 # Alaska Natural Gas In-State Demand Study
 # ASP 2001-1000-2650

Prepared on Behalf of the Alaska Department of Natural Resources

Volume 2: Technical Appendices

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Table of Contents – Volume II (Appendices)

Table of Figures

Table of Tables

Introduction to the Technical Appendices

Volume 2 includes three technical appendices associated with this project. All three of these technical appendices have been offered to the reader interested in a more detailed understanding of the analyses conducted during the course of this project. In many ways, these technical appendices have been provided as more lengthy substitutes for the abbreviate discussions included in the main body of the report.

Appendix 1, provides a detailed overview of historic natural gas price and usage trends in Alaska. The appendix covers a much longer time period than the information provided in Chapter 2.

Appendix 2 provides a detailed overview of the natural gas supply and demand modeling literature. This discussion includes some of the observations on empirical modeling that were included in Chapter 3. In addition, some discussion on individual pieces of the academic literature have been outlined in this appendix.

Appendix 3 provides a more detailed discussion of the natural gas demand models that form the basis for the baseline forecast, as well as the forecast sensitivities. The empirical results of the models have been presented, in addition to a host of other statistics associated with the estimated price and income elasticities of demand.

APPENDIX 1
DETAILED HISTORIC OVERVIEW OF ALASKA NATURAL GAS MARKETS

This technical appendix examines past long run historical trends in Alaska's natural gas markets. The trends examined here are for a duration (1970-1999) longer than the analysis included in Chapter 2, which addresses the period 1990-1999. This appendix examines long run trends in natural gas prices and usage for major customer classes in Alaska including residential, commercial, industrial, and electric utility.[1]

A.1.1: Data Used in the Analysis of Alaska Natural Gas Usage

The following discussion, as well as the models that we will develop in subsequent chapters, utilizes data from the EIA 176 database published by the U.S. Department of Energy, Energy Information Administration (EIA). This database is developed and maintained from annual survey information collected by the EIA under EIA Form 176. All major interstate natural gas pipeline companies, intrastate natural gas pipeline companies, investor and municipally owned natural gas distributors, underground natural gas storage operators, synthetic natural gas plant operators, among other providers of natural gas service, are required to complete this form. The completion of this report is mandatory under the Federal Energy Administration Act of 1974.

For a typical LDC, the EIA Form 176 requirements include annual reporting on the disposition of all gas flows over the company's system. This includes accounting for all gas sales, prices (average revenues), and customers for residential, commercial, industrial, and any other retail customer class. In addition, LDCs must report any transportation services (and volumes) for non-core customers. Thus, if a commercial or industrial customer is within the city gate, but receives gas from a third party, the LDC is required to report the volumes it transports to these customers even though the LDC is only providing transportation services.

In the information reported for Alaska natural gas companies, two LDCs filed information on sales, customers, and transportation volumes. The majority of their disposition was associated with traditional retail sales (i.e., residential, commercial, industrial, etc.). However, starting in 1992, Enstar began reporting transportation volumes for one industrial customer.[2] In 1995, the Company began reporting transportation volumes for commercial customers as well. Since

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[1]The transportation sector has been excluded since total usage is small, and for many years, information is simply missing.

[2]In such a situation, if an LDC is transporting gas on behalf of a customer within the city gate, then that customer is being served by a competitive third party, presumable a competitive retail natural gas marketer. Thus, identifying transportation customers within an LDC's service can give some indication of the degree of competition within that particular area.

1995, the number of non-core commercial customers for Enstar has grown significantly. In 1995, there were 62 commercial customers receiving transportation service only from Enstar. This increased to 187 in 1996; 401 in 1997; and 768 in 1998. By 1999, this number has grown to 883 commercial customers taking only transportation service.

Other companies with pipeline assets are also required to report transportation and sales volumes even if they are not an LDC. According to the data included in the EIA 176 database, there were 6 non-LDCs reporting either transportation and/or direct sales. These included Arco Alaska, Inc., Chevron USA, Marathon Oil Company, Phillips Alaska Natural Gas Company, Ukpeaqvik Artic Slope, and Union Oil Company of California (UNOCAL). In 1999, these companies, collectively, served 11 commercial customers, of which 2 were transportation customers alone. In the same year, these companies collectively served 9 industrial customers. Enstar provided transportation service to three industrial customers.

The EIA database that we used in our historic trends analysis, as well as in the development of our forecasting models, excludes information from other natural gas uses that are reported separately to the DOE. These include field uses of natural gas in oil and gas production, internal company use of natural gas, pumping and compressor station use of natural gas, and liquefied natural gas (LNG). None of these gas usage activities are included in the commercial and industrial series analyzed in this chapter, nor were these natural gas uses included in commercial or industrial forecasting models. Gas Dispositions to the Kenai LNG Plant are excluded from the EIA data series because the LNG it is exported and not considered as an in-state requirement. However, the role of LNG in Southcentral Alaska is important since it accounts for close to 36 percent of total gas dispositions in the Cook Inlet area (see discussion in Chapters 7 and 9).

In addition to usage and price information included in the EIA Form 176, we compiled additional information to supplement the data we would use to specify our demand equation. This includes energy price information for alternative fuels such as diesel, fuel oil, and electricity. This information was also collected from the US Department of Energy, and is published every year in the Annual Energy Report. We also collected employment and state gross product information from the US Department of Commerce, Bureau of Economic Analysis (BEA).

A.1.2: Historic Natural Gas Retail Price Trends

Historic trends in Alaska natural gas prices are presented in Figure A.1.1. These price trends are in nominal dollars (i.e., unadjusted for inflation) and broken out for each major customer class. Retail prices that are presented in Figure A.1.1 are an approximation. The true definition for the series is average revenues, which are calculated as total revenues divided by total usage. Average revenues are typically used in industry analysis since they reflect, on average, what is paid for natural gas service.

However, rates can be complicated and may not exactly reflect the values that appear in a simple examination of average revenues. For instance, rates are typically charged in the form of a two-part tariff: a fixed customer charge, in addition to an incremental volumetric rate. Further, rates can be complicated by increasing and decreasing block rates, minimum or base usage charges, as well as other complicated riders and surcharges. Nevertheless, average revenues, as a general approximation, do reflect the general tendencies in prices that customers pay over time.

Residential rates over the past 30 years reveal three distinct trends. From 1970 to 1982, residential rates were relatively constant, increasingly at an average annual rate of only 1.5 percent. However, beginning in 1983, rates began a dramatic increase. From 1982 until 1991, residential rates increased at an annual average rate of 10.1 percent. From 1991 until 1999, residential retail rates have started to decline at an average annual rate of 1.5 percent. Rates in 1999 are almost identical to their 1989 level in nominal dollars.

Commercial natural gas rates have followed trends similar to those of residential customers. Shifts in these trends, however, tend to be accelerated by about two years relative to the historic experiences seen for the residential class. For instance, rates for commercial customers were relatively flat throughout the 1970s. However in 1980, rates began to move in a sharp upward trend. This trend was not reflected in residential rates until 1982.

During the period 1980 until 1991, commercial rates increased at an annual average rate of 9.4 percent. This rate of growth was more significant than that experienced by residential customers. During the period 1991 until 1999, this upward trend in rates was reversed, and commercial rates fell at an average annual rate of 1.8 percent. This decrease was much faster than that associated with residential customers.

Industrial rates during the historic period followed different trends than those experienced for residential and commercial customers. For instance, during the period 1970 to 1979, rates for industrial customer followed a relatively steady increase of 11.2 percent on an annual average basis. Between 1979 until 1981, rates fell for industrial customers by 34.5 percent. After 1981, rates increased at an annual average rate of 9.8 percent. In the two most recent years (1997-1999), natural gas rates for commercial customers have been falling.

As seen in Figure A.1.1 natural gas rates charged to electric utilities, to run their natural gas generation, followed somewhat similar trends to those experienced by industrial customers. From 1970 until 1979, rates charged to electric utilities increased at an annual average rate of about 10.3 percent. Like industrial customers, these rates fell, but less drastically during the 1979-1980 period. The drop in rates during this year was nearly 45 percent. However, rates began to rise steadily at an annual average of 14 percent from 1980 until 1990, only to drop nearly 67 percent in 1999.

During the period of 1991-1998 electric utilities experienced a significant percentage increase that averaged 21.1 annually. By 1999, electric utilities saw an 11.7 percent decline in their natural gas rates.

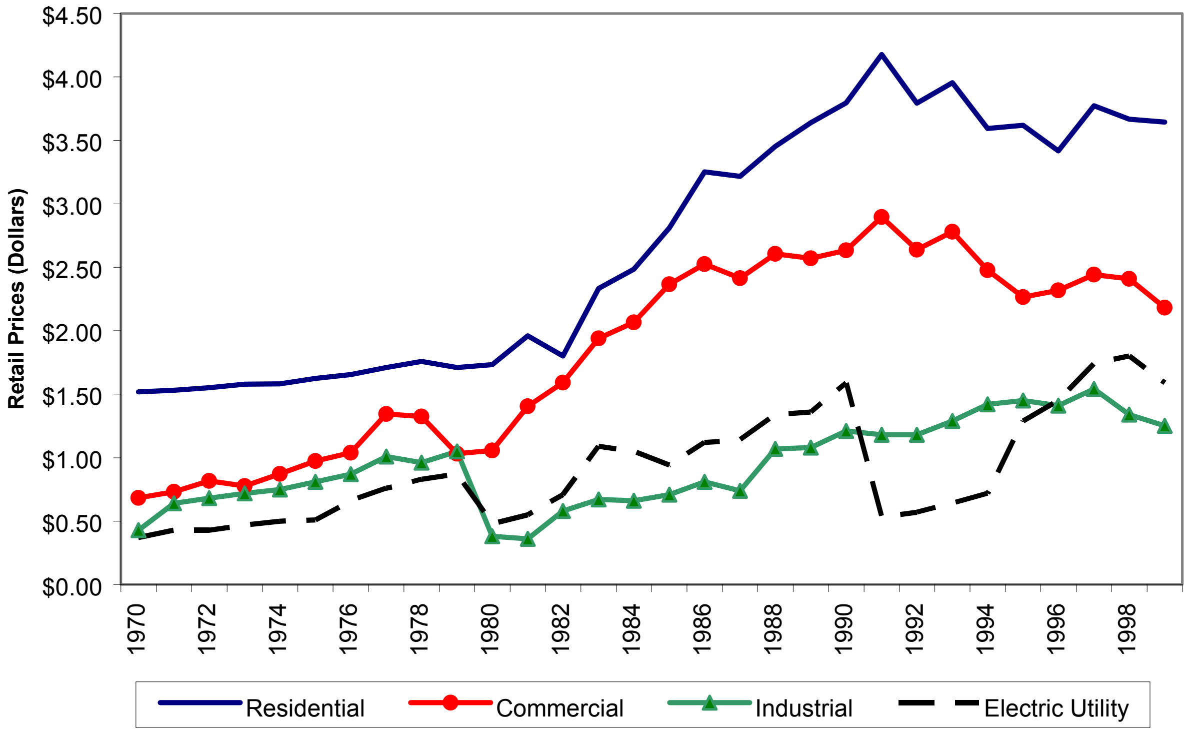

Figure A.1.1: Alaska Retail Natural Gas Prices 1970-1999 (Nominal Dollars)

Source: US Department of Energy, Natural Gas Annual

Figure A.1.2 presents a different representation of natural gas price changes. In this figure, we have plotted price changes in constant, as opposed to nominal dollars. In order to estimate these constant dollar prices, we multiplied the GDP deflator by the nominal prices presented in Figure 2.1. The result defines prices of natural gas in terms of their 1999 value.

In constant dollar terms, natural gas prices for residential customers actually fell throughout the 1970s. Constant dollar prices for residential customers bottomed out in 1982 at $2.85 per Mcf. Constant dollar prices began an upward trek beginning in 1983 for residential customers, and peaked at a rate of $4.88 per Mcf in 1991. Since 1991, natural gas prices, in constant 1999 dollars, have decreased at an average rate of 3.4 percent annually. In 1999, constant dollar natural gas rates for residential customers was $3.65 per Mcf – an amount not seen since 1984.

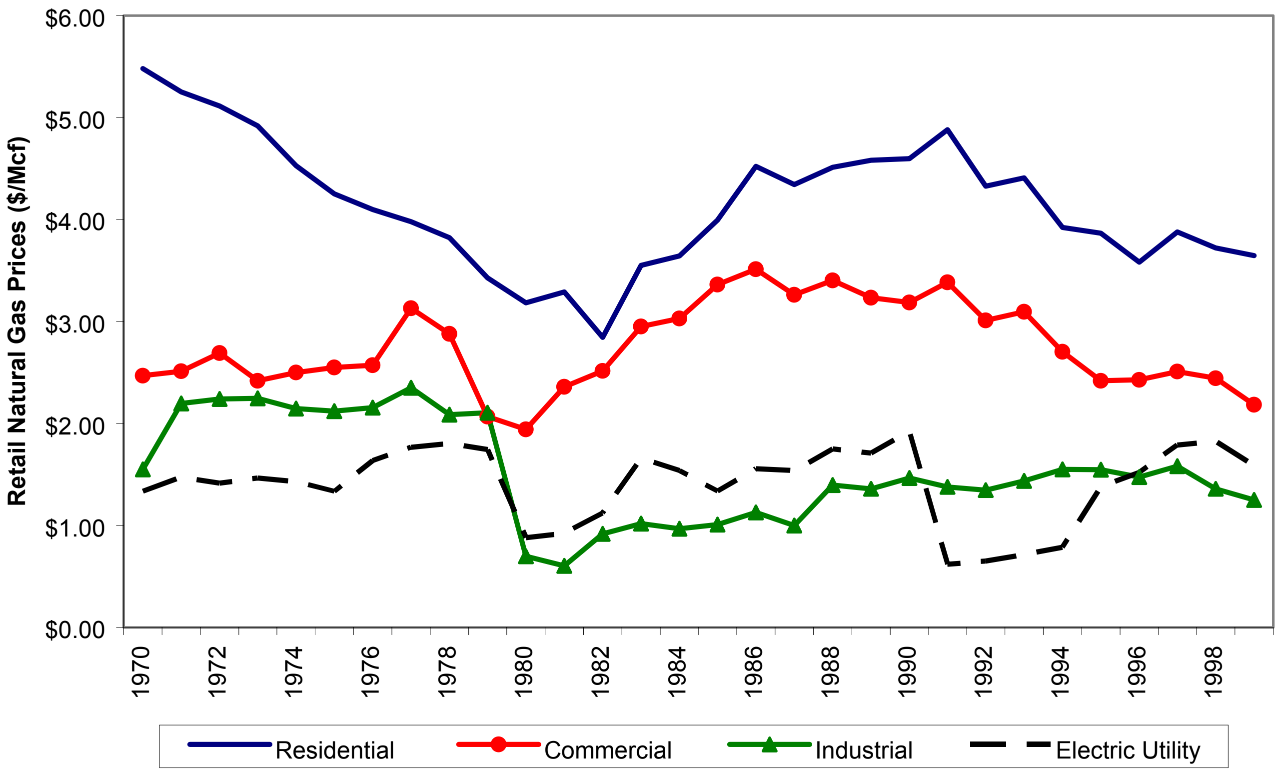

Figure A.1.2: Alaska Retail Natural Gas Prices 1970-1999 (1999 Dollars)

Source: US Department of Energy, Natural Gas Annual.

Constant dollar natural gas rates for commercial customers have followed similar trends to those of residential; there are, however, a few notable exceptions. During the period 1976-1977, commercial customers saw their rates leap by 21.7 percent, during a period in which residential customers saw their rates decrease. Constant dollar rates for commercial customers, while falling from 1978-1980, saw a sustained increase starting in 1981.

During the period 1981-1991, commercial customers saw their rates generally increasing, similar to residential customers. However, the rate of this increase was much greater for commercial customers. During the peak of this run up in prices (1981-1985), constant dollar commercial rates increased by 42.5 percent compared to a 21.3 percent increase during the same period for residential customers. Since 1991, constant dollar rates for commercial customers have been falling. In 1999, constant dollar commercial natural gas rates, were $2.18 per Mcf – a rate approaching the all time low constant dollar price of $1.94 per Mcf 1980.

Constant dollar prices for industrial customers and electric utilities have followed patterns similar to each other, but under trends which differ in various years from residential and commercial customers. Relative to historic trends, constant dollar industrial rates were high during the period 1970 to 1980. For instance, the average retail rate for industrial customers during this period was some 159.2 percent of today's rates in constant dollars. The opposite is true for electric utilities which saw the relative average level for the period somewhat lower, at 93.2 percent of current rates in constant dollars.

From 1980 to 1990, constant dollar rates increased by 142.3 percent and 108.4 percent for industrial and electric utilities, respectively. From 1990 onwards, industrial rates decreased by an annual average of 1.5 percent. Electric utility rates, however, saw a sharp decrease from 1990-1993, followed by a steady increase through 1998. In 1999, industrial rates, in constant dollars, are at levels that are lower to their 1970 level while electric utility rates are slightly higher than 1970 rates.

A.1.3: Historic Total Natural Gas Usage Trends

Figure A.1.3 presents historic trends in Alaska natural gas usage between 1970 to 1999. The figure shows significant growth for in-state natural gas usage from 1970 until 1979. However, after 1979, annual changes in natural gas usage follow a rather saw-toothed trend. On average, the period 1979-1999 has seen relatively stable and low natural gas usage growth with the biggest variations in total usage coming from the state's industrial customers. Since 1982, total sales varied between approximately 130,000 and 150,000 Mcf per year.

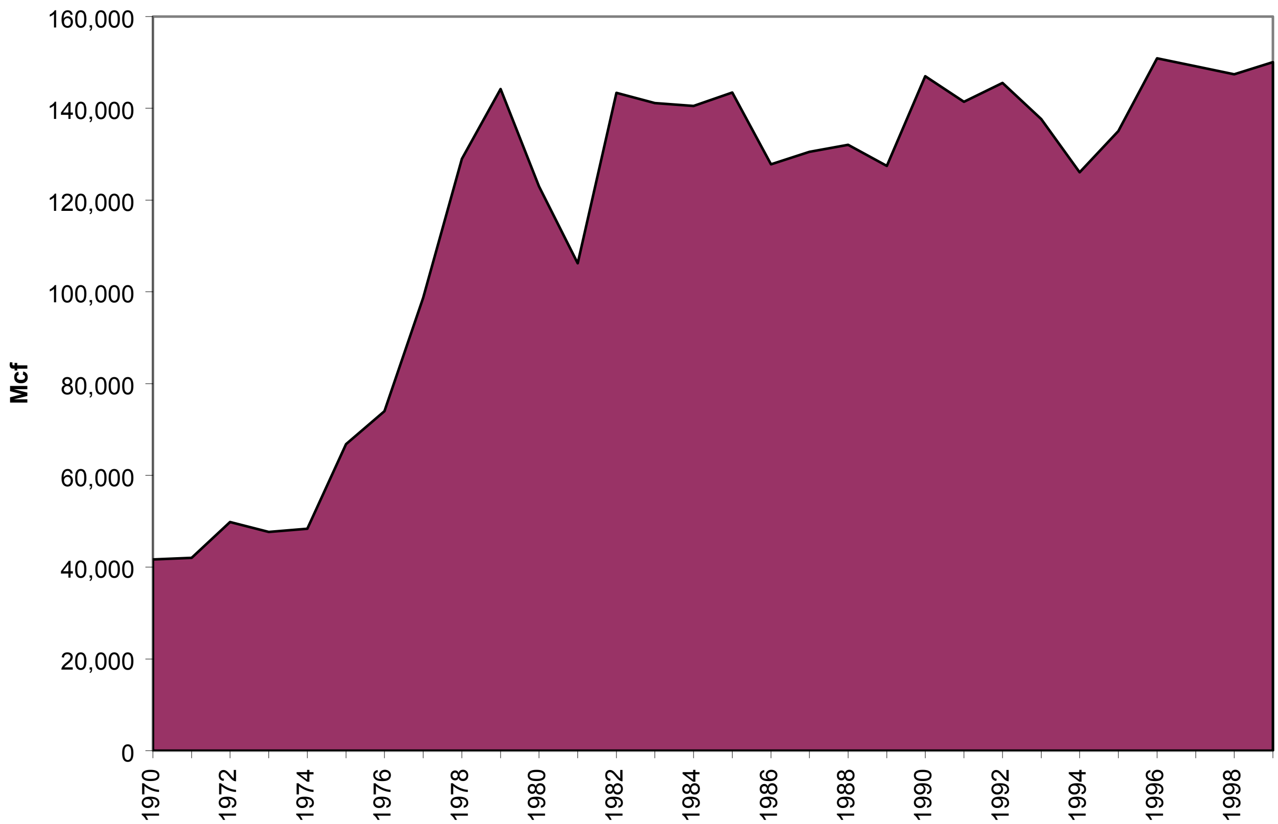

Figure A.1.3: Alaska Total Natural Gas Usage (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

Figure A.1.4 decomposes natural gas usage into its respective customer classes. As the figure reveals, the residential, commercial, and electric utility classes all show a somewhat slow and steady growth path over the past thirty years. There are some periods that show large amounts of growth in volume, such as residential growth of nearly 150 percent between 1974 to 1975, but average growth over the period in all three categories has slightly outpaced customer growth.

As noted before, the industrial class accounts for the majority of the variation in Alaska natural gas usage. There is a substantial increase in industrial natural gas usage during the late 1970s of over 550 percent. This rise is immediately followed by a decline of approximately 43 percent in the following two years. Sales to industrial customers over the past several years have hovered between the extremes set in 1979 and 1981, respectively. In 1999, industrial natural gas usage was approximately equal to its level in 1977. Commercial and residential usage are 184 percent and 121 percent higher than their respective levels in 1970.

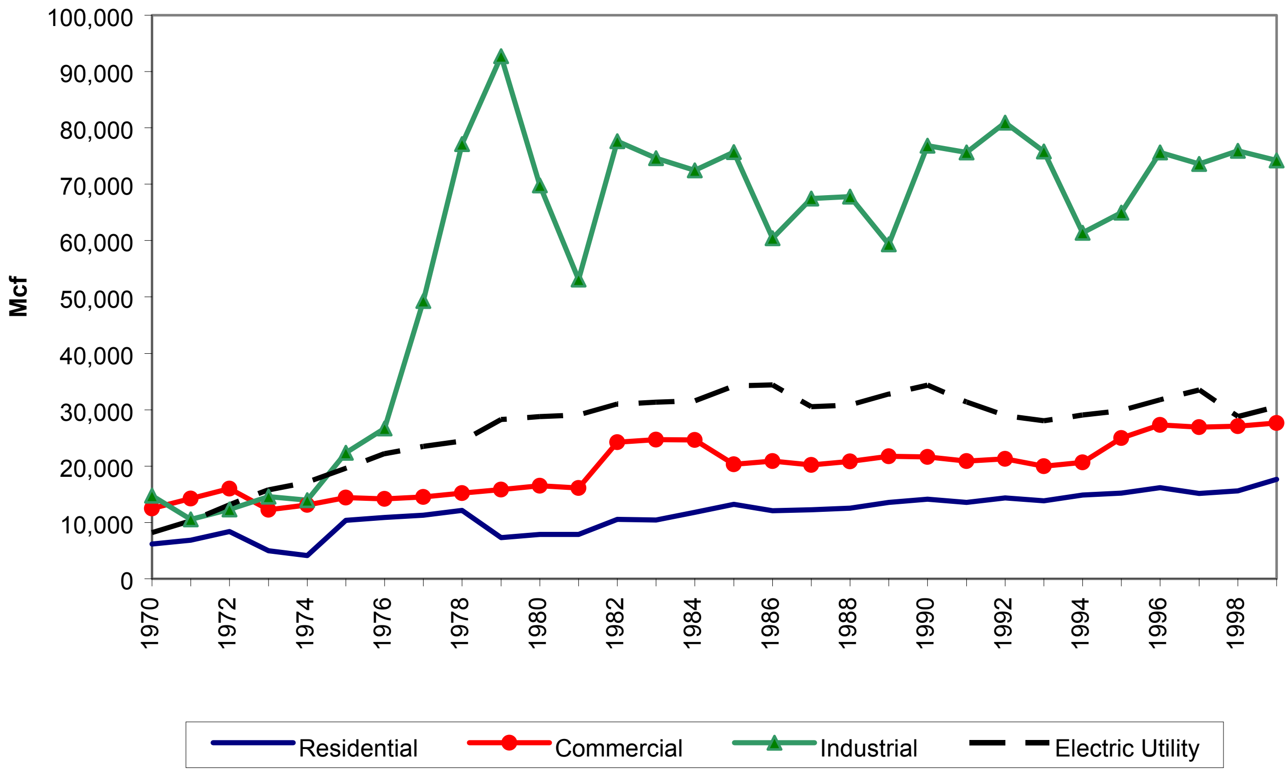

Figure A.1.4: Natural Gas Usage by Major Customer Class (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual.

A.1.4: Historic Residential Natural Gas Usage Trends

Figure A.1.5 analyzes residential customer and usage growth during the period 1970 to 1999. The left hand axis measures the number of total residential customers, while the right hand axis measures total residential usage. There are two large discontinuities in the usage trend occurring in the early and late 1970s. These leaps are associated with the energy crises and the tendency to shift consumption away from oil and towards more natural gas usage. After 1980, however, we see relatively stable trends in residential customer and usage growth. Between 1981 and 1983, residential customer growth leaped by 37.5 percent.

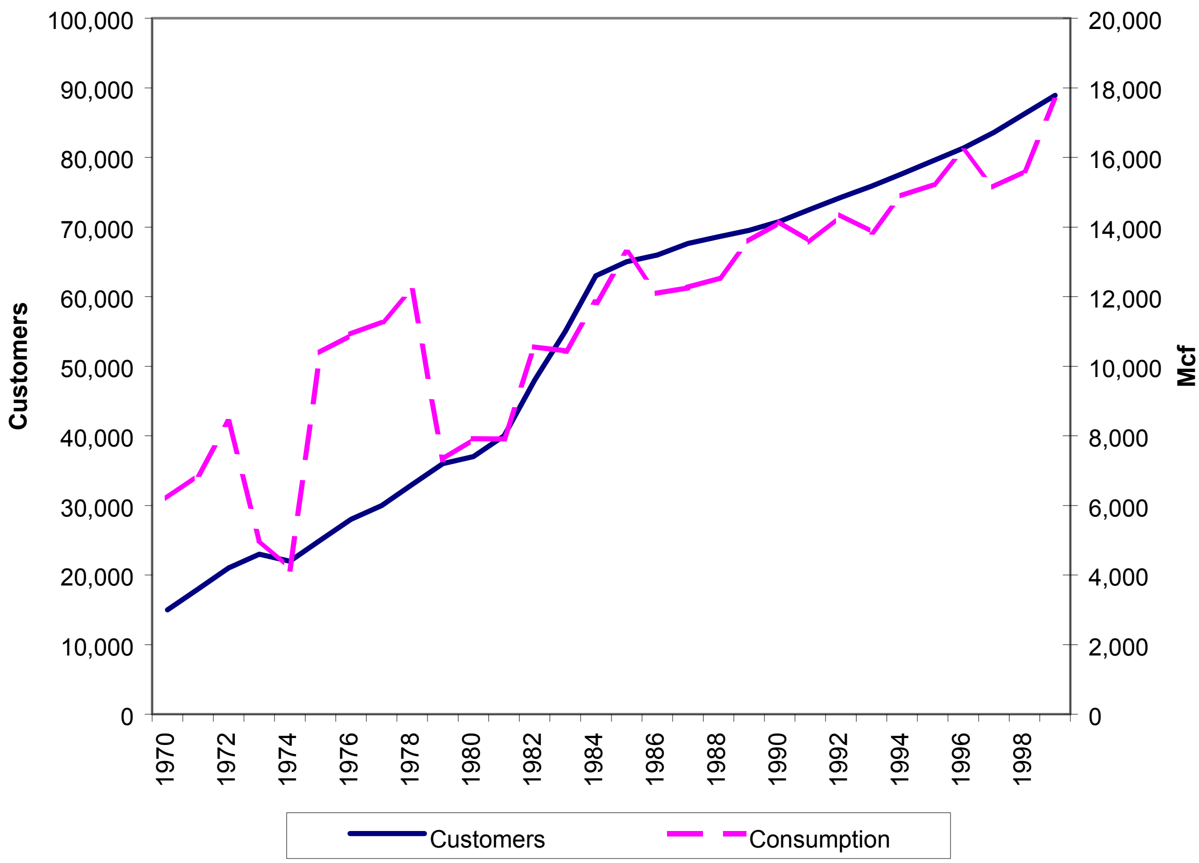

Figure A.1.5: Alaska Residential Customers and Usage (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

Figure A.1.6 presents the historic evolution of residential usage per customer and price. Residential average usage followed a number of erratic leaps during the early and late 1970s. After 1979, usage per customer followed a relatively stable trend. Between 1982 and 1991, residential natural gas prices increased by an annual average of 10.1 percent. Average usage during this period, remained relatively flat falling by about 1.5 percent on an annual average basis.

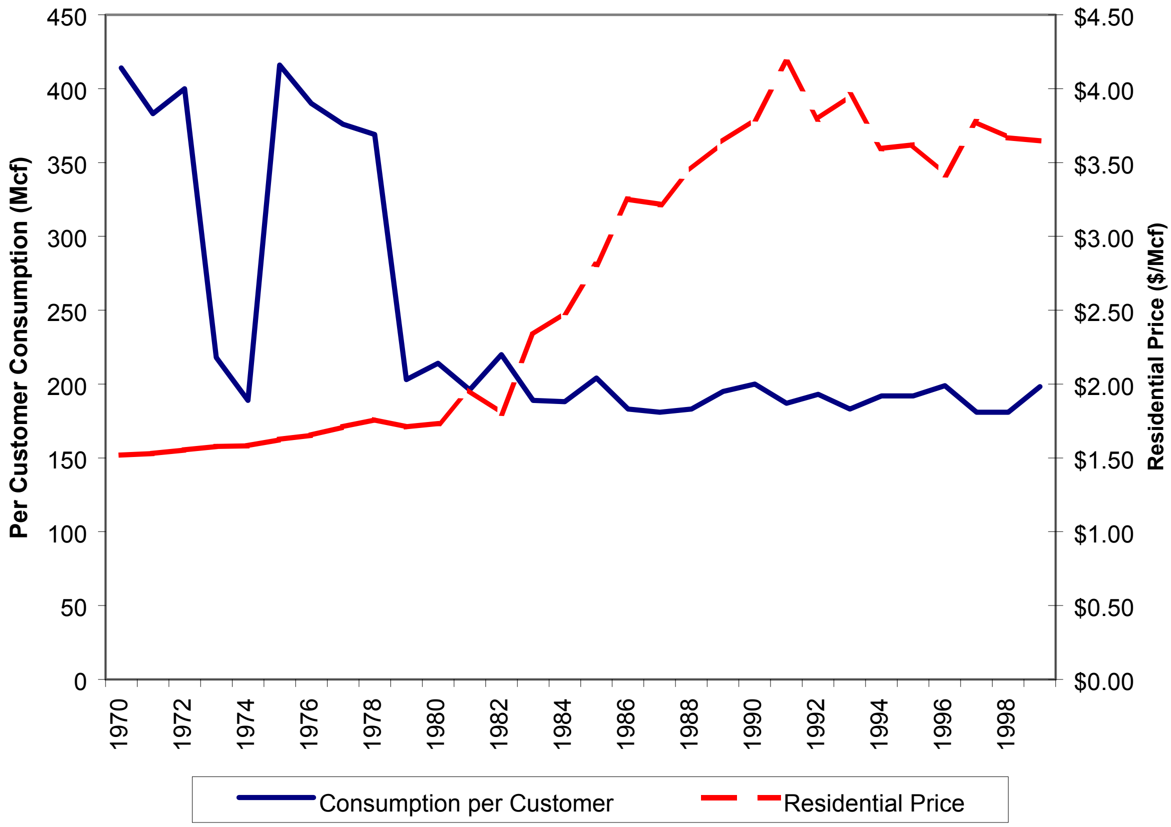

Figure A.1.6: Alaska Residential Average Usage and Price (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

A.1.5: Historic Commercial Natural Gas Usage Trends

Figure A.1.7 plots the relationship between customer growth and total usage for commercial customers. The trends represented in the graph are similar to those for residential customers. Again, during the period 1981-1984, there was a significant increase in the number of commercial natural gas customers. During this period, commercial usage also saw a relatively substantial leap – by as much as 20 percent between 1984 to 1985. However, commercial usage saw a sharp decrease in 1984, and followed a relatively stable trend until 1994, when usage for commercial customers saw another significant increase. Between 1994 and 1995 commercial usage increased by more than 20 percent.

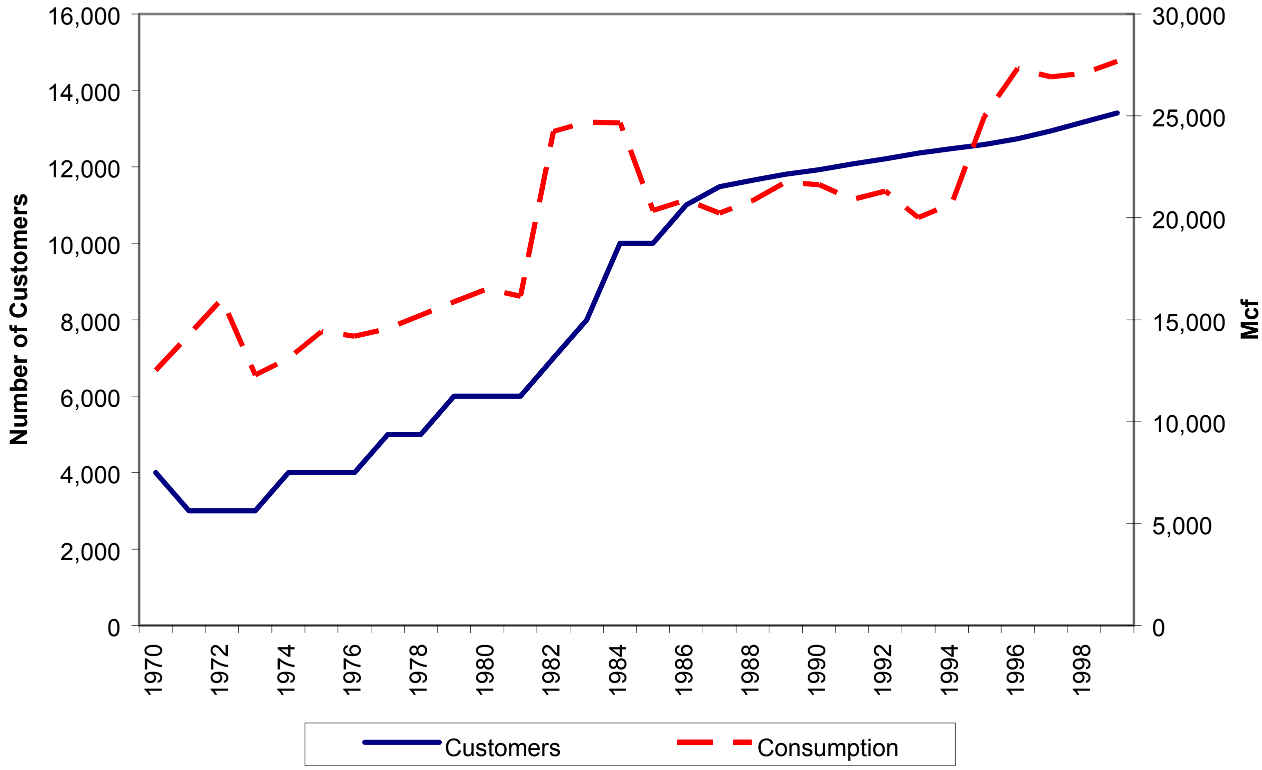

Figure A.1.7: Alaska Commercial Customers and Usage (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

Figure A.1.8 plots historic trends in average commercial usage and price. Overall, commercial customers tend to be relatively responsive to shifts in natural gas prices. During the period 1970-1981, natural gas rates were increasing, while average commercial usage fell. The sharp increases in commercial natural gas prices beginning in 1980 resulted in significant decreases in average commercial usage. For instance, during the period 1980 to 1985, commercial prices increased by 123.5 percent. During the same period, average commercial usage fell by 26.1 percent. In 1992, commercial prices began to fall again, while average commercial usage increased, albeit to a much less extent. Between 1992 and 1999, commercial prices have fallen at an annual average rate of 17.3 percent. Average usage, over the same period, increased at a rate of 18.2 percent.

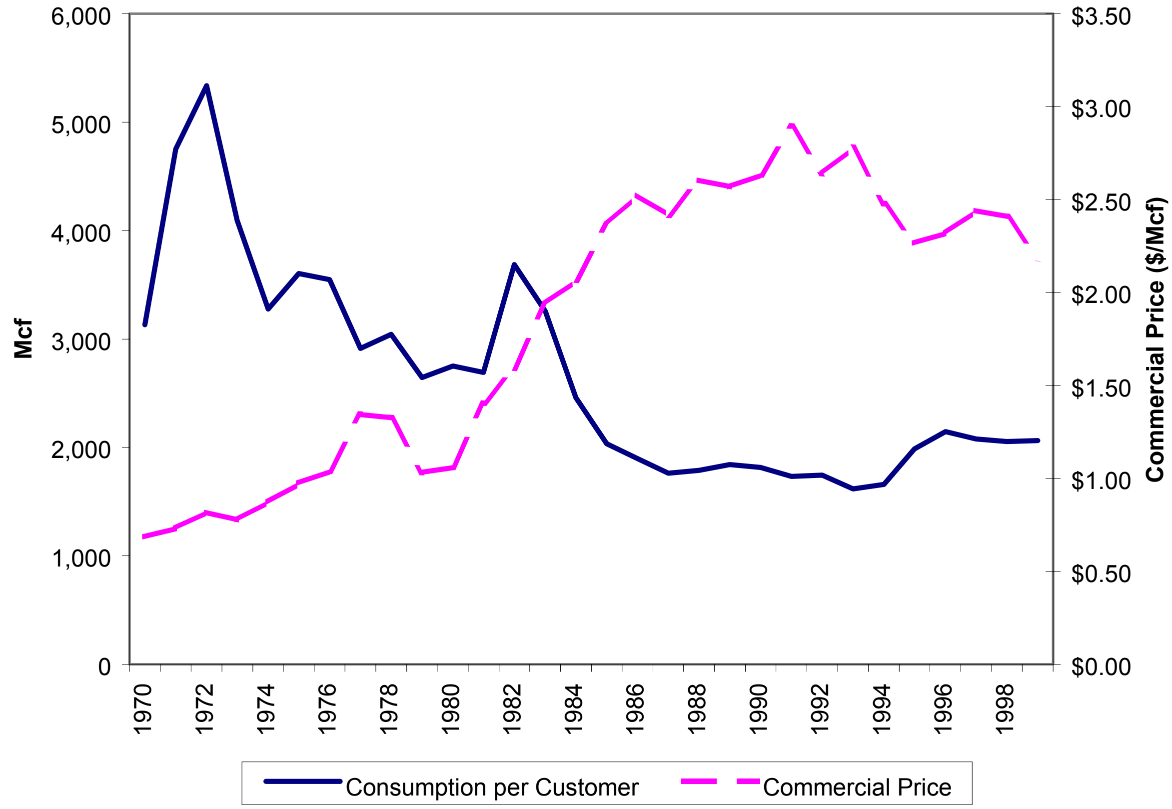

Figure A.1.8: Alaska Commercial Average Usage and Price (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

A.1.6: Historic Industrial Natural Gas Usage Trends

Figure 2.9 plots total usage and prices for industrial customers. Given the small number of customers in this class, average usage has not been presented because small shifts in customers can create large distortions in average usage. This figure highlights some of the problems associated with using average revenues as a proxy for price. For customer classes with small numbers of overall customers, like the industrial class in Alaska, sudden shifts in usage can be interpreted directly into shifts into average revenues, since they are simply the quotient of total revenues and sales.

Prior to 1989, industrial total usage and prices shifts followed similar patterns. For instance, between 1970 and 1979, both usage and prices (average revenues) increased for industrial customers. After 1979, both series saw dramatic decreases. From 1982 until 1989, both series followed a similar, and consistent, up and down movement. However, after 1989, natural gas prices and usage followed more traditional patterns, albeit with what appears to be a one year lag.

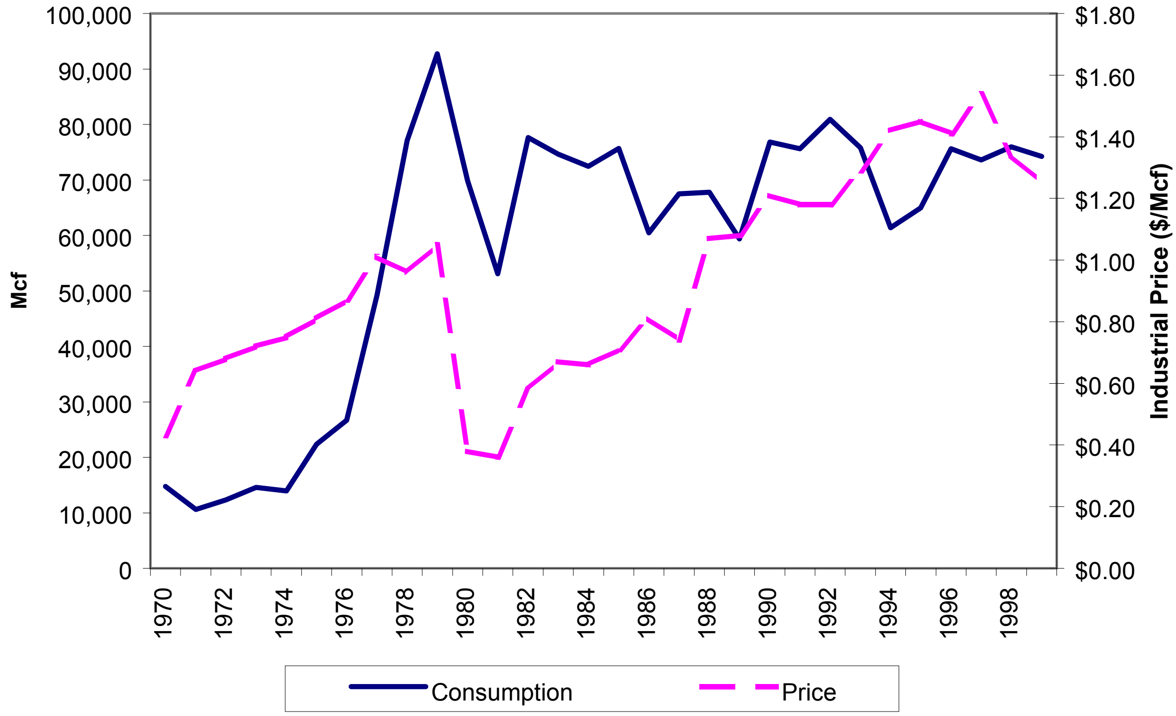

Figure A.1.9: Alaska Industrial Usage and Price (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

A.1.7: Historic Electric Utility Natural Gas Usage Trends

Historic electric utility usage and natural gas prices have been presented in Figure A.1.10. Given that electric utilities are required to generate electricity for their retail customers, and have historically had limited fuel substitution abilities, these trends may be more understandable. For instance, electric utility natural gas usage increased substantially throughout the 1970s and into the 1980. As will be seen later, this was also a period when electric customer growth was substantial and there was an increasing share of gas-fired generation to meet this new electricity growth.

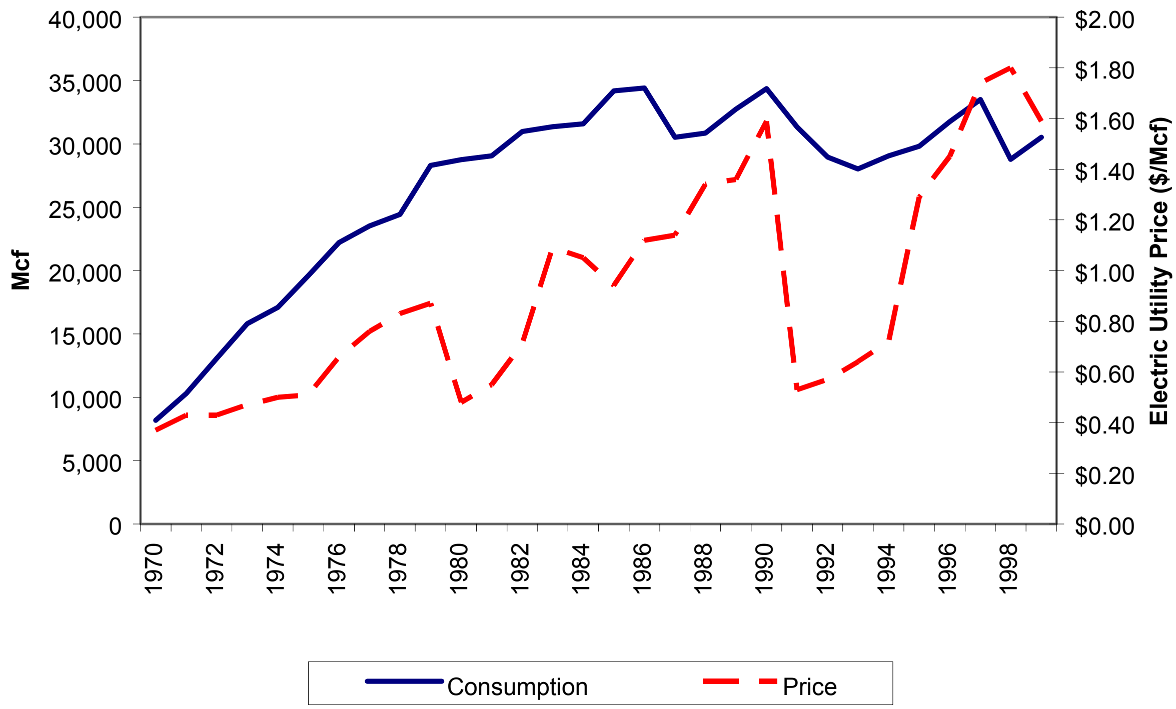

Figure A.1.10: Alaska Electric Utility Usage and Price (1970-1999)

Source: U.S. Department of Energy, Natural Gas Annual

A.1.8: Historic Electric Power Market Trends

Electric power generation is the second largest source of natural gas usage in Alaska. The demand for natural gas by electric utilities is driven by their need to generate electricity from gas-fired turbines and steam units. Understanding the changes in Alaska's power markets, therefore, can offer insights into how and why electric utilities have developed gas fired generating resources in the state. The following subsections offer some insights into changes in Alaska's power markets, and their implications for natural gas usage.

Electric Utility Customer Growth: Between 1970 and 1999, the number of electric utility customers in Alaska has risen by a dramatic 250 percent. This represents an average annual growth of 4.4 percent. As shown in Figure A.1.11, the trends of residential and total customers are very similar. Residential customers increased over 200 percent between 1970 and 1999, at an average annual increase of 4.3 percent. The largest increase occurred from 1983 to

1984, where the number of residential utility customers increased from 140,317 to 157,081, an increase of over 18,000 customers. Commercial customers have also followed this trend, increasing at an average annual rate of 4.5 percent. Industrial customers have also increased over the years at an average annual increase of 4.6 percent. Given their small relative numbers, industrial customers have been excluded from Figure A.1.11. In 1999, there were 473 industrial customers in the state. Over the period, growth for this class also averaged around 4.5 percent.

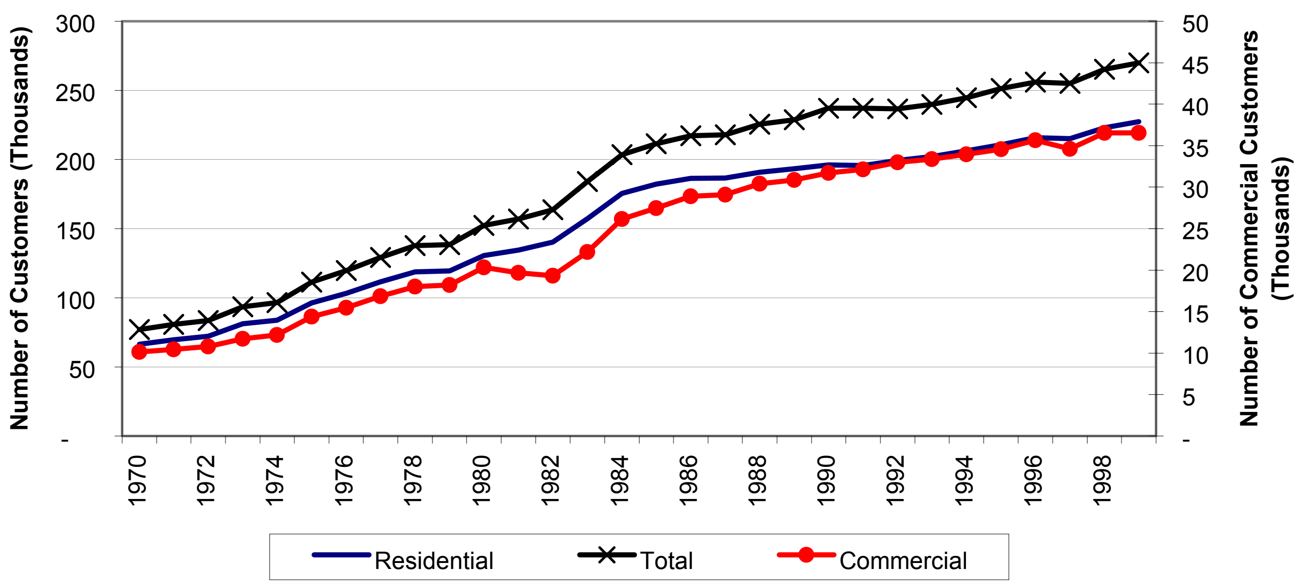

Figure A.1.11: Growth in Electric Utility Customers (1970-1999)

Source: U.S. Department of Energy, Electric Power Annual.

<u>Electricity Usage Trends:</u> Alaska's total electricity usage patterns followed a similar path to that of the number of customers. Total consumption increased by 379 from 1970 through 1999 – at an average annual rate of 5.6 percent. The largest increase was experienced between 1979 to 1982 when consumption grew from 1.07 to 1.67 billion kilowatthours (kWhs) representing a 57 percent increase. As shown Figure A.1.12, residential consumption rose steadily at an average annual rate of 4.5 percent. Commercial consumption increased significantly between 1983 and 1984, jumping close to 105 percent. Commercial electricity usage followed a more moderate growth trend from 1985 through 1999 at an average annual rate of 2.2 percent. Industrial usage followed a less consistent path from 1970 to 1984, and then evened out at an average annual rate of growth of 6.2 percent from 1984 through 1999.

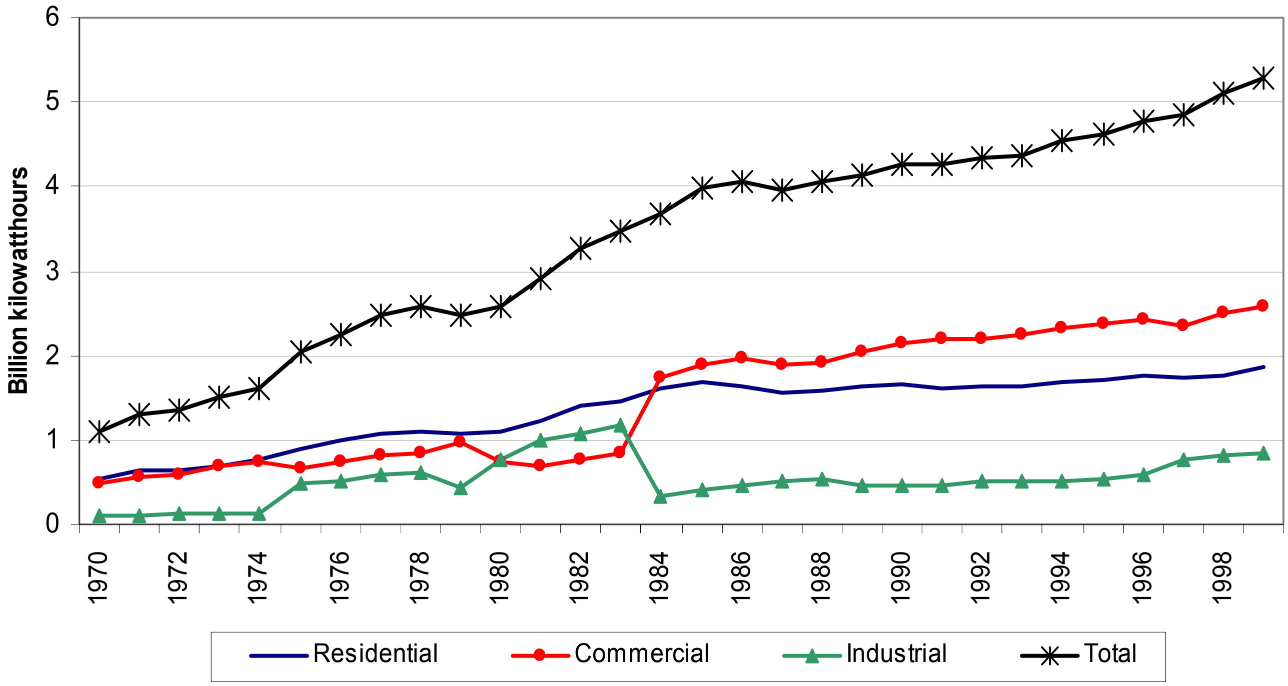

Figure A.1.12: Historic Electric Usage Trends by Customer Class (1970-1999)

Source: U.S. Department of Energy, Electric Power Annual

Retail Electricity Prices: Figure A.1.13 shows historic trends with real and constant dollar electricity prices. Here, electricity prices have been approximated on a per customer class bases by average revenues. There are three distinct trends in Alaska electricity prices over the past 30 years. The first trend occurred during the period 1970-1979, where electricity rates were only moderately increasing. The second trend occurred during the period 1979-1988, where electricity prices were growing rapidly as more power industry infrastructure was added to meet the state's increasing electricity needs. From 1988 onwards, electricity rates have followed a relatively flat growth rend in nominal dollars, and have actually decreased in constant dollar terms.

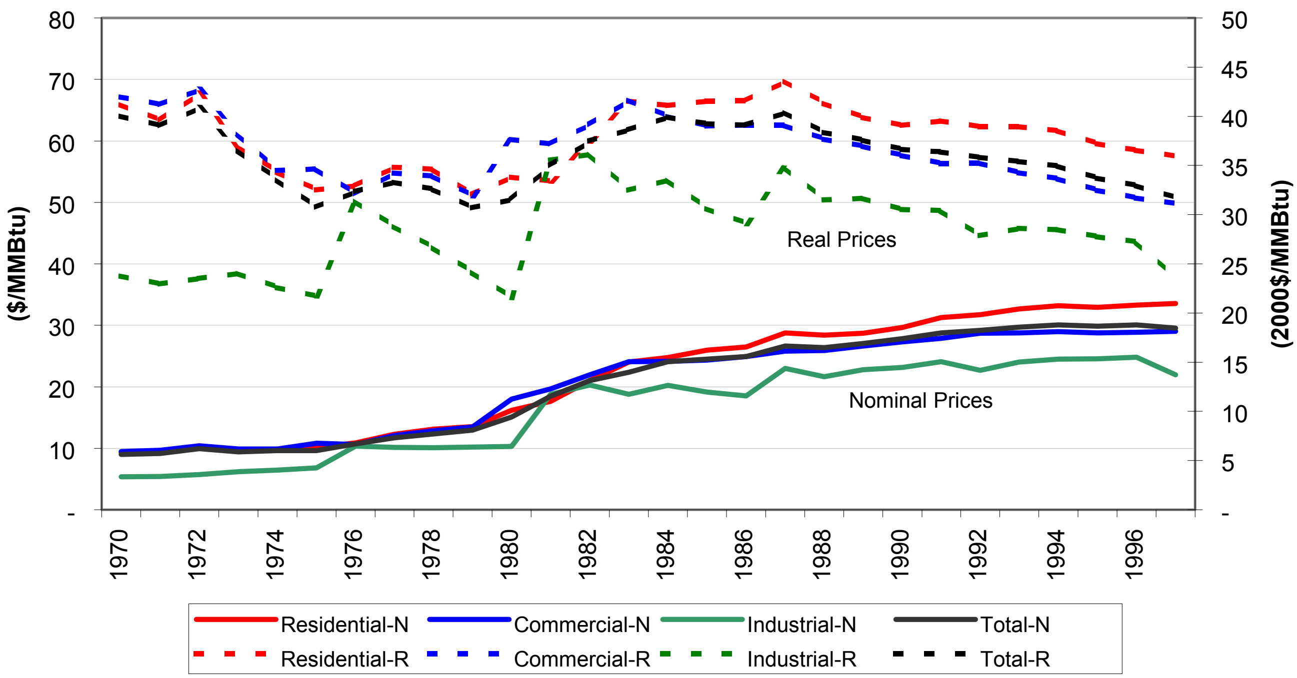

Figure A.1.13: Historic Trends in Electricity Prices Per Customer Class (1970-1999)

Source: U.S. Department of Energy, Electric Power Annual

Power Generation Trends: As of 1999 there are 676 electric generating units online in Alaska -- 567 of which are utility owned. These 676 units have a generating capability of 2,043 MW (1,743 MW or 85 percent for utility-owned units). According to the Energy Information Administration's Form 860, of the units that are still online, the oldest units are hydro powered. There are 6 units with generating capability of 6.9 MW that came online between 1900 and 1946. The first non-hydro unit was a unit fired by No. 2 Fuel Oil that came online in

1947. Since then, 475 utility-owned and 23 non-utility owned, oil fired units have come online – the majority of which (328) since 1980.

Figure A.1.14 shows the number of units by type of fuel and which decade they came online. This graph indicates that the majority of units (in number) are powered by fuel oil – especially those that have come online since 1970. Only 28 of the 567 utility-owned units are fired by natural gas, representing a capability of 666 MW. In contrast, 56 of the 109 non-utility owned units are natural gas fired, representing a generating capability of 161 MW.

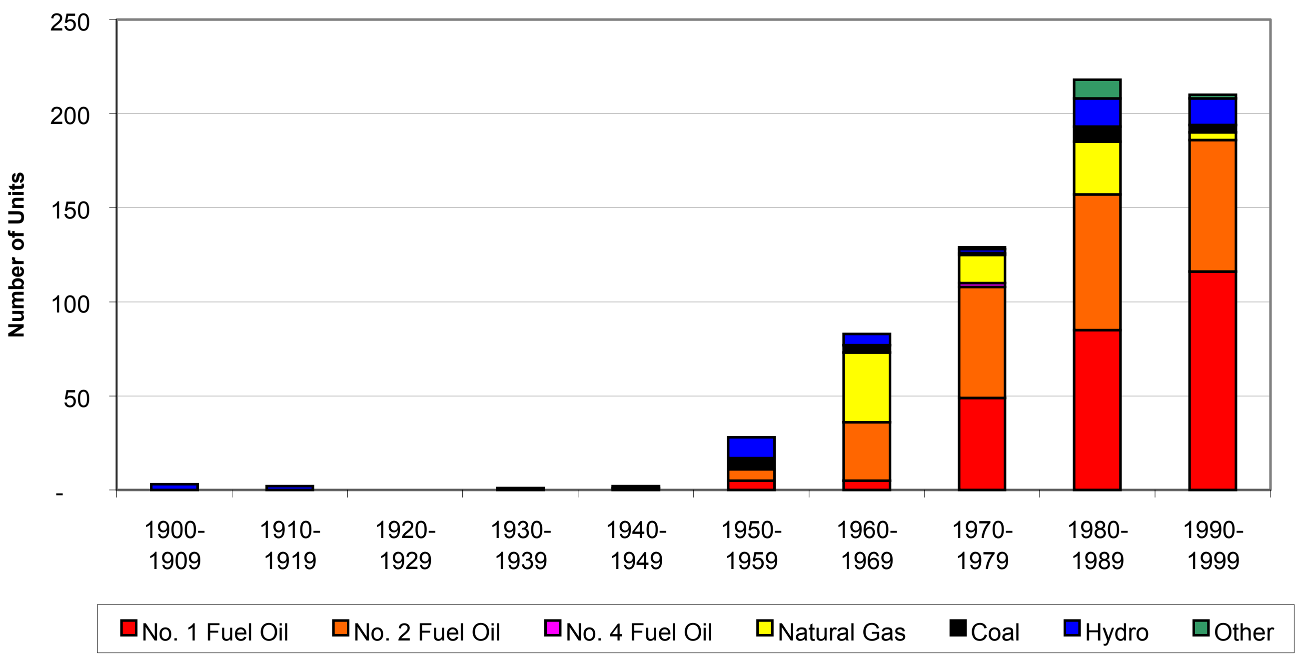

Figure A.1.14: Total Number of Generating Units in Operation by Year in Service and Fuel Type (Utility and Non Utility Owned)

Source: U.S. Department of Energy, Energy Information Administration: Forms 860A and 860B: Annual Electric Generator Report, 1999.

Although the actual number of natural gas fired units is significantly less than fuel oil, they do represent a considerably greater amount of generating capability than any other type of generating unit (See Figure 2.15). In fact, natural gas fired units represent over 40 percent of the generating capability of all the units currently online. Fuel oil units represent 30 percent and hydro units represent 18 percent of generating capability in Alaska.

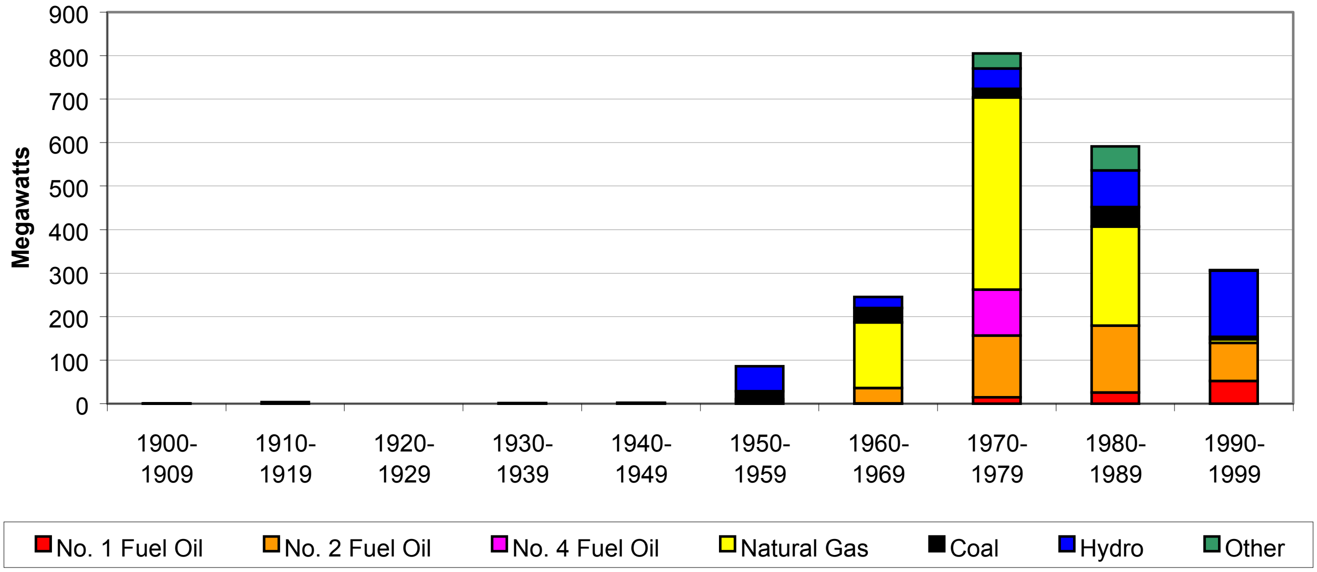

Figure A.1.15: Total Capacity of Generating Units in Operation by Year in Service and Fuel Type (Utility and Non Utility Owned)

Source: U.S. Department of Energy, Energy Information Administration: Forms 860A and 860B: Annual Electric Generator Report, 1999.

Net Generation and Fuel Consumption: Figure A.1.16 further demonstrates that natural gas-fired units play an important part in Alaska electric generation. An average of 2,600 GWh per year were generated by natural gas-fired units. Hydro plants generated an average of 1,100 GWh and fuel oil plants generated only about 550 GWh per year.

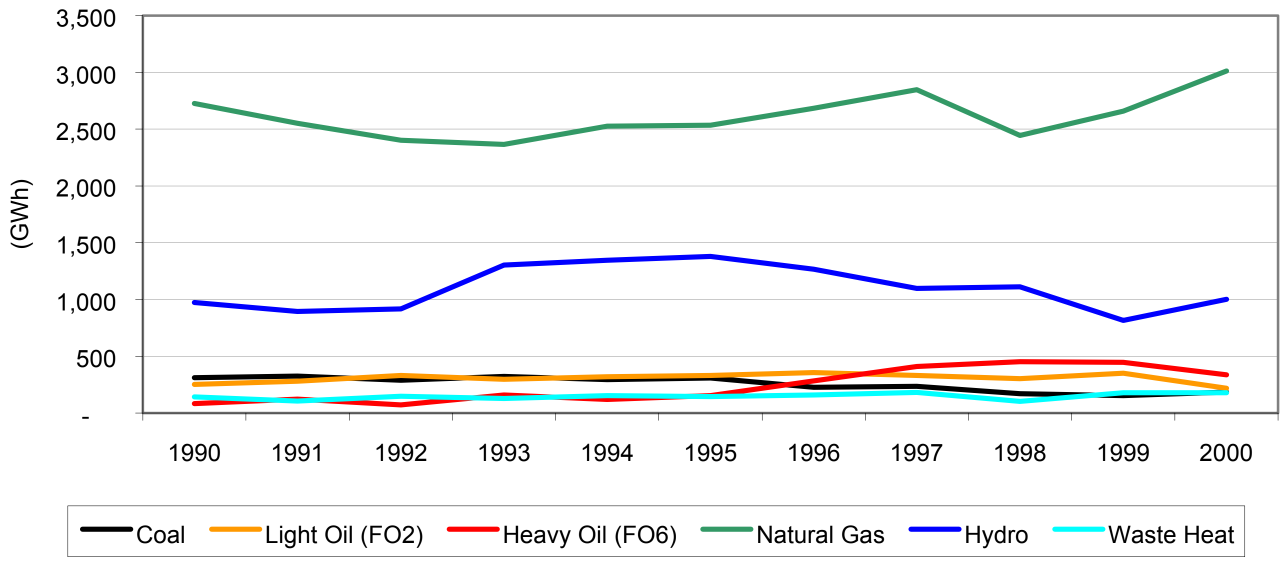

Figure A.1.16: Annual Net Generation by Fuel Type (1990-2000)

Source: U.S. Department of Energy, Energy Information Administration. Form 906: Power Plant Report, 2000.

APPENDIX 2
DETAILED REVIEW OF DEMAND AND SUPPLY MODELING LITERATURE AND DATA SOURCES USED IN THE BASELINE FORECASTS

This appendix has been offered as a substitute to Chapter 3 for those readers interested in greater detail on empirical modeling methods and the development of the literature.

A.2.1: General Issues in Modeling Demand and Supply

Modeling natural gas demand and supply in local, regional, and national markets is important for a number of reasons. These models give researchers and other market observers information about the structure and composition of demand and supply. Futhermore, the results of these models inform users about the magnitude of future demand and its sensitivity to key determinants such as energy prices and income. This information is used to understand:

- Past trends and the determinants of realized demand and supply;
- The responsiveness of demand and supply to changes in its important determinants; and
- Future demand and supply under different assumptions about future scenarios.

From its most basic perspective, the relationships of demand and supply can be summarized as:

- Demand is a function of prices, income, and tastes and preferences; and
- Supply is a function of input factor prices, technology, and other factors.

Transforming these theoretical relationships into measurable statistical equations is difficult. The way empirical data is measured may not conform with the structure implied by theory. For instance, theory suggests that the quantity demanded is a function of prices and other important variables. Yet the "appropriate" prices may not be readily available or easily generated. Furthermore, in many energy pricing situations, prices are set in a multitude of different manners (i.e, average rates, two-part tariffs, increasing block rates, decreasing block rates, time of day and seasonal pricing, etc.) Data measurement problems in terms of definition, sampling, and aggregation complicate model specification and statistical estimation.

Most quantitative analyses of supply and demand is broken into two types : cross sectional and time series. Cross sectional models typically examine causal relationships across a collection of variables over a fixed period of time. As suggested by the nomenclature, time series models focus on time dependency.

Cross sectional models are used to examine existing determinants of either supply and demand. These models are structural in nature since they attempt to flush out causality and typicially employ many different determinants of demand or supply as independent (explanatory) variables. Thus, a model of the industrial demand for energy, could consider a number of different explanatory factors that include economic characteristics (i.e., relative energy prices, output levels, etc.) and technical characteristics of the facilities (i.e., number of boilers, fuel switching abilities, heat to power ratios, etc.).

Cross sectional models provide useful information on the relative statistical importance of these variables at a given period of time but are less useful in estimating how relationships change over time. Thus, their ability to serve as a springboard for forecasting is limited. In addition, these types of approaches usually require detailed disaggregate information (usually at the firm or production unit level), that can be difficult to acquire, particularly for independent research.

Time series models, on the other hand, are more useful in examining the dynamic determinants of demand or supply. The advantage of time series models is that they can convey information about how supply or demand relationships have varied historically and where particular “structural breaks” in certain trends have occurred. These models are equally useful as a starting point for forecasting since most forecasts are developed from historical trend relationships. Their disadvantage is that data availability usually limits the range of the determinants measuring the supply or demand relationship.

Another consideration in time series models is that they can be developed in two different fashions. The first is traditionally referred to as an “econometric” approach while the second is commonly referred to more generally as a “time series” approach.[1] The econometric approach is concerned with the estimation of relationships suggested by economic theory across time. For instance, in demand analysis we might look at the relationship of energy demand relative to prices, income, weather, and other relevant variables. Such models serve two purposes. First, they allow economic hypotheses to be tested empirically.[2] Second, they provide a framework for making rational and consistent predictions (i.e., forecasting).

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[1] A seminal text on the econometric analysis of time series is Andrew Harvey. (1991) *The Econometric Analysis of Time Series*. Second Edition. Cambridge, Massachusetts: The MIT Press.

[2] *Ibid.*, 1.

Pure time series approaches, on the other hand, are more generalized trend analyses based on statistical extrapolation techniques rather than theoretic relationships. Traditional time series analysis forecasts the time path of a variable with models that explicitly contain stochastic components to measure their dynamic relationships.[3] Difference equations, such as moving averages of either the error term, the dependent variable, or both, are at the core of these types of approaches. Uncovering the dynamic path of a series improves forecasts since the measurable components of the series can be extrapolated into the future.

There is a third option in facilitating what is known as cross-sectional/time series models. These approaches, as the name suggests, merge these two approaches to maximize the relative benefits, and minimize their relative shortcomings. The problem with these approaches is that, in many instances, they require relatively advanced statistical techniques, as well as being very data intensive.

Another important question in measuring either supply or demand relationships is the determination of which of the two general approaches should be facilitated. In many instances, this is usually done by purpose of the study as well as the practical limitations of the data. If a researcher is interested in examining the price elasticity of the residential demand for natural gas, then a cross sectional analysis of account-specific information would be a useful approach. However, many researchers outside of natural gas local distribution companies usually have limited to no access to this type of information. The US Department of Energy, however, does report aggregate information by customer class across time, thus some type of time series approach may be more readily facilitated.

Lastly, determining the appropriateness of a particular model is an important specification issue. Often, applied modeling can emphasize goodness of fit of a particular model to the expense of all other considerations. However, more balanced consideration should include such factors as:

- *Consistency with theory*. Ensuring the quantitative estimates of model parameters exhibit mathematical signs and magnitudes consistent with economic theory (i.e., negative price elasticities and positive income elasticities).

- *Consistency with goals*. Obviously specifying and measuring time series models can be more important for forecasting goals, while cross sectional models can be more important for research questions related to the relative importance of structural determinants.

[3]Walter Enders. (1995). *Applied Econometric Time Series*. New York: John Wiley and Sons, Inc.

- *Parsimony*. Ensuring that models that are not overly specified and are straightforward.

- *Robustness*. Ensuring that models are not overly dependent upon unique specifications or time periods under consideration.

The modeling of supply and demand for natural gas builds on a broad arena of industry-based energy modeling. Natural gas supply modeling, for instance, is conditioned by a number of earlier studies in petroleum supply modeling. Natural gas demand modeling is heavily linked to the electric power industry.

The study of natural gas supply and demand also is linked to technical-engineering models, sociological models, economic models, and hybrid models that employ varying combinations of these factors. Econometric analysis, as opposed to time series approaches, has dominated much of the supply and demand modeling literature as we will see in later chapters. The preference for these econometric approaches is probably to be expected. First, econometric approaches are useful in explaining the changes in natural gas disposition that result from general changes in the industry—particularly, the response to shifts in price and the general degree of price volatility in the industry since the early 1970s.

Second, while data measurement and implementation is still a challenge in the analysis of energy demand and supply, accessibility of the information has improved considerably. Reporting requirements and data collection developed at the U.S. Department of Energy gives researchers a consistent source of information to examine and corroborate existing studies in the energy industry. With the advent of the internet, the electronic availability of the information enhances the ability to concentrated important efforts in understanding empirical relationships rather than collecting basic information on industry disposition and trends.

Third, over the past twenty years, econometric approaches have become more accessible to industry practitioners as software packages have reduced the programming work needed to do the earlier models by an exceptional order of magnitude. Today, many readily available statistical packages can estimate either supply or demand models in matter of seconds. The reduction in computational difficulty has helped facilitate the development of a large body of analysis related to important energy relationships.

A.2.2: Empirical Studies of Natural Gas Demand

One of the pioneering authors in demand modeling, for many sectors that go beyond just energy demand modeling, is Hendrick S. Houthakker. His studies in energy demand modeling were extensive, and provided some of the first insights into the importance many structural determinants of energy demand. His work is still commonly cited in principals textbooks of microeconomic theory.[4] Houthakker's work in energy demand modeling, developed in the early 1950s, was a basis for his broader work in overall demand modeling.[5]

On the more practical side, there is a considerable amount of work in natural gas demand modeling that rests outside the traditional academic literature. This work is associated with the modeling conducted within the process of regulated natural gas distribution companies, commonly referred to as local distribution companies or LDCs. These LDCs use forecasting models for internal planning process in meeting supply (commodity) and capacity (transportation and storage) needs.[6]

Many of the theoretic developments of natural gas demand modeling have come from the academic literature. A good portion of this analysis has focused on residential, and to a lesser degree commercial, demand for natural gas. These models are primarily econometric in nature since the purpose of many are to get accurate estimates of price, income, and weather related sensitivities of natural gas demand.

Another practical consideration in reviewing the literature on natural gas modeling is its relationship with its sister energy industry, electricity. A number of the earliest works in energy demand concentrated in the area of electricity (i.e., Houthakker) and not natural gas. It seems likely that one of the initial reasons for more comprehensive development of demand modeling in the electricity industry is associated with its greater degree of data availability. Thus, any survey of natural gas demand modeling will have to include some references to the development in the power industry as well.

There are a number of surveys in the literature dedicated to natural gas and energy demand modeling in general. One of the earliest and most comprehensive surveys of energy demand modeling was prepared by Douglas R. Bohi for the Electric Power Research Institute (EPRI).[7] While the overall purpose of the study was to examine price elasticities, the study is an excellent overview of demand modeling since price elasticities are usually outputs derived

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[4]Hendrick S. Houthakker and Lester D. Taylor. (1966). *Consumer Demand in the United States, 1929-1970*. Cambridge: Harvard University Press.

[5]For instance see: Hendrick S. Houthakker. (1951), "Some Calculations of Electricity Consumption in Great Britain." *Journal of the Royal Statistical Socie*ty. Series A, 114, Part III, 351-71.

[6]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.

[7]Douglas R. Bohi. *Price Elasticities of Demand for Energy: Evaluating the Estimates*. Palo Alto: Electric Power Research Institute.

from an overall analysis of demand determinants. An update to this study was prepared in 1984 by Bohi and Zimmerman.[8]

A more recent study, which emphasizes the development of the literature in residential energy demand modeling, was presented by Reinhard Madlener.[9] In the survey, Madlener attempts to update the earlier Bohi work, as well as breaking the existing econometric literature into a number of useful different categories. These include studies associated with log-linear functional forms, transcendental logarithmic (translog) functional forms, qualitative choice models (also know as discrete choice models), household production theory (end-use modeling), and pooled time series-cross sectional models.

Madlener presents a table associated with each of these types of models. We have replicated portions of that table, and added some supplementary comments and analysis, in Table A.2.1. Our survey will follow the same lines as Madlener, since it provides such a useful frame of reference to consider the development of energy demand modeling. The following survey will differ, however, by placing a larger explanation on the methods and their advantages, and highlighting in more detail, the seminal pieces of literature within each of these modeling categories. We also concentrate on the more generalized areas of: log linear and double log models, transcendental logarithmic (translog) functional forms, qualitative choice and end-use models (also know as discrete choice models).

A.2.3: Log-Linear and Double Log Models

The typical log-linear and double log models are relatively straightforward and tend to be the model of choice, particularly for industry practitioners. This model generally takes the form:

$$\log D = \beta_0 + \beta_1 P + \beta_2 Y + \beta_3 W + \beta_4 X \qquad \text{(eq. A.2.1)}$$

$$\log D = \beta_0 + \beta_1 \log P + \beta_2 \log Y + \beta_3 \log W + \beta_4 \log X \qquad \text{(eq. A.2.2)}$$

Where:

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

[8] Douglas R. Bohi and Martin B. Zimmerman. (1984). "An Update on Econometric Studies of Energy Demand Behavior." *Annual Review of Energy*. 9: 105-54.

[9] Reinhard Madlener. Econometric Analysis of Residential Energy Demand: A Survey. *Journal of Energy Literature*. 2:3-32.

The benefit of the log-linear and double log form is that coefficients can easily be translated into elasticities. In the double log form presented in equation A.2.2, the parameter for price is interpreted as the price elasticity of demand, while the parameter estimate for income can be interpreted as the income elasticity of demand.

The log-linear literature starts with Houthakker and continues with Balestra and Nerlove (1966), who suggested a dynamic approach to the modeling of the demand for natural gas. This model contained a pooled cross sectional approach to modeling natural gas demand since it examined residential households, across several different regions, across time. The model is important since it uses an error-components specification and demonstrates the importance of relative fuel prices in determining both natural gas demand and fuel substitution.

For instance, in their study, Balestra and Nerlove assumed that the new demand for gas was a function of the relative price of gas and the total new requirements for all types of fuel. The problem with this approach was that the concept of new energy demand was difficult to translate into observable variables. The total new demand appeared as the sum of the incremental change in consumption and "replacement" demand, which represented the portion of the total demand for fuel "freed" by the retirement and replacement of old appliances. Specific equations were developed for each type of demand model, and ultimately fed into a larger equation examining total fuel use.

This total fuel use equation facilitated data from 1950 through 1962. The fuel use variables and price information was standardized into a Btu equivalent. Usage was normalized for weather in each state, and prices and income were measured in constant dollars. There were 13 observations per state, though only 36 states had gas service over the entire period. All states were grouped together and estimations were performed on the combined sample of cross sectional and time series data. Additional equations were estimated using dummy variables for each state.

While the estimation results presented negative and significant results for the impact of own price changes on energy demand, the greatest statistical significance rested with the state-specific dummy variables. The results would tend to suggest that there were a number of state-specific implications for energy usage that could not be directly modeled (i.e., regulation, etc.) The overall predictive capabilities of the model were very good, with 99 percent of the demand for natural gas being explained by the model's independent variables.

Because the demand function was for new gas demand, the average price elasticity was attainable from the model results. According to Balestra and Nerlove, the estimated average price elasticity of new gas demand ranged from –0.58 to –0.69 given the various functional forms estimated.

Beierlein, Dunn, and McConnon (1981) took the general framework discussed by Balestra and Nerlove and applied a Cobb-Douglas framework which has a double-log component. Their specification for energy demand included specific equations for fuel oil, natural gas, and electricity. This model is also a pooled cross-section approach since it examined energy usage across fuel type, state, customer class, including residential, commercial, and industrial, and year.

The independent variables were the average deflated price of gas per 1000 therms, the average deflated price per kWh of electricity, the average deflated price per gallon of fuel oil, lagged per capita fuel consumption, and per capita deflated income represented by disposable personal income, value of retail sales, and value added by manufacturing.

The model facilitated an error component and error component/seemingly unrelated regression (SUR) approach. The Cobb-Douglas framework allowed for constant elasticity of substitution, thus the estimated parameters for price, were the elasticities for each variable. The estimated own-price elasticity of gas for the residential sector was between –0.23 and –0.35 depending on the technique and between –0.61 and –0.63 for the natural gas industrial sector. The fit on the estimations showed that between 94 and 99 percent of the variation in the fuel consumption by various sectors was attributable to their respective independent variables.

The MacAvoy-Pindyck (M-P) model (1973) used similar techniques in what was a basically a demand component in a supply model.[10] In the demand module of this model, MacAvoy and Pindyck focused on wholesale natural gas markets. Supply of production out of reserves had to be measured against demand for the production after it had been transmitted to wholesale markets by pipelines, and the quantity demanded by direct industrial consumers as well as retail consumers.

MacAvoy and Pindyck modeled demand as a function of the prices for wholesale gas contracts, the prices for alternative fuels consumed by the final buyers, and economy-wide variables that determined the overall size of energy markets. For the model, the demands for production were approximated by curves fitted on a disaggregated basis into wholesale equations for (1) gas sales for resale,[11] (2) gas sales directly off the pipelines for final consumption (mainline sales), and (3) intrastate sales by producers and pipelines to final consumers. The wholesale prices of gas were computed by adding a markup to the field price based on (1) mileage between the production district and the consuming region, and (2) volumetric capacity of the pipeline.

[10]The discussion of the supply model can be found in the later section of this chapter on supply modeling.

[11] Split in to commercial-residential gas and industrial gas on the basis of percentages distributed to those two groups for ultimate consumption.

Before the wholesale demand equations were estimated, the M-P model looked at wholesale price markups. Markups over field prices were a function of mileage and volumetric capacity of the lines transmitting to each region. These field prices were the rolled in wellhead price for the wholesale region under investigation. The coefficient of volumetric capacity as determined by the M-P model was negative, as a larger capacity implies lower average costs. The fit of the estimated equation[12] showed that 56 percent of the variation in wholesale price of gas sales for resale could be explained the variation in the independent variables.

Gas sales for resale were broken down in to gas that ultimately is resold for residential and commercial consumption and gas for industrial consumption and the M-P model had a separate equation for each category for each of the five regions of the country. For each of these equations, new or additional demand was used as the dependant variable. The M-P model assumes that all fuel-burning equipment had an average lifespan of 14 years and chose a depreciation rate *r* equal to 0.07. Independent variables in the models included average wholesale price of gas, the wholesale price of oil, income, population, value added in manufacturing, capital investment by industry, and a price index of alternative fuels. In the South Central, Southeast, and West regions the residential and commercial sales were aggregated with industrial sales to make up for lack of stable elasticity estimates in the disaggregated form. All equations were estimated over the years 1964 through 1970.

Similar equations were developed for Northeastern region on a specific user basis. Results showed that an increase in the price of oil increases the demand for gas, additional units of value added in manufacturing increased the demand for natural gas, and additional units of capital investment increased the demand for natural gas.

MacAvoy and Pindyck, instead of using gas price for the current year, used the average wholesale price of gas for the previous two years and also did the same for the wholesale price of oil. The fit of this equation showed that 90 percent of the variation in total demand for the region was attributable to variation in the independent variables.

As noted earlier, additional units of capital investment in industry increased the total demand for natural gas. The fit of the equation showed that 80 percent of the variation in total demand for the region was attributable to the variation in the independent variables. The equation for Southeast-residential and commercial revealed that the coefficient for income is positive, which meant that additional units of income would increase the region's residential and commercial demand for natural gas. The fit of the equation showed that 26.7 percent of the variation in residential and commercial demand for the region was attributable to the

[12] As taken from each equation's R^2 values.

variation in the independent variables. The final regional gas sales for resale equation, that for Southeast-industrial demand, revealed that the coefficients for the price index for alternative fuels and value added in manufacturing exhibited a positive relationship. The fit of the equation showed that 37.3 percent of the variation in the industrial demand for the region was attributable to the variation in the independent variables.

The quantity of mainline sales to industrial buyers was estimated. The wholesale price for mainline sales was represented by the average of the wholesale price in the current year *t* and the previous year *t-1*. The same operation was also performed on the price index of alternative fuels. The coefficient of the price index of alternative fuels showed that an increase in the price index led to an increase in the quantity of mainline sales. The fit of this equation showed that only 15 percent of the variation in the quantity of mainline sales was attributable to the variation in the independent variables.

Finally, the quantity of intrastate demand was estimated. Like the mainline sales equation, the wholesale price of gas was represented by the average of the wholesale price for current year *t* and the previous year *t-1*. The fit of this equation showed that 21 percent of the variation in the quantity of intrastate demand was attributable to the variation in the independent variables.

Six of the ten demand equations had significant coefficients for the negative price effects on demand, with the strongest effects in regions closer to producing centers with more alternative sources of energy. MacAvoy and Pindyck concluded that size-of-market variables such as consumer incomes or industrial investment did not appear to be causal factors in all sectors of the natural gas market.

MacAvoy and Pindyck also calculated interregional flows of gas in order to be able to calculate excess demand of consuming regions. Estimates of interchange at an aggregate level were made using the five demand regions, West, Northeast, North Central, Southeast, and South Central, and eight production regions. Total flow, the fraction of a consuming region's demand which comes from a particular production region, and the fraction of gas from a production region going to a particular consuming region were calculated. Demand was forecasted for the period 1966 through 1970, and the mean demand error[13] was –2.5 Tcf with an RMS[14] demand error of 2.5. Estimated demand quantities for each year were about 13 percent lower than the actual values.

[13] Mean error is the average of the errors of the predicted values. The error of a predicted value is calculated by subtracting the actual value from the predicted value.

[14] RMS error, or Root Mean Square error, is simply a quantitative measure of the deviation of model predictions from actual observations. Smaller RMS error is better.

Lyness (1984) developed a gas demand forecasting model which focused on the temperature-gas demand relationship. He identified three regular cyclical patterns in gas demand: (1) the diurnal swing during each day, which had peaks at breakfast time and the evening and a trough during the night, (2) a weekly cycle, and (3) an annual cycle related to seasonal changes in temperature. All three cycles were superimposed on each other and were treated as being related.

Lyness forecasted long-term demand almost exclusive on temperature and the underlying concept of seasonal normal temperature (SNT). For each day of the year a long-run average temperature could be derived and those could be smoothed to form a sinusoidal curve for the entire year. Thus daily, weekly, or monthly SNT's were known in advance and the forecast of demand for the remainder of the year was obtained through the insertion of the appropriate SNT values into the current forecast demand and temperature relationship.

While he provided no specific model for the forecasting of temperature, Lyness did provide two ways to look at this variable. The approach considered, within a linear framework, a number of different seasonal, daily, and temperature influences on natural gas demand. Lyness left the addition of market data to the individual modeler, as different regions had different market conditions and thus market variables. The model was broken down in to separate equations corresponding to the market sectors. For each forecast year, parameters in each market sector equation were scaled in the ratio of the forecast annual market sector demand to the current market sector demand and then re-aggregated to arrive at an equation for the forecast year that was consistent with the total forecast demand for that year.

Herbert and Kriel (1989) built on the studies by Beierlein (1981), Grady (1986), Green (1987), Blattenberger (1983), and Lin (1987) by creating a natural gas demand model which incorporated both heating degree day data as well as wealth data, and estimated the model based on monthly information. The main equation in the model estimated monthly aggregate residential sales as the function of six variables: (1) the index of changes in total personal income in constant dollars received by gas customers and changes in the number of gas customers, (2) heating degree days weighted by gas residential space-heating customers, (3) cooling degree days weighted by population, (4) household wealth in constant dollars measured by financial and non-financial asset holdings, (5) the price index of natural gas in constant dollars, and (6) the seasonal shift in residential gas demand for the one-month period from mid-December to mid-January.

Weighted heating degree days were indexed to changes in the percentage of space-heating to total gas customers. The authors also estimated regressions for real wealth, which was a function of time, and real personal income, which was a function of the number of residential customers in a given quarter and Census Division and personal income in a given quarter and Census Division.

The fit of the estimated equation showed that 99 percent of the variation in monthly aggregate residential sales was attributable to the variation in the independent variables. The model was used to forecast values for the year 1984, and the mean error was 217 Mcf and individual differences ranged from one percent to five percent.

Hsing (1992) built on the work of Taylor (1977), Blattenberger (1983), and Griffin (1979) in an exercise for estimating the own-price and income elasticities of natural gas for each of the 50 states except Hawaii for the year 1989. The model had the demand for natural gas for each state in a given period as its dependent variable. The independent variables included the price of natural gas, disposable income per capita, the price of residential electricity, and the number of heating degree days. The model also included dummy variables for the South (SO) and West (WE) as well as the years 1985 and 1986 but no reason is given for these inclusions.

Hsing estimated the elasticities from the results of the linear regression of the model. His results included Alaska-specific estimates of –0.29 for the price elasticity of demand and 0.37 for the income elasticity of demand.

A.2.4: Transcendental Logarithmic (Translog) Models

Translog models became popular in the 1960s with the advent of the Christensen, et al. (1973) approach of estimating industrial production, and later with utility functions.[15] This approach was applied to the electric power industry in 1976, and the approach has become commonplace for a considerable amount of energy economics research.[16]

The translog specification is a quadratic function with its elements expressed in terms of their natural logarithm. This specification is a second order approximation around a given point for the Cobb-Douglas production function. The Cobb-Douglas production function is a flexible functional form for a production function that allows declining marginal products for all inputs, and also assumes that opportunities exist to substitute inputs in production without gaining or losing output.

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[15] Laurits Christensen, Dale Jorgenson, and Lawrence Lau. (1973) "Transcendental Logarithmic Production Frontiers." *The Review of Economics and Statistics*. 55:28-45. Laurits Christensen, Dale Jorgenson, and Lawrence Lau. (1975) "Transcendental Logarithmic Utility Functions." *The American Economic Review* 65: 367-83.

[16] Laurits Christensen and William Greene. (1976). "Economies of Scale in U.S. Electric Power Generation." *Journal of Political Economy*. 84 (4): 655-76.

The advantage of the translog approach is that it provides some structure on the assumed production/utility function under investigation. The parameters associated with the own and cross-price terms provide estimates of own and cross-price elasticities of demand. In additional, the translog approach allows for a more flexible functional form that enables empirical validation of utility-function properties. For example, while the Cobb Douglas function imposes unitary elasticity of substitution among inputs, the translog enables the data to determine the degree of input substitutability. In general, this flexible functional form enables the data to determine if the assumed functional form is correct, and imposes fewer a-priori restrictions on model specification.

The approach, however, is not without its potential problems. First, translog models require a significant amount of information which can be difficult to attain. Second, these models can be relatively difficult to apply and interpret. This has led many practitioners to steer clear of these approaches. Third, the parameter estimates in many instances do not tend to be robust or stable, and can lead to some erroneous results. Last, the model tends to lend itself better to cross-sectional analyses, and, as a result, is not a very useful tool for forecasting.

The translog specification[17], usually takes the form:

$$\log D = \beta_0 + \beta_1 \log P + \beta_{11}(\log P)^2 + \beta_{12}(\log P)(\log Y) + \beta_{13}(\log P)(\log W) + \beta_{14}(\log P)(\log X) + \beta_2 \log Y + \beta_{22}(\log Y)^2 + \beta_{23}(\log Y)(\log W) + \beta_{24}(\log Y)(\log X) + \beta_3 \log W + \beta_{33}(\log W)^2 + \beta_{34}(\log W)(\log X) + \beta_4 \log X + \beta_{44}(\log X)^2 \quad \text{(eq. A.2.3)}$$

Where:

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

Christensen and Jorgensen introduced the translog approach in 1969 and then again with Lau in 1973, and Pindyck (1979) used the approach extensively to analyze demand in his work on world energy demand. Estrada and Fugleberg (1989) took Pindyck's work and applied it to the natural gas markets in West Germany and France in order to determine own-price and cross-price elasticities of demand. Using a translog equation based on Pindyck's, Estrada and Fugleberg estimated a number of equations for the household and commercial sectors:

The resulting equations included estimates with lagged price variables in order to test the underlying hypothesis that long-term changes in the composition of

[17] From Brynjolfsson and Hitt (1995).

energy demand were the result of changes in relative fuel prices, infrastructural changes in the economy, and the technology incorporated in equipment used to consume different fuels. The authors hypothesized that the response to an increase in the relative prices of fuels would take one to two years as consumers replaced their old equipment with types that were more energy efficient.

The actual estimation of the elasticities was done using a two-step process, the first of which was the calculation of partial own-price and cross-price elasticities: The second step was to incorporate the partial elasticities in to equations for total elasticities. The authors found that the own price elasticity for gas was much higher in Germany and believe that this was because the German government did not regulate prices as much as the French, and changes in fuel costs were more rapidly reflected in consumer prices.

A.2.5: Qualitative Choice and End Use Models

Most demand models prior to the early to mid 1970s, and even to this day, facilitate continuous variables for consumption. There are equally interesting empirical applications that examine not how much of a particular resource is utilized, but whether or not that resource is utilized at all. Such approaches are discrete in nature and have led to the development of qualitative choice, or discrete choice models of energy usage.

Discrete choice models are those in which the dependent variable is a discrete variable. The simplest application is one where the dependent variable is a binary choice variable that represents a simple positive or negative response. The dependent variable takes the value 1 if the choice is made, and 0 if the choice is not made. Independent variables are then used to estimate parameters influencing that choice.

Consider a generalized binary choice model that takes the form:

$$y = x\beta + e \qquad \text{(eq. A.2.4)}$$

Where:

y = A discrete variable (eg. gas heating) that takes the value 1 if the choice is made, 0 otherwise

x = A matrix of explanatory variables, such as characteristics of the alternatives or socioeconomic variables

β = A vector of parameter estimates

e = A sequence of error terms which can take either logistic or normal distribution

Discrete choice models can be powerful tools to examine individual customer choice behavior and the factors influencing those decisions. Sensitivities, developed through the calculation of odds ratio statistics, can then be derived. These odds ratio statistics given some indication on how the probability of making a particular discrete energy consumption decision change as the independent variables change.

These qualitative based models, however, usually require specific and relatively comprehensive end use information. Typically, data used in these types of analyses are from individual consumer surveys. Thus, such empirical approaches are limited, if customer, or decision making unit information is not available. In addition, these types of models can tend to be more static in nature making it difficult to use for long forecasting and trend analysis.

Some of the representative works in this area include the work of the State Utility Forecasting Group (1999) in Indiana, which used a logit form of discrete choice model to determine fuel choice among residential energy consumers. The dependent variable of the model was the ratio of electricity's share of the space heating market to that of all other fuels. Market share was used because it captured current activity, was independent of the rate of customer growth, and exhibited greater year-to-year variation than measures of market saturation. The group used a double-log functional form of the logit model, which allowed for easy calculation of elasticities. The national energy outlook model released by the Energy Information Administration (2001) also used discrete choice modeling for fuel choice components of the overall model.

A.2.6: Relevant Literature in Natural Gas Supply Modeling

Unlike the natural gas demand literature, natural gas supply modeling has been relatively restricted to log-linear or double log functional forms.

Some of the earliest natural gas supply models were developed in the early 1960s starting with Adelman (1962) and Fisher (1964). Adelman's work specified two distinct equations for natural gas production. The first equation defined a simple relationship between price of non-associated[18] natural gas and production. The second equation was more forward looking by specifying that the production of natural gas in year *t+1* was a function of price in the previous year. In other words, production decisions were based upon a lagged function of price.

Adelman found there was a positive relationship between the price and supply of natural gas in both types of models. His model provided quantitative estimates of the sensitivity of natural gas production to price (i.e., price elasticity of supply).

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[18]Non-associated natural gas is the production of natural gas that is not the byproduct well that is not primarily designated as producing oil. Hence, its primary function is to produce natural gas.

Adelman found that a one cent increase in the price of natural gas brought about a 750 to 1,000 Bcf increase in non-associated gas reserves. In the model where production was posited to react to current prices, Adelman found that 60 to 66 percent of the variation in the quantity supplied can be statistically explained by the variation in price. In the models where production is a lagged function of price, Adelman found that 75 percent of the variation in the quantity supplied can be statistically explained by the variation in price. The result tended to support the notion that while production was highly sensitive to price, it did respond instantaneously.

Two years later, Fisher (1964) focused on the sensitivity of petroleum exploration and discovery to economic incentives. Fisher examined four different types of equations as being potentially important determinants of petroleum exploration and discovery. The natural logs of four facets of production, including the number of new field wildcats drilled, the success ratio of productive to total new field wildcats, the average size of oil discoveries per productive new field wildcat, and the average size of gas discoveries per productive new field wildcat, were the dependent variables in their respective equations. The independent variables, however, varied per equation and included the average depth of new field wildcats, crude oil and natural gas prices, and core drilling time.

The effective value of new discoveries in Fisher's model was calculated as being the product of the number of wildcats drilled, the success ratio, and the average size of discovery per successful wildcat. Fisher examined production trends during the period 1946-1954 and found that all four equations had good fits. The predictive capabilities of each of these models varied between 72 to 85 percent

Fisher's models also produced estimates of the elasticities of wildcat drilling to the price of crude oil. He also found that the elasticity of wildcat drilling with respect to the price of crude was about +2.85, which meant that a one percent increase in the deflated crude price of oil at the wellhead resulted in a 2.85 percent increase in the number of new field wildcats drilled. The elasticity for the relationship was +2.45, or a one percent increase in the deflated crude price of oil resulted in a 2.45 percent increase in the number of new wildcats drilled, when shutdown days and lagged depth were included in the equation.

Fisher's hypothesis that price affected the characteristics of prospects was supported, as the elasticity of the success ratio with respect to price was –0.36, indicating that for a one percent increase in the deflated price of crude oil, the resulting success ratio of productive to total new field wildcats decreases by 0.36 percent, showing a worsening of prospect characteristics when prices rise. As well, the price elasticity of oil discovery size was –2.18 and the price elasticity of natural gas discovery size was –2.01, which meant that a one percent increase in the deflated price of crude oil resulted in a 2.18 percent decrease in the average size of oil discoveries and a 2.01 percent decrease in the average size of gas discoveries, thus as price rose, the number of small prospects that were deemed worth drilling rose as well. Fisher's estimations showed that the price elasticity for both new oil and new gas discoveries was +0.9, where a one percent increase in the deflated price of crude resulted in a 0.9 percent increase in new oil and gas discoveries, though he hypothesized that the price elasticity result from a separate estimation of +0.3 was closer to the truth, as he believed that new oil and gas discoveries were less price responsive than his original estimations showed.

Fisher concluded that there was an important substantive distinction between the supply curve of exploratory effort and the supply curve of new discoveries. Fisher found that economic incentives not only influence the quantity of exploration that occurs; they determine its characteristics, as a price increase could bring about added discovery in more marginal fields.

The regulation of natural gas ceiling prices in the early 1970s brought about the next wave of natural gas modeling, and in 1971 the results of two models, the Khazzoom Federal Power Commission (FPC) (1971) model and the Erickson-Spann (1971) model, were published.

The Khazzoom model focused mainly on gas discoveries, as Khazzoom claimed that discoveries were the driving force behind gas supply. The model was split into two sections, the first being "new discoveries," which represented the amount of recoverable gas estimated to exist in newly discovered reservoirs and the second being "extensions and revisions," which consisted of additions to or subtractions from the initial estimates of gas discovery due to changing economic conditions or the availability of new information on reservoir size or reservoir characteristics. Both parts of the model also included a dummy variable for each of the six groupings of the 21 FPC districts included in the study,[19] and each part of the model was estimated with and without the dummy variables.

The new discoveries equation included new discoveries in time *t* as the dependant variable. The independent variables were the real ceiling price of gas, the real price of crude oil at the wellhead, the real price of liquefied gases and ethane, and a new discoveries variable. Because of the specification of the equation, each dependant variable was "lagged," which means the actual values used to determine new discoveries at time *t* are taken from previous periods. In this case, the values used are the average of the variables in periods *t-1* and *t-2.* Khazzoom found that the independent variables explained 79 percent of the variation in new discoveries, though the prices of oil and liquefied gas and ethane were statistically insignificant.

The extensions and revisions equation included independent variables representing the ceiling price of gas, the real price of oil, and the real price of liquefied gases and ethane, new discoveries from the previous year and

[19] The six groupings were Upper Gulf Coast (UG), Gulf Coast (GC), South Mid-Continent (SMC), Panhandle-Hugoton (PH), Permian Basin (PB), and Rocky Mountain (RM).

extensions and revisions from the previous year were also included. The results for this equation were much better when the FPC district groupings were included, because without them every price in the equation was statistically insignificant and with them only the price of oil was insignificant. Overall, the independent variables explained 61 to 64 percent of the variation in extensions and revisions.

Pindyck (1974) criticized the use of a lagged dependant variable in Khazzoom's model, stating that the lagged variable in the new discoveries equation accounted for too much of the variation in new discoveries in time *t*, thus making the estimates of the price coefficients inconsistent. Pindyck also reestimated Khazzoom's model for the years 1964 through 1969 (as opposed to the original estimation period of 1961 through 1969). Due to lack of data, the variable for gas liquids was eliminated. The number of dummy variables was reduced as well, as only three regional variables were used instead of six.

In the re-estimation of the new discoveries equation, Pindyck found that only the significant coefficient was that of the lagged new discoveries variable, though the fit of the equation increased to where 89.5 percent of the variation in the dependent variable could be explained by the variation in the independent variables. The improved fit of the equation was explained through the elimination of years 1961 through 1963 in which prices and discoveries had the greatest variation.

Pindyck's reestimation of the extensions and revisions equation, again with the elimination of the gas liquids variable and three of the regional variables, over the years 1964 through 1969, resulted in findings similar to those of Khazzoom's, with the exception of insignificant coefficients for the constant, the price of gas, and one of the three regions. The fit of the equation increased from 63 percent in Khazzoom's estimation to 81.4 percent of the variation in the dependent variable attributable to the variation in the independent variables, though as previously stated, this had to do with the elimination of the years 1961 through 1963. Again, criticism is levied at the use of lagged dependent variables, as the lagged new discoveries and extension and revisions variables account for much of the variation in the dependent variable.

The Erickson-Spann (E-S) (1971) model focused on the price responsiveness of new discoveries of natural gas. The basic relationships estimated by Erickson and Spann were the price elasticities of wildcat well drilling and total discoveries,[20] the success ratio, and average discovery size.[21] Erickson and Spann defined wildcat well drilling as a measure of the amount of exploratory effort undertaken in a given period and the success ratio and average discovery size are measures of the results of this activity. Total discoveries were defined

[20] Price elasticity of total discoveries is the sum of the price elasticities of each of the component elements whose product is total discoveries.

[21] The success ratio, average discovery size, and prices are all measured in logarithms.

as the product of the number of wildcat wells multiplied by the fraction of the wildcat wells that are successful multiplied by the average discovery per wildcat well.

Erickson and Spann used four equations in their model: “wildcatting;” the “success ratio;” “average oil discovery size;” and the “average gas discovery size.” The equations were all estimated for the years 1946 through 1959.

The wildcatting equation had the logarithm of the number of new field plus new wildcats drilled as its dependent variable. Independent variables measured as logarithms included the deflated price per barrel of crude oil at the wellhead, deflated wellhead price per thousand cubic feet of gas by year of basic contract, success ratio of the previous year, and average depth of wildcats the previous year, in feet. Independent variables not measured as logarithms were the number of wildcats drilled by major companies in a given district in a given year as a percent of total U.S. wildcats drilled by those companies in that year, Texas shutdown days, and dummy variables for each petroleum district. The resulting fit of the equation was quite good, with 97.2 percent of the variation in the logarithm of the number of new field wildcats drilled attributable to the variation in the independent variables.[22]

The success ratio equation had as its dependent variable the logarithm of the success ratio, which is the ratio of productive to total new field plus new pool wildcats. The independent variables were the same as the wildcatting equation with the exception of the logarithm of the lagged success ratio, wildcats drilled by major companies, and the logarithm of the average depth of wildcats drilled. The fit of the results of this equation was also good, with 80.2 percent of the variation in the logarithm of the success ratio attributable to the variation in the independent variables.

The average oil discovery size equation had as its dependent variable the logarithm of the average size of oil discoveries per productive new field plus new pool wildcat. The independent variables were the same as for the success ratio equation with the inclusion of the logarithm of the lagged success ratio. As was the case with the two previous equations, the fit of the resulting equation was good, with 89.3 percent of the variation in the logarithm of the average oil discovery size attributable to the variation in the independent variables.

The average gas discovery size equation had as its dependent variable the logarithm of the average size of gas discoveries per productive new field plus new pool wildcat. The independent variables were the same for this equation as they were for the average oil discovery size equation. The resulting equation

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[22] Erickson and Spann made little mention of the significance of the coefficients other than to say that they were “not especially satisfactory” for each equation. The reason for this was that there were missing gas prices for eleven observations in PAD districts I-IV, thus reducing the number of observations over 20 percent.

does not have as good a fit as the three other equations in the model, with only 60 percent of the variation in the logarithm of the average gas discovery size attributable to the variation in the independent variables.

The significant contribution of the E-S paper was the model's ability to calculate elasticities. Erickson and Spann found the own price elasticity of gas discoveries to be +0.69, meaning that for the time period 1946 through 1959, a one percent increase in the price of gas lead to a 0.69 percent increase in gas discoveries. This own price elasticity was the sum of the elasticity for wildcat drilling, which was +0.35, the success ratio, which was +0.01, and the average gas discovery size, which was +0.33.[23] The overall cross elasticity of gas supply with respect to oil price was –0.25, meaning that for the time period, a one percent increase in the price of oil resulted in a 0.25 decrease in the supply of gas.[24]

Pindyck (1974) reconfigured the E-S model to exclude unavailable data such as company specific wildcatting and Texas shutdown days, and reestimated the reconfigured model with data from 1964 through 1969. The fit of the estimated equations left much to be desired, as the success ratio and discovery size equations both had 75 percent of the variation in the dependent variables *not explained* by the variation in the independent variables. As well, Pindyck's estimated own price elasticity of gas was +2.36, far higher than Erickson and Spann's estimation of +0.69. Pindyck cited the size of discovery equation as the source of the problem, as a small change in price tended to result in large increases of average discovery size.

Natural gas shortages in 1970 and 1972 provided the impetus for the creation of two new supply models published in 1973, the Total Energy Resource Analysis (TERA) (1973) model, and the MacAvoy-Pindyck (1973) model.

The focus of the MacAvoy-Pindyck (M-P) model was the simultaneous treatment of the field market for reserves[25] and the wholesale market for production.[26] This structure allowed the M-P model to incorporate the linking of the two markets by interstate pipeline. MacAvoy and Pindyck also stressed the importance of incorporating the demand side of the gas industry, especially when policy implications are involved in the modeling process. Khazzoom, Erickson, and Spann are complimented on their efforts to create supply models, but the models themselves are deemed inadequate to represent policy effects.

The field markets were defined as the point of transactions between oil and gas producers with volumes of newly discovered reserves and pipeline buyers

[23] Erickson and Spann also calculated a similar set of elasticities for crude oil and found the own price elasticity of crude oil to be +0.83.

[24] Conversely, the overall cross elasticity of oil supply with respect to gas price was calculated to be +1.07.

[25] Gas producers dedicating new reserves to pipeline companies at the wellhead price.

[26] Pipeline companies selling gas to retail utilities and industrial consumers.

seeking to obtain by contract the right to take production from these reserves. The amount of reserves committed by the oil and gas companies were based primarily on the amounts of inground deposits of oil and gas, with additions to the reserves coming from additions in gas associated with newly discovered or developed oil reserves ("associated" gas) as well as gas volumes found in reservoirs not containing oil ("non-associated" gas).

MacAvoy and Pindyck also noted that any economic modeling of the gas industry should take into account the depletion effect on reservoirs, using indicators of depletion or of decreasing returns as variables explaining supply. Four important characteristics of field markets were identified: (1) more gas will be made available for sale if the buyers offer higher prices, (2) the lag adjustment process bringing forth additional supplies of reserves is likely to be long and complex, (3) production out of reserves is determined by a combination of technical and economic circumstances but is likely to be greater the larger the volume of reserves available and the higher the contract prices pipelines are paying for the gas they are taking, and (4) demands depend on prices but are also derived from final residential, commercial, and industrial consumption.

The first equation of the M-P model dealt specifically with the additions to reserves. Total gas reserves were calculated as the sum of reserves from the previous year, new discoveries of both associated and non-associated gas, extensions of associated and non-associated gas, revisions of associated and non-associated gas, minus changes in underground storage, and subtraction resulting from production.

The section of the M-P model representing the field market contained nine equations, seven of which were stochastic and two of which were identities. Most of the data used was from the years 1964 through 1971. The first two field market equations were identities representing associated and non-associated discoveries. Associated discoveries equaled the associated average discovery size multiplied by total exploratory well drilling. Non-associated discoveries equaled the non-associated average discovery size multiplied by total exploratory drilling.

Exploratory well drilling was found to respond to three economic incentives. The first was the deflated[27] lagged total revenues from sales of new oil and gas at the wellhead, which were used as a surrogate for anticipated returns from exploration. The second incentive was the deflated lagged average total drilling costs. The final incentive was the measure of relative risk between different regions. Relative risk between different regions, which is not time sensitive, is the sample variance, measured over recent years, of payoff size in each district.[28] The estimation of the equation showed that all three incentives have

[27] Deflated by a GNP price index.

[28] Districts included were Louisiana South, the Permian region, and Oklahoma, Kansas, and Texas Railroad Commission Districts 2, 3, and 4.

significant coefficients, thus drilling increases as lagged prices increase and lagged costs and risk decrease. The fit of the equation tells us that 49.5 percent of the variation in exploratory well drilling can be explained by the independent variables.

The equation for non-associated average discovery size had as its dependent variable the average discovery size of non-associated, or gas only, discoveries. The independent variables were the average wellhead price of gas for the three previous years, the average drilling costs per well of exploratory drilling for the previous three years, and the cumulative number of wells drilled for the previous year. The cumulative number of wells drilled was used to represent the depletion variable. Three regional dummy variables are also included in the equation. The fit of the equation was such that 63 percent of the variation in the non-associated average discovery size was attributable to the variation in the independent variables.

The equation for associated average discovery size was similar to that for non-associated gas, with except that the average price of oil was substituted for the price of gas. The fit was similar to the non-associated equation, with 60 percent of the variation in associated average discovery size attributable to the variation in the independent variables.

Both average discovery size equations showed strong lag effects of the price and cost averaging as well as strong depletion effects. The price of gas was found to have a strong positive effect on the size of non-associated gas discovery, while the price of oil had a negative but insignificant effect on the size of associated gas discovery.

Extensions of both associated gas and non-associated gas are accounted for with separate equations that differ only in the new discoveries variable. The independent variables for the equation were total exploratory drilling for the previous period and previous gas discoveries. Regional dummy variables were also used. The fits for both equations were good, with 72.5 percent of the variation in non-associated extensions and 69 percent of associated extensions attributable to the respective independent variables.

The revision equations for both associated and non-associated gas were the same except for the dependent variable. The revision of both associated and non-associated gas were a function of the regional variables and the change in the previous period's reserves of gas. MacAvoy and Pindyck ceded that associated revisions were erratic and difficult to explain with a simple linear regression model and admitted that their identification of the relationship between associated revisions and the lagged reserves of gas was dubious.[29] Neither

[29] MacAvoy and Pindyck stated that the associated reserves are tied more closely to oil reserves, but chose not to model that relationship.

equation had explanatory power, with R^2 values of 0.289 and 0.398 for associated and non-associated, respectively.

The next section of the model differentiated production out of reserves[30] between Louisiana South and the rest of the United States, as Louisiana South had cost characteristics that required separate treatment. Both Louisiana South and the rest of the United States had total production regressed against the log of the wellhead price of gas and total reserves. The rest of the United States equation included the dummy variables for the Permian region and Oklahoma, Kansas, and Texas Railroad Commission Districts 2, 3, and 4. The fit of this equation showed that 83 percent of the variation of total production for the rest of the United States can be explained by the variation of the independent variables.

The Louisiana South equation was similar to the rest of the United States equation with the exception of the dummy variables and too had a good fit, with 96.4 percent of the variation in Louisiana South total production attributable to the variation in the independent variables. Both equations showed positive and significant effects of prices and total reserves, thus with higher prices, both short-run and long-run production should increase.

A historic simulation of the M-P model for years 1966 to 1970 showed that the error of the forecasts was relatively small. The mean supply error was 0.3 Tcf, with a maximum overestimation of 1.9 Tcf and a maximum underestimation of 1.5 Tcf. Error for demand of production was slightly larger, with a mean error of –2.5 Tcf. The model routinely underestimated demand over the simulation period, though MacAvoy and Pindyck explained this by citing overestimations of wholesale prices over the same period.

The revised work of Pindyck (1974) has already been discussed in terms of specific reestimations of the Khazzoom and E-S models, but the ultimate goal of his 1974 work was to take the Khazzoom and E-S models and simulate them as part of the M-P model.

Because the Khazzoom model predicted both new discoveries and extensions and revisions, the two equations from the model were substituted for the seven equations of the M-P model that predicted wells, discoveries, extensions, and revisions. The E-S model predicted only new discoveries, so Pindyck substituted it for only the new discoveries equations in the M-P model, and retained the four extension and revisions equations. Pindyck reestimated the M-P model three times for the period of 1965 through 1971, once with each alternate insertion, and once with the straight M-P model. The key areas estimated were new discoveries, additions to reserves, and supply of production.

[30] Production out of reserves as a function of price was the marginal cost in the short-term of developing existing reserves so that a particular level of flow could be achieved.

Pindyck found that over the seven years from 1965 through 1971, the straight M-P model, with the smallest mean errors and RMS error, performed best in terms of new discoveries. The Khazzoom formulation had the lowest RMS error for additions to reserves, but Pindyck questions the level of meaning behind this because (1) the Khazzoom extensions and revisions equation depends on new discoveries, which were being underpredicted, thus if Khazzoom's new discoveries performed better the extensions and revisions would perform more poorly and (2) the previously mentioned autoregressive component of Khazzoom's equation helps the equation pick up the trend but not turning points, thus it is not as useful an equation for policy analysis. All three formulations of the model performed about equally well in terms of supply of production.

A forecast through 1980 was also performed, using two alternative sets of assumptions. The first set of assumptions was called "cost of service," in which price increases were set at one cent per Mcf per year. The second set was called "deregulation," and a 15 cent per Mcf increase in price was set for 1974, with four cent per Mcf per year increases each year following. For both sets of assumptions, other variables were assumed to take "medium" growth paths.

Forecasts using the Khazzoom model showed a lack of price sensitivity, as there was no response in reserve additions in response to increases in wellhead prices. Even under the deregulation set of assumptions, excess demand reached 7 Tcf by 1980. On the flip side, the forecast using the E-S equations was so price sensitive that by 1980, the industry had produced an excess supply of 18 Tcf. Right in the middle of these two extremes was the M-P model, which eliminated excess demand by 1979 under the deregulation assumptions and had an excess demand of 10 tcf under the cost of service assumptions.

In 1977, Neri (1977) released an evaluation of the TERA and M-P models. He simulated both models over the historical period of 1965 through 1972 and the forecast period 1975 through 1980. Over the six year historical period, the M-P model performed best in terms of drilling, new discoveries, and production. Neri found that both models tend to overpredict drilling activity, new discoveries, and additions to reserves. Both models had low RMS errors for gas production, with the TERA model overpredicting and the M-P model underpredicting.

Neri also performed long-run forecasts with both models for the period of 1975 through 1980. Two policy simulations were used. The first considered regulation and set the wellhead price for new contracts at $0.50/Mcf, and allowed then to rise at $0.01/Mcf per year. The second simulation considered phased deregulation and set the wellhead price at $0.65/Mcf and allowed contracts to rise at $0.05/Mcf per year. The forecast results for the models were very different, with the TERA model forecasting reserve additions 30 to 50 percent lower than the M-P model, and with each model's production forecasts moving in different directions. Under both situations, the TERA model predicts a reduction in the production of natural gas, while the M-P model predicts significant growth in production under both situations. The TERA model's 1980 price elasticity for production is 0.06, while the M-P model has a price elasticity of 0.24. Neri cited several reasons why the divergence occurred, including differences in accounting for drilling success, discovery size, extensions and revisions, offshore discoveries, and production, and concluded that there is no precise way to decide which forecast is preferred.

Huntington (1990, 1992) summarized the work performed by the Energy Modeling Forum working group. The group focused on the evolution of the North American natural gas market through 2010. Two types of models were used within the group, both of which used a partial equilibrium framework to determine gas prices and quantities. The first type of model was spatial equilibrium models, which focused on the equilibria between different region markets, and the second type was engineering-economic simulation models, which focused on the processes and determinants of gas supply and demand.

Table A.2.1. Summary of the Strengths and Weaknesses of Modeling Approaches

Approach	*Strengths*	*Weaknesses*
Log-linear/double-log	1) Relatively easy to specify and estimate 2) Estimated coefficients are directly interpretable as short-run elasticities, and long-run elasticities are easy to calculate 3) Estimated standard errors provide measure of the variability of the estimated elasticities	1) Constant elasticity assumption often unrealistic and not justifiable 2) Sometimes problems of consistency with the underlying economic theory 3) Appropriate only when one has reason to believe that the variables enter multiplicatively in to the equation
Translog	1) Imposes a minimum of restrictions on demand behavior and is very flexible 2) Firmly based in economic theory 3) Particular demand characteristics are testable (eg. separability, homotheticity, etc.) 4) Allows the analysis of substitutional relations	1) Sometimes lack degrees of freedom due to the large number of regressors 2) Only well-behaved for a limited range of relative prices 3) Estimated elasticities are not directly interpretable 4) More complicated estimation techniques are required 5) Static formulations dominate
Qualitative choice	1) Appropriate when dependent variable comprises a finite set of discrete alternatives 2) Relatively easy to estimate 3) Flexible specification 4) Tobit models allow for observations to equal zero	1) Inefficient estimates in the case of zeros (logit, probit) 2) Theoretically not based on assumptions of utility maximization (logit) 3) Relies on rich and reliable data sets
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
Source: Madlener (1996)		

A.2.7: Methods and Data Used to Develop the Baseline Demand Model

As noted above, there are a number of empirical modeling techniques that have been facilitated in the literature. However, one of the most common and successful approaches for examining natural gas demand are the log-linear and double log models first developed in the 1960s. Our baseline models of natural gas demand are based upon those approaches. There are a number of advantages associated with the traditional double-log models. These include:

- They are straightforward approaches that are parsimonious and flexible;

- They are general models that are applicable to a wide range of data;

- In the absence of detailed, account specific survey data, these models serve as the best approach for fitting demand curves for the broad customer classes we are examining (i.e., residential, commercial, and industrial);

- The majority of the past academic and trade literature has been based upon these approaches; and

- These approaches have the advantage of providing considerable descriptive information in addition for being good tools for developing forecasts.

We have developed baseline models for each major consuming sector in Alaska's natural gas markets. These include residential, commercial, industrial, and electric utility.

In looking at natural gas demand our goal was to find a consistent source of information that was documentable and widely accepted as authoritative. Based upon our past experience, we have found that the information provided by the Department of Energy, Energy Information Administration (EIA) provides the most comprehensive, and documentable source of information for natural gas usage. This information is compiled annual by the EIA in EIA Form 176. A discussion of EIA Form 176, and the data collected in this annual survey, has been provided in Chapter 2.

APPENDIX 3
DETAILED DISCUSSION OF BASELINE IN-STATE DEMAND MODELS: STATISTICAL MODELS AND RESULTS

A.3.1: Introduction

Our modeling approach has attempted to use widely accepted statistical approaches for developing estimates of in-state natural gas demand. The goal has been to develop a statistical understanding of the important determinants of Alaska natural gas demand, and then use this information to develop forecasts of potential in-state natural gas usage.

One issue driving our modeling approach was data availability. Given time and resource constraints for this project, we attempted to facilitate the best available information to estimate Alaska natural gas demand. Our primary source of information for current in-state natural gas demand comes from Form EIA-176. This form, providing local distribution company (LDC) and transportation company natural gas disposition information, is a required filing to the US Department of Energy. Information is collected annually and is broken out by major customer class. This data was used to form the core of the forecasting approach.

The empirical forecasts have been developed in a three fold manner. First, structural models were developed that facilitate a traditional econometric approach. This econometric approach examines the relationship of natural gas usage for each customer class based upon changes associated with income, prices, weather, and other important determinants of natural gas demand.

Second, a trend, or time series, approach was developed to model in-state natural gas demand. This time series approach simply looks at the underlying trend relationship in usage growth over time. This approach is useful because it extrapolates longer term trends over an extended period of time without regard to the underlying reasons for those shifts.

Third, a combination forecast was developed that combines the structural, or econometric approach, with the trend analysis. Such an approach helps pick up the peaks, valleys, and underlying trends in data and is a useful tool for forecasting.

The econometric models are based upon the double-log methods described in Appendix 2. In general, these models examine the statistical relationships between usage, as a dependent variable, and prices, weather, and income as independent variables. These models work well in measuring shifts in consumption due to shifts in the underlying explanatory variables. They work well in capturing the ups and downs of energy consumption, but can be less accurate out over long forecasting periods.

The double log econometric based approach was chosen for several reasons. First, one goal was to facilitate methods that could be applied to a general, documented, and reliable source of detailed natural gas usage data. The primary source of information used in this study came from the EIA-Form 176 database. The double log methods used in this model fit will with the data, and provide a convenient method by which independent researchers could verify and replicate the results of this study.

Second, the double log models that have been facilitated in this research, while perhaps not the most sophisticated in the academic literature, are the most common for developing econometric natural gas usage models. Forecasting practitioners for both electric and gas utilities use these approaches on a regular basis. The popularity of these approaches are evident by the large number of companies, as well as their respective regulatory commissions, that use them on a regular basis.

In addition to the standard econometric approach, the baseline in-state natural gas usage models are also comprised of an overall time series model of natural gas usage on a per customer class basis. The time series model use straightforward stochastic approaches to “trend” natural gas usage. These forecasted time series, or trends, are then extrapolated into the future to develop forecasts of natural gas usage. These time series models work well in predicting long run averages, but are not very instructive in providing information on the underlying empirical determinants of natural gas demand.

The last approach utilized is referred to as a combination of forecasts, or amalgamated forecast. This approach was developed by Newbery and Granger (1974).[1] The Newbery and Granger approach showed that if two forecasts are developed that have no consistent biases, then the combination of these forecast will be unbiased. This approach allows us to combine the strengths of both the econometric and time series approach to develop an overall forecast that incorporates known empirical determinants of natural gas demand, and a trend component.

A.3.2: Residential Natural Gas Demand Models

The results from the residential natural gas usage econometric model are presented in Table A.3.1. The model uses total residential natural gas usage as its dependent variable. Independent, or explanatory variables, include price, income, heating degree days, and number of customers. Early empirical analysis indicated that there appeared to be some lagged response to prices,

[1] P. Newbery and C.W.J. Granger. (1974). “Experience with Forecasting Univariate Time Series and the Combination of Forecasts.” *Journal of the Royal Statistical Society*. 137: 131-46.

particularly with residential and commercial customers. As a consequence, prices were modeled as a polynomial distribution lag.

A polynomial distributed lag, or PDL, is a common form of finite distributed lag that accounts for delayed responses in consumption relative to changes in price. The PDL posits that the total response to a shift in a dependent variable does not come all at once, but over a period of time. From a practical perspective, using PDLs in price terms allows the modeler to estimate both short run and long run price elasticities of demand. The terms are cumulative, thus, the summation of all the parameter estimates for price, over the period examined, provides an estimate of the long run price elasticity of demand.

The overall residential econometric model results are highly explanatory as represented by the adjusted R-square value. The parameters for most all of the explanatory variables, with the exception of customers, was statistically significant at commonly accepted values. The number of heating degree days exhibited the strongest statistical properties in the model. The elasticity with respect to the weather is 0.56, indicating a one percent increase in heating degree days would increase residential usage by 0.56 percent.

Income also tended to be a highly significant empirical determinant of residential natural gas usage. The econometric model estimates an income elasticity of approximately 1.5 which is a strong degree of income responsiveness. This would entail that a one percent increase in income results in a 1.5 percent increase in residential natural gas usage.

Pricing terms were equally significant from a statistical perspective, and validated the use of the one-period PDL. Table A.3.1 shows two price elasticity values, representing current and lagged term effects.

Table A.3.1: Econometric Results from Residential Natural Gas Demand Model

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		

The estimate a short-run price elasticity of demand is –0.2042. The lagged price elasticity of demand for residential customers is estimated to be –0.1021. The sum of these parameter estimates (–0.3063) represents the total, or long run, price elasticity of demand. Longer lag structures were explored, but the one period lag produced the best statistical fit since other lag period proved to be statistically insignificant.

The parameter estimate for the lagged price term is –0.1021 indicating a decaying response to shifts in consumption due to changes in price. Such a result is consistent with other demand models, and the general body of work on estimating price elasticities of demand.

The econometric model was subjected to a number of commonly accepted statistical diagnostic techniques. Of particular concern in most time series models is the potential presence of autocorrelation: or a correlation in the error term of the model over time. If not corrected, autocorrelation can lead to unreliable tests of statistical significance. An examination of the results of the residential model indicated a potential problem with first order autocorrelation. The final results presented in Table A.3.1 have been corrected for this potential bias.

The time series model of residential natural gas demand was developed using the SAS/ETS (Econometric Time Series) software and SAS-based "Time Series

Forecasting System." The Time Series Forecasting System forecasts future values of time series variables by extrapolating trends and patterns in the past values of the series. The system provides both graphical and statistical features to help choose the best forecasting method for each series. In selecting the best model for natural gas demand by customer class, the Time Series Forecasting System automatic model fitting option was utilized. This option allows a user to find the best model by trying on over 40 different functional specifications (e.g., Holt exponential smoothing, random walk with drift, variously parametrized ARMA and ARIMA models) for time series analysis. Since the trends and temporal patterns of natural gas demand vary by customer class, we use different time series models for each variable. The statistical results for the residential time series model have been presented in Table A.3.2.

Table A.3.2: Time Series Results for Residential Natural Gas Demand Model

Residential Log Linear Trend Model	Parameter	Standard Error	t-Statistic
Intercept	16.292	0.021	786.41
Linear Trend	0.024	0.002	10.03
R Square	0.883		
Mean Absolute Percentage	2.905		

A graphical representation of the econometric and time series models has been presented in Figure A.3.1. This figure has four different lines represented the actual and forecasted values for residential natural gas usage. The analysis is limited to the historic period over which the forecast was developed. The figure has been provided to give the reader an understanding of each model's fit relative to the historic actual values.

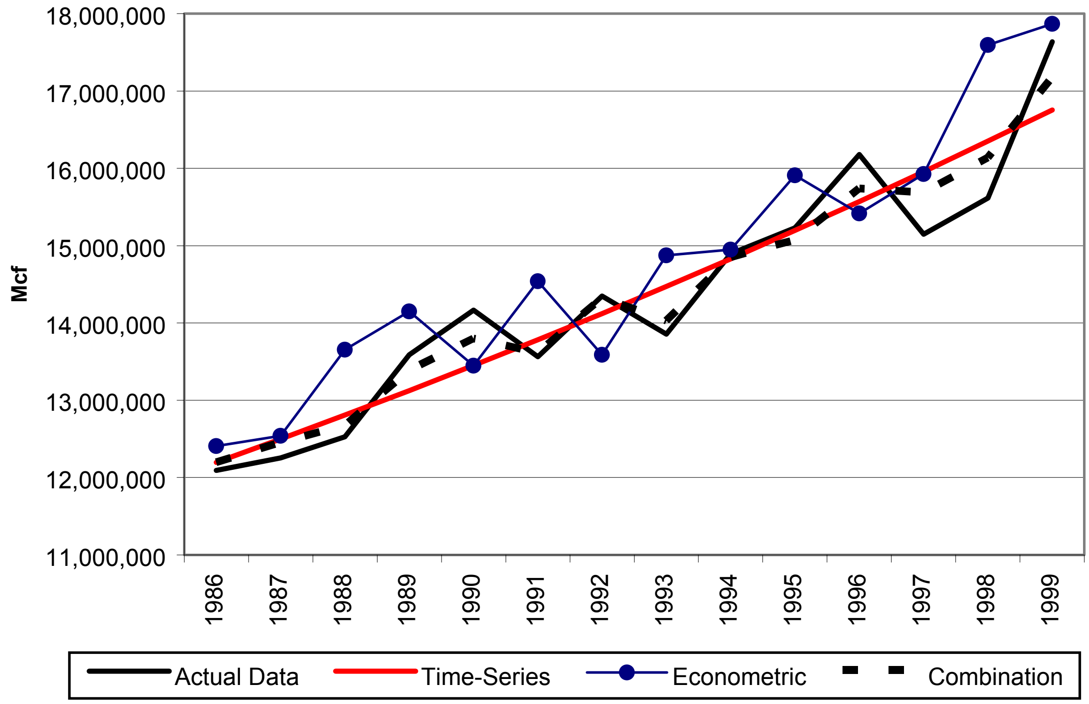

Figure A.3.1: Actual and Predicted Values of Alaska Residential Natural Gas Usage

Figure A.3.2 presents the baseline forecasted values for residential natural gas usage out to the year 2020. The three series plotted represents each of the different forecasting methods: econometric; time series; and combination of forecasts. Based upon the combination of forecasts, baseline residential natural gas usage is estimated to grow at an annual average rate of about 2.5 percent. This is somewhat less than the 1987-1999 average of 3.1 percent. However, the 1998-1999 annual growth of some 13 percent keeps the overall period annual averages high. Excluding this year, residential natural gas usage was over the 1987-1988 period was approximately 2.3 percent. Thus, the baseline forecast annual average growth rate of 2.5 percent is much more in keeping with overall recent historic trends, adjusting for the significant growth in the 1998-1999 time period.

The baseline econometric model used to forecast residential natural gas usage growth is based upon a simple five year trend of existing several explanatory variables. Prices were assumed to be constant in real dollars over the baseline forecast period. Obviously, changes in the expected growth rates of any of the independent variables will have implications for future residential natural gas usage levels. Sensitivities to these underlying assumptions, and the resulting changes in natural gas usage, have been provided in Section 5 of this report. Table A.3.3 presents the actual and baseline residential usage forecast.

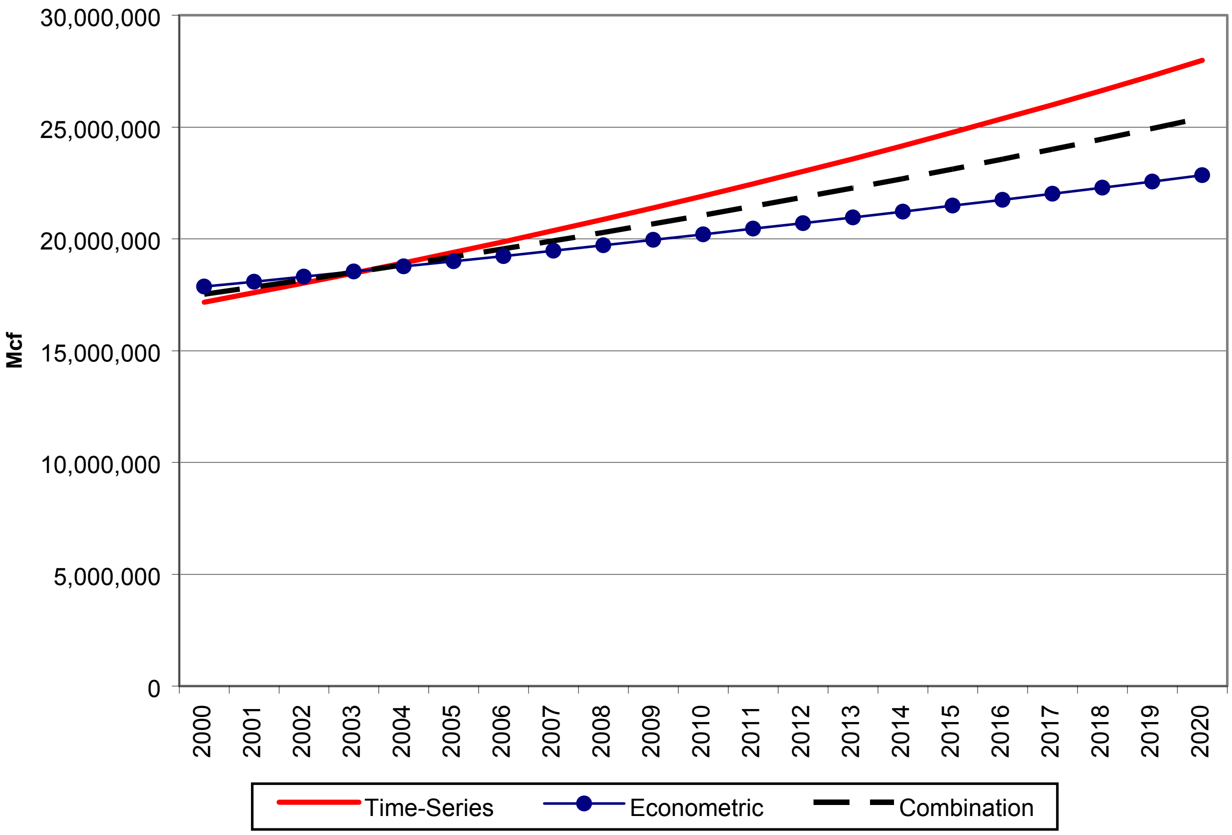

Figure A.3.2: Forecasts of Alaska Residential Natural Gas Usage

Table A.3.3: Alaska Residential Natural Gas Usage: Actual and Baseline Forecast (Mcf)

Date	Actual Data	Predicted Time-Series	Predicted Econometric	Predicted Combination
1986	12,090,998	12,198,225		12,198,225
1987	12,256,280	12,499,708	12,406,056	12,452,882
1988	12,529,140	12,808,641	12,540,566	12,674,604
1989	13,588,767	13,125,210	13,655,173	13,390,191
1990	14,164,886	13,449,602	14,151,008	13,800,305
1991	13,561,759	13,782,013	13,445,474	13,613,744
1992	14,349,944	14,122,639	14,537,644	14,330,141
1993	13,857,568	14,471,683	13,585,834	14,028,759
1994	14,895,199	14,829,354	14,873,428	14,851,391
1995	15,230,778	15,195,865	14,947,440	15,071,653
1996	16,179,216	15,571,435	15,908,103	15,739,769
1997	15,146,116	15,956,287	15,415,471	15,685,879
1998	15,616,617	16,350,651	15,926,681	16,138,666
1999	17,633,864	16,754,761	17,594,905	17,174,833
2000	--	17,168,859	17,867,599	17,518,229
2001	--	17,593,192	18,087,424	17,840,308
2002	--	18,028,012	18,310,890	18,169,451
2003	--	18,473,578	18,537,190	18,505,384
2004	--	18,930,157	18,766,257	18,848,207
2005	--	19,398,021	18,998,187	19,198,104
2006	--	19,877,448	19,232,955	19,555,201
2007	--	20,368,724	19,470,649	19,919,686
2008	--	20,872,142	19,711,255	20,291,698
2009	--	21,388,002	19,954,860	20,671,431
2010	--	21,916,612	20,201,450	21,059,031
2011	--	22,458,286	20,451,117	21,454,701
2012	--	23,013,349	20,703,866	21,858,607
2013	--	23,582,129	20,959,711	22,270,920
2014	--	24,164,967	21,218,750	22,691,858
2015	--	24,762,210	21,480,954	23,121,582
2016	--	25,374,215	21,746,434	23,560,325
2017	--	26,001,345	22,015,159	24,008,252
2018	--	26,643,974	22,287,242	24,465,608
2019	--	27,302,487	22,562,653	24,932,570
2020	--	27,977,274	22,841,498	25,409,386

A.3.3: Commercial Natural Gas Demand Models

Table A.3.4 presents the econometric results from the commercial natural gas usage model. Modeling commercial usage is difficult because this class, unlike residential customers, tends to be very heterogeneous. The econometric model of commercial natural gas usage is based upon prices, income, heating degree days, and the number of customers. The overall fit of the model, as represented in the adjusted R-square value, is relatively good.

Table A.3.4: Econometric Results from Commercial Natural Gas Demand Model

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		

The commercial price elasticity of demand is –0.8 for the current period, -0.54 for lag 1, and –0.27 for lag 2. These estimated elasticities indicate a high degree of price responsiveness. All the price elasticities are significant. Income elasticity is estimated to be 0.15, which is also of the correct sign, yet is statistically insignificant. The relationship between commercial usage and number of customer is negative, yet insignificant. The statistical results from the time series model have been presented in Table A.3.5.

Table A.3.5: Time Series Results from Commercial Natural Gas Demand Model

Commercial Time Series: Damped Trend Exponential Smoothing	Parameter	Standard Error	t- Statistic
LEVEL Smoothing Weight	0.999	0.23	4.338
TREND Smoothing Weight	0.001	0.19	0.005
DAMPING Smoothing Weight	0.999	0.05	19.967
R Square	0.785		
Mean Absolute Percent Error	3.891		

Figure A.3.3 presents a graph of the commercial natural gas usage models. Actual, econometric, time series, and combination models have been plotted on the graph.

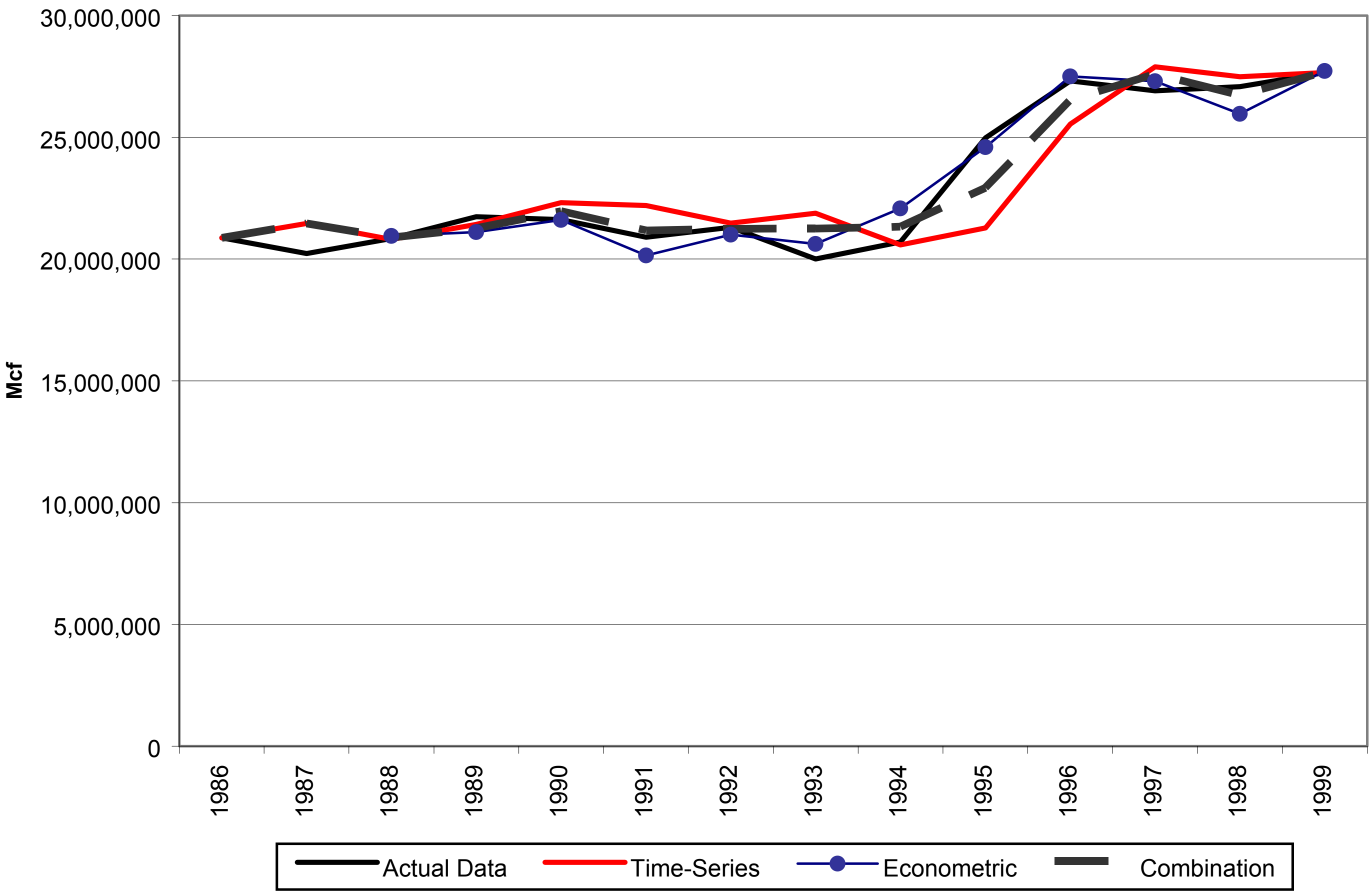

Figure A.3.3: Actual and Predicted Values of Alaska Commercial Natural Gas Usage

Figure A.3.4 plots the results for baseline forecasted commercial natural gas usage from the period 1999 until 2020. The combined model predicts that commercial natural gas usage will take an early dip in 2001, to be followed by some upward growth opportunities. The combination forecast anticipates commercial natural gas usage to grow by an annual average rate of about 1.0 percent through the year 2020. This is below the 1987-1999 average of 2.4 percent.

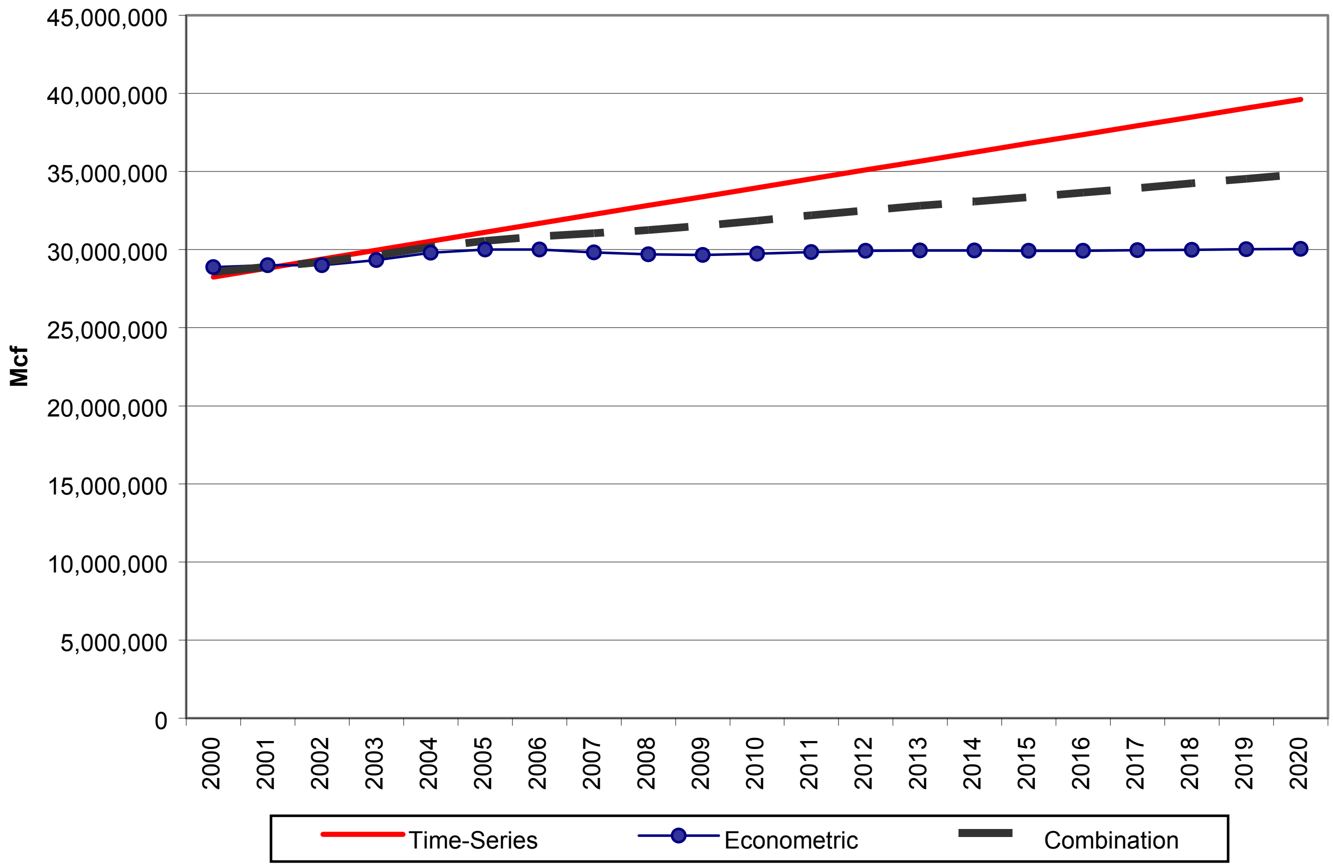

Figure A.3.4: Forecasts of Alaska Commercial Natural Gas Usage

Table A.3.6 presents the actual and baseline commercial usage forecast. Annual average rates of growth for both the historic period, and the forecast period are provided.

Table A.3.6: Alaska Commercial Natural Gas Usage: Actual and Baseline Forecast (Mcf)

Date	Actual Data	Predicted Time-Series	Predicted Econometric	Predicted Combination
1986	20,874,011	20,872,099		20,872,099
1987	20,224,143	21,459,238		21,459,238
1988	20,842,041	20,808,703	20,952,886	20,880,795
1989	21,738,412	21,424,696	21,111,727	21,268,211
1990	21,621,850	22,320,431	21,608,730	21,964,580
1991	20,897,429	22,203,516	20,147,636	21,175,576
1992	21,299,274	21,477,732	20,996,129	21,236,931
1993	20,002,655	21,877,606	20,617,698	21,247,652
1994	20,697,859	20,580,149	22,079,885	21,330,017
1995	24,978,977	21,272,817	24,597,540	22,935,179
1996	27,314,942	25,553,385	27,507,854	26,530,620
1997	26,908,231	27,892,388	27,310,569	27,601,479
1998	27,078,631	27,486,776	25,963,527	26,725,151
1999	27,667,159	27,655,530	27,727,955	27,691,742
2000	--	28,242,988	28,890,145	28,566,567
2001	--	28,818,167	28,999,111	28,908,639
2002	--	29,392,686	29,012,758	29,202,722
2003	--	29,966,545	29,338,263	29,652,404
2004	--	30,539,746	29,796,778	30,168,262
2005	--	31,112,288	30,016,438	30,564,363
2006	--	31,684,173	29,997,933	30,841,053
2007	--	32,255,402	29,832,200	31,043,801
2008	--	32,825,975	29,696,295	31,261,135
2009	--	33,395,893	29,666,724	31,531,308
2010	--	33,965,156	29,738,479	31,851,818
2011	--	34,533,766	29,843,132	32,188,449
2012	--	35,101,723	29,920,323	32,511,023
2013	--	35,669,028	29,946,149	32,807,588
2014	--	36,235,682	29,937,088	33,086,385
2015	--	36,801,685	29,923,989	33,362,837
2016	--	37,367,038	29,929,179	33,648,108
2017	--	37,931,743	29,955,787	33,943,765
2018	--	38,495,799	29,993,163	34,244,481
2019	--	39,059,207	30,028,044	34,543,626
2020	--	39,621,969	30,053,513	34,837,741

A.3.4: Industrial Natural Gas Demand Model

Table A.3.7 presents the results for the econometric industrial natural gas demand model. Like commercial models, these models are difficult to estimate given the wide range of heterogeneity of the firms within this customer class. In fact, the problem of aggregation is probably most exaggerated for industrial customers as opposed to any other class. Nevertheless, all of the explanatory variables, with the exception of customer growth, have tended to take the appropriate values and signs for the industrial model. These parameter estimates, however, are statistically insignificant. The results for the time series model have been presented in Figure A.3.8.

Table A.3.7: Econometric Results from Industrial Natural Gas Demand Model

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		

Table A.3.8: Time Series Results from Industrial Natural Gas Demand Model

Industrial Natural Gas Demand Linear Trend	Parameter	Standard Error	t- Statistic
Intercept	65,380,932	3,683,266	17.751
Linear Trend	684,265	432,578	1.582
R Square	0.173		
Mean Absolute Percent Error	6.8		

Figure A.3.5 graphs the results from each of the models developed and compared the results to the actual values. Figure A.3.6 presents our forecasted results.

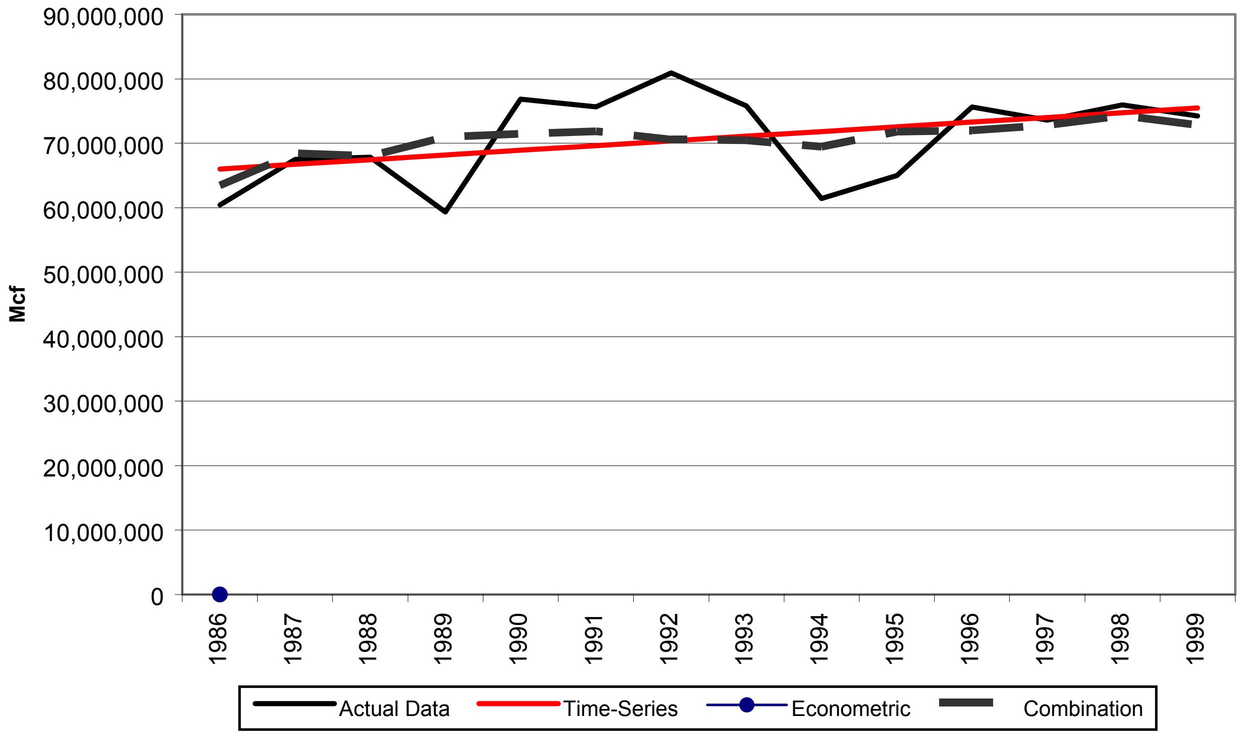

Figure A.3.5: Actual and Predicted Values of Alaska Industrial Natural Gas Usage

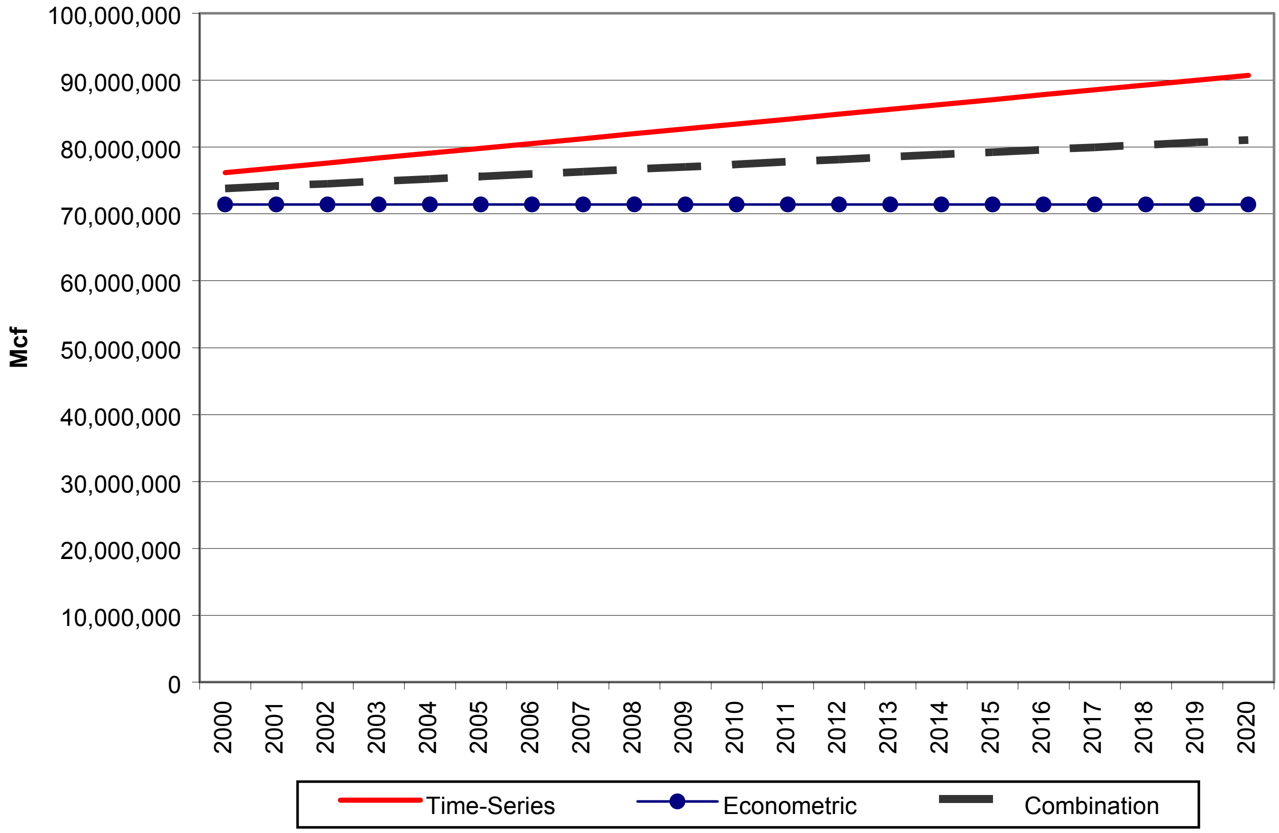

Figure A.3.6: Forecasts of Alaska Industrial Natural Gas Usage

Table A.3.9 presents the actual and baseline industrial usage forecast. Annual average rates of growth for both the historic period, and the forecast period are provided.

Table A.3.9: Alaska Industrial Natural Gas Usage: Actual and Baseline Forecast (Mcf)

Date	Actual Data	Predicted Time-Series	Predicted Econometric	Predicted Combination
1986	60,438,785	65,983,516	60,953,186	63,468,351
1987	67,467,489	66,711,763	70,090,074	68,400,918
1988	67,804,860	67,440,010	68,568,283	68,004,146
1989	59,341,410	68,168,256	73,723,646	70,945,951
1990	76,849,333	68,896,503	73,991,984	71,444,243
1991	75,637,177	69,624,750	74,064,575	71,844,662
1992	80,937,950	70,352,997	70,766,558	70,559,778
1993	75,794,979	71,081,244	69,802,135	70,441,689
1994	61,404,028	71,809,491	67,148,789	69,479,140
1995	64,977,342	72,537,737	71,056,370	71,797,053
1996	75,616,070	73,265,984	70,741,268	72,003,626
1997	73,599,299	73,994,231	71,538,235	72,766,233
1998	75,946,906	74,722,478	73,864,793	74,293,635
1999	74,224,056	75,450,725	70,231,772	72,841,248
2000	--	76,178,972	70,298,379	73,238,676
2001	--	76,907,218	70,365,044	73,636,131
2002	--	77,635,465	70,431,784	74,033,625
2003	--	78,363,712	70,498,588	74,431,150
2004	--	79,091,959	70,565,442	74,828,701
2005	--	79,820,206	70,632,373	75,226,290
2006	--	80,548,453	70,699,354	75,623,904
2007	--	81,276,699	70,766,412	76,021,556
2008	--	82,004,946	70,833,520	76,419,233
2009	--	82,733,193	70,900,705	76,816,949
2010	--	83,461,440	70,967,941	77,214,690
2011	--	84,189,687	71,035,253	77,612,470
2012	--	84,917,933	71,102,616	78,010,275
2013	--	85,646,180	71,170,057	78,408,118
2014	--	86,374,427	71,237,547	78,805,987
2015	--	87,102,674	71,305,116	79,203,895
2016	--	87,830,921	71,372,748	79,601,835
2017	--	88,559,168	71,440,431	79,999,800
2018	--	89,287,414	71,508,192	80,397,803
2019	--	90,015,661	71,576,003	80,795,832
2020	--	90,743,908	71,643,893	81,193,900

A.3.5: Electric Utility Natural Gas Demand Model

The baseline forecast for electric utility natural gas demand proceeded differently than the other natural gas customer classes in Alaska given the limited number of utility power generation units, and their limited number of existing fuel switching opportunities. The analysis proceeded along two lines.

First, utilities demand natural gas to fire their generators to serve their electrical load. In order to determine the amount of natural gas electric utilities would demand, a general forecast of electricity usage in Alaska needs to be developed. A generalized time series model of Alaska electricity usage was developed to determine longer run power generation trends.

Second, a trend analysis of natural gas fuel shares in the Alaska power generation market was developed as an indicator of how much natural gas fired power generation would be used to meet new load requirements. The forecast of overall power generation needs, was then multiplied by the fuel mix trend to determine overall electric utility generation from natural gas. Finally, the gas consumption requirement was estimated by multiplying the forecast for generation from gas by the 5-year moving average gas conversion rate (ratio of gas consumption to power generation from gas) consumption requirements. Figure A.3.7 presents the forecast of those natural gas requirements for Alaska electric utility power generation.

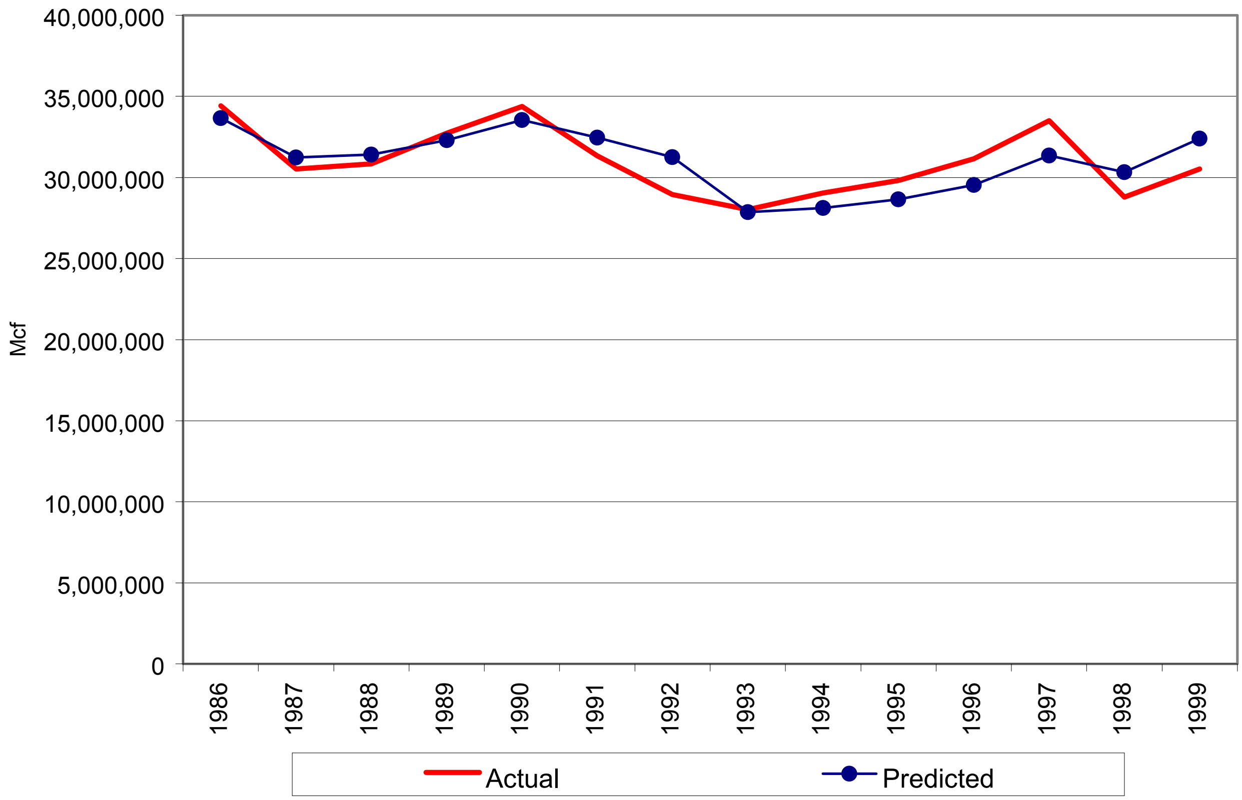

Figure A.3.7: Actual and Predicted Values of Alaska Electric Utility Natural Gas Usage

Figure A.3.8 presents a graph of the baseline electric utility forecast while Table A.3.10 presents the actual and our baseline electric utility natural gas usage forecast levels. Annual average rates of growth for both the historic period, and the forecast period are provided.

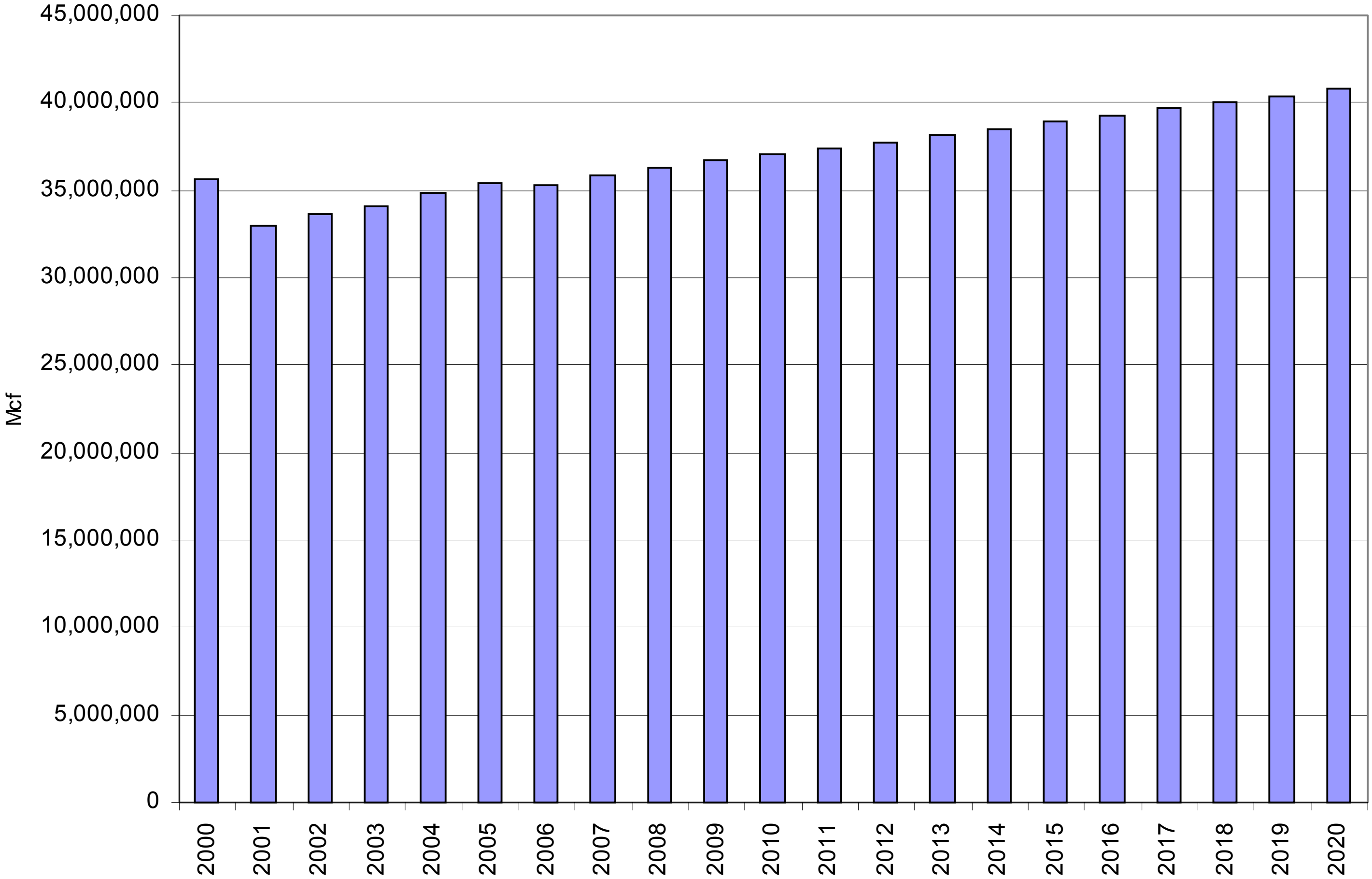

Figure A.3.8: Forecasts of Alaska Electric Utility Natural Gas Usage

Table A.3.10: Alaska Electric Utility Natural Gas Usage: Actual and Baseline Forecast (Mcf)

Date	Actual Data	Predicted Time-Series
1986	34,409,000	33,670,793
1987	30,530,000	31,234,619
1988	30,841,000	31,418,047
1989	32,746,000	32,312,018
1990	34,366,142	33,549,084
1991	31,329,758	32,470,899
1992	28,953,390	31,259,209
1993	28,024,737	27,867,045
1994	29,047,703	28,129,752
1995	29,808,627	28,661,334
1996	31,154,273	29,541,429
1997	33,509,748	31,362,521
1998	28,784,955	30,332,479
1999	30,527,841	32,409,397
2000	--	35,656,886
2001	--	32,949,652
2002	--	33,655,948
2003	--	34,119,758
2004	--	34,899,977
2005	--	35,406,497
2006	--	35,330,693
2007	--	35,813,699
2008	--	36,248,792
2009	--	36,677,751
2010	--	37,031,714
2011	--	37,353,364
2012	--	37,759,602
2013	--	38,149,476
2014	--	38,529,726
2015	--	38,899,627
2016	--	39,272,923
2017	--	39,657,179
2018	--	40,036,768
2019	--	40,414,176
2020	--	40,790,982

A.3.6: Total Natural Gas Usage

The summation of the baseline forecasts for each customer class can be used to analyze total in-state demand until 2020 under business as usual conditions. The total baseline forecast is developed from the individual customer class combination forecasts. Total in-state, baseline usage, is presented in Table A.3.11, while Figure A.3.9 presents a graphical representation of annual baseline usage levels.

In-state baseline forecasted natural gas usage over the forecast period will grow by 27 Bcf. Residential customers will account for 28.5 percent of this growth, commercial customers will account for 22.7 percent of this growth, industrial customers will account for 28.9 percent of this growth, and electricity utilities will account for 19 percent of this growth. Sensitivities to the overall baseline forecast, and total forecasted use by the year 2020, are explored in the baseline sensitivities section of the report (Chapter 5).

Table A.3.11: Total In-State Baseline Demand Forecast

Date	Actual Data	Baseline
1986	127,812,794	130,209,467
1987	130,477,912	133,547,658
1988	132,017,041	132,977,591
1989	127,414,589	137,916,372
1990	147,002,211	140,758,213
1991	141,426,123	139,104,881
1992	145,540,558	137,386,059
1993	137,679,939	133,585,145
1994	126,044,789	133,790,300
1995	134,995,724	138,465,219
1996	150,264,501	143,815,443
1997	149,163,394	147,416,112
1998	147,427,109	147,489,931
1999	150,052,920	150,117,221
2000	--	154,980,358
2001	--	153,334,730
2002	--	155,061,745
2003	--	156,708,696
2004	--	158,745,146
2005	--	160,395,253
2006	--	161,350,851
2007	--	162,798,743
2008	--	164,220,859
2009	--	165,697,439
2010	--	167,157,253
2011	--	168,608,985
2012	--	170,139,507
2013	--	171,636,103
2014	--	173,113,957
2015	--	174,587,941
2016	--	176,083,191
2017	--	177,608,996
2018	--	179,144,660
2019	--	180,686,203
2020	--	182,232,010

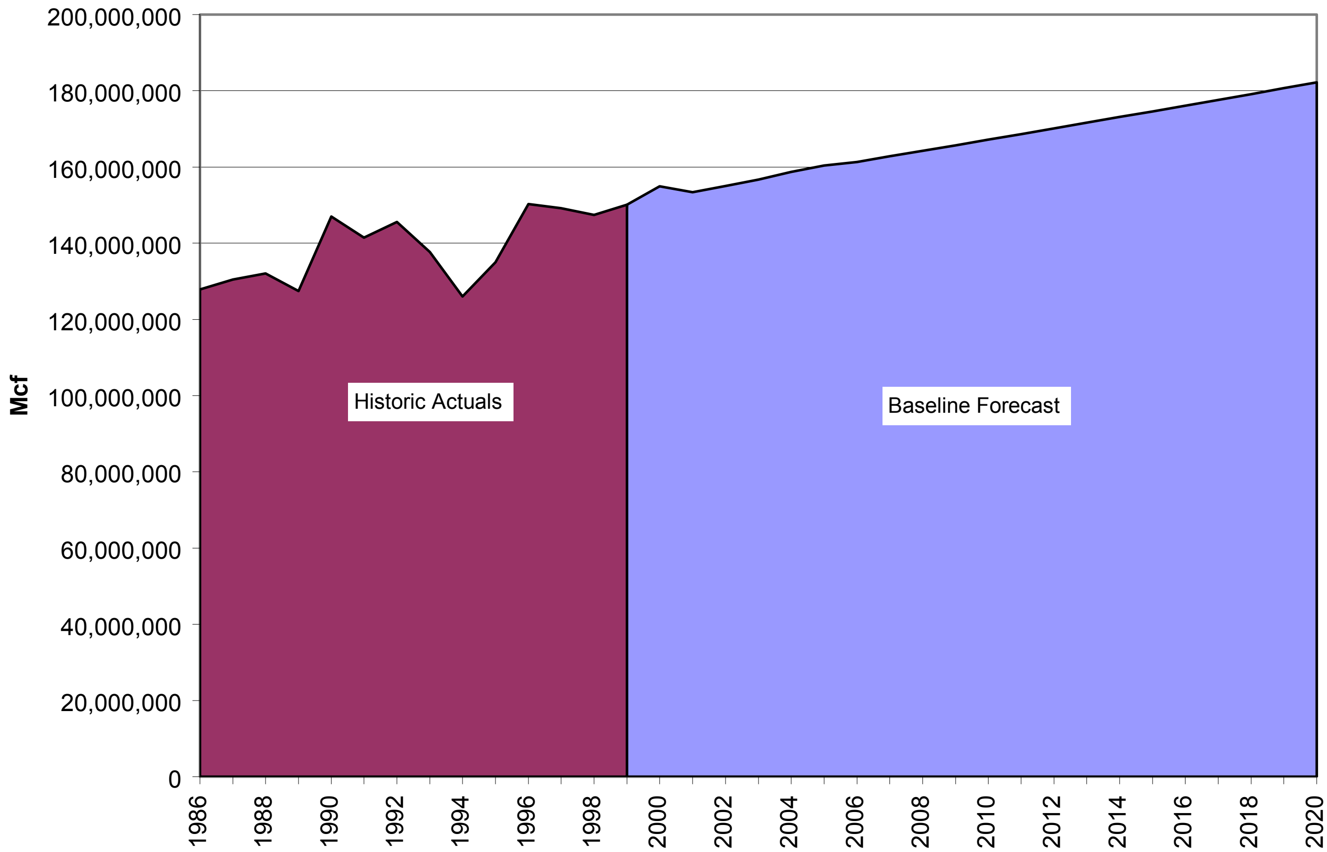

Figure A.3.9: Total In-State Natural Gas Usage – Baseline Forecast