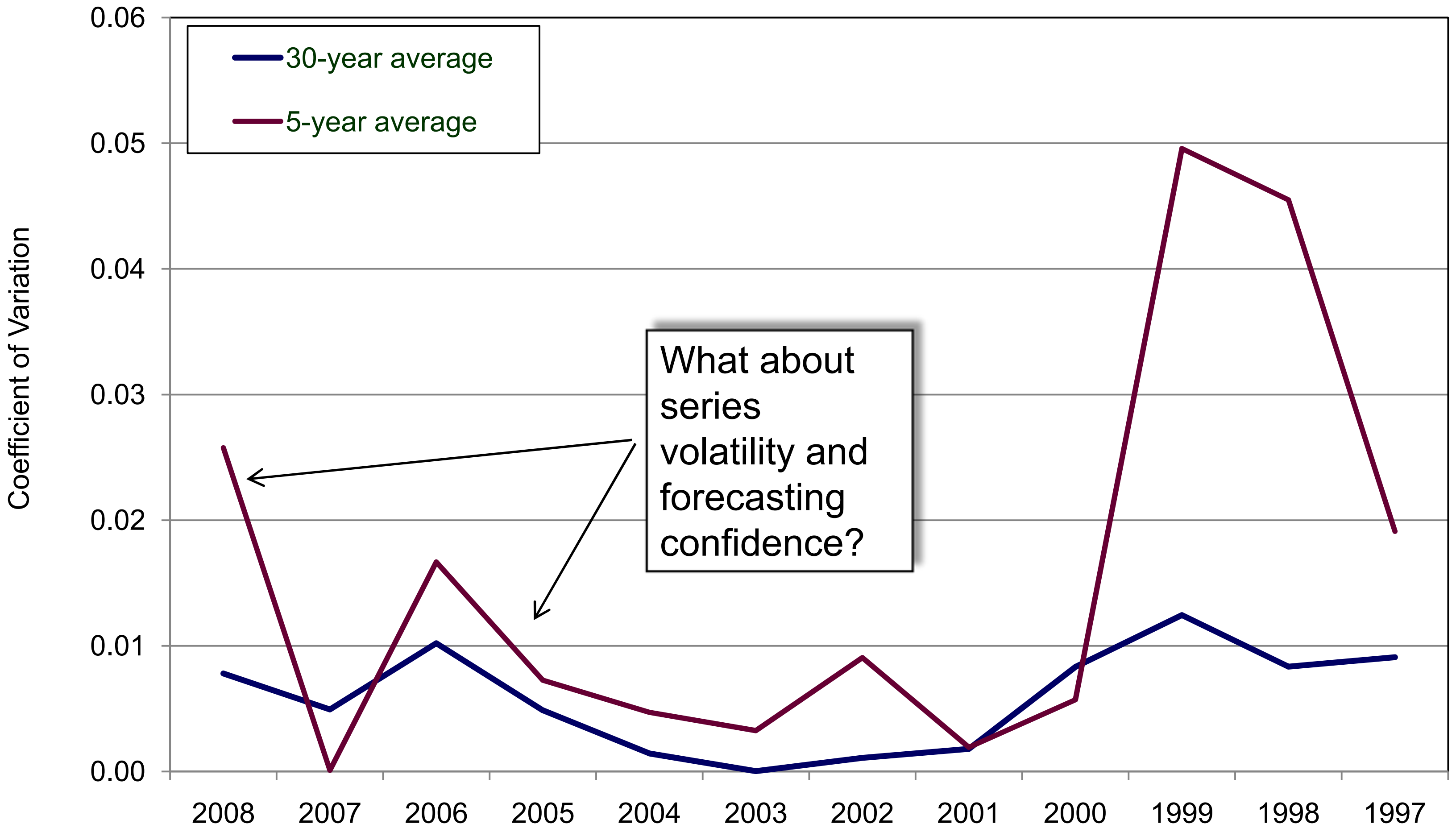
Company	Number of Months Covered by Clause	Mechanism Type	Customer Classes	Number of Years (Normal)
South Dakota				
Montana-Dakota Utilities	7	1	Residential, General	30
Tennessee				
Atmos Energy	6	1	Residential, Commercial	30
Chattanooga Gas	6	1	Residential, Commercial	30
Piedmont Natural Gas	5	1	Residential, Commercial	30
Texas				
Atmos Energy	8	1	Residential, Commercial, Public	
Utah				
Questar Gas	12	1	Residential, General	30
Virginia				
Appalachian Natural Gas Distribution	12	1	All	30
Atmos	12	1	Residential, Small Commercial	30
Roanoke Gas	12	1	All	30
Southwest Virginia Gas	12	1	All	30
Virginia Natural Gas	6	1	Residential	30
Washington Gas Light	8	1	All	135*
West Virginia				
Eight small LDCs	12	1	Residential, Small Commercial	30
Wyoming				
Questar Gas	12	1	General	10

Note: n.a. is not available.
*Washington Gas Light's definition of normal weather is based on a trendline regression analysis. The Virginia Division uses 135 years; the Shenandoah Division uses 25 years.

Common Forecasting Adjustments: Demand/Billing Determinants – Weather



Common Forecasting Adjustments: Demand/Billing Determinants – Weather

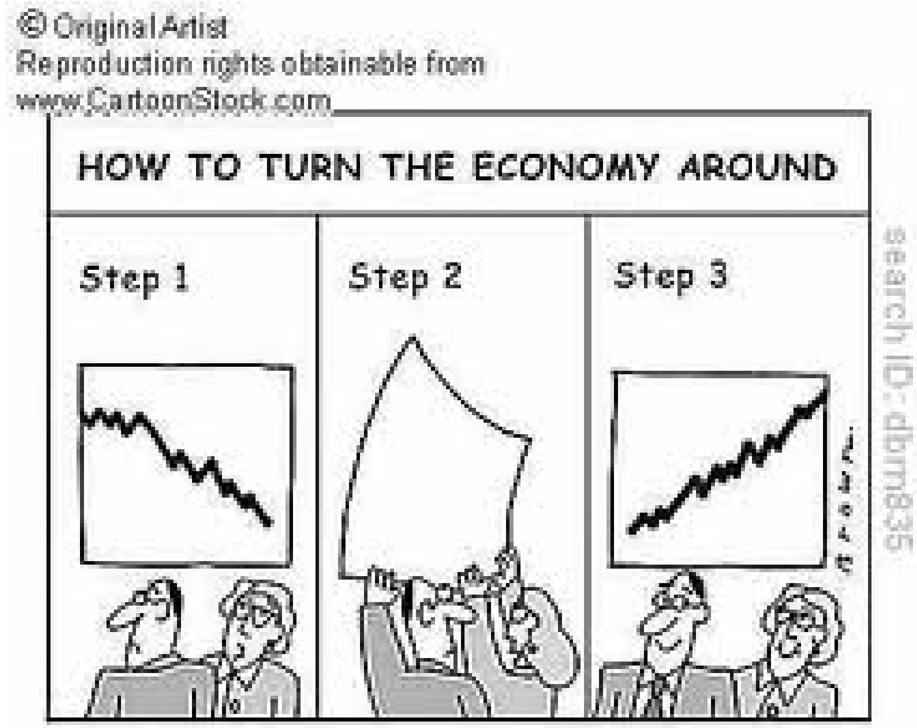


Common Forecasting Adjustments: Demand/Billing Determinants – Income/Economy

Income/Economic Adjustments

Utility forecasts will tend to include an economic projection developed by third-party commercial sources (or independent state forecasting units) to extrapolate loads and/or customer growth.

Can become problematic in a recession since the economic activity during these periods is not "normal."



If recession year billing determinants are used, utility will have considerable up-side opportunities post-rate case.

Common Forecasting Adjustments: Demand/Billing Determinants – Unusual Events

<u>“Unusual Event” Adjustment</u>

A related type of economic/load adjustment that can be made by utilities during rate cases or other types of regulatory proceedings

These are often related to the economic adjustments discussed earlier since:

(a) they can tend to be based off (or used with) the same models.
(b) they reflect a one-time event that is not normal to standard operations

Examples can include weather-related events, usually resulting in large scale outages. Can include other factors such as large-scale transmission-generation outages.

Common Forecasting Adjustments: Demand/Billing Determinants – Price

<u>Price Elasticity Adjustment</u>

Price elasticity defines the percentage change in quantity demanded resulting from a percentage change in price.

Like other parameters, it can usually be extracted from unbiased load forecast or other statistical demand analysis.

Can be used to adjust billing determinants for significant changes in price.

Use in typical ratemaking for electric and gas has been “hit-or-miss.”

Considerable discussion in the early 1990s as means of adjusting for the risk-shifting nature of revenue decoupling (but not adopted).

Common Forecasting Adjustments: Demand/Billing Determinants – Energy Efficiency

Energy Efficiency Adjustment

The role of energy efficiency on usage will be ongoing modeling challenge.

For gas distribution industry, no good source of information to use to do broad analysis.

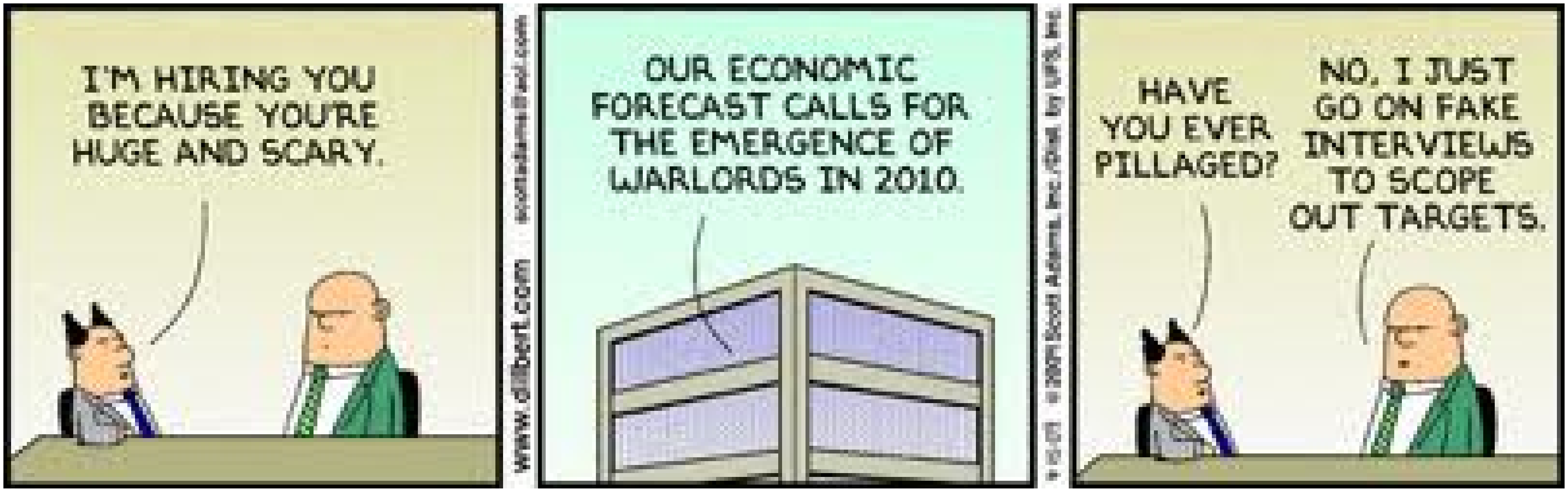
Modeling typically limited to time trend variables (not very explanatory).

Electric slightly better.

Empirically, could be a situation that creates endogeniety problem – no real general equilibrium/simultaneous equation methodology for doing integrating these impacts over time.

5 Litigating forecasts and empirical analyses

Common Forecasting Adjustments



The Ten Commandments

The Ten Commandments of Applied Econometrics & Forecasting

Source: Peter Kennedy, Guide to Applied Econometrics, 6th Edition, 2008.

The Ten Commandments

Commandment 1: Use Common Sense and Economic Theory

Note that all that often, common sense is not all that common:

- **failure to match per capita models with per capita variables**
- **Failure to estimate with real variables rather than nominal.**
- **Inappropriate construction of dummy variables.**
- **Incorrect transformations.**

- **Confusing correlation with causation.**

Commandment 2: Avoid Type III Error

Definition of Type III Error: coming up with all the right answers for all the wrong reasons or using all the wrong methods.

An approximate answer to the right question is always better than a precise answer to the wrong question.

Technical details about the question are often important.

Knowledge helps condition appropriate designation of the null hypothesis, test statistics, and variables under investigation.

The Ten Commandments

Commandment 3: Know the Concept and Data Under Investigation

Extension of Commandment 2 – know the details, history, and institution of the industry and process under investigation.

Example – modeling changes in demand for utility with 20 year history of energy efficiency programs may be entirely different than those starting new programs.

How closely do measured variables actually correspond to theory (and does it matter)?

Be Neo….

Commandment 4: Inspect the Data

Graph the data, develop summary statistics know the means, standard deviations, minimum values, maximum values, sample counts, kurtosis, skewness, and normality.

Be the Zen Master of the data.

Commandment 5: Keep it Sensibly Simple

Ensure parsimony but don't confuse this concept with "keep it simple, stupid" since lots of models can be unnecessarily stupid and simple and lead to biased results, errors, and other problems.

Commandment 6: Use the "Interocular Trauma" Test

Do the results hit you square between the eyes?

Closely examine and investigate those things that appear strange.

Are coefficients of the correct sign? Order of magnitude?

By examining the information you get to know the information.

Commandment 7: Understand the Costs/Benefits of Data Mining

Developing data to improve results and generate a certain degree of "robustnes" = good.

Developing data to improve the likelihood of attaining a certain result = bad

Commandment 8: Be Prepared to Compromise

Can often be a gap between theory and results.

Often forced to compromise to lean to a particular result – may lose overall predictive capabilities for theoretic and applied consistency. (recall earlier example on the residential electricity example).

Commandment 9: Don’t Confuse Statistical and Economic Significance

Some parameter estimates may large, of correct sign, but not at traditional significance levels.

Some estimates may be significant, but order of magnitude is small.

The standard error (confidence interval) of a particular estimate may have considerably implications.

Commandment 10: Report Sensitivities

Anticipate and prioritize the most important sensitivities.

Mindful of those that are not that entirely robust.

Litigating forecasts and empirical analyses – Staff Objectives

Secure data, programming code, other input information. Request all variables be identified, variable transformations explained, identify all missing or excluded data (and rationale), and clearly identify and explain all assumptions.

Obfuscation is a dead-ringer for a problem. While software is usually commercially protected against distribution, no MODEL nor its OUTPUT is confidential.

Review sensitivities and diagnostics.

Research and verify relative to theory and practice.

Conduct independent analysis and where needed, supplement the record for your Commissioners: do not attempt to make your case through cross.

Litigating forecasts and empirical analyses – Regulatory Priorities

- **Confidence in forecasting reasonableness given current information and analysis goals.**
- **Base decisions on solid, tested and well-grounded methodologies and approaches: "state of the art" is not the same as "best practices."**
- **Make sure decision is based upon independent output that can be verified – stay away from the "black box."**
- **Decisions informed by important scenarios/sensitivities.**
- **Empirical consistency and accountability across proceedings and analyses (i.e., IRP vs. rate case)**

Questions, Comments, & Discussion

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