A STATISTICAL ANALYSIS OF THE NATURAL GAS FUTURES MARKET:
THE INTERPLAY OF SENTIMENT, VOLATILITY AND PRICES

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ABSTRACT

This paper attempts to understand the price dynamics of the North American natural gas market through a statistical survey that includes an analysis of the variables influencing the price and volatility of this energy market. The analysis develops a theoretical model for the conditional reactions to weekly natural gas inventory reports, and develops an extended theory of errors in natural gas inventory estimates. The central objective of this thesis is to answer the fundamental question of whether the volatility of natural gas futures are conditional on the season or the level of the natural gas in inventory and how accurate are analysts at forecasting the inventory level.

Commodity prices are volatile, and volatility itself varies over time. I examine the role of volatility in short-run natural gas market dynamics and the determinants of error in inventory estimates leading to this variance. I develop a structural model that equates the conditional volatility response to the error made in analyst forecasts, inherently relating analyst sentiment to volatility and price discovery.

I find that in the extremes of the inventory cycle (i.e., near peak injection/withdraw) that variance is particularly strong, and significantly higher than non-announcement days. The high announcement day volatility reflects larger price changes. With statistical significance, we can conclude that when the natural gas market is under-supplied, the near-term Henry Hub Natural Gas futures contract becomes nearly twice as volatile than in an oversupplied market. Furthermore, analysts are more prone to make errors in their estimates of weekly inventory levels around these same time periods.

Natural gas is an essential natural resource and is used in myriad aspects of the global economy and society. As we look to develop more sustainable energy policies, North America's abundant clean-burning natural gas will hold an essential role in helping us to secure our future energy independence. An ability to understand the factors influencing it is supply and demand, and thus price, are and will continue to be essential.

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I. INTRODUCTION

This paper attempts to understand the price dynamics of the North American natural gas market through a statistical survey that includes an analysis of the variables influencing the price and volatility of this energy market. The analysis develops a theoretical model for the conditional reactions to weekly natural gas inventory reports, and develops an extended theory of errors in natural gas inventory estimates. The central objective of this thesis is to answer the fundamental question: is the volatility of natural gas futures conditional on the season or the level of the natural gas in inventory and how accurate are analysts at forecasting it?

Financial decisions are generally based upon the tradeoff between risk and return and therefore, an analysis of risk is an essential part of any portfolio decision. Therefore, an understanding of risk, or the volatility, of a commodity such as natural gas is essential for prudently trading the asset. We know that commodity prices are volatile, and volatility itself varies over time. Accordingly, I examine the role of volatility in short-run natural gas market dynamics and the determinants of error in inventory estimates leading to this variance. I develop a structural model that equates the conditional volatility response to the error made in analyst forecasts, inherently relating analyst sentiment to volatility and price discovery.

In order to understand analyst accuracy at forecasting natural gas inventories, which are reported weekly by the Energy Information Agency ("EIA"), it is important to have a framework for thinking about how errors develop. At a high-level, the logic is such that (A) supply and demand shocks to the natural gas market lead to (B) errors that ultimately have a (C) causal price and volatility impact. The theoretical model central to my investigation is depicted below in Figure 1 – High Level Logic for Theory of NG Inventory Shocks.

**High-Level Logic for a Theory of Shocks in Natural Gas Inventories**

![Figure 1 - High Level Logic for Theory of NG Inventory Shocks](image-url)
The motivation for this paper is predicated on the increasingly important role that natural gas has come to play in securing our energy future. Unfortunately, this rise in importance comes amidst some of the highest price volatility ever seen in the commodity since its futures contracts began trading in the 1980's (Treat, 2000). Clearly, an understanding of the influential factors and volatility dynamics of this commodity are not only important to trading it as an asset class, but also in developing sound policy for ensuring our long-term energy independence. The organization of this analysis will first address in Section II the background behind the North American natural gas market, with an explanation of the regional hub-and-spoke and transmission networks, an overview of the NYMEX natural gas futures market, a review of relevant literature and an exploration into a theory of shocks in natural gas inventories. Section III addresses the methodology behind the analysis, including tests for normalcy in NG futures and seasonal forecasting models. In Section IV, I address the results, followed by Section V, which concludes and touches upon trading and policy implications developed from the results.
II. BACKGROUND, LITERATURE REVIEW & THEORY

A. BACKGROUND

1. The North American Natural Gas Market

As one of our countries most prolific and widely used natural resources, the United States consumes approximately 23.2 trillion cubic feet ("Tcf") of natural gas per year, accounting for 23.8% of our nation’s energy supply.\(^1\) To put this in perspective, 37.1% of our energy supply comes from petroleum, and 22.5% from coal. Power generation and Industrial uses each make up nearly a third of natural gas consumption, with residential and commercial uses consuming 21% and 13%, respectively.

![Diagram of U.S. Natural Gas Consumers]

Figure 2 – Breakdown of U.S. Natural Gas Consumption by use (2008)

While there is an abundance of natural gas in North America, it is a non-renewable resource, the formation of which takes thousands to millions of years. Technology has dramatically increased recovery through improved drilling efficiency and effectiveness in recent years, however, it is impossible to know just how much natural gas is in the ground until we begin to extract it with the drill bit. The U.S. has about enough proven natural

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gas reserves to meet nearly 10 years of U.S. energy demand, and enough reserves with a high probability of recovery to meet nearly 80 years of demand.²

2. The North American Natural Gas Futures Market on NYMEX

The North American natural gas market is highly liberalized, and as a consequence, prices are very competitive, responding quickly to supply and demand forces. Natural gas prices may be measured at different stages of the supply chain. At the start, there is the wellhead price. According to the UNCTAD, prices are also measured for different end-user groups as residential, commercial, industrial consumer or electric utilities.³ Prices at the wellhead show high volatility depending on weather and different market factors. Increasing efficiencies in transport, storage and delivery allow for consumers to reduce the impact of price volatility. In general, the main components of natural gas price are:

1. Wellhead price (i.e., the cost of extracting the natural gas itself)
2. Transportation (i.e., gathering, processing and pipeline costs)
3. Local distribution (i.e., end-user pipeline costs)

As recounted by the United Nations Conference on Trade and Development’s (“UNCTAD”) report on natural gas prices, in North America, wellhead prices were the first to be deregulated. Transportation costs are still regulated by National Energy Boards, while local regulatory boards regulate local distribution costs.

A futures contract is a standardized contract to buy or sell a specified commodity of standardized quality at a certain date in the future and at a market-determined price (the futures price). The contracts are traded on a futures exchange where the price is derived from the equilibrium of supply and demand among competing buy and sell orders on the exchange at the time of the purchase or sale of the contract. Buy and sell orders are ultimately predicated on supply and demand for the gas itself, and thus the futures

contract is ultimately derived from the underlying commodity (hence a futures contract is considered a derivative instrument).\textsuperscript{4}

The market mechanism by which equilibrium prices clear is through the natural gas futures exchange. The New York Mercantile Exchange ("NYMEX") launched the World's first natural gas futures contract in Apr-90, with options on natural gas futures following in Oct-92. Natural gas in the United States is traded as a futures contract on NYMEX in months ranging from the current spot market to 10 years forward. Each contract is for 10,000 million British Thermal Units ("MMBTU," equivalent to gigajoules, or 10 billion BTU).\textsuperscript{5} Trading terminates on the third-to-last business day of each month prior to the maturity month, with a delivery period over the course of the delivery month. According to (Linn & Zhu, 2004), natural gas futures contracts are extremely liquid markets with upwards of 50,000 contracts trading for front month contracts and upwards of 30,000 contracts trading for second month contracts in recent years.

Because contracts are offered for future deliveries, a term structure of prices develops and its shape has important significance for our interpretation of the state of the market. For instance, the below Figure 3 shows a 3-D time series of the natural gas term structure at various points from Jun-08 to Nov-09. You will notice that in the summer of 2008 there was an extreme upward slope, or backwardation.

\textsuperscript{4} A great introductory explanation is available at: \url{http://en.wikipedia.org/wiki/Futures_contract}. For a fantastic detailed tome on derivatives, please see John C. Hull’s, "Options, Futures and Other Derivatives"

\textsuperscript{5} For more information on the Henry Hub Nature Gas futures contract traded on NYMEX, please visit: \url{http://www.cmegroup.com/trading/energy/natural-gas/natural-gas_contract_specifications.html}
3-D Timeseries of NYMEX Henry Hub Natural Gas Term Structure
(Forward Months 1-12, Jun-08 to Nov-09)

Summer 08: Market is heavily backwardated; NG trades near historical highs of $14-15 / mcf

A contango is normal for a non-perishable commodity, such as natural gas, which has a cost of carry. Such costs include warehousing and storage fees as well as interest forgone on money tied up to hold the asset. Contango may also be a sign of trader's perceptions for a future shortage or short-term supply glut, the latter of which likely describes the current situation.

3. The Discovery of Shale Gas Has Been Both a Blessing and a Curse

In recent years, drilling technology has advanced to the point where operators can not only drill deep vertical wells, but also drill horizontally at depths of several thousand feet. The advent of horizontal wells has led to the discovery of shale gas, or gas produced from
the fine-grained sedimentary rock composed of clay and other minerals such as quartz and calcite whereby natural gas actually exists in the microscopic pores of the rock. Horizontal wells are able to fracture the rock, thereby opening up these pores and making extraction of the gas possible at unbelievable depths and pressures.

**Split of Natural Gas Wells by Production Type**

*Relative Directional, Horizontal Shale and Vertical Well Composition for North American Onshore Natural Gas Market*

![Graph showing the split of natural gas wells by production type from 1991 to 2009.](image)

*Source: Baker Hughes*

**Figure 4 – Split of Natural Gas Wells by Production Type (1991 – 2009)**

Since 2002, Horizontal well use has increased at a compound annual growth rate (CAGR) of over 18% (see above Figure 4). This has led to an unprecedented surge in supply coming on to the market. The consequences of shale gas are two-edged: on one hand, it has given new hope to securing our energy independence, and on the other, it has bred a glut of supply, which against current anemic demand has led to unprecedented price drops recently. An understanding of how inventory levels influence natural gas prices is essential for any practitioner trading the commodity.

4. **Storage and Transmission**

The main difficulty in the use of natural gas is transportation and storage because of its low density. While natural gas pipelines are economical, they are impractical for
transoceanic delivery. Whereas crude is a global commodity that is easily transported across continents, natural gas market tend to be isolated to their respective continent of production and consumption, and thus predominantly influenced by local factors, such as regional weather and the local economy. Consequently, a vast national natural gas transportation network in the U.S. moves around 21 trillion cubic feet (“Tcf”) per year of natural gas to about 70 million customers across 300,000 miles of pipelines.

The network, excluding gathering system operators, is made up of more than 200 mainline transmission pipeline companies, more than 1,300 local distribution companies, and about 125 underground natural gas storage operators. This complex network of natural gas exploration, production, transmission and storage helps to accommodate regional variations in supply of and demand for natural gas. However, while the United States produces nearly 20.6 Tcf of natural gas per year, like many other commodities such as oil, it can only be held for future consumption in storage facilities for a finite period of time.

For instance, household energy use varies significantly across the United States, largely due to different climates and home energy efficiencies. For instance, an average home in the Pacific region consumes nearly one-third less energy than a home in the South Central region. Accordingly, the market for natural gas futures traded on the NYMEX has developed to involve a complex series of "basis contracts," or contracts that reference the gas prices at specific marketing regions throughout the U.S., as determined by the local supply and demand for the commodity. These contracts tend to be less actively traded than the benchmark Henry Hub contract, which is the commonly referenced contract traded on the NYMEX. We will explore in detail the statistical characteristics of these regional benchmarks in Section IV.

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6 In recent years, technology has allowed for the deep cooling of natural gas into a higher-density liquid, Liquefied Natural Gas ("LNG"). LNG is more commonly exchanged outside of the United States, and as of 2008 only constituted 352 Bcf of imports, or 1.71% of total U.S. production (Source: EIA). Additional information is available at: http://en.wikipedia.org/wiki/Liquefied_natural_gas
7 (Analysis for Natural Gas Basics )
8 http://en.wikipedia.org/wiki/Energy_in_the_United_States
5. Regional Differences in Natural Gas Prices

When you hear the media quote the price of natural gas, it is typically in reference to the regulated prices at Henry Hub, located in Erath, Louisiana. Spot and future prices set on NYMEX at Henry Hub are commonly accepted to be the primary price for the North American natural gas market. A NYMEX futures contract specifies physical delivery at the Henry Hub. Owned by Sabine Pipe Line, LLC, Henry Hub is the main artery for the U.S.' gas transportation network; it interconnects with nine interstate and four intrastate pipelines and can transport 1.8 Bcf per day of natural gas,\(^9\) gathering gas produced from encircling regions that accounts for 49% of total U.S. production in 2000.\(^{10}\) Figure 5 below depicts the U.S. natural gas pipeline capacity.

![Figure 5 - U.S. Natural Gas Pipeline Capacity (2009, Source: EIA)](image)

However, natural gas is produced and consumed across many regions throughout the country, each with their own internal economic microstructure and uniquely influenced by similar variables (i.e., energy demand, chemicals production, weather, etc.)

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Accordingly, hub and wellhead natural gas points for many of these regions are also quoted and traded on futures exchanges. However, these regional prices will often trade with some basis differential relative to Henry Hub. For instance, in Figure 6 below, Kern River Rocky Mountain natural gas traded at $3.22/MMBtu, which implies a negative basis of $0.51/MMBtu relative to the Henry Hub benchmark average.¹¹

![Figure 6 - Regional Natural Gas Basis Prices (Source: Bloomberg)](http://www.eia.doe.gov/emeu/steo/pub/Sctab.pdf)

The existence of this basis differential, referred to as "basis risk," is one of the primary drivers behind hedging needs for the NYMEX natural gas futures market. This analysis attempts to better understand the statistical characteristics of these less-actively traded (i.e., "less liquid") regional prices relative to the more liquid NYMEX Henry Hub contract.

The following Figure 7 below highlights the various regional basis prices, expressed in $/MMBtu from 2000 to 2010.

![Regional Basis to Henry Hub ($/MMBtu) - (03-Jan-2000 - 23-Mar-2010)](image)

Figure 7 – Regional Spot Basis Differentials ($/MMBtu)

From these various basis prices, I calculated the mean and standard deviation of the basis differential. I then percentiled this across the Jan-2000 to Mar-2010 period to create an index that relates the level of dispersion amongst basis prices. In Section IV starting on page 38, the analysis will incorporate this level of basis dispersion into inferring the volatility response for a given level of variance between basis prices. The output of the Basis Dispersion Index is given below in Figure 8.
6. Factors influencing Natural Gas Prices

As mentioned, end-users of natural gas are generally grouped as residential, commercial, industrial, and power generators, and each group has their own risk profile and unique influence on the commodity. I have attempted to capture those factors influencing gas prices below. These factors will serve as explanatory variables in my analysis under Section IV.

Natural Gas Seasonality, Supply and Inventory Levels:

The total consumption for natural gas peaks between December and January, typically arising from residential and commercial customers’ space heating demand. Consumption reaches its nadir in the summer when the space heating demand is low. However, in the summer, consumption reaches a “local peak” typically between July and August as cooling demand increases the electric power needs from natural gas. Heating and cooling demand are driven by weather, the temperature in particular.
The highly seasonal demand for natural gas causes inventory of the commodity to play an important role in balancing supply/demand conditions and for smoothing production. Because the total consumption of natural gas exceeds production during the winter months but falls below it in summer months, natural gas inventory also has a strong seasonality tied to the commodity. Specifically, natural gas inventory builds up from April to October ("injection season") while withdraws from November to March ("withdraw season").

Because natural gas must be injected and stored under ground during injection season, there are natural limitations on how much natural gas can be held in inventory. The EIA provides a "Weekly Natural Gas Storage" report that notifies the market of the current level of inventory as well as the amount of natural gas withdrawn or injected. These inventory reports are influential catalysts on changes in gas prices. As will be demonstrated, unexpected variations outside of historical injection/(withdraw) rate can lead to severe price volatility.

When inventory levels approach the capacity limits (currently at approximately 4 Tcf), exploration and production companies that drill for the gas are often forced to "shut in" their wells, or simply stop production at the wellhead thereby reducing the amount of natural gas coming into the market. The "rig count" is a proxy for the level of North American drilling activity, as typified by the Baker Hughes Rig Count (see below Figure 9). Accordingly, the Baker Hughes Rig Count has become an important barometer for the drilling industry and future supply of natural gas to the market. The active rig count also acts as a leading indicator of demand for products used in drilling, completing, producing and processing hydrocarbons. As you can see from Figure 9 – Active Rig Count at Top-5 Drilling Basins below, the rig count has come in dramatically since Sep-08 as producers have tried to rein in oversupply to the market amidst record low natural

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12 Some natural gas storage facilities are man-made, however, the majority of natural gas storage facilities are in the empty caverns of abandoned oil wells and or exhausted salt mines. There is a markedly long delay to bringing new storage capacity online, and as such, capacity has oscillated from between 3,600 - 4,000 Bcf in recent years.

13 The Weekly Natural Gas Storage Report is freely available at: 
http://www.eia.doe.gov/oil_gas/natural_gas/ngs/ngs.html

14 For additional information on the Baker Hughes rig count, including details on production by state and country, please visit: http://investor.shareholder.com/bhi/rig_counts/rc_index.cfm
gas prices. From conversations with several natural gas traders, the level of inventory and number of rigs have an important bearing on the supply-side price discovery process.

Active Rig Count at Top-5 Drilling Basins
(From Jan-06 to Oct-09)

The Rig Count has come in dramatically since Sep-08 in an effort to contract supply amidst record low natural gas prices.

Figure 9 - Active Rig Count at Top-5 Drilling Basins

Weekly Inventory Reports

From January 1994 to April 2002, the American Gas Association ("AGA") provided a weekly survey of inventory levels for working gas in storage facilities across the U.S., making the results available to the public on a weekly basis. In April 2002, the EIA took over this report,\(^{15}\) making it available to the public every Thursday morning at 10:30 AM\(^{16}\), detailing the level of natural gas in storage for the prior week. This report tracks U.S. natural gas inventories held in underground storage facilities. Changes in reported stock levels reflect all events affecting working gas in storage, including injections, withdrawals, and reclassifications between base and working gas. In the report, gas inventories are broken down into three regions (Consuming East, Consuming West and Producing)\(^{17}\), and a historical

\(^{15}\) The Weekly Natural Gas Storage Report can be found online at: [http://ir.eia.gov/ngs/ngs.html](http://ir.eia.gov/ngs/ngs.html)

\(^{16}\) When the AGA conducted the survey, they released it to the public on Wednesdays; the storage report is now released on Thursday by the EIA. Accordingly, the timeframe for my analysis concerning inventory reports starts in 2003 to avoid any spurious interpretations.

\(^{17}\) Details about which states are included in each region can be found online at: [http://ir.eia.doe.gov/NGS/notes.html](http://ir.eia.doe.gov/NGS/notes.html)
comparison of current levels relative to a year ago and 5-year average is provided.\textsuperscript{18} From anecdotal conversations with one quantitative natural gas trader, they typically download the data instantly via the CSV format made available from the EIA, and instantly input the new data points into their own quantitative trading models. In addition, the EIA provides some qualitative color summarizing the state of the natural gas market.

As noted, natural gas is highly seasonal. A number of sell-side analysts forecast the level of inventory each week, and this data is made readily available on Bloomberg prior to the Thursday morning EIA announcement.\textsuperscript{19} These analyst forecasts can have a substantial influence over the short-term impact on price and return for natural gas. As highlighted by (Chang, Daouk, & Wang, 2009), who find that that oil futures prices rise (fall) when analysts forecast a decrease (increase) in supplies. Most interestingly, both relationships are stronger for more accurate analysts, implying that investors learn about analyst accuracy.

Accordingly, on the point of analyst quality, these forecasts are subject to error, most notably exogenous supply and demand shocks. It is these very shocks that have captured my interest. Understanding how analysts make errors, when and why is central to understand the price impact and particularly the volatility response post the Thursday announcement. I will return to this point in detail in Section II.D on page 29. As Figure 10 – Median Analyst Inventory Estimate Error as a Percent of 5-Year Normalized Inventory Levels By Month of Year (Feb-2003 to Mar-2010) below illustrates, analysts make errors in a season fashion, most notably in the winter and transition months of December through March.

\textsuperscript{18} Information about the method used to prepare weekly data to compute the 5-year averages, maxima, minima, and year-ago values for the weekly report can be found in a Methodology Report prepared by the EIA and available online at: \url{http://ir.eia.doe.gov/ngs/methodology.html#5year}

\textsuperscript{19} This information can be obtained from Bloomberg by typing “DOE <GO>” and selecting “Natural Gas” from the options menu.
Weather:

Weather affects the natural gas industry on both the demand and supply side and temperature is the main driver of heating and cooling demand (Mu, 2004). Since industrial use of natural gas does not vary much in the short-term (i.e., daily or weekly basis), weather variation provides a good indicator for the variability of natural gas demand. According to (Miller, 2007), the residential and commercial groups have fairly stable base load demands and large, variable heating demands.

Over the short term, residential and commercial heating demand is weather sensitive, varying primarily in response to the severity of the winter temperatures. Due to the importance of the weather factor, natural gas demand is highly seasonal. Typically natural gas is injected into storage during the spring and summer months and withdrawn during the fall and winter months.

Degree days are the measure used to quantify the level of heating or cooling demand. Heating degree days ("HDD") and cooling degree days ("CDD") are quantitative indices designed to reflect the demand for energy needed to heat or
cool a home or business, respectively. A degree-day compares the outdoor temperature to a standard of 65°F; the more extreme the temperature, the higher the degree-day number and the more energy needed for space heating or cooling.

Hot days, which require the use of energy for cooling, are measured in cooling degree-days. On a day with a mean temperature of 80°F, for example, 15 cooling degree-days would be recorded. Cold days are measured in heating degree-days. For example, a day with an average temperature of 40°F, 25 heating degree-days would be recorded. Two such days at 40°F would result in a total of 50 heating degree-days for the period. The U.S. Energy Information Administration publishes regional averages for degree days.20

Figure 11 below illustrates total U.S. weekly HDD/CDD usage from 2002 to 2010, as reported by the EIA via Bloomberg.

![U.S. Weekly HDD / CDD Usage](image)

Figure 11 - U.S. Weekly HDD/CDD Total Usage

20 For more information, please visit: http://tonto.eia.doe.gov/energyexplained/index.cfm?page=about_degree_days
When assessing the level of natural gas demand via the magnitude of HDD/CDD, it is often compared by traders to a historical benchmark of previous degree-days for each census region, as depicted below in Figure 12.

Figure 12 - HDD/CDD by Census Region (2008)

![Heatmap of HDD/CDD by Census Region](source: Energy Information Administration, Annual Energy Review, Table 8.9 (June 2008))

Traders are ultimately concerned with exogenous weather shocks that will impact demand disproportionately to market expectations and historical trends. In Section III.B on page 33 I will address this by defining a measure for weather “surprise.” In the meantime, we can therefore equate demand shocks with the exogenous weather shocks that lead to HDD/CDD deviations from typical historical levels for the given time period.

**Power Generation:**

Natural gas competes with other sources of energy such as oil and coal. As shown by (Brown and Yucel 2007), for many years, natural gas and refined petroleum products were seen as close substitutes in U.S. industry and electric power generation. Industry and electric power generators readily switched back and forth between the two, using the lower marginal cost option. Consequently, U.S. natural gas price movements generally followed those of crude oil. As shown by (Yucel

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21 (Brown & Mine, 2007)
and Guo 1994), crude oil prices were shaped by world oil market conditions, and U.S. natural gas prices adjusted to oil prices.

However, today we rely mainly on coal, nuclear, natural gas, hydroelectric, and petroleum for our base load energy generation. Despite its disproportionate attention in the media and among policy makers, only a small amount of energy generation comes from alternatives like solar energy, tidal harnesses, wind generators, and geothermal sources.

As you can see from Figure 13 – U.S. Baseload Generating Capacity below, natural gas provides the largest amount of energy generating capacity, however capacity does not equate to the actual throughput, which depends on the current energy demand and marginal cost per BTU to meet that demand. Coal and Nuclear tend to have lower marginal costs per BTU and hence run consistently around the clock for baseload, leaving natural gas generation to also address peak-load demands across many regions.

**U.S. Baseload Generating Capacity**

Comparison of Summer and Winter Capacity (Gigawatts)

![Graph showing U.S. baseload generating capacity](image)


Figure 13 – U.S. Baseload Generating Capacity

Natural gas is most commonly generated in a modern combined cycle gas turbine ("CCGT") plant. CCGT plants offer efficiencies of up to 60% and can be readily

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23 See the EIA's Electricity Generation by Energy Source and Existing Generation Capacity by Fuel Type for more information. Available at [http://www.eia.doe.gov/fuelelectric.html](http://www.eia.doe.gov/fuelelectric.html)
turned on and off to not only provide additional base load capacity but also to help meet demand during peak hours or seasons (notice the variability in NG capacity in the above figure between winter and summer months). The decision to activate CCGT assets amongst diversified power generation companies are highly dependent on the season (and thus the energy demand) as well as the marginal cost of natural gas relative to their other coal and petroleum generating assets.

B. Literature Review

There is a wealth of literature that provides deep understanding into the dynamics of commodities, natural gas in particular. A substantial portion of the research is aimed at developing structural models of price dynamics, descriptive analyses of underlying influential factors, and even some addresses the volatility dynamics of energy commodities, most notably the works by Robert Pindyck of the Massachusetts Institute of Technology. This section will provide a brief overview of the relevant literature that has formed a substantive basis for my own research.

As previously mentioned, the goal of this paper is to be able to understand, model and ultimately forecast the price dynamics of natural gas, specifically the commodity’s volatility dynamic. To do so, it is important to understand what work has already been done on understanding the underlying factors that influence the price dynamics of natural gas, which are highlighted in the previous Sub-Section II.A on BACKGROUND.

The most relevant literature to this analysis has been on the dynamics of the commodity spot and futures market, most notably from Pindyck (1999, 2001, 2004), as well as about how markets process information related to news releases as analyzed by Ederington & Lee (1993, 1994, 1995). Additional literature on techniques and methodology, as presented by Campbell, Lo, & MacKinlay (1997) and Al-Fattah (2006). The work of Ederington & Lee (1993, 1994, 1995) has focused on how fixed income and foreign exchange futures markets respond to the “announcement effect” of macroeconomic and news releases. This literature has salient relevance to my own research on the natural gas market’s response to weekly EIA inventory storage reports.

Elaborating on the work of (Ederington & Lee, The Short-Run Dynamics of the Price Adjustment to New Information, 1995), they use 10-second returns and tic-level data to find that prices adjust in a series of numerous, small, but rapid price changes that begin within 10 seconds of the news release, and is mostly completed within 40 seconds of the announcement. Furthermore, they find that while volatility tends to be higher than normal just before the news release, there is no evidence of information leakage.

As they point out, two aspects of the market response have been explored in the literature:
1. How long it takes information to be fully reflected in the market prices, in the sense that volatility returns to normal levels.

2. How quickly and how efficiently markets incorporate new information.

However, it seems that a bulk of the research has focused on the adjustment of equity prices following earnings and dividend announcements. For instance (Woodruff & Senchack, 1988) and (Brown, Clinch, & Foster, 1992) found that the mean duration between and earnings announcement and the first post-announcement trade is roughly under fifteen minutes. Nearly half of the total adjustment comes within the first 30 minutes. Most interestingly, (Brown, Clinch, & Foster, 1992) found that following extremely bad or good earnings releases, prices tend to trend in the same direction for approximately four hours. These findings, while related to the equity markets and at a higher frequency than my analysis are of key interest. They help to capture how sentiment plays a role at influencing price discovery, and ultimately the volatility patterns that ensue.

From a different lens, (Pindyck R., Volatility and Commodity Price Dynamics, 2004), highlights how volatility affects prices, production, and inventories in two principal ways:

1. First, it directly affects the marginal convenience yield, which is the marginal value of storage that encapsulates the flow of benefits from an extra unit of inventory. As Pindyck reveals, when prices are more volatile, so too is production and demand, thereby leading to a greater demand for inventories, which are needed to smooth production. This ultimately helps to smooth deliveries of the commodity to end users, thereby reducing marketing costs. Therefore, Pindyck concludes that an increase in volatility may lead to inventory build-ups and raise prices in the short run.

2. Second, for a depletable resource, Pindyck demonstrates that volatility affects the total marginal cost of production via the "option premium." As he describes it, producers hold operating options, with an exercise price equal to direct marginal production cost and a payoff equal to the spot price. Total marginal cost equals the direct marginal cost plus the opportunity cost of exercising the incremental operating option. An increase in price volatility raises the value of this option and the associated opportunity cost, and can therefore lead to a reduction in production.
Extending Pindyck's second finding, (Litzenberger & Rabinowitz, 1995) used a two-period model to demonstrate that this option premium may lead to some backwardation in the futures market. Within the energy complex, they use data for crude oil, and demonstrate production is negatively correlated, and the extent of backwardation is positively correlated, with price volatility. Pindyck extends this result, which is consistent with the theory, to show how volatility and option value can be incorporated in a model of the dynamics for a commodity market.

On the topic of conditional volatility, examining intraday volatility, (Linn & Zhu, 2004) demonstrate that unconditional natural gas price volatility is substantially higher around the time when the natural gas storage report is released.

Another important component to this analysis is the impact of weather on influencing the volatility of natural gas futures prices. (Roll, 1984) wrote a capstone paper that examined the relationship between forecast error of temperature in Florida and the returns of orange juice futures. Roll found a statistically significant relationship, but with an $R^2$ that was too low. These findings are often cited as evidence of excess volatility or noise trading. This is relevant to my own research, as I intend to similarly understand the interaction between prices and a truly exogenous determinant of value, the weather.

C. The Theory of Storage

The Theory of Storage states the spot and forward prices of storable commodities are integrated when the storage is held from one period to the next. This implies that surprise weather may lead to higher conditional volatility in both spot and futures markets.\(^{25}\) The theory of storage has a rich history, most notably from the initial works of (Working, 1949) and (Samuelson, 1971) amongst others, with more recent contributions from (Pindyck R. S., 1994).

(Working, 1949) attempts to understand the factors that determine the inter-temporal price relationship, or the relationship between expected prices for the delivery of a commodity at different points in time. Analyzing the U.S. wheat market, he finds that so far as supplies are concerned, it is only supplies \textit{already in existence} which have any significant bearing on a current

inter-temporal price relations. Working's result is particularly useful because it places in proper perspective the dominating role that stocks play in determining inter-temporal price relationships.

(Samuelson, 1971) finds that because a commodity can be carried forward from one period to the next, speculative arbitrage serves to link its prices at different points of time. Since, however, the size of commodity stock (he uses wheat) is based on complicated probability processes that are impossible to forecast with certainty, he determines that the minimal model for understanding market behavior must involve stochastic processes. He further relates that it is the expected rather than the known-for-certain prices that enter into all arbitrage relations and carryover decisions, and ultimately determines the behavior of price as the solution to a stochastic-dynamic-programming problem. The resulting stationary time series possesses an ergodic state and normative properties like those often observed for real-world exchanges.

Pindyck suggests that competitive producers hold inventories to reduce costs of adjusting production and to reduce marketing costs by facilitating scheduling and avoiding stockouts. Using data for copper, heating oil, and lumber, he estimated these costs within a structural model of production, sales, and storage. He finds that inventories play a “production-smoothing” role only for heating oil (only relative to copper and lumber) and during periods of low or normal prices. Subsequently, he finds that inventories also play a more important role in reducing marketing costs. Given the similarities of heating oil and natural gas as both important energy commodities for similar purposes (i.e., home heating), as well as their nature as a “flow” commodity, it seems rational to extend Pindyck’s findings on the role of inventories to that of natural gas.

D. Theory of Shocks in Natural Gas

As stated in (Engle, 2001), “…volatility is a response to news, which must be a surprise. However, the timing of the news may not be a surprise and gives rise to predictable components of volatility, such as economic announcements.” As previously mentioned, the objective of this analysis is to answer whether volatility of natural gas futures is conditional on the season or the level of the inventory and secondly, how accurate analysts are at forecasting inventory levels.

26 From probability theory and Markov chains, an ergodic state is one that is aperiodic and (non-null) persistent.
To understand analyst inventory estimate accuracy, I developed a framework for thinking about errors, or shocks. At a high-level, the logic is such that shocks to natural gas market (either supply-side or demand-side) leads to errors, which ultimately have a price impact. This theoretical model, which is central to my investigation, is depicted below in Figure 14.

**High-Level Logic for a Theory of Shocks in Natural Gas Inventories**

![Figure 14 - High Level Logic for a Theory of Shocks in Natural Gas Inventories](image)

To build intuition around the market’s response to inventory reports, I examine the price and volatility impact due to errors made in inventory estimates, as caused by various exogenous shocks. Delving deeper into the price and volatility impact (Component C), I make the conjecture that price and volatility will be impacted in different ways depending upon the nature of the shock, most notably if it is considered by the market to be short-term or long-term in nature. This exposition of Component C of our Theory of Shocks is depicted below in Figure 15.

**Theory of Shocks in Detail: Framework for Price Impact (C)**

![Figure 15 - Component C in Detail: Framework for Price Impact](image)

My conjecture is that we can infer the market’s perception of the type of shock, such as whether it is expected to be short-term or long-term in nature, by looking at how the individual natural gas futures contracts move across the term structure for a particular inventory report. Specifically, one of my thesis’ hypotheses is that short-run shocks will evidence themselves in either a spread price change or spot-price change and that long-run shocks will likely evidence themselves as a broader change in absolute price levels across the natural gas futures curve. Expounding upon this logic, it is typically the case that short-run
shocks in natural gas are typically demand-side related. We can relate the use of natural gas inventory as a proxy for broad energy demand, as supported by the HDD/CDD level. Therefore, we can connect demand-side shocks to outsized HDD/CDD levels. If there is a surprise use of inventory due to outsized shocks in HDD/CDD levels, and it is believed to be short-term in nature, we should expect that the nearby futures contract and spot-price changes will likely trade at a higher premium relative to longer-dated contracts. The logic is that peak-load issues arise from power producers needing to meet immediate incremental energy demand. Secondly, supply-side shocks are typically less common, and examples of which would be shut-ins related to hurricanes or extremely cold weather; these types of events typically take some time to recover from.

Looking at this theoretical model for shocks to natural gas inventory more holistically, my research aims to evaluate the following theoretical model for natural gas inventory report reactions. This theoretical model is depicted below in Figure 16.

**Theoretical Model for Natural Gas Inventory Report Reactions**

1. Determine Trend
2. Characterize Market
3. Condition on Expectations
4. React to Outcome

Assumes a Multiplicative model such that:

\[ \text{Data} = \text{Trend} \times \text{Seasonal} \times \text{Cyclic} \times \text{Irregular} \]

**Figure 16 – A Theoretical Model for Natural Gas Inventory Report Reactions**

III. METHODOLOGY

A. General Data

This analysis involved substantial volumes of data from multiple sources. To facilitate the analysis, I developed a comprehensive SQL database of over 300,000 records containing daily natural gas futures prices, daily natural gas Exchange-Traded Fund ("ETF") prices, daily market data (i.e., S&P 500, MSCI World, etc.), daily interest rates, weekly inventory storage levels from Jan-94 to Mar-10. Source data was extracted with appropriate licensing from Bloomberg, WRDS, EIA/DOE, and the Global Financial Database. Extensively using Matlab, VBA and Statools™, my analysis consists of the following segments:

1. Exploratory data analysis
2. Developing summary statistics of each future contract and market factor
3. Testing for normalcy in the gas data
4. Developing seasonal models (using Winters' Model) for analysis and forecast
5. Exploring regression-based multi-factor models for describing the influence of explanatory variables on natural gas markets

Looking at the last traded end of day prices for natural gas futures data from Bloomberg, I analyzed spot prices and rolling 1-12 month futures. Spot prices are not recorded at a centralized exchange, but collected by agencies like Bloomberg who base their price estimates on polls of traders. The futures prices are collected in such a way, that they roll on a pre-specified time each month, effectively helping to ensure that the collected price reflects the active contract by volume and open interest. I focus my analysis on the day of the inventory report (Thursday of each week), compared to the volatility of the day before, the average volatility over the prior two days, and the average volatility over the prior three days with volatility being measured as the rolling 20D historical annualized standard deviation and the daily log-return squared. The conjecture is that if there is a measurable announcement effect in

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28 ETF's like the UNG (NYSE:UNG) are recently developed securitized products that offer retail investors a means to synthetically participate in the natural gas futures market but through an equity exchange as opposed to the NYMEX. In short, this allows anyone to buy or sell natural gas by purchasing (or selling short) shares of the UNG.
29 I will frame some portions of my analysis to exclude parts of 2006 which were biased by the collapse of hedge fund, Amaranth Partners. (Till, 2007) and (APPA, 2007) provide an excellent summary of Amaranth's influence on the gas market and chronicle the steps leading to its demise.
30 Mu, X. (2004), page 7 addresses some of the potential complications this can introduce.
natural gas futures, we should expect to see a statistically significant difference in the ratio of announcement day volatility, when the information is incorporated quickly into the new equilibrium prices, and the volatility over the prior day and several days pre-announcement.

B. Measure of Weather Surprise

I extend the work of (Mu, 2004), to create a standardized measure of weather surprise, as defined below in Equation 1. This will serve as a proxy for the demand shock and defined as the forecasted deviation of heating degree days (HDD) and cooling degree days (CDD) from normal based on Z-score.

Weather Surprise Index

$$WS_t = \left[ \frac{DD_t - \mu_{DD}}{\sigma_{DD}} \right]$$

Where

$$DD_t = HDD_t + CDD_t$$

Equation 1 - Standardized Weather Surprise Index

I use the 1994 – 2002 weekly CDD/HDD data to standardize the 2003 – 2010 weather levels, thereby constructing a unitless measure of relatively how warm or cool a given week is to what has been typical in the past. They hypothesis is that outsized weather surprise, $WS_t$, values should lead to greater volatility on natural gas futures prices as well as higher analyst error.

C. Bullish/Bearish Inventory Report Indicator

Additionally, I developed an indicator, $\Phi$, of whether a given weekly inventory storage report is bearish or bullish by looking at the Z-score of the deviation of actual inventory announcement from the median analyst estimates, expressed as percentage of the 5-year normalized inventory level for that week. To account for noise, indicator values that are greater than 0.2 are considered Bearish (implying an over-supplied market), and values less than -0.2 are considered Bullish (implying a more constrained market). The indicator is calculated each week from 2003-2010 as follows from Equation 2 - Inventory Report Bullish/Bearish Indicator:

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31 As discussed in the Literature Review Section II.B, Ederington, L. H., & Jae, L. H. (1993) provide a fantastic discussion of the rapid price-adjustment process of other futures contracts to news releases.
Inventory Report Bullish / Bearish Indicator

Classification of Indicator

Bullish: $\Phi < -0.2$ (i.e., inventory lower than expected, more constrained market)

Bearish: $\Phi > 0.2$ (i.e., inventory higher than expected, more over-supplied market)

\[ x_t = \frac{\text{Actual Inventory Release}_t - \text{Analyst Median Estimate Of Level}_t}{\text{Normalized Level}_t} \]

Where:

- $x_t$ = Weekly announcement day (Thursday)
- $\mu$ = 1994 - 2003 training period average of $x_t$
- $\sigma$ = 1994 - 2003 training period standard deviation of $x_t$

Equation 2 - Inventory Report Bullish/Bearish Indicator

D. Individual Analyst Estimates for Guaging Analyst Quality/Skill

I constructed a time series of individual analyst estimates, looking at all 23 analysts that provided an estimate into the most recent weekly inventory report, as of Mar-18, 2010. Using these 23 analysts, I then pulled out their estimate history going back to the greater of either January 1st, 2001 or when data was available. Due to data availabilities, I truncated the time series to Feb-28, 2003, as this is when Bloomberg appears to have started recording consolidated data around individual analyst estimates. I then repeated this same exercise, but using the universe of analysts reporting as of Sep-7, 2006, the mid-point of the estimate data series, and not already included in the universe of analysts reporting as of Mar-18, 2010.

E. Inventory Cycle Indicator

It is important to understand the stage of the natural gas inventory cycle. Natural gas goes through two fundamental stages: injection and withdraw. Additionally, there are several "fringe" weeks around the inflection points when natural gas shifts from injection to withdraw and from withdraw to injection. These ambiguous periods are times when it may be more challenging for analysts to infer the turning point during the cycle. My hypothesis is that the volatility patterns of natural gas will vary depending upon whether the state of inventory is in a withdraw, injection, withdraw-fringe or injection-fringe period. Therefore, it becomes necessary to develop a systematic way of characterizing the stage of the inventory cycle.
The fringe periods are important to understand because they constitute times when the change in inventory is less certain, obscuring the turning point when we switch from natural gas withdraw to injection or from injection to withdraw. This uncertainty can be captured quite robustly by comparing the week-over-week change in inventory relative to a moving average of this change, in effect encapsulating the degree of uncertainty in inventory changes.

Accordingly, I developed a simple framework for such classification. As you can see from Figure 17 on page 36, inventory levels fluctuate seasonally based on demand for natural gas. From a crude measure, we can identify the following stages of the inventory cycle below in Table 1 - Inventory Cycle Stage Designation:

<table>
<thead>
<tr>
<th>Stage</th>
<th>Numeric Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Withdrawal</td>
<td>-2</td>
</tr>
<tr>
<td>Withdrawal Inflection</td>
<td>-1</td>
</tr>
<tr>
<td>Injection</td>
<td>+1</td>
</tr>
<tr>
<td>Injection Inflection</td>
<td>+2</td>
</tr>
</tbody>
</table>

Table 1 - Inventory Cycle Stage Designation

Looking at the total U.S. inventory levels (in Bcf)\textsuperscript{32} for each year from 1994 to 2010 by week, I statistically characterized the stage of the inventory cycle into one of four numeric levels, which will be later used to facilitate ANOVA analysis and regressions around inventory stage. Relative to actual inventory data, the classification looks crudely as follows from Figure 17 - Inventory Levels by Week of Year and Cycle Stage Designations.

\textsuperscript{32} From Bloomberg, this is the "DOENUST1_Index" security identifier
Figure 17 - Inventory Levels by Week of Year and Cycle Stage Designations

To determine the markets inventory cycle stage, I developed an algorithm that looks at the week-over-week changes in inventory, effectively a first derivative in inventory with respect to time. To determine the two inflection points, I examined the weekly change in inventory levels, effectively solving for the global maxima/minima points at which this derivative in inventory levels equaled zero. The procedure for determining the fringe periods around these inflection points was a bit more complex.

To do so, I applied a heuristic moving average smoothing technique, which was then compared to the weekly change in inventory levels. This spread represents the deviation in weekly changes relative to the moving average change in inventory each week. Looking at the absolute value of this spread in ratio to the actual inventory level, revealed fringe periods where inventory changes were more erratic. Then looking at the full year’s time series of this ratio, I characterized all weeks in the first half of the year where the ratio exceeded 1 standard deviation as being the withdraw inflection “fringe” period, and all weeks in the second half of the year below -1 standard deviation as being the injection inflection “fringe” period. This approach holds up robustly across all years from 1994 – 2010. An example of the output from this cycle detection algorithm for 1994 is provided below in Figure 18 - Inventory Cycle Analysis for 1994.
Inventory Cycle Analysis for 1994

Inventory Level for 1994

WoW Change in Inventory Level vs. 3W M.A. for 1994

Ratio of Abs(Inv. Change and 3W M.A. Spread)

Inventory Cycle Status (-2: Withdrawal / -1: With. Inflec. / +1: Injection / +2: Inj. Inflec.)

Figure 18 - Inventory Cycle Analysis for 1994
IV. RESULTS

A. Exploratory Data Analysis:

1. Natural Gas Futures Contract Daily Returns

As the below Figure 20 - Box Plot of Daily Natural Gas Futures Returns illustrates for the NG1 - NG12 futures returns, there are extreme outliers, both on the up and downside. Additionally, the volatility of near-dated contracts is meaningfully higher than contracts farther out in the term structure. Most interestingly, these outliers tend to cluster around EIA reports. Jumps to the upside appear to be more frequent (87.3%) than jumps to the downside (76.4%) following these reports. The implication of this could be that markets tend to over-react more optimistically to unexpectedly bullish inventory reports.
Figure 20 - Box Plot of Daily Natural Gas Futures Returns

2. Natural Gas Futures Contract Daily Returns

The below Figure 21 - Box-Whisker Plot of Comparative Daily Returns illustrates that natural gas prices are considerably more volatile than other commodities, and even more so than the S&P 500. As will be discussed further, regional natural gas averages (i.e., USREAPPA for Appalachia region, USREPJMR for Pennsylvania, New Jersey and parts of the mid-Atlantic, USREUSNY for New York and Long-Island, USRENEWE for New England and USRELOSE for Lousianna and the Southeast) appear to exhibit greater volatility and more outliers relative to the Henry Hub contract.

Figure 21 - Box-Whisker Plot of Comparative Daily Returns
3. Volatility Over Various Time Windows

This portion will proceed by looking at the unconditional volatility of natural gas futures returns over a variety of time horizons. Then the analysis will move to analyzing the volatility of natural gas futures over a variety of conditional periods, such as when the market is over or under supplied. For consistency when comparing the volatility response on a daily level, I define volatility, or the variance as the squared daily returns. I will explicitly mention when using any other measure, such as rolling standard deviation.

In first examining the unconditional volatility of natural gas, Figure 22 – Volatility of NG1 Squared Daily Returns by Year (1994 – 2010) below, the volatility, of NG1, illustrates substantially more volatile periods for the commodity in 2001, 2006, 2007 and 2009.

![Figure 22 - Volatility of NG1 Squared Daily Returns by Year (1994 – 2010)](image)

**Figure 22 - Volatility of NG1 Squared Daily Returns by Year (1994 – 2010)**

Looking at the volatility on a monthly basis in Figure 23 - Volatility of NG1 By Month of Year (1994 - 2010), from 1994 – 2004 you will note that the fall and winter months (months 9-12 and 1-3) are substantially more volatile. These results are not conditioned on the weather index, basis dispersion nor inventory levels.
Looking at the volatility on a day of week basis and consistent with (Murty & Zhu, 2004) and (Mu, 2004), I also find that natural gas price volatility is significantly higher on Monday and the day when the natural gas storage report is released. A Box-Wisker plot of the daily squared returns for each day of the week from 1994-2010 is provided in the following Figure 24.
The seasonal pattern shows a larger mean and larger variability during the winter months. The intuition behind this may be that colder temperatures lead to a higher occurrence of demand shocks, specifically outsized-HDD levels, thereby engendering greater uncertainty over inventory withdraws, and thus subsequent natural gas prices.

Now the analysis turns to the volatility response *conditioned* on the season, using the classification of Table 1 - Inventory Cycle Stage Designation on page 35. By applying an ANOVA regression to the volatility during each of the 4 periods from 2003 – 2010, I note that there is a higher degree of variance, particularly outlier volatility levels, in the injection and withdrawal months. This is highlighted in Figure 25. However, the ability to discern different volatilities between these periods, unconditional on other factors, such as analyst error or weather, leads to an insignificant p-value of 0.81 and 0.41 when more crudely classifying as either withdraw or injection, such as in Figure 26. Therefore, volatility does not appear to be conditional solely on the inventory cycle.
ANOVA: Inventory Cycle Stage vs. Ratio of Vol to Average of 3D Prior Vol. on Announcement Day
(p-value: 0.80923)

Figure 25 - Box-Plot of Inventory Cycle Stages (-2: Withdraw / -1: Withdraw Inflection / +1: Injection / +2: Injection Inflection)

ANOVA: Inventory Cycle Stage (-1: Withdraw / +1 Injection) vs. Ratio of Vol to Average of 3D Prior Vol. on Announcement Day
(p-value: 0.39613)

Figure 26 - Box-Plot of Inventory Cycle Stages - Simplified (-1: Withdraw & Withdraw Inflection / +1: Injection & Injection Inflection)
4. **Inventory Levels**

2009 was a particularly unique year for natural gas prices. Going into the winter, the market had so over-supplied since 1994, when this report's analysis began.

![Inventory Levels by Week of Year (1994-2010)](image)

**Figure 27 - Inventory Levels by Week of Year (1994-2010)**
To appreciate just how over-supplied the current market was, 1999-2010 inventory levels have been standardized in Figure 28 - Inventory Level by Week of Year (Z-Scored) below, assuming a normal distribution with mean and variance based upon each weekly level in rolling prior 5-years from 1999 - 2010. Remarkably, the inventory levels going into the withdraw winter months were almost 7 standard deviations over-supplied in 2009.

![Inventory Level by Week of Year Z-Score - (1999 - 2010)](image)

Figure 28 - Inventory Level by Week of Year (Z-Scored)

5. The Impact of Contango/Backwardation

Extending our Theory of Schocks, I described the two types of shocks to natural gas prices:

1. **Demand Shocks**: typically weather related (i.e., HDD/CDD demand), much more common.

2. **Supply Shocks**: typically less common (i.e., hurricanes, which take supply off, are a form of exogenous weather shocks but affect supply more directly).
I conjectured that the expected duration of the shock will evidence itself in the degree of contango. For instance, if the shocks is expected to be more short-term in nature, then we would anticipate a greater degree of backwardation between front month contracts and spot prices. The rationale is that short-term shocks will lead to a higher clearing price for natural gas in the near-term, thereby raising the nearby relative premium of nearby contracts to longer-dated contracts. As the below Figure 29 - NG1-NG12 Contango/Backwardation from 1994 – 2010 illustrates, the degree of contango and backwardation varies considerably throughout time. Its distributional properties are also highlighted in Figure 30 - Distribution of NG1/NG12 Contango ($/MMBtu) on page 47.

Figure 29 - NG1-NG12 Contango/Backwardation from 1994 – 2010
B. Summary Statistics

1. Natural Gas Futures Contract (Henry Hub and Regional) Daily Returns

<table>
<thead>
<tr>
<th>Henry Hub Natural Gas Futures Contracts (Months 1-12)</th>
<th>Regional Average Natural Gas Spot Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>(0.07%)</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>3.70%</td>
</tr>
<tr>
<td>Median</td>
<td>0.11%</td>
</tr>
<tr>
<td>Mean Abs. Dev.</td>
<td>2.60%</td>
</tr>
<tr>
<td>Minimum</td>
<td>(14.89%)</td>
</tr>
<tr>
<td>Maximum</td>
<td>26.75%</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>1.02%</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>1.19%</td>
</tr>
<tr>
<td>IQR</td>
<td>0.17%</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.92</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.10</td>
</tr>
</tbody>
</table>

Figure 30 - Distribution of NG1/NG12 Contango ($/MMBtu)

Figure 31 - Summary Statistics of NG Futures and Regional Spot Prices

From the preceding summary of daily returns over the last two and a half years (652 trading days), the Henry Hub futures prices for months 1-12 appear to have similar average returns across the term structure. However, the volatility appears to decrease in the farther-dated natural gas futures contracts. This is empirical evidence of the
"Samuelson Effect", whereby volatility declines with time-to-maturity (i.e., backwardation in futures volatility). Also worth note, longer-dated NG futures contracts appear to have negative skew and higher kurtosis (fat tails). I will explore this momentarily in the tests for normalcy, but the existence of these higher moments could be due to the more persistent market backwardation, whereby futures prices have experienced sustained downward pressure.

<table>
<thead>
<tr>
<th>UNG ETF</th>
<th>Additional Macro Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>[0.12%] [0.25%] [0.01%] [0.09%] [0.04%] [0.06%] [0.08%] [0.03%]</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>[3.17%] [3.52%] [0.64%] [7.21%] [2.01%] [1.66%] [1.54%] [3.35%]</td>
</tr>
<tr>
<td>Median</td>
<td>[0.31%] [0.11%] [0.04%] [0.57%] [0.08%] [0.08%] [0.07%] [0.13%]</td>
</tr>
<tr>
<td>Mean Abs. Dev.</td>
<td>[2.46%] [2.63%] [0.46%] [5.31%] [1.35%] [1.13%] [1.12%] [2.77%]</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>[2.19%] [2.45%] [0.25%] [4.25%] [0.94%] [0.78%] [0.74%] [1.69%]</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>[1.91%] [1.81%] [0.32%] [3.80%] [0.83%] [0.73%] [0.95%] [1.68%]</td>
</tr>
<tr>
<td>IQR</td>
<td>[4.09%] [4.26%] [0.68%] [8.07%] [1.77%] [1.51%] [1.69%] [3.30%]</td>
</tr>
<tr>
<td>Skewness</td>
<td>[0.03] [0.26] [0.10] [0.33] [0.14] [0.33] [0.11] [0.15]</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>[3.81] [5.67] [5.97] [4.95] [8.19] [7.97] [7.70] [6.25]</td>
</tr>
</tbody>
</table>

# Days/Observ. 652 652 652 652 652 652 652 652

Figure 32 - Summary Statistics of Natural Gas ETF and Additional Macro Factors

As expected, the regional natural gas spot prices exhibit far greater volatility and lower skew with higher kurtosis than the Henry Hub spot price (NG1). The increased volatility could perhaps be due to lower trading activity in the regional gas markets. Lower trading activity leads to reduced liquidity which can cause more violent price movements.

2. ETF and Other Market/Macro Factors

Since we will be using several macro and market factors in constructing our multivariate regression, it is important to have an understanding of the data's characteristics. Interestingly, over the same time period the UNG ETF, which is supposed to identically track the price movement of the NG1 Henry Hub contract, appears to exhibit a lower average return (-26 bps versus -7 bps for NG1), with less volatility (3.17% standard deviation versus 3.70% for NG1), and effectively no positive skew (0.03 versus 0.92 for NG1) and more normal kurtosis (3.81 versus 8.51 for NG1).

The reduced kurtosis could possibly be due to this summer's suspension of share issuance for the UNG, which dampened price movements and led to a sustained premium of UNG shares relative to the underlying NG net asset value (the two should be identical, in theory). Recent fear of widespread price manipulation in the natural gas market by speculative hedge funds and other institutional investors has placed increasing focus on understanding the unprecedented prices moves in these markets over the past year. Regulatory scrutiny towards ETF's which have offered investors a means to synthetically participate in these commodity markets, has forced some ETF commodity funds to either shut down, limit the number of new share issuance, or offer alternative means to realign a disconnected market value-to-NAV ratio. At one point in August 2009, the UNG held a near 20% premium to NAV due to a halting of share issuance and a recent swaps-for-shares plan for the UNG. These regulatory factors may help to explain the UNG ETF's puzzling statistical characteristics.

C. Analysis of Analyst Errors

Having defined summary characteristics of the natural gas market, as well as periods when the commodity is more volatile, it is important to return to our framework for understanding analyst error, as highlighted in Figure 14 on page 30. I have thus far characterized component C, or the volatility response. Now the analysis moves further up the tree to component B, analyst errors in inventory estimates. I looked at median analyst errors in estimating the inventory level as both an absolute deviation in Bcf, as well as the percentage error relative to the 5-year normalized inventory level, as reported by the EIA. The following Figure 33 illustrates the time series of analyst errors versus inventory levels. As you can see, there is a high degree of seasonality in analyst errors.

Analysis of Analyst Errors Versus Inventory Levels

The seasonality of error is further apparent when looking at the median analyst errors by month and week of year in Figure 34 and Figure 35, respectively. In the winter months, from months 1-4 or weeks 1 – 15, the degree of error is substantial, on both a percentage and absolute Bcf basis. As the year goes on, analysts are much more accurate at forecasting the inventory level.
Median Analyst Inventory Estimate Error as a Percent of 5-Year Normalized Inventory Levels Boxplot by Month of Year (28-Feb-2003 - 19-Mar-2010)

Figure 34 - Median Analyst Inventory Estimate Error (Percent) by Month of Year (2003 - 2010)

Analyst Median Estimate Error (Absolute Bcf) by Week of Year

Figure 35 - Analyst Median Inventory Estimate Error (Absolute Bcf) by Week of Year (2003 - 2010)
It is important to acknowledge that some analysts are more accurate than others at forecasting inventory. Using the Individual Analyst Estimates for Guaging Analyst Quality/Skill of Section III.D on page 34 I analyzed individual analyst ability to forecast inventory levels. Figure 36 below displays a 3-D plot of the individual analyst inventory estimate error (in Bcf) for 2006 - 2010. As you can see, while analysts do tend to make errors around the same time periods, there is some variation between individual analyst quality, or skill.

Accordingly, to ascribe a “quality ranking” to analysts by applying Thiel’s U-Statistic, I developed a means to understand the volatility response conditioned on analyst error and the quality of the analyst. The Thiel’s U-Statistic denoting a series of interest as \( y_i \) and a forecast of it as \( f_i \), the resulting forecast error is given as \( e_i = y_i - f_i \), for \( t = 1, ..., T \). The statistic is defined below in Equation 3 - Thiel's U_1-Statistic as follows:

\[
U_1 = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^{T} (y_t - f_t)^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} y_t^2} + \sqrt{\frac{1}{T} \sum_{t=1}^{T} f_t^2}}
\]

Equation 3 - Thiel’s U_1-Statistic
The more accurate the forecasts, the lower the value of the $U_1$ statistic. The $U_1$ statistic is bounded between 0 and 1, with values closer to 0 indicating greater forecasting accuracy. However, when performing an ANOVA regression on the volatility response when high-quality analysts (defined as top 50th-percentile based on each analysts $U_1$ value) and low-quality analysts make an error, I found no statistically significant, nor discernable evidence that the volatility response was any different. This seems counter to intuition, as well as to findings in other markets, such as was documented in (Chang, Daouk, & Wang, 2009) for the crude oil market.

As one explanation, it is important to acknowledge the possibility of survivorship bias. It would be reasonable to assume that the analysts with the longest track-record are likely to be the most accurate, as poor, inaccurate analysts are likely fired and withdraw from the survey. It is also worth noting, that some of the analysts may have either left or had been fired because their firm had gone out of business. For instance, Lehman Brothers used to contribute to the weekly inventory report estimate, however, that firm is no longer in business. These issues could have perhaps contributed to the indiscernible volatility response conditioned on analyst quality.

D. Tests for Normalcy

1. Lilliefors Test for Normalcy

As expected from the higher moments noticed in the exploratory data analysis, natural gas prices are non-normal. Using the Lilliefors Test, we can successfully reject the null hypothesis of normalcy for all 12 Henry Hub futures contracts (NG1-NG12) at the 1% significance level.
At the 1% significance level, we can similarly reject the null hypothesis for normalcy with the regional natural gas prices, however, we cannot reject the null hypothesis for the UNG ETF, which seems anomalous given the regulatory issues previously mentioned.

![Normal and Empirical Cumulative Distributions](image)

Figure 37 - Test for Normalcy in NG Futures

2. Autocorrelation Analysis

The autocorrelation structure tells us how a series is related to its own past values through time. Under the assumptions of randomness, it can be shown that the standard error of any autocorrelation is approximately \( \frac{1}{\sqrt{T}} \), where \( T \) denotes the number of observations in the study. If the series is truly random, then only an occasional autocorrelation will be larger than 2 standard errors in magnitude. Therefore any autocorrelation that is larger

![Lilliefors Test Results](image)

Figure 38 - Lilliefors Test for Normalcy (99% Confidence Level)
than 2 standard errors in magnitude is worth our attention. Significant autocorrelations for NG1 - NG12 contracts are highlighted in bold below:

There are three methods for dealing with seasonality:

1. Winters’ exponential smoothing model, which is similar to Holt’s method, except that it includes another component and smoothing constant to capture seasonality.

2. De-seasonalize the data, then use any of our forecasting methods to model the de-seasonalize data, then re-seasonalize these forecasts.

3. Use multiple linear regression with dummy variables associated with the seasons.

I have explored both additive and multiplicative seasonal models. In the additive seasonal model, we add an appropriate seasonal index to a base forecast. In the multiplicative seasonal model, we multiply a base forecast by the appropriate seasonal index.

Figure 39 - NG Futures Autocorrelation Analysis (1-23 Day Lags)

There is evidence of statistically significant negative autocorrelation (mean reversion) in the 1 day lagged returns of NG1-NG3 futures contracts, followed by positive autocorrelation (trending) in day 2 lags for NG1-NG6. However, it is important to acknowledge that the magnitude of this daily autocorrelation is relatively small.

E. Forecasting Model

There are three methods for dealing with seasonality:

1. Winters’ exponential smoothing model, which is similar to Holt’s method, except that it includes another component and smoothing constant to capture seasonality.

2. De-seasonalize the data, then use any of our forecasting methods to model the de-seasonalize data, then re-seasonalize these forecasts.

3. Use multiple linear regression with dummy variables associated with the seasons.

I have explored both additive and multiplicative seasonal models. In the additive seasonal model, we add an appropriate seasonal index to a base forecast. In the multiplicative seasonal model, we multiply a base forecast by the appropriate seasonal index.

While the simple exponential smoothing model generally works well if there is no obvious trend in the series, the high-degree of trend in natural gas futures prices leads us to more robust forecasting methods like Winters' Model.

1. **Winters' Exponential Smoothing Model to Forecast Henry Hub Natural Gas Prices**

Based upon weekly price data from Oct-1994 to Mar-2009, I have segmented the data into a training, validation (52 weeks) and forecast testing sets (52 weeks). Winters' exponential smoothing method was applied with optimized parameters for $\alpha$, $\beta$ and $\gamma$ on a weekly seasonal period. The results are as follows:

**Forecasting Constants (Optimized)**

| Level (Alpha) | 1.000 |
| Trend (Beta)  | 0.000 |
| Season (Gamma)| 0.000 |

<table>
<thead>
<tr>
<th>Winters' Exponential</th>
<th>Estimation Period</th>
<th>Holdouts Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Abs Err</td>
<td>0.259</td>
<td>2.142</td>
</tr>
<tr>
<td>Root Mean Sq Err</td>
<td>0.388</td>
<td>2.286</td>
</tr>
<tr>
<td>Mean Abs Per% Err</td>
<td>5.39%</td>
<td>55.57%</td>
</tr>
</tbody>
</table>

Table 2 - Results of Winters' Exponential Smoothing Model on NG1 Prices

**Winters' Forecast and Original Observations for Henry Hub Natural Gas Spot Price (NG1)**

![Figure 40 - Winters' Forecast Compared to Original Observations (NG1 Prices)](image-url)
The optimal smoothing constants, $\alpha = 1.000$, $\beta = 0$ and $\gamma = 0$ intuitively mean that Winters’ model has reduced to a simple exponential smoothing model that reacts immediately to changes in level ($\alpha$). Given the high degree of error on the holdouts/validation set, this model does not seem appropriate for forecasting the prices. It is quite possible that there are additional lurking variables beyond the level, trend and season that need to be considered in order to accurately forecast natural gas prices.

2. **Winters’ Exponential Smoothing Model to Forecast Inventory Levels with Weekly Seasonal period**

Based upon weekly inventory data from October 1994 to October 2009 (790 data points), I have segmented the data into a training, validation (52 weeks) and forecast testing sets (52 weeks). Winters’ exponential smoothing method was applied with optimized parameters for $\alpha$, $\beta$ and $\gamma$ on a weekly seasonal period. The results are as follows:

<table>
<thead>
<tr>
<th>Forecasting Constants (Optimized)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level (Alpha)</td>
</tr>
<tr>
<td>Trend (Beta)</td>
</tr>
<tr>
<td>Season (Gamma)</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Winters’ Exponential Period</th>
<th>Estimation</th>
<th>Holdouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Abs Err</td>
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<td>304.93</td>
</tr>
<tr>
<td>Root Mean Sq Err</td>
<td>33.80</td>
<td>438.75</td>
</tr>
<tr>
<td>Mean Abs Per% Err</td>
<td>1.32%</td>
<td>10.07%</td>
</tr>
</tbody>
</table>

Table 3 - Results of Winters’ Exponential Smoothing Model on Inventory Levels
Winters' Forecast Errors for North American Natural Gas Storage Levels

The optimal smoothing constants, \( \alpha = 1.000, \beta = 0.401 \) and \( \gamma = 0.925 \) intuitively mean that we react immediately to changes in level (\( \alpha \)), but we react in a slower, dampened fashion to trend (\( \beta \)), and we react quite quickly to changes in the seasonal pattern (\( \gamma \)), albeit at a slightly dampened rate. It is important to acknowledge that physical constraints limit North American natural gas storage at approximately 4 Tcf\(^{39} \), which is not accounted for in the forecast of current Winters Model.

F. Multivariate Regression

To understand the variables influencing the weekly return of natural gas prices, I developed a multifactor regression model that incorporated a number of explanatory variables, including inventory Z-score, futures curve steepness (backwardated/contango), dollar index, volatility index (VIX), U.S. equities (SPX), MSCI World Equity index (MSDUWI), Gold spot return (GOLDS), Crude Oil spot (CL1) and U.S. Treasury interest rate steepeness (10 year - 2 year). I looked at a pairwise regression table of all available variables and attempted to eliminate highly correlated variables and thus avoid potential multicollinearity problems. The results of the pairwise correlation matrix of returns from 1994-2010 were as follows:

\[^{39}\text{http://tonto.eia.doe.gov/dnav/ng/ng}\]
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>US GDP 1Q</td>
<td>0.96</td>
<td>1.00</td>
<td>1.00</td>
<td>0.99</td>
<td>0.96</td>
<td>1.00</td>
<td>0.98</td>
<td>0.97</td>
<td>0.96</td>
<td>0.94</td>
<td>1.00</td>
<td>0.99</td>
<td>0.96</td>
<td>1.00</td>
<td>0.98</td>
<td>0.97</td>
<td>0.96</td>
<td>0.94</td>
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</tr>
<tr>
<td>US GDP 2Q</td>
<td>0.88</td>
<td>0.96</td>
<td>1.00</td>
<td>0.94</td>
<td>0.91</td>
<td>1.00</td>
<td>0.89</td>
<td>0.88</td>
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<td>0.93</td>
<td>0.89</td>
<td>1.00</td>
<td>0.92</td>
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<td>0.84</td>
<td>1.00</td>
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</tr>
<tr>
<td>US GDP 3Q</td>
<td>0.82</td>
<td>0.88</td>
<td>0.96</td>
<td>0.86</td>
<td>0.84</td>
<td>0.96</td>
<td>0.84</td>
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<td>0.96</td>
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<td>0.80</td>
<td>0.78</td>
<td>0.96</td>
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<tr>
<td>US GDP 4Q</td>
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<td>0.82</td>
<td>0.90</td>
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<td>0.74</td>
<td>0.90</td>
<td>0.72</td>
<td>0.70</td>
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<td>0.64</td>
<td>0.88</td>
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<td>0.71</td>
<td>0.88</td>
<td>0.74</td>
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<td>0.66</td>
<td>0.64</td>
<td>0.88</td>
<td></td>
</tr>
<tr>
<td>US GDP 1Q</td>
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<td>0.80</td>
<td>0.86</td>
<td>0.76</td>
<td>0.73</td>
<td>0.86</td>
<td>0.72</td>
<td>0.68</td>
<td>0.61</td>
<td>0.55</td>
<td>0.80</td>
<td>0.70</td>
<td>0.66</td>
<td>0.82</td>
<td>0.72</td>
<td>0.68</td>
<td>0.61</td>
<td>0.55</td>
<td>0.80</td>
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<tr>
<td>US GDP 2Q</td>
<td>0.80</td>
<td>0.85</td>
<td>0.90</td>
<td>0.76</td>
<td>0.72</td>
<td>0.90</td>
<td>0.71</td>
<td>0.67</td>
<td>0.59</td>
<td>0.52</td>
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<td>US GDP 4Q</td>
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<td>1.00</td>
<td>0.74</td>
<td>0.69</td>
<td>0.60</td>
<td>0.51</td>
<td>0.90</td>
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<td>0.75</td>
<td>0.90</td>
<td>0.74</td>
<td>0.69</td>
<td>0.60</td>
<td>0.51</td>
<td>0.90</td>
<td></td>
</tr>
</tbody>
</table>

Matrix (1994-2010)
The results of the initial regression were as follows:

### Table 4 - Multivariate Regression #1 Results

The regression has a high-adjusted R-Square of 88%, and is statistically significant with a p-Value <0.0001. However, a closer inspection of the explanatory variables reveals that only the intercept, inventory Z-score level, futures curve steepness and interest rate steepness are statistically significant at reasonable p-Values (i.e., even a liberal 25% threshold excludes all others except the S&P 500 Index). Accordingly, in the pursuit of accuracy and parsimony, I created a second, more streamlined model that included only inventory Z-score levels and the S&P 500 index return. I believe the SPX is influential for qualitative reasons, as it is a barometer of overall market sentiment, and thus economic demand for commodities like natural gas. The results of this second regression were as follows:

### Table 5 - Multivariate Regression #2 Results
With an adjusted R-Square of 53% and a p-Value of <0.001, this multiple linear regression with these explanatory variables serves moderately well to describe the return of natural gas, much beyond the influence of inventory levels.

G. Applying the Inventory Cycle Indicator to Understand Price Volatility

Comparing the timing patterns of when each of the four inventory cycles occurs during the year reveals fascinating information about the state of the market on a relative basis. This framework helps to explain some of the extreme price volatility of natural gas futures. For instance, in 2009, the year gave witness to dramatic price action and volatility, with prices ranging from $5.90 to $2.51/MMBtu, and 30-day historical annualized volatility peaking at 131%, a pinnacle not seen since 2003.

We can see that under this new inventory cycle stage classification metric that in 2009, the inventory withdraw period ended 2.6SD earlier (approximately 2.5 weeks) than is typical of the 1994-2002 period. Accordingly, the injection period started earlier than is typical, on the back of an over-supplied market.

**Standardized Inventory Cycle Statistics for 2009**
(Standardized relative to 1994-2007 Inventory Cycle Data)

![Standardized Inventory Cycle Statistics for 2009](image)

*Figure 43 - Z-Scored Inventory Cycle Stage Analysis for 2009*
Figure 44 - Inventory Cycle Stage Analysis for 2009

This inventory classification is helpful to uncover important nuances in the stage of the inventory cycle. As previously discussed, natural gas inventory levels can vary dramatically between years depending up a variety of factors, most interestingly exogenous demand shocks, such as weather (i.e., HDD/CDD demand), which is of our current interest. Now we will turn to the results of natural gas volatility, conditional on the state of inventory supply and the stage of the inventory cycle.

H. One-Way ANOVA of Market Supply Level and Rolling 20D Natural Gas Volatility

The underlying purpose of this research is to develop a deeper understanding through a statistical lens of the dynamics influencing the natural gas market, ultimately with the hope of developing better informed trading strategies. Unfortunately, the regression-based forecasting tool yielded less-than inspiring results. However, since an elegant mechanism to more intelligently trade the natural gas commodity on price along seems to be relatively intractable,
our attention turns to a mechanism for trading the volatility of natural gas prices, thereby speculating on natural gas volatility and not price forecasts.

This is relevant because NYMEX offers options to buy and sell futures contracts on natural gas for nearly all actively traded maturities. Embedded within an options premium is a level of volatility implied by the market. Options with higher volatility tend to command a higher premium because it is more likely that they will expire in the money. If one has a view that a natural gas contract will become more volatile, and this is not yet reflected in the options premium, then one can purchase options to simultaneously buy and sell the futures contract (i.e., a straddle trade). If the contract does in fact become more volatile, as anticipated, then the options will demand a higher premium and one gains on the increased volatility. This allows one to earn a profit by speculating on volatility while remaining agnostic to the direction of the underlying natural gas future's price.

Using one-way ANOVA analysis and a categorization of whether the market is over or under supply (based upon previous Z-Score analysis), I developed just such a potential strategy to speculate on natural gas volatility. The results of the ANOVA analysis are as follows:

![ANOVA: Box-Whiskers of Ratio of Announcement Day Sq. Ret. to Prior 2D Average vs. Market Level](image)

Figure 45 - Box-Whisker Plot of NG1 20-Day HVOL in Oversupplied vs. Undersupplied Markets
Table 6 - ANOVA Analysis Results for NG1 20-Day HVOL in Oversupplied versus Undersupplied Markets

<table>
<thead>
<tr>
<th>Categorization</th>
<th>Mean Value of Ratio of Announcement Day</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Squared Returns to Prior 2-Day Average</td>
</tr>
<tr>
<td></td>
<td>Squared Returns (p-Value = 0.0039)</td>
</tr>
<tr>
<td>Over-Supplied Market</td>
<td>7.55</td>
</tr>
<tr>
<td>Under-Supplied Market</td>
<td>14.35</td>
</tr>
</tbody>
</table>

With statistical significance, we can conclude that when the natural gas market is undersupplied, the Henry Hub Natural Gas futures contract (NG1) becomes nearly *twice* as volatile.
V. CONCLUSION

In answering the central objective, I find that the volatility of natural gas futures is highly conditional on the season and even more so on the level of the natural gas in inventory. I further find that the degree of volatility is inversely correlated to analyst accuracy at forecasting inventory levels. Analysts exhibit the same degree of seasonal accuracy.

Expanding upon this, I find that in the extremes of the inventory cycle (i.e., near peak injection/withdraw) that variance is particularly strong, and significantly higher than non-announcement days. The high announcement day volatility reflects larger price changes. With statistical significance, we can conclude that when the natural gas market is under-supplied, the near-term Henry Hub Natural Gas futures contract becomes nearly twice as volatile than in an oversupplied market. Furthermore, analysts are more prone to make errors in their estimates of weekly inventory levels around these same time periods.

Stepping back for a moment, it is essential to acknowledge the limits of this research. There are extreme challenges with modelling an asset as complex as natural gas. As (Lo & Mueller, 2010) acknowledged, we must ask whether markets and investors are driven primarily by emotions, such as fear and greed, that cannot be modeled, or is there some "method to the market's madness" that can be understood through quantifiable means. We know that human behavior is not nearly as stable nor as predictable as physical phenomena. Accordingly, while the systematic, quantitative approach to solve financial problems has yielded significant advances for society, it is important to acknowledge that we cannot rely fully on our modelled perception of the world. Accordingly, I take that same heed of caution here.

As a suggestion for general improvements into future research, it would be a worthwhile endeavor to look at higher-frequency intra-day intervals to analyze how the higher announcement day volatility is realized on a microstructure level. For instance, I would seek to understand if volatility is actually a reflection of more price changes as opposed to just larger price changes. As (Ederington & Lee, The Short-Run Dynamics of the Price Adjustment to New Information, 1995) point out with respect to the fixed income and FX markets, the distinction is important because if the price jumps from an old to new equilibrium in only a few trades (i.e., bigger jumps as opposed to more changes), then it could have interesting implications for understanding the efficiency of the natural gas futures
market. As they discovered, the increased volatility following macro announcements are due primarily to more frequent price changes, and only secondarily to larger price changes. It is important to address the information flow process itself: what is the speed and efficiency with which natural gas markets adjust to new information. While this is challenging without high-frequency intra-day data, we can infer some general understanding as suggested by Ederington and Lee for other futures markets. Specifically, volatility tends to remain high after a news release, either because of slow price discovery or because additional information continues to flow into the markets. Accordingly, there are two possible reasons for slower information flow:

1. Details of the announcement take time to absorb and the focus of the market is more immediately on the headline numbers.

2. It takes time for traders to understand the full implications of the news announcement in a longer-term, more macro context.

I have found from anecdotal evidence from conversations with several natural gas traders, that it is this second component, of understanding the broader implications, that can occupy a bulk of their focus. This is particularly the case in the peak cycle periods of injection/withdraw months when they are trying to infer the turning points in the market.

If markets adjust slowly, returns within this adjustment period should likely be positively correlated. However, as previously mentioned, there is evidence of statistically significant negative autocorrelation (mean reversion) in the 1 day lagged returns of NG1 - NG6 futures contracts, albeit small in amplitude, followed by positive autocorrelation (trending) in day 2 lags. This might indicate that natural gas futures markets adjust quickly and efficiently in the very short-run.

From these results, it is also important to address how natural gas is different from other commodities. For instance, comparing natural gas to Roll’s work on orange juice futures, we note that even compared to natural gas, orange juice has great seasonality. The production cycle with orange juice is fundamentally different from natural gas, which is a "flow" commodity. Therefore,

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41 The data availability of this project allowed for only several months of high-frequency intra-day natural gas futures prices. The author believed that the time period was too short to draw meaningful and significant statistical conclusions for a larger time period, and thus only end-of-day data has been examined.
weather shocks with natural gas are inherently less permanent because of its well-developed inventory buffer that helps to dampen the effect.

Comparing natural gas to other parts of the energy complex, such as in (Pindyck 2001, 2004; Ye 2005, Susmel 1997; Movassagh 2005), we note that with petroleum products (e.g., CL, RBOB, MOGAS), due to their sources of production, supply shocks are far more prevalent because of geopolitical factors. However, geopolitical instabilities are a less relevant concern for the North American natural gas market.

Looking at these results more abstractly through a theoretical lens, I believe that the Adaptive Markets Hypothesis ("AMH"), as first introduced by (Lo, 2004) can offer invaluable insight into understanding this view of the natural gas market. AMH takes a biological, not physical view of the market whereby individuals act in self-interest, make mistakes, learn and adapt, and compete to drive adaptation and innovation. Ultimately, under AMH, natural selection shapes the market ecology leading evolution to ultimately determine the market dynamics.

We can perhaps understand the conditional volatility response and propensity for analyst’s errors in estimating inventory levels as a natural extension of the Adaptive Markets Hypothesis. For instance, power producers have a commitment to their customers to deliver an uninterrupted supply of energy, and will accordingly take necessary measures to secure their access to natural gas inventories. Hence power producers serve as agents of demand for natural gas, acting in their own self-interest, competing against other power producers. In order to survive, the must learn to adapt their natural gas inventory management against an every changing, highly variable market that is heavily influenced by the exogenous shocks of weather. An error in any given winter might lead to inadequate inventory supply, which is a fatal mistake. Applying AMH from a different perspective, we can also assume an evolutionary “survival of the fittest” around the quality of analysts estimating inventory reports. It would seem reasonable to assume that the inaccurate analysts are ultimately weeded out from the stronger, more accurate ones.

Bringing all of these points together, it is important to appreciate the broader context. Natural gas is an essential natural resource and is used in myriad aspects of the global economy and society. The EIA, in conjunction with the Oil and Gas Journal and World Oil publications, estimates world
proved natural gas reserves to be around 6,254 Tcf.\textsuperscript{42} 41% of the world total reserves are located in the Middle East, and with Europe and the former U.S.S.R. holding 32%. However, it is believed that with the possible recovery associated with North American shale gas, that the U.S. may have upwards of 1,748 Tcf of technically recoverable gas. As we look to develop more sustainable energy policies, North America’s abundant clean-burning natural gas will hold an essential role in helping us to secure our future energy independence. An ability to understand the factors influencing it is supply and demand, and thus price, are and will continue to be essential.

As one North America’s most prolific energy resources, natural gas markets are highly influenced by several factors, most notably the supply-demand dynamics of inventory levels, erratic weather patterns, and industrial demand. Interestingly, all three of these factors are simultaneously at historically unprecedented stress points: natural gas storage levels are coming in from record capacity thresholds, a potentially severe hurricane season looms in the distance and industrial demand, largely from chemical and fertilizer produces, remains at anemic levels due to one of the worst economic recessions since the Great Depression. Any one of these scenarios in their own right could have due influence on the price of natural gas markets, however, it is the confluence of factors that has led to such heightened volatility in this market. We have shown that statistical techniques can help us to better understand the dynamics of this commodity’s volatility, and may potentially offer value-added investment opportunities.

\textsuperscript{42} \url{http://www.naturalgas.org/overview/resources.asp}
VI. BIOGRAPHICAL NOTE

The author is a M.B.A. graduate student at the MIT Sloan School of Management, enrolled in the Track in Finance and with a degree in electrical engineering from Columbia University. He previously worked at Goldman Sachs as an analyst in the Hedge Fund Strategies and Alternative Capital Markets group, where he conducted quantitative research, risk modeling, marketing and served as a lead for an investor relations team on two of the Firm's fundamental equity and credit hedge funds. He recently became a top-5 finalist in the CFA's 2010 Global Investment Research Challenge ("IRC") and is currently preparing for the CFA Level I exam. After graduating from MIT Sloan, he will return to Goldman Sachs in the internal hedge fund, Liberty Harbor, which resides within the U.S. Corporate Credit team. There, he will be involved in quantitative and statistical methods for trading convertible bonds and volatility arbitrage as well as in performing fundamental investing across capital structures.
VII. REFERENCES


