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AN ANALYSIS OF NATURAL GAS COMMODITY ANALYST FORECASTING AND NATURAL GAS MARKET PRICES

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ABSTRACT

The thesis explores the effect commodity analyst's forecasting rank and ability has on the natural gas market. The thesis examines first how the market prices the natural gas commodity in regards to analyst estimates. It answers the question on whether the market prices the commodity based on the mean of the analyst estimates or the markets view of a "top analyst." Secondly, the thesis explores if analysts forecasting ability gets better through time and if the analyst tend to turnover if their forecasting ability does not improve. Finally, the thesis explores a trading strategy based on the market's view of a top analyst and compares the return against a benchmark. The thesis finds that the market prices respond more to the mean analyst estimate, rather than the markets view of a top analyst estimate. The paper also finds that relative forecasting ability does tend to get better with time otherwise the analysts tend to turnover. Finally, the paper identifies that a trading strategy based on the market's view of the top analyst is not viable.

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Chapter 1

Introduction

The commodities market is a multi-trillion dollar industry representing raw to primary materials and products. The commodity exchanges trade goods from minerals, plastics, metals, livestock, energy products, to organic chemicals (International Trade Centre 2013). Most commonly, Producers, manufactures, and traders trade these commodities via futures contracts on these exchanges. A futures contract is "…a contract between two parties in which the buyer agrees to accept delivery of a particular commodity at a specific price from the seller and in a designated month in the future if the commodity is not liquidated before the contract reaches maturity" (Spurga 2006). The prices of these contracts respond efficiently to market news.

An important aspect in pricing these commodities are the supply and demand of the commodity. As the supply of a commodity rises, the futures contract tends to decrease. As the demand for a commodity rises, the futures contract tends to increase (TradingCharts.com 2014). In some markets, Analysts produce forecasts on commodities supplies before actual reports are released. Specifically in Natural Gas, the U.S. Energy Information Administration (EIA) releases a weekly natural gas storage report. The EIA report outlines the amount of natural gas supplies around the United States. In this case, traders incorporate these analyst forecasts and EIA report releases when pricing the natural gas futures contracts.

In this thesis, I wish to explore the effect commodity analyst's forecasting rank and ability has on the natural gas market when these reports are released. First, I wish to explore how the market responds to analyst estimates. Does the market price the commodity based on a mean analyst estimate or on what the market views as a top analyst? Second, I wish to explore analysts forecasting ability by tracking their relative forecasting accuracy through time. I answer if analysts forecasting ability get better through time and do analyst turnover for poor relative performance. Finally, I wish to explore a trading strategy I develop, test it utilizing closing prices for a one-month natural gas futures contract, and compare the returns to a benchmark. From exploring these questions, the paper might be able to provide knowledge about how analysts perform relative to others, how the market utilizes forecasts in pricing a commodity, and how one can utilize an analysts reputation to develop a trading strategy.

Chapter 2

Literature Review

Analyst Reports on Commodities

Analysts routinely make reports about various asset classes and publically release their expectations of different asset performances. In the stock market, equity analysts make estimates on stocks and investors utilize this information to make investment decisions. It was a commonly held belief decades ago that bonus compensation for equity analysts were determined based on an analyst's ability to accurately predict a stock's movements. This is because research conducted by Brown (1987) & Fried (1982) found that analyst market expectations were more accurate than time-series models. Brown found that their superiority was attributed to a better utilization of information and use of information acquired between the date of initiating the time-series model and the date when the forecasts are published (Brown and Hagerman 1987). Fried found that the analyst expectations are most closely a measure of market expectations (Fried and Givoly 1982). Their forecasts are better to identify market performance and expectations than a time series model.

However, a Forbes Magazine article reported that "Time was when analysts were paid a salary and bonus based on trading revenues generated by their recommendations. Today most of an analysts compensation derives from investment banking revenues — fees earned from initial public offerings, secondary issues, debt offerings, even mergers and acquisitions" (Morgenson 1997). Bonus structures were not based on an analyst's ability to predict movements of equity. Mikhail (1999) investigated this statement further in his research looking at if accuracy of a forecast matters to the security analyst by developing a ranking scheme and looking at the turnover of an analyst.

I look at Mikhail's (1999) paper titled "Does Forecast Accuracy Matter to Security Analysts?" to explore forecast accuracy in analyst. Mikhail (1999) looks at several papers and finds that the information in the market place showed that an analyst's bonus is tied to an analysts's ability to generate more investment and trading volume for the brokerage house he worked for. This leads one to believe that an analyst would focus on generating skewed estimates in order to generate more business for the firm thus increasing the bonus for the analyst. Mikhail (1999) finds that "prior research provides no direct evidence that analysts have incentives to improve their forecast accuracy" (Mikhail 1999).

Mikhail (1999) conducts research looking at the correlation between an analysts ranking and turnover rate. Mikhail's (1999) ranking scheme provides a basis for ranking analyst estimates. Mikhail (1999) obtains quarterly forecast estimate data for 5,434 analysts and actual stock performance data. Mikhail (1999) adds a "turnover" attribute from 0 to 5 depending on an analyst's unique identifier code vs the firm code. To measure forecasting ability, he uses an absolute (proximity of the analyst forecast to actual earnings) and a relative (proximity of the forecast to the earnings realization relative to peer analysts) accuracy measure (Mikhail 1999). To calculate the absolute measure, he calculates the mean absolute percent error of the forecast to the actual. This gives a percent error score. Then, Mikhail (1999) calculates the relative accuracy measure. He ranks the analysts absolute percent error giving a rank from 1 to n with n being the total number of analyst making forecasts. He then divides the rank by n. This gives a range of possible relative scores from 1/n to 1. He develops this ranking scheme and compares different sets of groups to each other to get summary statistics (Mikhail 1999).

In his research, Mikhail (1999) concludes that analysts with no turnover had a better rank score in comparison to those who turned over more often. Mikhail (1999) interprets his findings to say that forecast accuracy matters to analyst relative to other analysts (Mikhail 1999). These findings however are different from commodity analyst predictions because the variables and/or information one utilizes to compute these predictions are extremely different. Mikhail (1999) provides a basis for this thesis. However, this thesis extends the research by applying the methodologies to the commodities market, exploring market dynamics in regards to analyst estimates, and tests a viable trading strategy utilizing the forecasting ability.

Commodity Market Dynamics

The commodities market is quite different from the equity markets. I give an overview of the commodity market dynamics and how those motivate a discussion on applying Mikhail's (1999) research methodology when looking at commodity analyst's forecasting ability: Humans have traded goods since civilization started. In the early days of civilization, humans traded goods for other goods. For example, person A would trade Good A to person B for Good B. This mode of trade often created opportunities for unfair trades and/or the inability to sell or buy a portion of a good. So, coined money soon was used to represent value. As trading continued and merchants started to become more sophisticated, merchants were forced to sell goods with their delivery being at a future date to increase business, because the merchant would sell out their inventory. Thus, the futures contract was born. "For over 300 years, commodity futures contracts were used. Merchants and processors of food would bid for a farmer's crop before or after planting"(Spurga 2006). In these types of contracts, the prices of future products are fixed, giving both parties protection against shifts in prices. This important aspect of commodity futures contracts still hold today (Spurga 2006).

Today, commodities are largely traded on "commodity exchanges."

> "A commodity exchange is an organized market of buyers and sellers of various types of commodities. It is public to the extent that anyone can trade through member firms. It provides a trading place for commodities, regulates the trading practices of the members, gathers and transmits price information, inspects and governs commodities traded on the exchange, supervises warehouses that store the commodity, and provides means for settling disputes between members." (Spurga 2006)

Commodity exchanges ensure fairness in the market place be regulating most aspects of the trade. The commodity exchanges specifically trade futures contracts instead of the spot market. The commodity markets are an important aspect of this thesis because the exchanges ensure fairness in the market place and allow commodities traders to enter into a position with minimal barriers to entry. The market price of the futures contract on the exchange will help formulate the trading strategy developed in the latter part of this thesis (Spurga 2006). Table 1 highlights the six major commodity exchanges markets housed in the United States.

Table 1. Major Commodity Exchanges (Spurga 2006)

Major Commodity Exchange	**Commodities Exchanged**
Chicago Board of Trade (CBOT)	Wheat, corn, soybeans, soybeal meal, soybean oil, iced broilers, silver (5,000 ounces), plywood, oats, gold, Ginnie Maes, commercial paper, Treasury Bonds, and Treasury Notes
Chicago Mercantile Exchange	Live cattle, fresh eggs, live hogs, lumber russet potatoes, pork bellies, turkey, stub lumber, feeder cattle, and iced broilers
International Monetary Market	Division of Chicago Mercantile Exchange, trades currency and interest rates futures
New York Mercantile Exchange (NYMEX)	Crude oil, natural gas, heating oil, gasoline, silver, copper, aluminum, platinum, and palladium
New York Board of Trade (NYBOT)	Coffee, cocoa, cotton, sugar, and orange juice commodities
Mid America Commodity Exchange (MIDAM)	Affiliated with CBOT trading grains, silver (1,000 ounces), silver coins (5 bags, $1,000 each), gold (1 kilo), hogs (15,000 lbs.), and cattle (20,000 lbs.)

The table summarizes the major commodity exchanges and the commodities exchanged in those major exchanges.

Futures contracts are quite different from equities. I define a futures contract as "…a contract between two parties in which the buyer agrees to accept delivery of a particular commodity at a specific price from the seller and in a designated month in the future if the commodity is not liquidated before the contract reaches maturity" (Spurga 2006). Some think futures contracts are like options, however, the contracts are different from an option in that one entering into a futures contract is required to perform delivery or receipt the entire way through. However, a futures contract investor is able to "remove" the contract from his book by executing a reversal in which the investor takes the opposite position in another futures contract. The exchange will automatically net the positions of the investor leaving the investor with no obligation in a futures contract and profit or loss due to the transactions. Only about 3% of all contracts are actually physically delivered (Schwager 1984). This will be important when developing the trading strategy in the latter part of this thesis.

Mikhail's (1999) paper motivates the discussion for researching commodity analyst's forecasting ability because the paper provides a viable methodology that can be used to evaluate forecasting ability in analysts. The methodology applied to commodity analyst forecasting ability may develop a different outcome from the findings of Mikhail (1999) because future contracts are different from stocks, bonds, and other well-known assets. The differences are that commodities are securities that derive their value from other securities, they are not claims on a corporation or entity, the maturity is small on real assets, and many commodity futures respond to seasonality. They are also quite different from real assets in that the value of future contract at the time of inception is zero. Commodity futures do not allow firms to raise resources. Instead, future contracts are a type of insurance to keep the same price for the investors on both sides of the contract (Gorton and Rouwenhorst 2006). This paper also further extends Mikhail's (1999) analysis by exploring commodity market dynamics as related to forecasting ability and tests a potential trading strategy utilizing the conclusions made in the earlier analyses.

Analysis of Natural Gas

To test forecasting ability in the commodities market, I look at the natural gas market. Natural gas is a fossil fuel that is valuable due to its ability to burn cleanly and provide high levels of energy in a relatively low amount of mass. Natural gas has been used since 500 BC when the Chinese forced the gas through pipes to distil drinking water. Britain first used natural gas commercially in the late 1700s to light streetlamps. It was not until the early 1800s, however, when William Hart dug into a well specifically to extract natural gas (Spurga 2006). Today natural gas is extracted by drilling into naturally occurring pockets in the rock layer and extracting the gas released. The United State uses the gas in the generation of power, heating, cooking, transportation, aviation, and other manufacturing processes.

Demand for natural gas is cyclical. There is a higher demand for natural gas in the winter months than in the summer months since natural gas is used to heat homes and buildings. The economy also plays a factor with the demand of natural gas. In a bullish economy, the demand for natural gas is high because companies with manufacturing plants produce more. In a bearish economy or recession, the demand is lower because companies will manufacture less in order to save money on production or lower demand for products.

In regards to the supply, a majority of the natural gas supply comes domestically. This is because natural gas is transported most efficiently via pipes running from the production site to the various users of natural gas. For example, Penn State is currently running a large capacity pipeline from the Marcellus Shale natural gas deposit. The university cannot get it trucked in due to high transportation cost. As a result, foreign natural gas markets have little effect on the United State natural gas market.

Weather and other drilling conditions affect futures contract prices because these factors affect the change the natural gas storage supplies. Therefore, the futures contract prices on the commodity are often affected weekly by storage reports that the U.S. Energy Information Administration (EIA) releases weekly. The EIA usually releases the natural gas reports around 10:30AM weekly on Thursdays reporting the natural gas storage around the different regions of the United States. The EIA "collects, analyzes, and disseminates independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment" (EIA 2014). The EIA is an independent governmental agency dedicated to providing statistics and information to the market place. Analysts from different banks and institutions make weekly estimates on what the EIA natural gas storage reports will be for the week. Investors can utilize these estimates and make trades based on their prediction on whether or not the estimates are over or under estimated. This relationship is what I am exploring in this thesis by applying the concepts learned in Mikhail's (1999) paper to rank analysts and explore their "rank scores."

Chapter 3

Results & Analysis

Summary Data Statistics

The data set includes the actual storage reports released by the EIA, 28 analysts and their weekly forecasts of the storage reports, by 28 analyst and daily natural gas futures closing prices. Appendix A to discover where the data are sourced from. Table 2 describes the summary statistics yearly for the Actual storage reports and the mean analyst estimate of the storage report.

Table 2: Yearly Average Actual and Mean Estimate Storage Report

Yearly Average Actual and Mean Estimate Storage Report

Year of Date	Avg. Actual Storage Report	Avg. Analyst Mean Estimate
2004	2,182.5	2,168.0
2005	2,284.0	2,282.0
2006	2,635.7	2,635.0
2007	2,592.8	2,592.0
2008	2,376.3	2,374.7
2009	2,779.5	2,779.1
2010	2,757.9	2,757.5
2011	2,669.3	2,669.2
2012	3,159.2	3,159.5
2013	2,794.9	2,795.3
2014	2,895.5	2,888.3

Avg. Actual Storage Report and Avg. Analyst Mean Estimate broken down by Date Year.

Table describes yearly average actual data and analyst mean estimate for natural gas storage reports.

Figure 1 visualizes the data in Table 2 monthly and describes the average actual vs. mean storage report estimate for the first two years in the data set relationship.

Figure 1: Actual Vs. Mean Estimate Storage Report

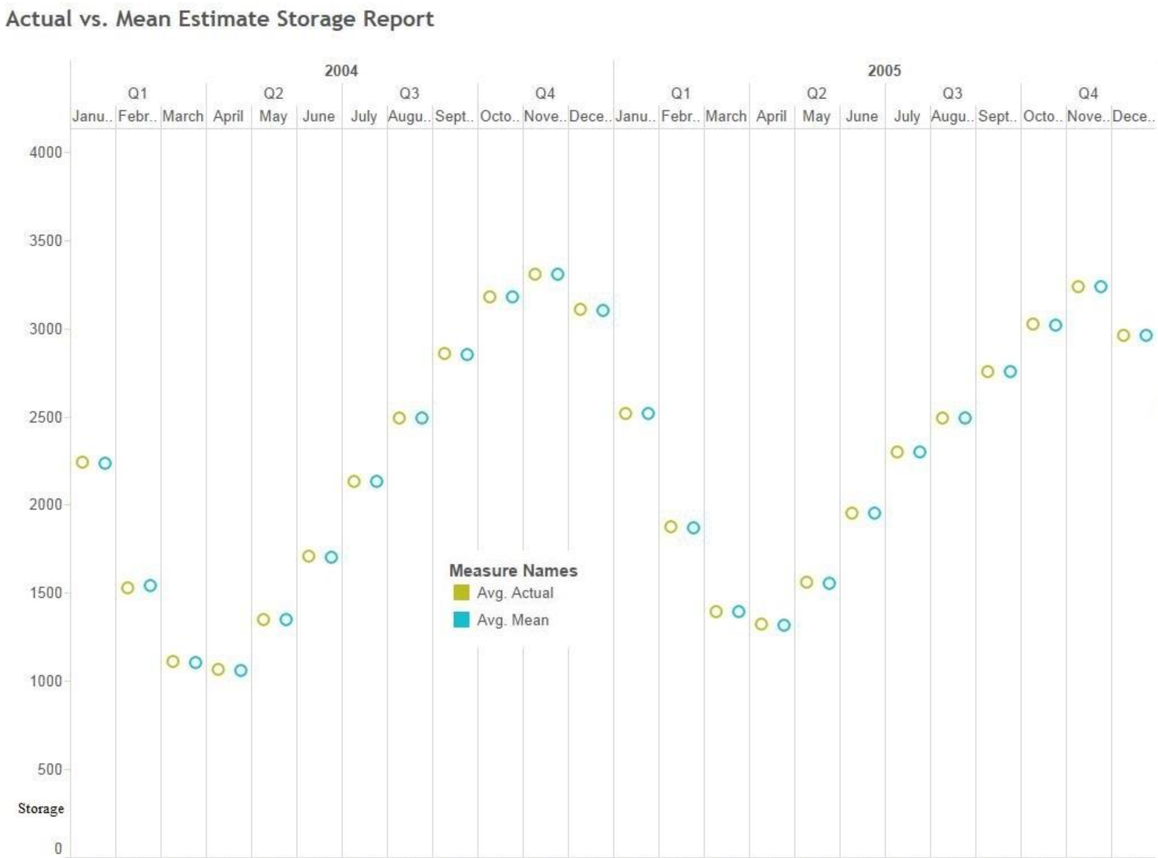

Figure 1 shows monthly average of actual vs. mean estimates for natural gas storage reports for 2004 and 2005.

The data in Figure 1 shows a cyclical change in natural gas storage production. Additionally, the graph shows the actual storage figures do sometimes differ from the mean estimate. This difference in the mean estimate and analyst estimate could explain the price changes after a storage report release. Figure 2 describes the price movements of the natural gas commodity of one-month futures between 2003 and 2014.

Figure 2: Daily Closing Price for Natural Gas 1 Month Continuous Futures

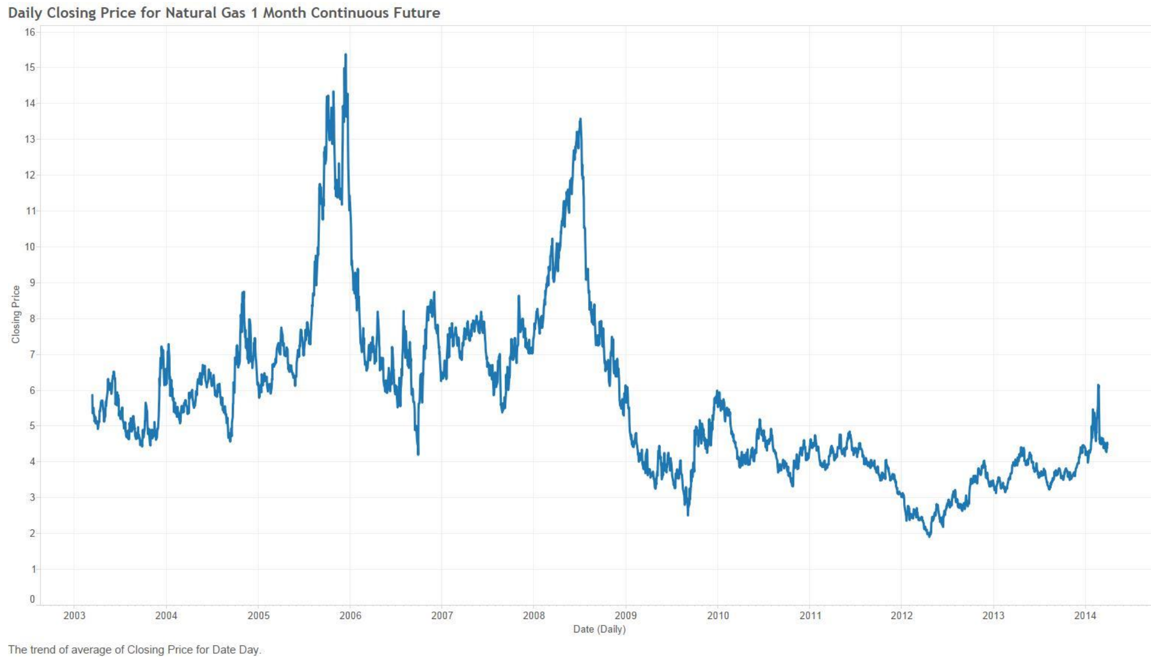

Figure 2 describes the price path of a 1-month continous natural gas futures ticker from 2004 to 2014.

In Figure 2, I see high variability in the pricing, especially around storage report releases. As a result, I would like to explore how much of the price variability around these storage reports are explained by analyst estimates of natural gas storage for the week.

Regression Analysis

I want to look at how the market prices a commodity before a storage report release. I examine the question: "Does the market price the commodity based on the mean analyst estimate?" Further, I wish to compare the result to see if the market prices are better explained by the markets view of the top analyst estimate. To test this, I conduct a regression analysis to compare the difference of the market closing prices (before and after the storage report release) and the difference of the actual storage reports to the analyst estimates (one regression for the mean estimate and one regression for the top analyst). In the data set, I bring in the weekly closing market prices for the day of the report release, the closing market prices for the day prior to the report release, the mean estimate of the storage report release, and the top analyst's estimate as determined by the trading strategy explained later in the thesis. I transform the data to calculate the daily return of the market prices, the percent error between the actual storage report release and the mean analyst estimate, and the percent error between the actual storage report and the top analyst estimate with the top analyst identified by the trading strategy above. I cleansed the data for any records where the top analyst estimate was not available for the week. First, a regression runs between the market price returns (Y variable) and the percent error of the actual to mean estimate (X variable). I compare the regression between the market price returns (Y variable) and the percent error of the actual to top analyst estimate (X variable).

I look at X coefficient, p-value, and R-square value from the regression analysis to access the statistical relevance. For both regressions, the first test is to see if the X coefficient is negative. The X-variable coefficient should be negative because I expect that if the actual storage report is greater than the estimates, then the market price should decrease since the supply of natural gas is higher than expected. This negative relationship is should reflect in the regression analysis. I expect that the actual vs. mean estimate regression better explain price movements in the data set. If the market bases the pricing of commodity solely on the mean analyst estimate, then I expect that the p-value for the actual vs mean estimate regression should be zero and the R-squared value should be 100%. The p-value is testing the null hypothesis that the X variable coefficient is zero. A low p-value indicates that the null hypothesis is rejected. For the analysis purposes, we reject the null hypothesis for any p-value less than 0.05. The R-square value determines the percent of variable variation that is explained by the liner model. If the market perfectly prices based on the mean estimate, then the R-squared value should be 100%. If the market perfectly reflects the mean estimate, then the regression analysis of the actual vs top analyst estimate indicates a greater p-value than the actual vs mean estimate regression. Further, if the actual vs. mean estimate regression indicates a 100% R-squared value, then the actual vs. top analyst estimate regression should indicate a R-squared value less than 100%.

These expectations are best-case scenarios; however, I do not expect the actual vs. market estimate regression to indicate the best case results. This is because I used end of day prices and the market responds to other variables when pricing the commodity and the market prices used incorporates that extra noise. I expect that the actual vs. mean estimate regression should indicate a higher R-squared value and a lower P-value than the actual vs. top analyst estimate regression.

Table 3 indicates the regression output for the Actual vs. Mean Estimate regression results.

Table 3: Actual vs. Mean Estimate Regression

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.3456							
R Square	0.1194							
Adjusted R Square	0.1174							
Standard Error	0.0352							
Observations	445							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.07428	0.07428	60.08720	6.27257E-14			
Residual	443	0.54761	0.00124					
Total	444	0.62189						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.00087	0.00167	-0.52215	0.601827042	-0.004154	0.002410	-0.004154	0.002410
X Variable 1	-3.40677	0.43949	-7.75159	6.27257E-14	-4.270522	-2.543021	-4.270522	-2.543021

Table 3 is a summary output of a regression analysis run between the return of the daily closing price before and after a natural gas storage release with the percent error of the mean analyst estimate of the storage reports.

The X-variable coefficient for the regression indicates a negative coefficient. The p-value is 6.2 E-14. The p-value is less than 0.05 indicating that the null hypothesis for the X-variable coefficient is rejected and that the X-variable coefficient of -3.41 is accurate. Finally, the R-squared value indicates that this regression explains 11.9% of the market returns. This value seems low; however, given that the data set incorporates a lot of noise due to using daily closing prices, the value is expected. It is more important to look at these values and compare them to the actual vs. top analyst estimate regression analysis. Table 4 indicates the regression output for the Actual vs. Top Analyst Estimate Regression.

Table 4: Actual vs. Top Analyst Estimate Regression

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.2538							
R Square	0.0644							
Adjusted R Square	0.0623							
Standard Error	0.0362							
Observations	445							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.04006	0.04006	30.49805	5.7054E-08			
Residual	443	0.58183	0.00131					
Total	444	0.62189						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.00159	0.00172	-0.92702	0.354423276	-0.004969	0.001784	-0.004969	0.001784
X Variable 1	-2.29453	0.41549	-5.52250	5.7054E-08	-3.111106	-1.477961	-3.111106	-1.477961

Table 4 is a summary output of a regression analysis run between the return of the daily closing price before and after a natural gas storage release with the percent error of the top analyst estimate of the storage reports.

The X-Variable coefficient is consistent with the actual vs. mean estimate regression in that the value is negative. The p-value is 5.705 E-8. The p-value is less than 0.05 indicating that the null hypothesis that the X-variable coefficient equals zero is rejected and that the X-variable coefficient of -2.29 is different from zero. The R-squared value is 6.44% indicating that 6.44% of the price movements are explained by the top analyst's estimate.

Comparing the two regressions, I find that the p-value for the actual vs. top analyst estimate regression is greater than the p-value for actual vs. mean estimate regression analysis.

Looking at the R-squared value, there are differences between the two analyses. The R-squared value in Table 4 of 6.44% is almost half the R-squared value in Table 3 of 11.94%. This is significant because the comparison of the regression analysis is saying that the market pays more attention to the mean analyst estimate than the top analyst estimate when pricing the commodity. If the analysis is better able to remove the daily price noise by utilizing intra-day prices, I expect that the R-squared values for both will drastically increase; however, I still expect with a high level of certainty that the R-squared value will be greater for the actual vs. mean estimate regression than that of the actual vs. top analyst regression analysis. When looking at the data set, a question arises on whether or not analyst estimates get better with more experience.

Do Commodity Analyst Estimates Get Better with More Experience?

Next I test if seniority played any role in an analyst being able to forecast the Natural Gas storage estimates. In Mikhail (1999), they conduct prior research and find a correlation between an analysts forecast ability and the prior experience in forecasting (Mikhail 1999). They test this assumption and find the correlation utilizing equity analysts. I wish to test if this also holds true for the commodities market, specifically looking at Natural Gas storage estimates.

To complete this analysis, I find a measure of accuracy. In Mikhail's (1999) paper testing equity analysts, he tests the relationship between *absolute* and *relative* forecasting ability. Absolute forecast ability looks at the error between an analyst's forecast and the actual outcome. Mikhail (1999) used a basic percent error measure to calculate the absolute forecast error reflecting the following equation:

$$Absolute\ Forecast\ Ability = \frac{|Estimated\ Forecast - Actual\ Forecast|}{Actual\ Forecast}$$

Relative forecast ability looks at the absolute forecast error compared to other analysts. Mikhail's (1999) results find the absolute forecast ability for each analyst for each report and then ranked each analyst for each period from 1 to n, with n being the total number of forecasts during that period. Because the number of reports per period varies, Mikhail (1999) divides the rank number by n, which I call RANK_SCORE. The RANK_SCORE varies from 1/n to 1. A lower RANK_SCORE indicates a better relative forecasting ability. After looking at the data set, Mikhail (1999) finds that analyst accuracy matters in regards to relative forecast ability and not absolute forecast ability.

For our methodology, I take the data set and find the absolute forecast ability for each analyst, which I call the mean absolute percent error (MAPE). From the MAPE, I rank utilizing the "=rank()" function in excel. A rank of one corresponds to the analyst that had the lowest MAPE. I then utilize the "=COUNTA" feature to get the number of forecasts made for that period (n). I divide the analyst's rank by n and find the rank score. To perform the analysis year by year, I slice the dataset into ten separate sheets each reflecting one year of data. I take the average RANK_SCORE for each analyst per year and formulated a date table. Table 5 shows the average RANK_SCORE for each analyst yearly.

Table 5: Average Rank Score for Each Analyst

Analyst Name	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Anthony Yuen									0.4534	0.4452
Bill Featherston	0.6157	0.5815	0.5626	0.4224	0.5839	0.5553	0.5923	0.6217	0.5750	0.5183
Cameron Horwitz					0.4444	0.4716	0.3828			
Daniel Biegler								0.3859	0.4319	0.5333
David Tameron			0.8116	0.5593	0.5939	0.5324	0.6912	0.6669	0.4347	0.4259
Donald Murry	0.6498	0.5595	0.5735	0.6848	0.7474	0.6293	0.7787	0.7232	0.7416	0.7793
Drew Wozniak		0.6636	0.6253	0.5427	0.5340	0.5787	0.5155	0.4528	0.4587	0.5370
Ed Kennedy/Tom Saal	0.5469	0.5325	0.5427	0.6136	0.5213	0.4427	0.6530	0.5440	0.6428	0.6378
Edward Kott						0.4688	0.4472	0.3571		
Edward Lutz	0.4782	0.4841	0.4820							
Jeremy Friesen						0.3884	0.4446	0.4581	0.5195	0.4247
Jim Duncan	0.4468	0.4923	0.5728	0.3833	0.4526	0.4761	0.3587	0.5249	0.4585	0.3882
Joe Allman	0.5372	0.5172	0.6299							
John Gerdes			0.3636	0.4567	0.4191					
Kent Bayazitoglu			0.4526	0.5263	0.6268	0.6516	0.5361	0.4969	0.6992	0.6734
Kyle Cooper	0.4463	0.4130	0.4779	0.3681	0.3551	0.4586	0.3677	0.4948	0.4135	0.4397
Laurent Key										
Lloyd Byrne	0.4793	0.4974	0.4585	0.5292	0.6381	0.4286				
Marshall Adkins	0.5367	0.5288	0.5222	0.4798	0.4722	0.5845	0.5440	0.4830		
Michael S. Haigh				0.3475	0.3325					
Robert Morris	0.5751	0.5165	0.5797	0.6327	0.8440					
Ron Denhardt							0.4981	0.4329	0.4467	0.9333
Samantha Kong								0.4383	0.3896	0.3423
Scott Young									0.3881	0.4888
Scott Hanold			0.4489	0.5276	0.5837	0.4719	0.3826			
Scott Speaker		0.3586	0.3648	0.3633	0.3922	0.3729	0.3946	0.3788	0.4463	0.3895
Sriram Vasudevan						0.4733	0.5182	0.6447		
Stefan Revielle								0.4857	0.4798	0.4582

Table 5 is a yearly average rank score summary for each analyst. The rank score is determined by finding the percent error of the analyst's forecast with the actual forecast, ranking the forecasts from 1 to n (1 being the top and n being the number of forecasts for that report) and dividing the rank by n to get the rank score.

If my analysis is consistent with Mikhail's (1999) research on equity analyst's relative forecasting ability, then we expect three outcomes in the data. First, analyst's forecasting ability will increase by continually improving their RANK_SCORE. Second, analyst will rarely turnover if their forecasting ability improves. Third, analysts who do not improve their RANK_SCORE will turnover more often. If the data does trend towards the three conclusions, I can say that Mikhail's (1999) research on equity analyst forecast also appear to be the case for natural gas.

I transform the data set into a visualization showing the trend of the average estimate over each year. I then remove the data set for each analyst who only had two or fewer yearly data points.

Figure 3 is a visualization of the data set for each analyst separately each year. The lower the position of each bar on the graph, the better the average RANK_SCORE is.

Figure 3: Visualization of Yearly Analyst Rank Score

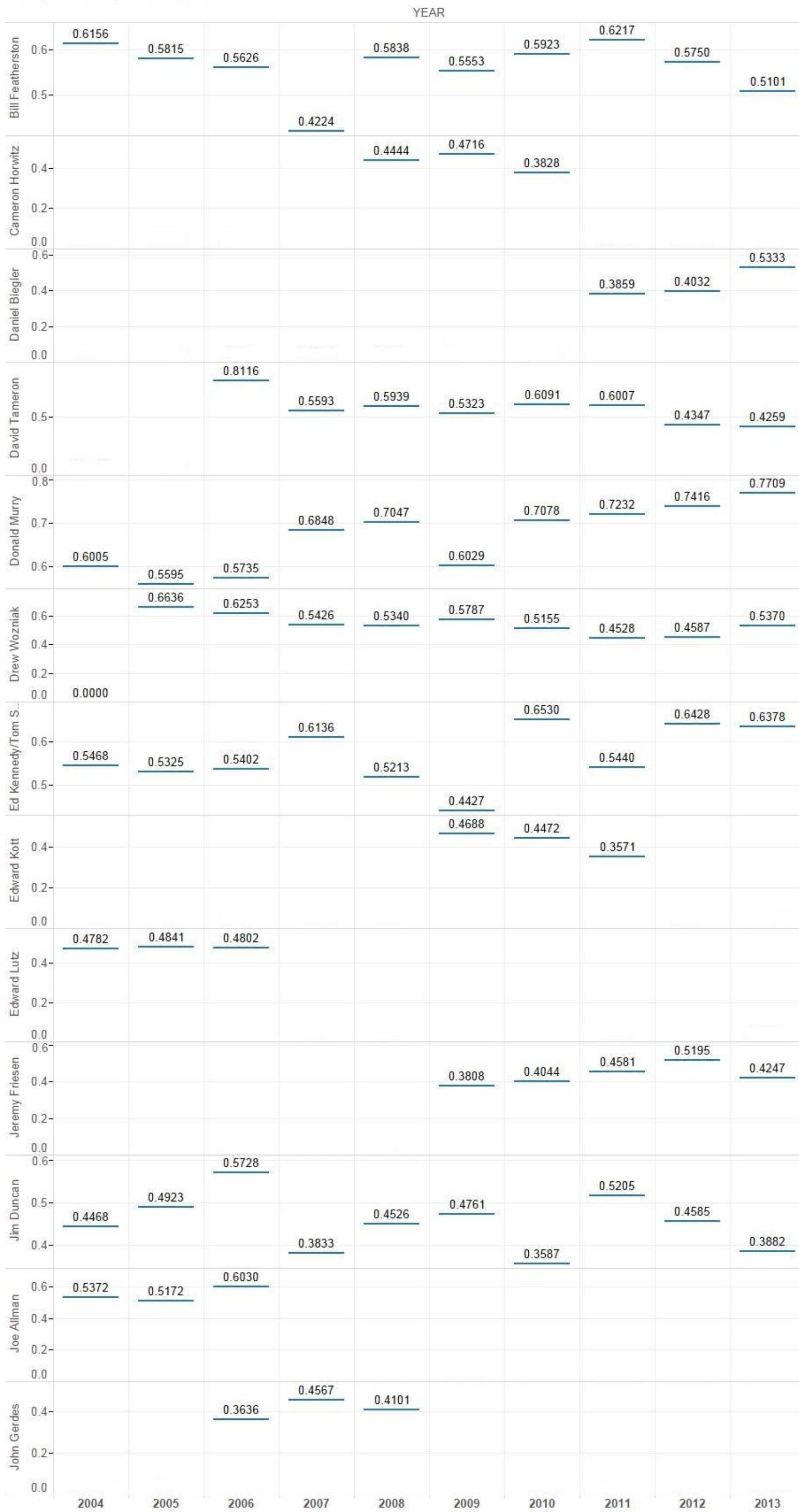

*Figure continued onto next page

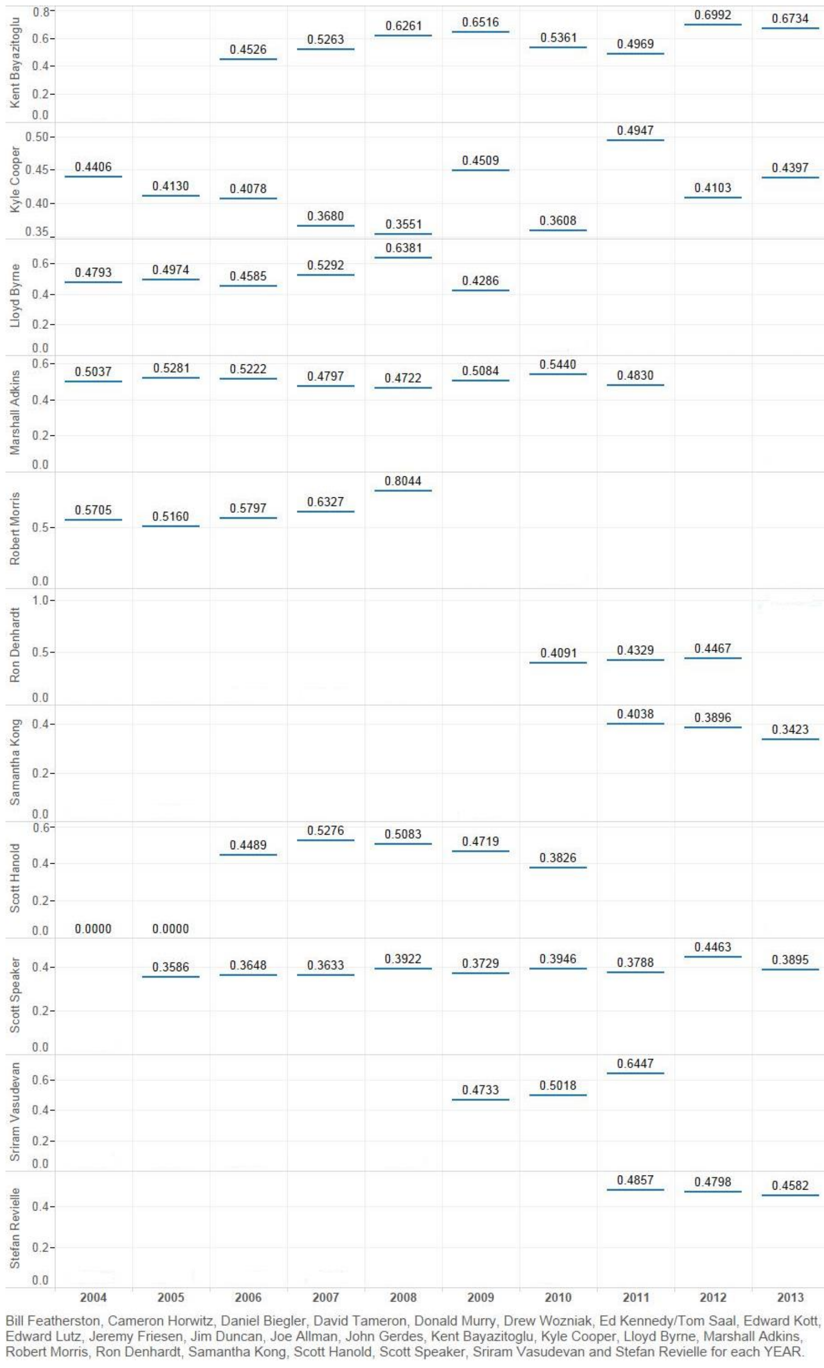

Figure 3 is a visualization of the data in Table 5. It describes the average analysts rank score. The lower the bar is on the graph, the better the rank score is.

Figure 3 shows the analyst having four behaviors. The first behavior keeps consistent with Mikhail's (1999) finding of more experience leading to better analyst forecasts. 11 analysts

(Bill Featherston, Cameron Horwitz, David Tameron, Drew Wozniak, Edward Kott, Edward Lutz, Kyle Coopers, Marshall Adkins, Samantha Kong, Scott Hanold, and Stefan Revielle) each displays this trend in their data. Their RANK_SCORE went down as they became more experienced. The second behavior is consistent with the trend Mikhail (1999) finds in that analysts will turnover if their RANK_SCOREs do not improve. There are 7 analysts (Daniel Biegler, Joe Allman, John Gerdes, Lloyed Byrne, Robert Morris, Ron Denhardt, and Sriram Vasudevan) who display the second behavior in that their forecasts did not improve as they gained experience and therefore changes employment. These six analysts all have turnover after they continually underperform in their relative forecast accuracy. These are all consistent with Mikhail's (1999) paper outlining that relative forecast accuracy does matter among analysts (Mikhail 1999).

The third behavior is consistency in that an analyst's relative ability to forecast the market stayed the same. Three analysts (Jeremy Friesen, Jim Duncan, and Scott Speaker) display this behavior. The fourth behavior is inconsistent with Mikhail's (1999) paper because these analysts make relatively worse forecasts each year, yet continued to stay and make forecasts. Three analysts (Donald Murry, Edkenndy/Tom Saal, and Kent Bayazitoglu) display this type of behavior. The effect of the first behavior likely explains the third and fourth behaviors' effect on the data set. Since 11 analysts improve their relative forecasting ability, another set of analysts have to perform relatively poor in order for the eleven analysts to have the average RANK_SCORE explained. In the case of the third and fourth behaviors, those six analysts probably stay with the firm because the analysts either have seniority or continued to make recommendations that continually make money for the institution. Overall, the data set correlates with Mikhail's (1999) findings that analysts get better with time or they tend to turnover from their institution. Utilizing this forecast ability information, I wish to explore if one can utilize analyst's rank score to develop a profitable trading strategy by looking at a pool of analyst past rank scores and developing a buy/sell decision on the natural gas commodity futures.

Developing a Profitable Trading Strategy Based on Rank Score

After find the that analyst's forecasting ability tends to improve with experience, I want to test and see if a profitable trading strategy can be developed. Specifically, I want to explore the profitability of a buy/sell, exit, hold trading strategy that relies on the earlier findings that the market prices the commodity based on the mean analyst estimate and not the markets view on the top analyst estimate.

On the day of a storage report release, if the actual EIA natural gas storage release reports that natural gas storage is higher than the market's estimate of storage for the week, then the price of the natural gas futures is predicted to drop because the supply of the natural gas is higher than expected, and vice-versa. If the market is able to use past forecasting ability to identify the top analyst for the week, then the market can utilize the top analysts forecast to identify if there is a greater probability that the mean analyst estimate over or under estimates the actual report. Therefore, I can make a buy/sell decision right before the release of the report and exit the position minutes after the report is released. If the trading strategy holds true, then I will be able to make a profit.

I first optimize the trading strategy using the data set from 2004 to 2008 by varying the number of weeks the trading strategy looks back to average. Should the trader average the last two weeks, or should they average the last ten weeks? Then I apply the optimal number of weeks to average to the trading strategy. To test the trading strategy, I transform a data table consisting of the actual storage report, the mean estimate storage report, day-of-report natural gas closing price, and prior-day-of-report natural gas closing price. The strategy then follows the logic of that if the top analyst estimate is greater than the mean, then this should indicate that the actual storage report will be higher than the mean estimate, and vice-versa. In this case, if the price will go down, then we should enter a short position on the commodity future before the report release and then reverse the position after the release of the report at a lower price, and vice-versa. I construct a data table with the inputs being the number of weeks w from 1 to 52 and the outputs being total daily return (sum), standard deviation, and compounded return for each data set, 2004 – 2008/2009-2013. The compounded return was found by investing $100 in commodity, executing the strategy, and reinvesting the total return in the following week. I then look at the data set to identify the w that gives the best return for the first five years and compare that with the second five-year result to see if the trading strategy still gives the most return. If the trading strategy works to make a significant return, then the optimal w for the first five years of the data set will be the same optimal w for the second data set.

Table 6 is the data table found from varying W.

Table 6: W vs. Trading Strategy Returns

W	Profit 04-08	Profit 09-13	Avg Return 04-08	Avg Return 09-13	StDev 04-08	StDev 09-13	Compound Return 04-08	Compound Return 09-13
1	($3.13)	($2.81)	-0.263%	-0.299%	3.783%	3.731%	$41.30	$38.09
2	$3.85	$4.22	0.089%	0.410%	3.832%	3.712%	$103.08	$244.01
3	$2.78	$1.81	0.137%	0.107%	3.827%	3.633%	$116.84	$111.21
4	$1.17	$1.67	0.095%	0.170%	3.862%	3.557%	$104.41	$132.03
5	$2.79	$1.92	0.145%	0.188%	3.894%	3.494%	$118.73	$139.47
6	$10.82	$2.77	0.644%	0.244%	3.336%	3.639%	$463.55	$158.91
7	$10.80	$1.57	0.637%	0.158%	3.317%	3.490%	$456.19	$128.89
8	$8.80	$1.99	0.499%	0.196%	3.352%	3.615%	$317.93	$140.64
9	$6.37	$1.21	0.361%	0.095%	3.250%	3.584%	$224.10	$108.32
10	$10.00	$1.24	0.539%	0.105%	3.318%	3.611%	$353.63	$110.81
11	$7.00	$2.41	0.485%	0.190%	3.333%	3.463%	$306.86	$140.17
12	$4.35	($0.17)	0.384%	-0.063%	3.347%	3.475%	$235.56	$72.38
13	$5.80	$1.24	0.441%	0.116%	3.337%	3.472%	$273.90	$115.55
14	$5.61	$2.53	0.436%	0.252%	3.292%	3.405%	$271.40	$165.90
15	$4.01	$3.37	0.327%	0.329%	3.405%	3.410%	$202.32	$202.57
16	$5.76	$2.97	0.446%	0.337%	3.319%	3.383%	$277.70	$207.54
17	$7.18	$4.07	0.505%	0.428%	3.285%	3.312%	$324.29	$264.61
18	$6.60	$3.54	0.478%	0.387%	3.297%	3.261%	$302.09	$239.08
19	$6.94	$3.42	0.491%	0.360%	3.310%	3.279%	$312.38	$222.27
20	$7.19	$3.40	0.485%	0.367%	3.317%	3.317%	$307.08	$225.42
21	$6.60	$2.76	0.435%	0.313%	3.310%	3.295%	$269.95	$196.03
22	$6.93	$2.53	0.504%	0.278%	3.755%	3.312%	$311.47	$178.73
23	$5.81	$1.60	0.464%	0.195%	3.771%	3.279%	$279.91	$144.40
24	$5.29	$1.19	0.373%	0.137%	3.380%	3.285%	$227.36	$124.18
25	$7.38	$0.61	0.509%	0.094%	3.796%	3.267%	$313.10	$111.17
26	$4.90	$0.94	0.293%	0.109%	3.810%	3.314%	$175.81	$115.01
27	$4.02	$1.04	0.250%	0.119%	3.836%	3.316%	$156.82	$118.24
28	$4.30	$1.67	0.271%	0.194%	3.798%	3.316%	$166.01	$143.64
29	$2.72	$1.17	0.196%	0.128%	3.819%	3.208%	$136.14	$122.01
30	$4.43	$1.86	0.288%	0.190%	3.830%	3.066%	$173.27	$145.04
31	$3.47	$2.45	0.230%	0.272%	3.824%	3.159%	$149.09	$178.70
32	$1.46	$3.07	0.177%	0.316%	3.845%	3.154%	$129.55	$200.87
33	$1.19	$1.73	0.150%	0.173%	3.871%	2.981%	$120.29	$139.96
34	$2.73	$1.79	0.229%	0.170%	3.839%	2.987%	$148.13	$138.96
35	$1.66	$2.69	0.179%	0.274%	3.878%	2.985%	$129.78	$182.42
36	$2.16	$2.25	0.198%	0.222%	3.852%	2.952%	$136.59	$159.51
37	$1.79	$2.03	0.174%	0.200%	3.894%	2.781%	$127.74	$152.38
38	$2.03	$1.56	0.201%	0.151%	3.874%	2.783%	$137.48	$134.29
39	$3.12	$1.55	0.248%	0.141%	3.887%	2.733%	$155.23	$131.23
40	$1.30	$1.48	0.164%	0.141%	3.892%	2.743%	$124.42	$131.11
41	$0.21	$3.26	0.108%	0.310%	3.897%	2.669%	$107.46	$204.83
42	$5.03	$2.80	0.343%	0.254%	3.891%	2.691%	$198.74	$176.80
43	$3.16	$3.68	0.255%	0.336%	3.910%	2.656%	$157.65	$219.31
44	$3.83	$3.02	0.290%	0.286%	3.910%	2.816%	$172.82	$190.75
45	$3.59	$2.52	0.277%	0.237%	3.901%	2.796%	$167.37	$167.83
46	$3.05	$3.11	0.253%	0.296%	3.898%	2.804%	$157.21	$195.92
47	$2.39	$2.83	0.212%	0.265%	3.900%	2.843%	$141.10	$180.19
48	$2.47	$1.70	0.217%	0.165%	3.896%	2.693%	$142.92	$140.06
49	$2.20	$1.56	0.203%	0.145%	3.898%	2.702%	$138.10	$133.04
50	$1.99	$1.82	0.189%	0.175%	3.891%	2.679%	$133.10	$143.86
51	$1.93	$1.75	0.194%	0.143%	3.870%	2.658%	$135.23	$132.64
52	$0.62	$1.12	0.134%	0.085%	3.879%	2.617%	$115.39	$114.35

Table 6 describes the return, standard deviation, and compounded returns for a trading strategy for the 2004 – 2008 and 2009 – 2013 data sets with varying W.

From the data set of Table 6, I find that the optimal W for the first five-years (2004 – 2008, inclusive) is a 6-year moving average of the analysts. This trading strategy yields a 0.644% average weekly return and finds a buy/sell, hold, return of 463.55% compounded return from 2004 to 2008. For the 2009 to 2014 data set, I find an average weekly return of 0.244% and a buy/sell, hold, return of 158.91% when utilizing the 6-year moving average. To further test the returns, I look at comparing the returns to a benchmark.

I compare the result with a commodities benchmark. I look at the International Monetary Fund's Commodity Fuel Energy Index. The international monetary fund is "an organization of 188 countries, working to foster global monetary cooperation, secure financial stability, facilitate international trade, promote high employment and sustainable economic growth, and reduce poverty around the world" (International Monetary Fund 2014). This fund is an index of the commodity market and provides a diverse set of baskets to compare to. Table 7 describes the indexes yearly price movements, the year return, and the compounded value of $100 invested since 2004 and since 2009.

Table 7: International Monetary Fund Commodity Duel Energy Index (International Monetary Fund 2014)

Commodity Fuel Energy Index				
YEAR	**PRICE**	**% Return**	**Compounded Return Since 2004**	**Compounded Return since 2009**
2004	60.35		$100.00	
2005	81.68	35%	$135.34	
2006	115.73	42%	$191.76	
2007	102.36	-12%	$169.61	
2008	168.58	65%	$279.34	
2009	94.95	-44%	$157.33	$100.00
2010	143.74	51%	$238.18	$151.38
2011	173.3	21%	$287.16	$182.52
2012	199.69	15%	$330.89	$210.31
2013	194.33	-3%	$322.00	$204.67
2014	189.14	-3%	$313.41	$199.20

Table 7 describes the International Monetary Fund Commodity Duel Energy Index. The prices are reported and the compounded return since 2004 and 2009 are calculate.

The trading strategy develops returns of 463% of compounded return from the start of 2004 to the start of 2009 and 158.91% of compounded return from the start of 2009 to the start of 2014. The Index only returns 157% of compounded value between 2004 and 2009 and 199% of compounded value from 2009 to 2014. The optimized trading strategy looking backward for 2004 to the start of 2009 (or end of 2008) gives a greater return in hindsight. But, theoretically looking forward with the optimized trading strategy for the data set between the start of 2009 and the start of 2014 produces a lesser-compounded return. Utilizing this benchmark comparison indicates that one cannot develop a basic trading strategy on the analyst recommendations and therefore the analysis does not support the trading strategy.

Chapter 4

Conclusion

The paper explores the effect commodity analyst's forecasting rank and ability had on the natural gas market. The paper first explores how the market responds to analyst estimates. Second, the paper explores analysts forecasting ability be tracking their relative forecasting ability through time. Finally, the paper explores a trading strategy, tests the trading strategy utilizing a one-month natural gas futures contract measure, and then compares the results to a benchmark.

The paper conducts a regression analysis looking at differences of the market closing prices before and after the storage report release and the difference in the mean analyst estimate and the actual storage report. Afterwards, the paper compares these results to a regression analysis conducted by looking at the difference of the market closing prices before and after the storage report release and the difference in a top analysts estimate with the actual storage report. From the comparison, the paper finds that the market prices respond more to the mean analyst estimate, rather than the markets view of a top analyst's estimates.

The paper analyzes analyst's relative forecasting ability through time. The paper tests if an analyst's forecasting ability gets better through time, and if not, what the implications are from underperforming relative to other analysts. By utilizing methodologies by Mikhail's (1999)s paper "Does Forecast Accuracy Matter to Security Analyst," I am able to effectively develop a rank score for each analyst's report as a measure for relative forecasting ability. By analyzing the rank score, the paper finds that the data correlates with Mikhail's (1999) findings in that analysts do get better with time and if they do not, the analysts tend to turnover.

Lastly, the paper examines a potential trading strategy utilizing the conclusions learned in the first two sections of the paper. An optimal trading strategy is developed using data from 2004 to 2008 and is tested using the data from 2009 to 2014. The trading strategy derives it basis on the conclusion that the market responds more to the mean analyst estimate rather than the markets view of a top analyst. The strategy utilizes a moving average of rank score to determine who the projected top analyst will be for the week. The strategy compares the top analyst estimate to the mean analyst estimate to determine if the mean analyst estimate will overestimate or underestimate the actual. Then a trade is executed before the report and reversed after the report release. The paper gathers that statistics and compares them to a benchmark. The analysis concludes that the trading strategy does not always produce more return than the International Monetary Fund Energy commodity index benchmark. Therefore, the data does not support a trading strategy based on an analyst's rank score.

Overall, the paper concludes that the market focuses more on a mean analyst estimate when pricing the natural futures contract and that analyst's relative forecasting ability do tend to get better as an analyst gains more experience, otherwise he or she will likely turnover. The data does not support a trading strategy utilizing the rank score measure.

Appendix A

Data Sources

Natural Gas Weekly Analyst Estimates in Bloomberg

In Bloomberg, Type {DOE <GO>} -> 3)Bloomberg Estimates -> Natural Gas Survey.

The estimates page will load.

At the top left key in any date and hit <GO> again.

A list of forecasters names appear.

Then highlight each analyst and click export.

Daily Natural Gas Futures Contract Prices in FactSet

In FactSet, open the FactSet Excel Side-bar.

Select cell A1, Under Data Item, Select Date in the FactSet sidebar, and select the start and end date, and click insert

In the search bar in the side-bar, type in Natural Gas Continuous and select the one-month continuous identifier

Click cell B1, then, select Price in the Data Item tab. In the preferences, select closing day prices and click insert.

EIA Natural Gas Storage Reports

Go to: http://ir.eia.gov/ngs/ngs.html

Click on the excel symbol denoted Historical Prices to download the report.

International Monetary Fund Commodity Fuel (energy) Index Monthly Data

Go to: http://www.indexmundi.com/commodities/?commodity=energy-price-index&months=180

Scroll down and click on “Export Data to Excel”

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ACADEMIC VITA

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Breaking Into Wall Street – Online Financial Modeling Course, 2012 – 2014

Professional Experience

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- Summer Business Analyst, Deloitte Consulting Strategy & Operations, Summer 2013
- Graduate, Wall Street Boot Camp, 2012
- Research Intern, CIBER Inc., Summer 2012
- Lead Marketing Intern, Penn State Football Marketing, 2011 – 2014
- Healthcare Analyst, Penn State Investment Association, 2012 – 2013

Activities

- Deputy Communications/Business Director, Lunar Lion, 2013 – 2014
- President & Founding Father, Chi Phi Fraternity, 2012 – 2014
- Presidential Leadership Academy, 2011 – 2014
- Member & VP of Leadership Development, Sapphire Leadership Program, 2010 – 2014
- Senator & Executive Board, University Park Undergraduate Association, 2010 – 2014
- Executive Board Member, Movin' On Music Festival, 2012 – 2014
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