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Applying a Heterogeneous Agents Model to the Natural Gas Spot and Futures Markets

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Preface and Acknowledgements

This thesis is to a large extent the culmination of broad range of personal and academic interests. A bachelor in International Economics and Business from Rijksuniversiteit Groningen provided the general economic background upon which I could build further knowledge. I moved to Rotterdam to learn more about Financial Economics, which proved to be a refreshing challenge from the broad approach of my bachelor. During my Masters, subjects relating to Behavioural Finance interested me greatly. My propaedeutic degree in psychology is exemplary of my curiosity in the human cognition, and it was a great adventure to work on a thesis that combines both my interest in financial economics with that in human behaviour. While at times it was a difficult process, I had a very good time writing this thesis.

But I did not do so without help. I want to thank Saskia ter Ellen and Remco Zwinkels for their exemplary work and helpful comments. I want to thank the Eviews community for existing in general and answering questions. But without question the most important aid I received was from my parents. This thesis and my degree would not have been possible if it were not for the many years of consecutive financial and moral support I received. Thank you for your patience.

Abstract

I estimate a heterogeneous agent model based on behavioral finance theory on data from the US natural gas spot and futures market, to test the merit of modeling speculators with heterogeneous expectations. The estimated model is compared with nested versions and benchmark models to evaluate performance. I find that for the futures market, the HAM model outperforms benchmark models in explaining price dynamics, which lends support to the notion that speculators impact the price dynamics of natural gas futures.

Keywords:
[Chartists, fundamentalists, heterogeneity, natural gas, futures, speculators]

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1 Introduction

Energy price behavior has received increasing attention since the importance of oil became painfully apparent in the oil crises of the 1970's and oil price shocks in 1990. Energy prices are used as input for investment decisions of companies, and, understanding the movements of energy prices can help identify speculative trading opportunities. The past decades saw the energy commodity markets become increasingly interwoven with financial markets. Derivatives based on energy prices are traded for hedging and speculative purposes, and the two most liquid energy derivatives are futures based on crude oil and natural gas.

While the crude oil market tends to receive most attention, the market for natural gas, heralded as the (medium-term) fuel of the future[1] has grown in size and importance. Spot markets for natural gas and oil are known as volatile, which is often attributed to fundamental factors that impact supply and demand. A volatile environment creates uncertainty for investments in the real economy, and is therefore an undesirable trait of energy commodity markets. While Pindyck (2004) reported that the increase in volatility of natural gas prices was of little economic importance, the following graph includes a post-2004 price path that suggests otherwise. The peaks and troughs visible in figure 1 are commonly attributed to hurricane-caused supply shortages, but some claim that speculators in the futures and spot markets might have exacerbated the movements.

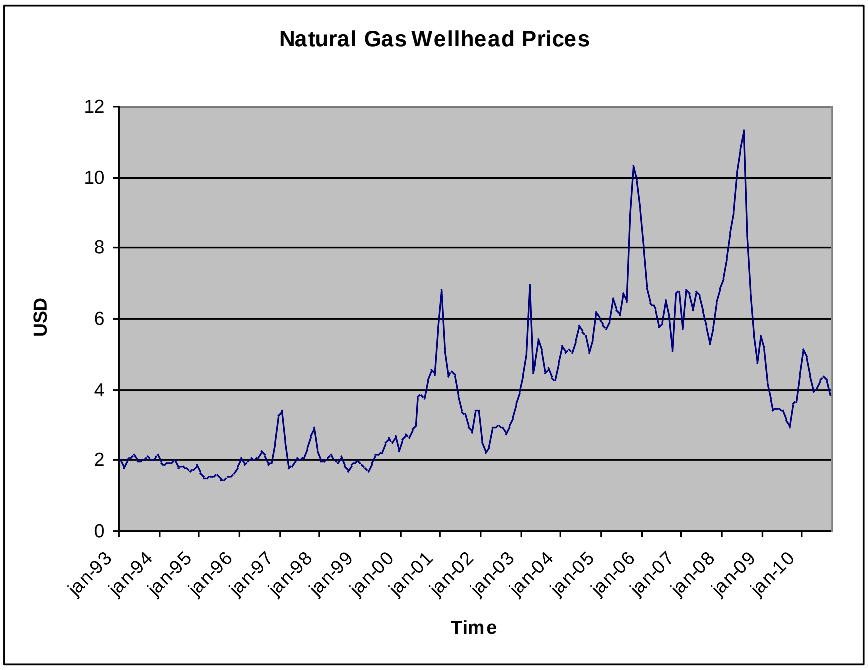

Figure 1 Natural Gas Prices. Data are wellhead prices, and obtained from the US Energy Information Administration.

A prominent example of this line of thinking is a United States Senate report that accused hedge funds Amaranth of purposefully influencing prices through cornering the natural gas market in 2006, by

[1] http://money.cnn.com/2010/03/29/news/economy/natural_gas/index.htm
http://www.scientificamerican.com/article.cfm?id=natural-gas-could-serve-as-bridge-fuel-to-low-carbon-future

trading large quantities of futures on the Nymex exchange. The research committee claimed that fundamentals of supply and demand were largely unchanged in that period, such that the observed volatile price movements must have been caused by speculative strategies[2]. While inquisitive behaviour by the United States Senate is no proof that speculators impact prices, it does reflect the widely carried view that movements in spot and derivative markets are not exclusively the result of market fundamentals.

Behavioural finance theory provides a framework that allows speculative motives to impact price dynamics. The theory uses bounded rationality and cognitive biases to explain how heterogeneous speculators form differing expectations on where they believe the market is moving. It explains how speculation can exacerbate upward and downward price movements, which cannot be modelled in a traditional rational agent framework. The behavioural finance approach is formalized in Heterogeneous Agents Models (HAM's), and they have been successful in explaining movements in the foreign exchange market (Manzan and Westerhoff, 2007) and other commodity markets (Westerhoff and Reitz, 2007). While they have been applied to the energy market (Ter Ellen and Zwinkels, 2010), they have not been applied to the natural gas market in particular. A new aspect of this thesis is that I also research the potential of HAM models to explain futures price formation.
In short, the thesis aims to contribute to existing literature on behavioural finance and commodity markets by looking for evidence of speculative impact on natural gas price dynamics in both spot and futures markets.

Using monthly spot and futures prices I am able to show how a HAM is able to explain observed price dynamics in the considered markets. The hypothesized chartists and fundamentalists feature distinct expectations, and they exhibit significant evidence of switching strategies over time in most markets. In addition, I demonstrate the added value of including asymmetry in fundamentalist and chartists' behaviour. In-sample tests show which nested models yield the most appropriate HAM, and results of in-sample comparison with benchmark models suggest that the selected HAM's provide better explanations than benchmark models in future markets, but not so in the spot market. The findings provide encouraging evidence of the applicability of HAM to the futures market of natural gas.

This paper is organized as follows. Chapter 2 will review the existing literature on the subjects of economic modelling and behavioural finance. In chapter 3 I develop the HAM - model. Chapter 4 discusses the characteristics of the natural gas market. Chapter 5 covers data and methodology. The results are discussed in chapter 6. I present conclusions in chapter 7.

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[2] Amaranth Advisors LLC controlled more than half the U.S. natural gas market, and evaded regulators trying to restrict its purchases. The hedgefund bet on the spread between futures, but eventually collapsed leaving its investors with a loss of 6.6 billion (Bloomberg webpage, 2010)

2 Literature Review

2.1 Traditional Approaches to Economic Modelling

Literature on the dynamics of natural gas spot prices has mostly centred on the use of fundamental factors in explaining and predicting movements. Prime examples of fundamental models can be found in the forecasting exercises published by the EIA[3]. They use data on inventory levels, production capacity and economic forecasts to develop predictions of future gas prices. This does well in explaining the *real* demand and supply for natural gas, the part used for production and consumption purposes. However, commodity markets are increasingly used for investment activities (Domanski & Heath, 2007) since they can provide more attractive returns than alternative markets (Edwards & Caglayan, 2001). It follows that fundamental models have a hard time explaining price dynamics caused by speculators, since their impact is by definition not explained by fundamentals.

Implicit in the fundamental models are the traditional and well-known assumptions used in economic representations of reality. These assumptions have received increasing resistance over the years. They are known as the as the rational expectation hypothesis, the efficient market hypothesis and the concept of the representative agent. Hommes (2006) summarizes that they are logically inconsistent and that the stylized facts these models create do not coincide with empirics of day-to-day market behaviour.

The rational expectations (RE) hypothesis (Friedman, 1953) has been confidently applied in economic theory since Lucas (1971) repeated his arguments. The rational expectations hypothesis posits that all investors make estimates of future prices that are not systematically wrong. This prohibits the impact of trading on trends, as an existing trend would be known to all, assuming semi-strong market efficiency. Friedman argued that irrational investors (speculators) could not survive in a competitive market, as they would be outperformed by their rational counterparts. Hommes (2006) points out that with rational agent theory there would in fact be no trade at all. If one agent has superior information and wants to sell, the potential buyer has inferred the decreased value and will not buy. This signalling mechanism prevents that trading takes place, which is in conflict with observations from markets across the globe.

Related to the RE hypothesis is the efficient market hypothesis. Attributed to Fama (1965), this hypothesis treats markets as information efficient. Trading ensures all information is reflected in the price of an asset. There can be no forecastable return structure, as rational arbitrageurs would trade these profit opportunities away. Price changes should be caused by fundamental economic factors, such as supply and demand. In contrast, actual price movements observed in foreign exchange, stock and commodity markets cannot be justified by movements in underlying fundamental factors. For instance, Shiller (2000) observes a disconnection from fundamental values for stocks and bonds.

[3] www.eia.org/naturalgas.htm

Similar findings in the exchange markets have led to one of the most well-known puzzles in finance, the volatility disconnect puzzle (Sarno, 2005).

Other explanations of non-fundamental sources of commodity price dynamics include the convenience yield the (Schwartz and Smith, 2000), but even that does not provide a conclusive story. Pindyck (2004) researches volatility in petroleum-based commodity markets and its effects on market factors such as storage and convenience yields. He remarks that fundamentals can only marginally explain spot price volatility and suggests that other factors might account for volatility, in particular investor irrationality and herding behaviour.

The representative agents approach in modelling is often attributed to the need to simplify reality in an economic model. It is practical, but no necessity to assume one rational agent who reflects the aggregate opinion of all. The "Lucas critique" (Lucas, 1971) is directed at the result of this aggregating. They point out that disregarding the actual different views held within the population overlooks the impact of interaction of these different views. Irman suggests: "A possible alternative to the representative agent approach to economics could be agent-based simulation models which are capable of dealing with heterogeneous agents". Such alternative is provided by behavioral finance (BF). BF offers alternative assumptions that are based on cognitive biases, bounded rationality and limits to arbitrage. Where the RE hypothesis expects arbitrageurs to trade away any mispricing, BF allows mispricing to continue, due to the existence of noise traders who do not behave rational (Barbaris and Thaler,2003). This is a fundamental contrast with the RE, where an overvalued asset would be driven down by rational investor who know the fundamental price. De Long et al. (1990a & b) prove that this is not completely true. Rational investors bear a risk, since irrational traders can drive prices above its fundamental value for considerable lengths of time. If these "noise" traders outlast the rational investor, the rational investors might be forced to take a loss on the asset, despite being right about fundamental value.

2.2 Biases

It is essential to consider what drives noise traders in the first place. A first explanation uses evidence on cognitive biases to explain deviations from rational pricing. Kahneman and Tversky (1974) are famous for evidence on this type of behavior. The significance of their findings was that they showed for the first time that investors indeed behave irrational. Kahneman and Tversky let test subjects make investment decisions under risk, and found that such decisions are often sub-optimal. Subject's decisions are influenced by cognitive biases. Since these biases are used in expectation formation of agents in this paper's model, they warrant a thorough analysis.

The representativeness bias works in tandem with the confirmation bias (Einhorn and Hogarth, 1978) and is relevant to speculators with extra-polative strategies. The representativeness bias relates to the tendency to select memory that is in line with existing beliefs. The confirmation bias relates to incorrectly assigning probability values to events that took place in the past. Together they explain why people tend to disregard the occurrence of past events and the base probabilities of these events when they conflict with prior notions. In an investment environment, these heuristics encourage investors to select information that supports existing beliefs. Consider an investor that holds a stock that he beliefs will do well in the future. This investor could take a series of recent positive returns to confirm his expectation that the next return will be positive too, without taking into account the negative returns that preceded the positive string (confirmation effect at work). As a result, he disregards the actual underlying distribution and assigns a large probability of the next return being positive too (representativeness effect).

The availability bias suggests that thoughts and memories which are easily recalled from memory, form the basis from which the likelihood of recalled events are extrapolated to the future. If events are easy to retrieve, they seem more frequent, and vice versa. This leads to attributing a higher likelihood to common events and lower likelihood to events that are hard to recall or imagine in an investment setting, resulting in incorrect decisions.

The anchoring bias reflects the observed behavior that the most recent value of an investment will influence an investor's estimate of the next estimate. Kahneman and Tversky prove that the initial observed value is adjusted to form the estimate, with no regard of underlying fundamentals. In an investment setting, recent prices or returns are seen as starting points for future estimates.

Finally, another well-known bias is the status quo bias, attributed to Samuelson and Zeckhauser (1988). They show that people prefer to stay in their current situation, unless very strong incentives encourage them to change their behaviour. This conflicts with rational agent micro-economic literature, which predicts that investors react to minor changes in variables to obtain optimal utility. The status-quo bias is important when modelling heterogeneous agents that switch trading strategies, as it helps explain why switching does not occur at optimal frequency and speed.

Tversky and Kahneman (1979) presented a second influential paper on the subject of prospect theory. This theory describes how subjects make investment decisions under uncertainty. The traditional approach to this type of problem was solved using expected utility theory. With expected utility theory, the utility of an outcome is determined by its weighted probability using final asset values. Instead of using final asset values in evaluating an investment, Kahneman and Tversky distinguish potential outcomes of the investment in gains and losses and find that investors behave differently in those scenarios. Investors are risk averse over gains, and risk seeking over losses, such that the value function for gains is concave, whereas the value function for losses is convex. An average investor will in general prefer a gamble of a small yet probable gain, over a small probability of a large gain with equal expected value. In contrast, for losses it implies that investors prefer a small probability of a large loss over a small loss with high probability of equal expected value. The observed behavior conflicts with rational agent theory, in which investors assign the same decision rules to both gains and losses.

Social phenomena like herding behavior can also help explain price movements in various markets (Pindyck ,2004). It describes the observed phenomenon that if prices go up in one market, prices tend to go up in other markets without changes in relevant fundamental economic variables. While gas prices are known to follow oil prices, Pindyck's finding suggests that in part these co-movements can be a social phenomenon.

2.3 Bounded Rationality

In close relation to biases is the concept of bounded rationality, in which heterogeneous investors have different expectations of future prices according to certain expectation strategies. The bounded rationality approach is attributed to Simon (1957), who noted that simple heuristics used for decisions under uncertainty are a better approximation of behaviour than fully optimal decision rules. The heterogeneity of expectations could originate from differences in information, or when agents use the available information differently. The approach is able to model investor behavior outside the rationality constraints, and is consistent with survey data on heterogeneous expectation (Takagi, 1993). Surveys show that investors have conflicting views of the future and that they use different strategies to form expectations of that future.

Since the rational expectations hypothesis lost in popularity, academic research shifted more to how investors form irrational expectations. Three general types of expectation strategies have been popularized by Frankel and Foot (1987). In their paper on exchange rate movements, they hypothesized an extrapolative strategy that expects the most recent trend to continue, an adaptive strategy where forecasts are a weighted average of the spot rate and lagged forecasted rates, and a regressive strategy that assumes a mean-reverting process. While they did not model agent interaction or agent co-existence, they did suggested modelling heterogeneous expectations in subsequent research. Takagi (1993) provides supportive evidence. His meta-study on surveys finds that short term expectations are influenced by lagged returns, extrapolating recent movements away from fundamentals. Long-term expectations are often against short term movements, moving towards a long-term "normal" (or fundamental) value.

The extrapolative and regressive strategies are generally used by two classes of speculator, chartists and fundamentalists. Allen and Tailor (1990) describe the distinction as follows: "chartists study only the price action of a market, whereas fundamentalists look for the reason behind that action". Chartists try to identify and trade upon patterns like trend continuation. Shiller (2001) argues that investors can rationally choose to follow a trend, if they expect that trend to continue. An increase in price volatility is inherent to the process. Boswijk, Hommes and Manzan (2006) find evidence of (temporary) destabilizing effect of chartists in the stock market when herding behavior encourages investors to follow a buy and hold strategy.

Fundamentalists represent the belief that current deviations from the fundamental value will disappear. How to estimate the fundamental value will differ per asset class, with an obvious candidate in the form of fundamental models. While it may seem as if fundamentalists are rational investors, they act irrational if they do not take into account the presence of other agents with different trading rules (Hommes, 2003). For practical purposes, a long-run average can be chosen as a proxy for true value (ter Ellen and Zwinkels, 2010).

2.4 Heterogeneous Agents Models

The exponent of Behavioural Finance theory is the Heterogeneous Agents Model (HAM). They allow investors with different beliefs or strategies to exist in one model and switch between those strategies. Their interaction determines price formation in the market, and the dynamics HAM's generate mimic stylized facts in financial data better than traditional models do (De Grauwe and Grimaldi (2006).

In previous years, HAM's have been successfully applied to a variety of markets. Shiller (1984) was the first to estimate a HAM in the money market, using a distinction between smart and ordinary agents. Examples of HAM's in commodity markets include Baak (1997) and Chavas (2000) in the hog and beef market. In the foreign exchange market, Winker and Gilli (2001) are first to estimate a model with a switching mechanism based on two types of agents, fundamentalists and chartist, following Kirman (1991). Winker and Gilli assume that there can be two reasons why an agent switches strategies. Either he is convinced through exposure to a second agent, or he randomly "mutates". De Grauwe and deWachter (1993) assume fundamentalists and chartist speculators in a monetary model, and allow the weights of the two investor types to be determined endogenously, depending on the deviation of the market rate from the fundamental rate. They find that their non-linear model is able to reproduce empirical facts of exchange rate behaviour. Brock and Hommes (1996 and 1997) use a different method for switching strategies. They let agents evaluate the performance of a strategy ex-post by comparing the return of the strategies. Investors switch when a return increases with respect to the other strategy. This switching mechanism is more appealing when modelling speculators due to their profit seeking nature.

A more recent contribution of HAM's to financial data using this approach is from De Grauwe and Grimaldi (2006), who again stress how the HAM model is consistent with stylized facts of foreign exchange markets. A different type of study by Menkhoff (2009) examines the determinants of heterogeneous expectations in foreign exchange markets and confirms existence of fundamentalist/chartist trading behaviour, consistent with stylized dynamics obtained by simulations. Boswijk (2006) is the first to estimate a HAM on the stock market, using a simple Gordon Growth model to provide a fundamental counterweight to chartist expectations. They find "statistically significant behavioural heterogeneity and substantial time variation in the average sentiment of investors", supporting the applicability of the heterogeneous agent approach to other markets.

Westerhoff and Slopek (2005) apply a HAM model to commodity markets and find that interacting fundamentalists and chartist can explain extreme changes to market direction. Ter Ellen and Zwinkels (2010) estimate a HAM model on the oil spot market and find that the model outperforms benchmark models when forecasting out-sample. Another market where a HAM has successfully been applied to is the DAX option market (Frijns et all, 2010), where it comfortably outperformed the benchmark GARCH model both in and out sample. However, no attempts have been made in applying a HAM model to the US natural gas market. The closest resemblance comes from Qin (2010) who uses a Markov process based two-regime switching model that allows for a bullish and bearish state in the natural gas market. The model's switching mechanism allows fundamental forces to have a different impact in either state; a characteristic resembles the strategy switching mechanism in HAM modelling.

3 Model

The general objective is to test to what extent market dynamics in the natural gas spot market can be explained by modelling speculators that switch between heterogeneous expectations. The first objective is to select the best HAM model, the second objective is to compare this model against benchmarks. The HAM models are based on the work of Ter Ellen and Zwinkels (2010), who successfully model and forecast Brent Crude and WTI price changes with heterogeneous agents. Before them, Brock and Hommes (1997) made important contributions. They observed that fundamentalists stabilize prices and chartists destabilized prices.

Within the model, asset price fluctuations are the result of the endogenous dynamic between chartists and fundamentalists weights, which can lead to complex price movements. The model rests on the assumption that changes in the price for natural gas are determined by a real and speculative component. The real component stems from fundamental market mechanisms, such as the demand and supply of natural gas for actual domestic use or industrial production. The speculative component stems from two types of agents, fundamentalist and chartists. I first develop the asymmetric model, which allows different behaviour in cases of over- and undervaluation with respect to fundamental value, and in cases of upwards and downward trends. This distinction stems from the evidence on prospect theory in the behavioural finance literature. In the market for natural gas, it translates to investors behaving differently in bullish and bearish forecasts, because of associated gains (bullish) and losses (bearish). The symmetric case is a simplified version of the more elaborate asymmetric equations, to evaluate the added parameters in light of parsimony.

3.1 Ham for Spot Market

Speculators are active in a market because they trade for profit. To make a profit in the spot market, investors must buy spot and sell in the subsequent period, or sell spot and buy in the subsequent period. I make three explicit assumptions with regard to the natural gas spot market.

1) Speculators can hold inventories
2) Speculators already hold inventories.
3) There are no costs of carry or entry barriers to storage.

The first assumption is required, since speculators must store the natural gas until they can profit from an expected increase in prices. The second assumption is required, since speculators must be able to profit from downward movements too. Since the natural gas spot market is not standardized, the asset is not short sellable, and the only way to exert downward pressure on prices is to sell existing inventories. Speculators sell when they expect prices to drop.
The third assumption is required since it allows ease of calculation. Costs of carry consist of storage costs and convenience yield. Accounting for cost of carry would impact the decisions rules on when entering into a trade is profitable. I did not incorporate them in this study, as they arguably only effect occasions when speculators forecast very small profit opportunities.

The assumption of no entry barriers to storage is backed by studies on speculative behaviour in commodity storage markets. For instance, McLaren (1999) researches commodity markets that are characterized by monopolistic or oligopolistic storage possibilities. He argues that producers can act as speculators through their use of storage. Deregulation in the US has made storage of natural gas by non-producers also possible, although evidence on the extent to which this takes place is scarce.

Speculator demand at time t for natural gas spot is based on the difference between the expected price at time t + 1 and the current price P_t. When speculators expect that the next period spot price $P_{t+1} > P_t$, they will buy P_t spot and store the commodity to sell later on. Conversely, when they expect the price $P_{t+1} < P_t$ they will sell from inventory.
The difference between current and expected price gives the profit opportunity, which determines speculator demand:

$$D_t^F = a^F[E_t^F(P_{t+1}) - P_t] \qquad (1)$$
$$D_t^C = a^C[E_t^C(P_{t+1}) - P_t] \qquad (2)$$

Here D_t^F and D_t^C equal net demand for natural gas of fundamentalists and chartists respectively. E_t reflects the expectation either agents holds for price P_{t+1}. The parameters a^F and a^C reflect reaction parameters, that control to what extent the expected profit opportunity is extrapolated to actual demand. If speculator forecasts do impact current demand, both parameters are expected to range between 0 and 1. Higher values indicate that speculators are confident in trading upon their forecast.

3.1.1 *Speculator Expectations*

Speculators could use many possible strategies to forecast the next period price P_{t+1}. We follow Ter Ellen & Zwinkels in opting for a chartist and fundamentalist strategy. Chartists use technical analysis when they form expectation of future prices. This strategy is attributed to the anchoring and the confirmation and representativeness bias. Anchoring takes place when the chartist takes the most recent observation (the recent return) as a starting point for his estimate of the next periods return. With the representativeness bias, an investor sees a string of historic returns as representative of the possible future value. This translates nicely to observing a previous trend, and extrapolating that trend. A trend can go either up or down, and asymmetric chartist expectations are formed by:

$$E_t^C(P_{t+1}) = P_t + b_1^C(P - P_{t-1})^+ \ + b_2^C(P - P_{t-1})^- \tag{3}$$

This equation reflects that chartists base their expectation of P_{t+1} on the current spot price, and extrapolate the most recent trend they observed. A discrepancy between an upward and downward trend allows the chartists to display different behaviour in line with prospect theory, with b_1^C and b_2^C determining to what extent the observed previous change in P is expected to continue for the upwards and downward trend respectively. The + sign and – sign signal a positive or negative trend, which is monitored by a dummy variable[4]. I expect the value of b_1^C and b_2^C to be positive and between 0 and 1. Negative values would suggest a contrarian strategy, where investors expect an opposite movement from the most recent observation.

The symmetric version with no distinction between positive or negative trend looks as follows:

$$E_t^C(P_{t+1}) = P_t + b^C(P - P_{t-1}) \tag{4}$$

Fundamentalists believe that the price of natural gas will move towards its true value in future periods. The fundamental value can be based on the fundamental factors of natural gas prices, explained earlier in this paper, but I opt for a 12-month moving average of historic prices to proxy this value[5]. This strategy is not truly fundamental, as it has investors using the average of past prices as the best estimate for the next periods price. Following reasoning of Ter Ellen and Zwinkels (2010), it serves its purpose by providing a useful counterweight strategy to chartists. A-symmetric Fundamentalist expectations are formed by:

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[4] The + sign and – sign signal over- or undervaluation and are monitored by a dummy variable. The dummy turns 1 when $(P - F_t) > 0 = TRUE$ and 0 otherwise. If true, this turns $dummy = 1,\ (1 - dummy) = 0$. Which allows distinction between $b_1^C(P - F_t)^+$ and fo r$b_1^C(P - F_t)^-$.

[5] Appropriate month length is determined empirically in Eviews using the Box – Jenkins method.

$$E_t^F(P_{t+1}) = F_t + b_1^F(P_t - F_t)^+ \; + b_2^F(P_t - F_t)^- \tag{5}$$

Fundamentalists expect the difference between the fundamental price F_t and the observed P_t to decrease. In line with prospect theory, I allow investors to change their risk attitude when confronted with over- or undervaluation. Here b_1^F and b_2^F govern reactions when the fundamental price is below or above the current price, respectively, and the + sign and – sign signal an over-or undervaluation governed again by dummy variables.

Again, symmetric fundamentalist forecasts will be tested to see if adding asymmetry (distinction between over- undervaluation) adds power to the model:

$$E_t^F(P_{t+1}) = P_t + b^F(P - F_t) \tag{6}$$

3.1.2 Real Demand

I now turn to the "real" component of demand. Intuitively, a spot market is a place where supply and demand of natural gas meet for relatively immediate consumption[6]. This real component in demand and supply is in part determined exogenously and in part by a price sensitive demand or supply function:

$$D_t^R = a^r - \; b^r P_t \tag{7}$$

$$S_t^R = a^s + b^s P_t \tag{8}$$

Here D_t^R represents real demand for natural gas, determined exogenously by a^r and in part by a price sensitive $b^r P_t$. This equation states that ceteris paribus, demand is lower when prices rise. Similarly, S_t^R represents real supply of natural gas, in part determined exogenously by a^s and in part by a price sensitive function $b^s P_t$. This equation states that ceteris paribus, supply is higher when prices rise. It follows that total market demand D_t^M is comprised of real demand D_t^R, and a weighted average of the two types of speculator demand:

$$D_t^M = D_t^R + W_t D_t^F + (1 - W_t)\, D_t^C \tag{9}$$

[6] A transaction in the natural gas spot market does not equate to immediate delivery. Instead, the delivering side is obligated to make the delivery throughout in the month following the spot transaction.

3.1.3 *Profit, Strategy, Performance and Weights*

Speculators switch between strategies if they establish that the other strategy is more profitable. A weighing rule (originally, Brock and Hommes, 1998) determines what the next ratio of chartists to fundamentalists will be. The relative accuracy of next period's price forecasts determines whether the chartist or fundamentalist was more successful in forecasting prices. Hence, the quality of speculator forecasts is assessed by squaring the difference between the forecast and realized value P_{t+1}. Since the accuracy of previous forecasts is known in the next period, it becomes:

$$A_t^F = -\sum_{K=1}^{K}\left[E_{t-1-k}^F(P_{t-k}) - P_{t-k}\right]^2 \tag{10}$$

$$A_t^C = -\sum_{K=1}^{K}\left[E_{t-k-1}^C(P_{t-k}) - P_{t-k}\right]^2 \tag{11}$$

Previous expectations are summed starting from previous period $t-1$ to final period $t-k-1$. The number of previous time periods that is considered when assessing the performance is captured by K. The number of previous periods K was determined emperically in Eviews by selecting the model with the highest Log-Likelihood score.[7] This approach is analogous to the Box – Jenkins method, which is used in time-series analysis to find the best fit of a time series to past values of this time series in order to make forecasts. Parameters A_t^F and A_t^C represent the sum of squared errors of fundamentalist forecasts and chartist forecasts respectively. The better strategy is the one where previous forecasted profit opportunities are close to realized prices, or where A is lowest. If the model works well, the strategy with low A will be the one where speculators switch to.

The strategy performance measures are then used to determine the weight of each speculator class dynamically. Speculators switch strategies after assessing the performance of either strategy:

$$W_t = \left[1 + \exp\left(\gamma\left[\frac{A_t^F - A_t^C}{A_t^F + A_t^C}\right]\right)\right]^{-1} \tag{12}$$

The weights of chartists versus fundamentalists change over time, with the γ parameter determining how eager speculators are to switch strategies. This parameter reflects the status quo bias (Samuelson and Zeckhauser, 1988). Speculators might be apprehensive in switching strategies, unless the incentive for change is compelling. The γ parameter is a vital parameter in the model. When $\gamma \to \infty$, speculators immediately respond to changes in strategy performance. When $\gamma \to 0$ speculators express a tendency towards the status quo. Obtaining negative γ would imply that investors opt for the worst performing strategy, which is against expectations. With $\gamma = 0$, they exhibit complete inertia and weights remain $W_t = 0.5$ for both classes. The impact of non-switching speculators is tested explicitly as a static model.

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[7] K=5 yielded the highest log likelihood scores on average and was selected for all markets. For comparison, ter Ellen and Zwinkels used 6 months for their paper on the oil market.

3.1.4 Price and Returns

Following conventional reasoning of supply and demand interaction, the new one-month price P_{t+1} is determined by excess net demand over supply for the current price. Hence:

$$P_{t+1} = P_t + \theta[D_t^M - S_t^R] + \epsilon_t \tag{13}$$

Where θ governs market frictions, D^M represents combined market demand and S_t^R is total supply of the natural gas. Finally, the noise term ϵ_t is added to capture random movements.
Putting the pieces together lets us obtain estimates of the next periods returns. The estimates yielded with equation 14 are used in the likelihood estimation procedure:

$$\Delta P_{t+1} = a + bP_t + W_t \begin{bmatrix} \alpha_1(P_t - F_t)^+ \\ +\alpha_2(P_t - F_t)^- \end{bmatrix} + (1 - W_t) \begin{bmatrix} \beta_1(P_t - P_{t-1})^+ \\ +\beta_2(P_t - P_{t-1})^- \end{bmatrix} + \epsilon_t \tag{14}$$

$$W_t = \left[1 + \exp\left(-\gamma \left[\frac{A_t^F - A_t^C}{A_t^F + A_t^C}\right]\right)\right]^{-1}$$

$$A_t^F = -\sum_{K=1}^{K} [\alpha_1(P_{t-k} - F_{t-k})^+ + \alpha_2(P_{t-k} - F_{t-k})^-] - \Delta P_{t-k+1}]^2$$

$$A_t^C = -\sum_{K=1}^{K} [\beta_1(P_{t-k} - P_{t-k-1})^+ + \beta_2(P_{t-k} - P_{t-k-1}{}^-] - \Delta P_{t-k+1}]^2$$

Where $a = \theta(a^r - a^s)$ and $b = \theta(b^r - b^s)$ represents net exogenous demand, and net impact of real market price-sensitivity. Furthermore, $\alpha_1 = \theta a^F b_1^F$, $\alpha_2 = \theta a^F b_2^F$ represent the price impact of fundamental analysis when current price is overvalued or undervalued with respect to fundamental price F. Finally, $\beta_1 = \theta a^C b_1^C$, $\beta_2 = \theta a^C b_2^C$ represent the price impact of chartist expectations when there is an upwards trend and downward trend.

The α_1, $\alpha_{2,}$ β_1, β_2 parameters will show how strong speculative tendencies of either agent category are in different scenario's associated with gains and losses. Since prospect theory suggests that investors are risk seeking over losses and risk averse over gains, I expect investors to be relatively risk averse in over-valuations (situation of high prices, associated with gains) and relatively risk seeking in undervaluation (situation of low prices, associated with losses).

For fundamentalists, I expect a negative sign with $\alpha_2 < \alpha_1 < 0$, such that fundamentalist have a lower impact on the subsequent return when they trade on an overvalued spot price. Alternatively, one could say that the differences in coefficients reflect a different type of bias. A bias that fundamentalists are more confident that low prices move up, than that high prices move down.

For chartists I expect a positive sign with $\beta_1 > \beta_2 > 0$, such that chartists have a higher impact on subsequent returns when they trade on an upward trending spot prices. The differences in parameters could either reflect aspects of prospect theory, or a bias where chartists are just more confident that upward trends continue, than that downward trend continue.

Estimates of the a and b parameter will determine if exogenous real supply and demand for natural gas spot, or price-sensitive demand and supply input is useful in modelling spot price movements.

3.2 HAM for Futures

It is important to stress the difference between the spot model and the futures model. The HAM model features a feedback system, in which the net excess demand predicts the return of the asset. This works not as straightforward for futures. A time series of one-month futures prices represents the prices of different futures all with delivery one month later. Each price is for a future with a different expiry, which makes each data point a different asset. However, the model treats the time series as if it were a continuing set of prices from the same asset.

An example makes it clear. The true profit opportunity for investing in three-month futures arises from the difference in X_{t+1}^{2} - X_{t}^{3}. For instance, true profit arises from $X_{t}^{July} - X_{t+1}^{July}$. This says that profit opportunity from trading a future with July delivery arises from the change in price for July delivery after one period. If $t = 0$ is April, X_{t}^{July} would be a three-month future. At X_{t+1}^{July} it has become a two month future, since we are now at $t = 1$ is May.

In contrast, the model's (proxied) profit from trading three-month futures is given by $X_{t}^{July} - X_{t+1}^{August}$. Where X_{t}^{July} and X_{t+1}^{August} are both subsequent three-month futures out of the dataset. The model says that profit arises from the difference in price between two subsequent three-month futures.

For a one-month future true profit occurs if the spot price $P_{t+1} > X_{t}^{1}$ (Hull, 2008). In the model, the one-month proxied profit is based on the difference of subsequent one-month futures. The choice for this type of proxy is motivated by the desire to aggregate same-length futures, so that results could be generalized. The following assumptions are required, but reasonable given high correlations amongst the assets:

1) Spot prices are correlated with one-month futures prices (table 3 in data section).
2) Futures with different expiry periods are highly correlated (Hull (2008), table 3 in data section).
3) The forecasted difference $E_{t}(X_{t+1}^{1})$- $\mathrm{X}_{\mathrm{t}}^{1}$ is a reasonable proxy for $E_{t}(P_{t+1})$ - X_{t}^{1}, with the latter being the actual expected profit opportunity at time t.
4) The forecasted difference $E_{t}(X_{t+1}^{2})$- $\mathrm{X}_{\mathrm{t}}^{2}$ is a proxy for $E_{t}(X_{t+1}^{1})$ - $\mathrm{X}_{\mathrm{t}}^{2}$, with the latter being the actual expected profit opportunity at time t. Similar reasoning applies to three-month futures.
5) Increased demand for X_{t}^{i} will increase the price of X_{t+1}^{i}.

Let any future with delivery next month be X_{t}^{1}. When a speculator predicts $X_{t+1}^{1} > X_{t}^{1}$ he assumes a long position in X_{t}^{1}. More elaborately, a speculator goes long a one-month future (eg. May delivery) contract if he predicts the next one-month future contract at $t + 1$ (June delivery) is priced higher. If he expects a downward movement, the speculator will short a futures contract.

His speculative profit originates from the associated movements in spot prices. Using assumption 1, when the speculator predicts that $X_{t+1}^1 > X_t^1$, it implies that he expects that $P_{t+1} > X_t^1$ which is where actual speculative profit stems from. Hence, P_{t+1} - $X_t^1 \approx \Delta X_t^1$. I argue that the correlated movements in P_{t+1} and X_{t+1}^1 will serve their purpose in showing if speculative motives exist. I expect that the estimated model performs better for two-month and three-month futures, as the correlation between futures prices will be higher than the correlation between one-month futures and spot prices.

Chartist and fundamentalist expectations and strategy comparison take place as in the original model. Now their combined expectations form the net demand for current X_t^i:

$$D_t^F = a^F [E_t^F(X_{t+1}^i) - X_t^i] \tag{15}$$

$$D_t^C = a^C [E_t^C(X_{t+1}^i) - X_t^i] \tag{16}$$

Real demand consists again out of exogenous and price-sensitive components:

$$D_t^R = a^r - b^r X_t^i \tag{17}$$

$$S_t^R = a^s + b^s X_t^i \tag{18}$$

In the final system of equations (equation 14) I expect that net price-sensitive impact of the real market is higher for futures markets than for spot markets. I expect a higher price-elasticity for futures than for natural gas spot. In the spot market there can be immediate pressure from consumers of natural gas to obtain their required amount, whereas producers will have pressure to sell all their production. This leads to a relatively in-elastic product when compared to futures, where consumers and producers have more time to assess their needs and as a result are more flexible in meeting their future demands.

Finally, next period's future prices is given by

$$X_{t+1}^i = X_t^i + \theta[D_t^M - S_t^R] + \epsilon_t \tag{19}$$

This equation states that excess demand for X_t^1 impacts the next period X_{t+1}^1. While it is clear how increased demand for natural gas spot leads to a higher price of natural gas spot, how would demand for a future influence the demand for a subsequent future? This thesis posits that speculators influence subsequent futures prices. Natural gas futures are highly correlated, in part because of inter-temporal substitution of natural gas consumption, and since the same fundamentals affect the availability of natural gas in multiple periods. If a large number of speculators enter a May future because they expect the price for May delivery to rise, this will drive the price for May delivery up. This increase in price signals to other investors that the value of natural gas has risen. Since delivery in June is a close substitute for delivery in May, the excess demand over supply for a May contract will have the price for the June contract co-move upward. Hence, demand for X_t^1 raises the price for X_{t+1}^1. Similar reasoning applies to 2-month and 3-month futures. Since futures lend themselves especially well for speculative purposes, I expect that speculators are more actively switching strategies when compared to the spot market, and switch with higher intensity.

4 US Natural Gas Market

To place the HAM model in its real world context, I examined the natural gas market. Historically, the natural gas industry was one of the most highly regulated sectors of the U.S. economy (Park et all, 2006). This lasted until the 1960's, after which federal regulation was initiated because of market power concerns. This change was expressed through a variety of acts and regulations. The Federal Energy Regulatory Commission (FERC) and its predecessor the Federal Power Commission (FPC) supervised the market and determined regulation. However, regulations involved price controls that led to shortages of natural gas in the 1970's. In 1978, the Natural Gas Policy Act was passed, starting the deregulation of the market. Price ceilings were removed, and local distribution companies were allowed to purchase gas on the spot market.

Since the onset of price deregulation, there has been constant evolution in the North American natural gas market. The emergence of a natural gas futures market, market hubs, spot markets and a secondary market for transportation capacity have transformed the industry (King, Martin, Cuc, Milan, 1996). Natural gas prices are determined in two markets: the cash or physical market, where physical quantities of natural gas are sold and purchased; and the financial market, where financial instruments whose prices are linked to the price of natural gas in the physical market are traded.

4.1 Spot Market

The natural gas market is large, with a 2009 marketed production volume of 21 trillion cubic feet. Parties that enter a trade in the spot market can do so for immediate or monthly delivery. Traders need to determine the price for which the gas is traded. They can either negotiate a price, or refer the prevailing market price for natural gas at their particular location. Industry newsletters take surveys of the price of transactions at the key locations where natural gas is sold or delivered, and publish daily summaries and monthly "indexes" of those prices. These prices can be used as reference points when setting the price of a natural gas contract, and prevent the need to individually negotiate a price for each contract. If a transaction takes place at a location where there is not a reliable reference price, the price is set at the prevailing price of a near location with a transportation premium added.

These locations are known as either "hubs," where many natural gas pipelines converge, or "city gates" where gas is delivered to a local distribution company. The Henry Hub in Louisiana is such a hub where a large number of pipelines converge, and is the most widely used reference location for natural gas prices in North America. The Henry Hub prices are most commonly used in studies on natural gas pricing. The daily spot market for natural gas is very active with trading taking place continuously throughout the week. The largest volume of transactions occurs in “bid week”, when the core of natural gas production is sold for the upcoming month. The delivery conditions can vary substantially on the spot market. Large natural gas users, such as industrial users or local distribution companies, usually purchase natural gas in the spot market on a daily basis for immediate delivery, or on a monthly basis for a fixed amount of gas to be delivered each day of the specified month or months. Monthly contracts that are agreed on the spot market may be entered into one or more months in advance of the delivery month, but are still considered spot transactions. The importance of long-term contracts between natural gas companies and users has decreased over the years. Instead, spot markets allow for greater flexibility to react to changing market conditions and have taken over in importance gradually.

4.2 Financial Market

Two US financial markets offer derivative products based on energy products. Natural gas futures are traded on the NYMEX in New York and natural gas swaps trade on ICE in Atlanta. It has been estimated that the volume of trading that occurs on the natural gas financial market is approximately twelve times greater than the value of the spot market [8]. Unlike the spot market however, trades in these markets rarely lead to actual delivery. Derivatives that are based on natural gas prices can be classed into futures, forwards, options or swaps, of which delivery in forward contracts is most common. For swaps and futures, positions are often offset by new, opposing positions. For instance, an investor that is three May natural gas future contracts long, will need to sell three May natural gas contracts to close his position. Futures are standardized contracts that specify delivery of gas according to pre-determined conditions. Future contracts must be traded on a certified exchange, where the price is determined by day-to-day demand fluctuations.

Futures allow market participants to hedge themselves against future price risks and they provide a market-based mechanism for price discovery. Futures have a price discovery function, as their price is a result of the market consensus on the value of future delivery. In a sense, a two month natural gas future price is a collection of estimations of fair future spot prices. Because of this feature, future prices are often used as forecasts of spot prices. However, for futures to be fair estimators they must be unbiased, which is still under debate (Movassagh and Modjtahedi, 2005).

Two type of market participants are active. Speculators trade futures contracts in order to obtain above normal returns by taking on price risks. Hedgers use the futures market to lock in the price of future purchases or sales. Speculators take the other side of the bet, and are an essential part of a financial market with sufficient liquidity.

[8] Miller, 2006. http://soba.fortlewis.edu/FCEQ/dgoherald_articles/07feb_hedg.pdf

4.3 Natural Gas: Fundamentals

The Energy Information Administration (EIA) at the Department of Energy classifies natural gas consumption into four sectors: residential, commercial, industrial, and electric power. These sectors differ in how demand changes throughout the year. The price of natural gas is determined by a variety of fundamental factors that influence supply and demand for each of the sectors. These market fundamentals include amongst others: aggregate storage levels, consumer responses to price changes, weather impact, the cost of gas exploration and production, oil prices, general economic conditions, and regional pipeline capacity relative to demand (Mu, 2007). [9]

The fundamental factors have different ways of impacting the natural gas price. Since natural gas consumption is seasonal, there will be high demand in winter months when buildings require heating. The total consumption peaks in December and January arising from residential and commercial customers' space heating demand, troughs in summer when the space heating demand is low. In the summer, it has a "local peak" around July and August as cooling demand increases the electric power use of natural gas. In addition, weather affects gas prices through exceptionally warm and cool days (above and below the norm temperature). At these days, increased demand for gas (demand for air-condition and heating, respectively) results in higher prices.

In contrast, natural gas production is not seasonal. This results in gas inventories being built up during the summer for use in the winter. According to the laws of supply and demand, large natural gas inventories should depress prices and low inventories (below the seasonal norm) boost prices. Since industrial production is relatively stable throughout the year, variability in the fundamental natural gas price can largely be explained by weather.

Disruptions of natural gas production due to disasters are well-known cause of higher prices, as exemplified by hurricanes Rita and Katrina. When a volatile hurricane season is forecasted prices jump upwards. Natural gas prices are also known to follow oil price changes, as oil is a close substitute of natural gas: higher oil prices are often followed by higher gas prices. Rules of thumb in use in the energy industry such as the 10-to-1 rule suggest that the natural gas price is approximately one tenth the price of crude oil. Finally, whenever industry forecast are favourable, industrial demand for natural gas is likely to increase which boosts future prices.

There are multiple variables that affect price formation in the natural gas market and multiple rules of thumbs that can infer the value from other oil. The recent deep-water horizon incident and the extreme weather events witnessed around the globe underline that any commodity market can have its fundamentals changed from day to day. While it is helpful to understand the fundamental factors that drive natural gas prices, they do not exclude the possibility of speculative influences.

[9] http://www.eia.doe.gov/oil_gas/natural_gas/info_glance/natural_gas.html provides a selection of articles on fundamental factors affecting natural gas.

5 Data & Methodology

5.1 Data

To answer the question on speculative influences on the natural gas market, a dataset consisting of monthly natural gas spot and futures prices proved valuable. This paper uses monthly spot and futures prices obtained from the Energy Information Administration (EIA) from 1993 to 2010 August.[10] The EIA collect surveys from natural gas producing and marketing companies to obtain their averages spot prices. Prices are based on the average wellhead prices for natural gas. The wellhead price is defined as: “the value at the mouth of the well. In general, the wellhead price is considered to be the sales price obtainable from a third party in an arm's length transaction. Wellhead prices pertain to all transactions occurring in the United States, encompassing purchase commitments with varying delivery locations. Pyndick (2004) stresses that natural gas spot prices are influenced by different delivery specifications and discounts between buyers and sellers. Taking monthly prices, the assumption that daily deviations cancel each other out seems legitimate. Spot prices are generally quoted in dollars per MCF, which represents dollars per thousand cubic feet[11]. One Mcf equals 1.027 mmBtu.[12]

	Spot*	**M1**	**M2**	**M3**
Mean	0.005979	0.005720	0.005520	0.005507
Median	0.007424	0.000000	0.004535	0.004640
Maximum	0.322933	0.406626	0.363435	0.295890
Minimum	-0.442791	-0.394129	-0.376309	-0.372313
Std. Dev.	0.122187	0.135302	0.123922	0.112640
Skewness	-0.406322	-0.069097	-0.090501	-0.025323
Kurtosis	4.151398	3.388989	3.217902	3.211779
Jarque-Bera	14.97858	1.285174	0.605163	0.357590
Probability	0.000559	0.525930	0.738908	0.836277
Observations	181	181	181	181

Table 1 Descriptive statistics for monthly log returns of spot and futures markets. The * represents that these values have been converted from McF to BTU values.

The EIA website also provided the data on natural gas futures. Natural gas futures are highly liquid, most notably for close delivery months. Prices represent dollars per million British Thermal

[10] http://www.eia.doe.gov/pub/oil_gas/natural_gas/data_publications/natural_gas_monthly/current/pdf/appendix_b.pdf

[11] http://www.eia.gov/dnav/ng/TblDefs/ng_pri_sum_tbldef2.asp

[12] http://www.natgas.info/html/natgasunitsconversion.html

Unit (mmBtu) and are based on delivery at the Henry Hub in Louisiana for a specific delivery month. Each contract covers 10,000 mmBtu. Natural gas contracts expire three business days prior to the first calendar day of the delivery month. Thus, the delivery month for a one-month contract is the calendar month following the final possible trade date.

The data sample for spot and futures comprised all months from January 1993 to August 2010, to ease comparison of results. Descriptive statistics are provided for spot and futures prices in table 1.

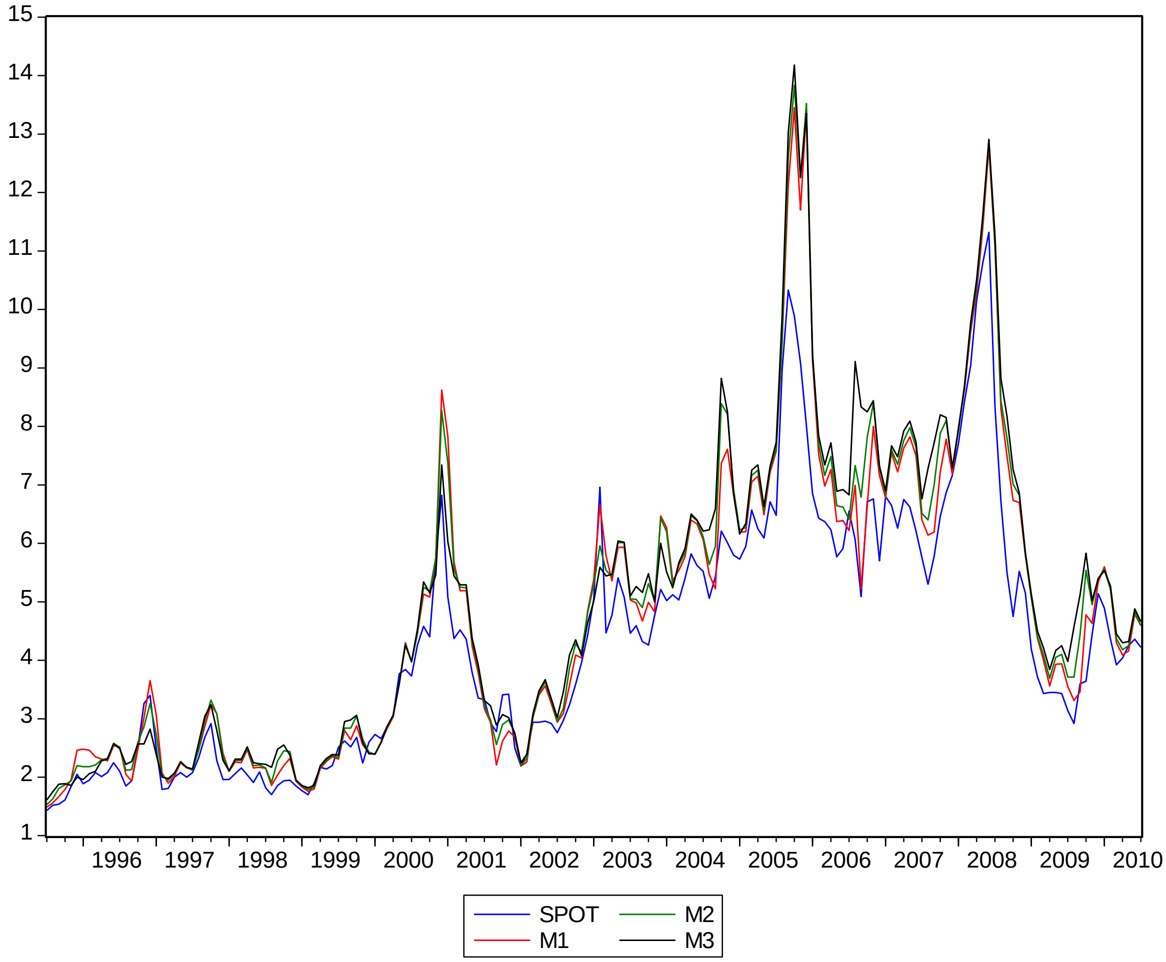

Figure 2 Dollar prices of natural gas spot and natural gas futures.

	SPOT	M1	M2	M3
SPOT	1,000	0,971	0,970	0,964
M1	0,971	1,000	0,996	0,983
M2	0,970	0,996	1,000	0,994
M3	0,964	0,983	0,994	1,000

Table 2 Correlation of prices across markets

	SPOT	M1	M2	M3
SPOT	1,000	0,682	0,666	0,598
M1	0,682	1,000	0,956	0,863
M2	0,666	0,956	1,000	0,946
M3	0,598	0,863	0,946	1,000

Table 3 Correlation of log returns across markets

Table 1 shows that the average log return was close to 0 in all four samples. A visual representation of returns is presented in histograms in the appendix figure 1-4. A formal Jarque-Bera test shows that futures returns seem to be in in line with the assumption of normality, whereas that cannot be said for spot returns. The excess kurtosis of spot returns indicates the distribution is peaked with fat tails. Spot prices have shown more extreme returns than future markets have, which can be explained by the inelasticity's associated with short-term demand and supply in the spot market. The standard deviation decreases when maturity increases, which is in line with findings from Mu (2007), who also documents that returns of first month futures are more volatile than those of second month futures.

Table 2 shows high correlation between the prices of both futures and spot prices, which is reinforced graphically by figure 2. Table 3 shows a different picture. Changes in spot price do not co-move extremely well with changes in futures prices. This can be explained by the fact that spot market exhibit different dynamics than futures market, as discussed in the subsequent chapter. The high correlation between futures with different time to maturity was expected, as these futures are close substitutes and the same dynamics and factors affect each future. Considering the assumptions as outlined in section 3.2, the lack of correlation suggests that the one-month future are not a perfect proxy for the spot at t+1.

5.2 Estimation

The objective of the estimation is to determine the parameters that maximize the probability (likelihood) of the sample data. The method of choice is quasi maximum likelihood (QML) estimation (Ter Ellen and Zwinkels, 2010). It is based on the more maximum likelihood method, but allows non-normal distribution of residuals. The maximum likelihood (ML) approach would be the appropriate choice if we are more certain of a normal residual distribution (White, 2000). The prefix quasi reflects the possibility that the likelihood specification might be incorrect, but that the maximum likelihood estimators are none the less consistent. How the asymptotic distribution of the quasi estimators differs from the ML distribution is discussed in depth in Verbeek (2002). The general likelihood function is given by

$$\mathrm{Ll} = -\frac{T}{2}(1 + \ln(2\pi) + \ln(\mathrm{RSS/T}) \tag{20}$$

Where T is the number of observations and RSS give the sum of squared residuals. Generally:

$$\mathrm{RSS} = \sum_{t=0}^{T}(y_i - \theta_i)^2 \tag{21}$$

Here y_i equals the observed return ΔP for the spot market or ΔX for the futures market. θ_i is estimated return in a period, governed by equation (14). The difference between actual return y_i and estimates θ_i give the residuals.

The principle of likelihood parameter estimation is to find the parameter values that make the observed data most likely, or with the highest likelihood value. The QML provides estimates of the considered variables according to equation (14) and provides Z-values that convey the probability that an estimated coefficient of such variable is equal to zero. In the results section, P-values are provided to show the confidence with which I can claim the parameter to be different than zero.

Through an iterative process, Eviews selects parameter values such that the log-likelihood function is at its maximum. Due to the nature of the iterative process, there is a risk that the optimisation algorithm stops too early and returns a sub-optimal estimate of the parameter. As a result, the problem with non-linear likelihood estimation is its sensitivity to appropriate starting values, as there might me local maxima and minima. The remedy is to specify the model well, and to use different sensible starting values to see if the same parameter estimate arises.

5.3 Nested Model Selection

There are two objectives. The first is to establish which of the models is able to fit the data best in light of parsimony. Second, we want to compare that model fit with benchmark models, to evaluate if the best HAM out-performs other models. The performance of a model can be both assessed in-sample and out-sample. Intuitively, out-sample forecasting performance comparison would unambiguously point towards the best model. However, Inoue and Killian (2002) argue that for small samples, in-sample testing might be a better alternative than out-sample testing, as using the full sample size allows more accurate estimation of parameters.

A characteristic of the static, switch, asymmetric and symmetric model setup is that they are nested models, meaning that all parameters used in the restrictive versions are used in the unrestrictive version[13]. Additional parameters will always increase the likelihood of model estimation; but it might be a reflection of fitting to noise in observed data. A statistic that works well for nested models while rewarding parsimony, is the log likelihood ratio (LLR) test.

$$D = -2\log(Ll_0 - Ll_1) \tag{22}$$

Where $Ll_0$is the likelihood score of the restricted model and Ll_1 of the unrestricted model. Whether this difference is significant is assessed using the probability distribution of D, which approximates a

[13]All parameters used in the restrictive (ie. static-symmetric) model are present in the unrestricted (ie. a-symmetric switch) model

Chi-square distribution with $V_1 - V_0$ degrees of freedom, where V_0 and V_1 give the number of variables used in the restricted and unrestricted model.
One rejects the restricted model if the test statistic if $D$is greater than the 1-a quantile of the Chi-squared distribution with $V_1 - V_0$ degrees of freedom. If that is not the case, the restricted model remains the best candidate.

5.4 Benchmark models

The log-likelihood selection exercise yields the model with which to compare benchmark models against. Following Ter Ellen and Zwinkels (2010), the other models I consider are the Random Walk (RW) and the Vector Auto-Regression model (VAR). The random walk hypothesis is a popular way to describe the evolution of financial asset prices, in particular with log prices.
The VAR is selected because it uses historical values to predict future values, an idea shared by many investors.

The RW assumes that asset prices follow a stochastic process in which it randomly moves up or down with respect to the previous value. A random walk specifies that the current observed value is the best estimate of next period's value. A time-series is a random walk without drift if:

$$P_{t+1} = P_t + \epsilon\text{, or equivalently } \Delta P_{t+1} = \epsilon \qquad (23)$$

P represents the natural log of either spot of futures prices. $\Delta P_{t+1} = \epsilon$ states that changes in log price (returns) are only due to "white noise" around a finite mean and finite variance, and is assumed to be independently and identically distributed. The equation shows that the best estimate of the future value of the asset is the current value of the asset. This property makes the random walk a natural benchmark to compare other models against.
Alternatively, $\Delta P_{t+1} = \mu + \epsilon$ where μ provides the average difference of P_t. This is the random walk model with drift, and is an approximation when the data is trending. If the estimation of the random walk shows that μ = 0, there is no trending over time. If $\mu \neq 0$ there is a trend.

A VAR is generally estimated on financial data when P_t and P_{t-1} are correlated and this relationship shows persistence. Each variable is a linear function of its own past values with a serially uncorrelated error term:

$$P_t = a + b_1 P_{t-1} + b_2 P_{t-2} + b_3 P_{t-3} + b_k P_{t-k} + \epsilon_t \qquad (24)$$

Again a is an intercept which can be interpreted as a general trend over time. While it may be the case that additional lags carry information, incorporating that lag should be considered in light of model parsimony. When compared to the Random Walk, the VAR will have more information to work with. Since the VAR can use more lags than the RW, the VAR will always at a minimum equal in performance to the Random Walk model, as VAR = RW for 0 lags. To penalize the use of extra lags, the Akaike Information Criterion is used to optimize lag length.[14]

Since the VAR and HAM model are not nested versions of each other, a different comparison criteria is required. An adjusted Akaike Information Criterion (AICc) is selected to compare the relative performance of the HAM and VAR models. The AIC values high likelihood scores of different models and compares them with model parsimony in mind. The AICc is based on the AIC but more appropriate for smaller samples, according to amongst others Burnham and Anderson (2000). The AICc adjusts the AIC criterion when sample sizes are relatively small compared to estimated parameters. The rule of thumb says the AICc should be selected over the general AIC whenever $T/K < 40$, but Burnham and Anderson argue that the AICc should always be selected, as for large sample sizes it converges to the general AIC. In their words: "a pervasive mistake is the use of AIC when AICc should be used." Eviews provides the general AIC and divides by sample size as follow:

$$\text{AIC} = -2l/T + 2K/T \tag{25}$$

In contrast, the AICc is calculated as:

$$-2l + 2K + (2K(K+1))/(T-K-1) \tag{26}$$

To transform Eviews AIC values to AICc values the appropriate adjustment is to multiply by T, and add $+(2K(K+1))/(T-K-1)$. It is important to note that K consists of all the number of explanatory variables. For the asymmetric switch HAM model, K=8 including the error term. When a random walk with drift is estimated, a constant and an error term are used, so K=2. For a VAR, the number of lags plus a constant and an error term give total K.

[14] The Eviews VAR estimation procedure features a Lag Length Test that helps select the number of lags for based on the AIC score.

6 Results

6.1 Spot Market

Table 4 shows the values obtained from the likelihood estimation and shows in brackets the probability with which the estimated coefficients are the same as zero, the null hypothesis. The table on spot data shows a mixed picture. Log-likelihood scores are close across the board. The γ-value is of the expected size and significance in the asymmetric model, while not within reasonable bounds in the symmetric model. The former indicates a low status quo bias in line with expectations, whereas the latter suggests that investors switch to the worst performing strategy. The low significant value there suggests we should focus our attention on the asymmetric model.

Spot		**Asymmetric**		**Symmetric**
Fundamentalist	Static	Switch	Static	Switch
$\boldsymbol{\alpha_1}$	-0.392939**	-0.659483 **	-0.084856	-0.046696
	(0.0175)	(0.0330)	(0.2555)	(0.3768)
$\boldsymbol{\alpha_2}$	0.064585	0.256494		
	(0.5752)	(0.2247)		
Chartists				
$\boldsymbol{\beta_1}$	0.292000	0.474503**	0.460318***	0.352799***
	(0.1623)	(0.0234)	(0.0016)	(0.0075)
$\boldsymbol{\beta_2}$	0.581860***	0.375537**		
	(0.0042)	(0.0321)		
Real Demand/Supply				
$\boldsymbol{a}$	0.071123**	0.072609**	0.056030**	0.058976*
	(0.0229)	(0.0145)	(0.0498)	(0.0520)
$\boldsymbol{b}$	-0.034390	-0.028125	-0.040657**	-0.042257**
	(0.1080)	(0.1756)	(0.0463)	(0.0371)
Switching				
$\boldsymbol{\gamma}$	-	1.217906**	-	-4.559574
		(0.0244)		(0.4069)
Log-Likelihood	**132.6885**	**133.1732**	**130.5882**	**131.7472**

Table 4 Estimation Results Spot Market. *, **, *** Represent significant values at the 0.01, 0.05 and 0.10 level respectively.

Table 4 shows that the α1 coefficients are of the hypothesized sign in the all cases, meaning that fundamentalists indeed expect a correction when natural gas spot is above fundamental value. This tendency is more present when speculators are allowed to switch strategies. In contrast, fundamentalist reaction to undervaluation α2 is not significant and points at a direction not in line with expectations for all cases. In the symmetric case, the α1 parameter represents general fundamentalist reaction. No significant results are obtained, which should not surprise considering the two opposing signs of the asymmetric fundamentalist parameters.

The chartist coefficients β1 and β2 show a reaction to upward trends and downward trends in the asymmetric models and are expected to exhibit $\beta_1 > \beta_2 > 0$. This is true only for the asymmetric switch version, whereas the asymmetric static β_1 does not turn significant. General chartist reaction is again highly significant in the symmetric versions and suggests that chartists indeed extrapolate trends. On the real demand and supply side, the presence of an extraneous supply and demand factor is present, given the obtained significance values. Price-sensitive influences are also likely, given significance factors of hypnotized sign on all values.

Spot	**Asymmetric**		**Symmetric**	
	Static	Switch	Static	Switch
Log-Likelihood	132.6885	133.1732	130.5882	131.7472
ΔLog(switch) (1DF)	NA	0.9694 (0.3248)	NA	2.318 (0.1278)
ΔLog(symmetric) (2DF)	2.852 (0.2403)	4.2006 (0.1224)	NA	NA
ΔLog(both) (3DF)	NA	5.17 (0.1597)	NA	NA

Table 5 This table presents the log-likelihood scores of the different HAM models for the spot market. ΔLog notes the difference between compared models, with a significance value in brackets. DF stands for degree of freedom, and differs per model version. The colored cells show which models are compared (horizontally).

Table 5 summarizes whether the switch mechanism and asymmetry add to model fit. Allowing switching fails to improve the model for both symmetric and asymmetric versions. This is not an alarming finding in the symmetric version ,given the highly unlikely value of the switching parameter. But the lack of significant improvement is an alarming finding for the asymmetric version; it seems not likely that speculators actively switch strategies.

While the parameter estimates do point towards a degree of heterogeneous expectations, a changing dynamic cannot be proven. In addition, the lack of fundamentalist direction in case of undervaluation warrants additional scepticism. When taking a different perspective, we also note that adding asymmetry to the symmetric model fails to improve the model significantly, which suggests that in the spot market prospect theory seems not to be of influence. In light of the failure to accept the switch models as the superior models, there is still some value in investigation of figures 3 and 4. They show how the weight of fundamentalists versus chartists changes over time for the two models. In general, the chartists dominate the market for both asymmetric and symmetric model versions, and investors do switch to fundamentalists beliefs fairly frequently. The asymmetric version shows a more smooth transition from chartists to fundamentalists strategies, whereas the symmetric figure shows a market when speculators have the estimated negative status-quo bias. Interesting to note is that investors are in this case eager to switch to the worse performing strategy and do so at very high frequency, which results in very different weights over time when compared to the asymmetric strategy. Since the fundamentalists reaction parameter in the symmetric switch version is estimated to be close to zero, the estimates of the this model imply that investors switch to zero change expectations after they have enjoyed the profits of a chartist strategy, given the negative value for γ. The *a* and *b* parameter show that the real economy plays a significant role, but real demand and supply keep eachother mostly in balance given opposing signs.

6.2 One-month Futures

Table 6 shows estimation results on the nearest-month futures. We start by noticing that the switch parameters are quite high, especially in the symmetric version, indicating a high willingness to switch strategies. For the symmetric version, the sign of γ is different from zero at a 0.10 significance level, while the asymmetric switching parameter is given with more confidence. Like in the spot market, we note that introducing the switch increases the significance of the chartists and fundamentalist estimates with respect to their static counterparts. Investors exhibit less status quo bias in case of the symmetric model, given the higher value of γ when compared to the asymmetric case γ. Both values indicate that switching does take place, and that it improves overall model fit given increased log-likelihood.

Again, we see that fundamentalist do not respond well to an undervaluation, indicating a problem with the specification of fundamentalist expectation formation in such scenarios. It suggests that fundamentalists are not confident that the value of natural gas corrects upwards. In contrast, chartists expectations are as anticipated present across all models. The size of the chartist parameters increases when introducing the switching mechanism, and features the anticipated $\beta_1 > \beta_2 > 0$ in case of the asymmetric case. The symmetric switch version performs particularly well, with all parameters turning significant at hypothesised signs. Net exogenous demand is positive again, but the negative net price-sensitivity is not as strong as in the spot market. The e *a* and *b* parameter show that the real economy plays a significant role, but real demand and supply keep each other mostly in balance given opposing signs. The net effect of the real economy on price dynamics continues to be small for two-month and three-month futures.

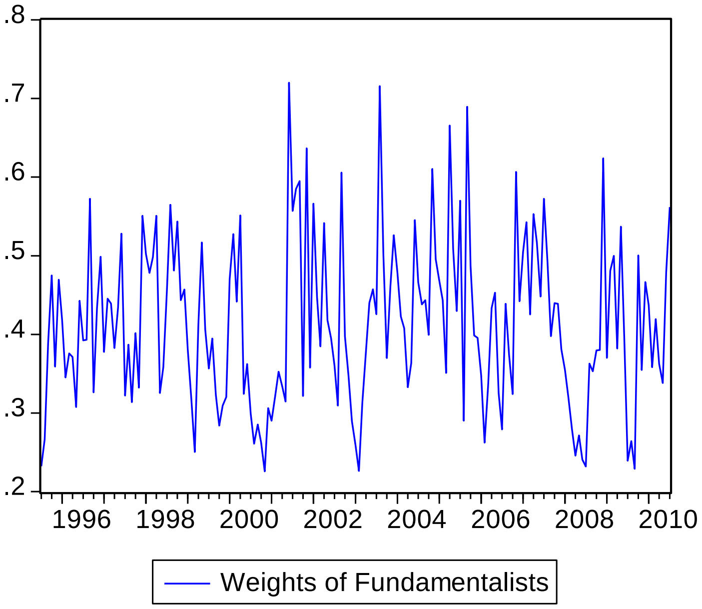

Figure 5 Natural Gas Asymmetric Spot

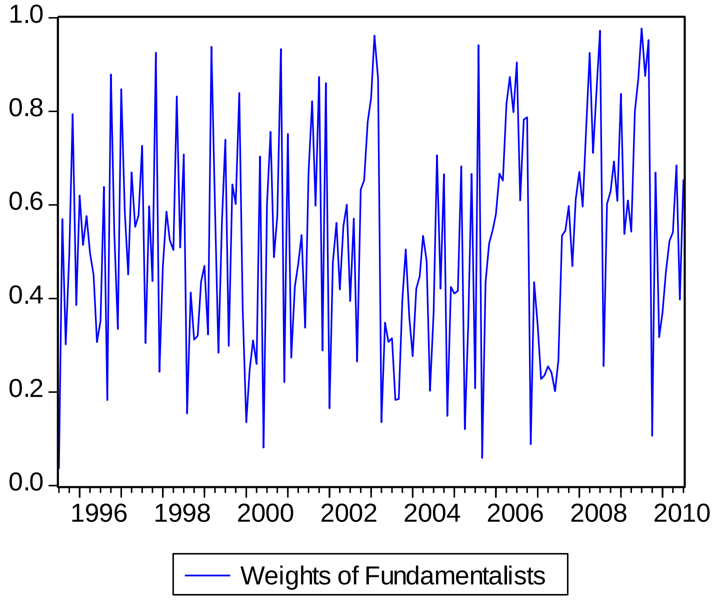

Figure 6 Natural Gas Symmetric Spot

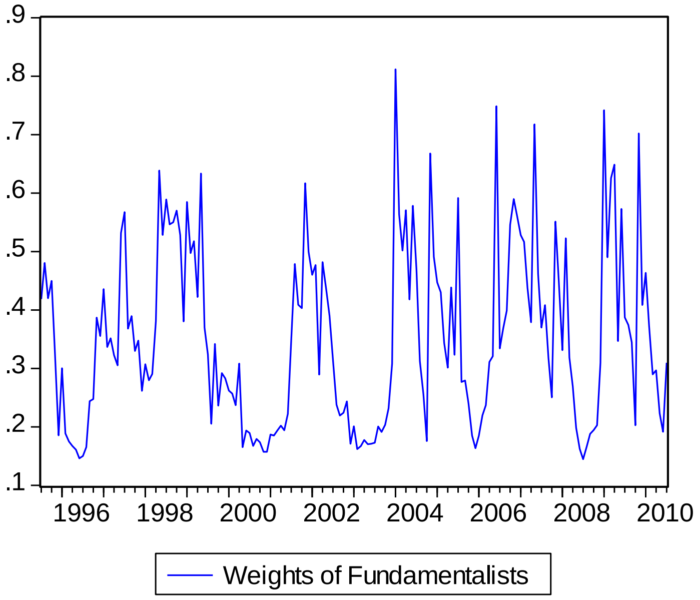

Figure 4 Natural Gas Asymmetric One-Month Future

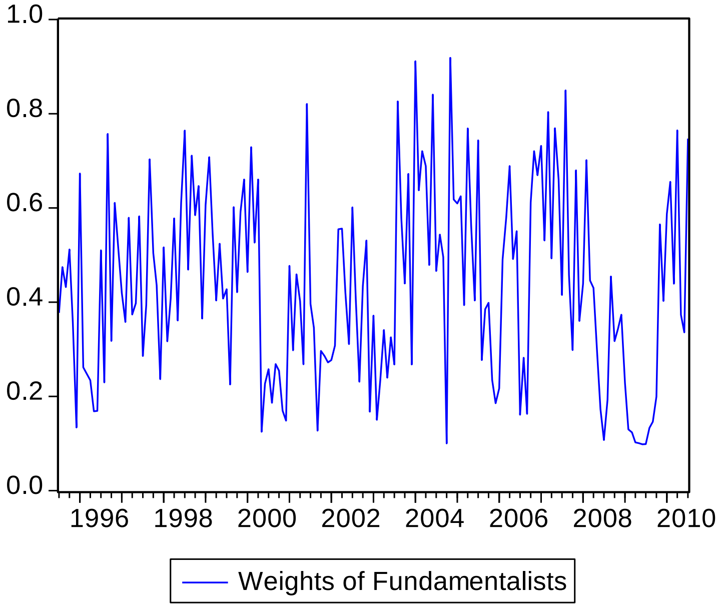

Figure 3 Natural Gas Symmetric One-Month future

M1	Asymmetric		Symmetric	
Fundamentalist	Static	Switch	Static	Switch
$\boldsymbol{\alpha_1}$	-0.285327*	-0.905408*	-0.100145	-0.240552**
	(0.0612)	(0.0732)	(0.1925)	(0.0485)
$\boldsymbol{\alpha_2}$	0.056553	0.233915		
	(0.7027)	(0.1236)		
Chartists				
$\boldsymbol{\beta_1}$	0.448849	0.584559**	0.515171***	0.567482***
	(0.1831)	(0.0111)	(0.0029)	(0.0003)
$\boldsymbol{\beta_2}$	0.634660**	0.483897*		
	(0.0433)	(0.0689)		
Real Demand/Supply				
$\boldsymbol{a}$	0.076104**	0.084388***	0.062142**	0.056514*
	(0.0196)	(0.0059)	(0.0498)	(0.0658)
$\boldsymbol{b}$	-0.033398	-0.027500	-0.039439*	-0.033602*
	(0.1051)	(0.1620)	(0.0504)	(0.0855)
Switching				
$\boldsymbol{\gamma}$	-	1.852325***	-	3.038.255*
		(0.0059)		(0.0828)
Log-Likelihood	**114.2297**	**119.2427**	**113.0664**	**116.3989**

Table 6 Estimation Results One-Month Futures. *, **, *** Represent significant values at the 0.01, 0.05 and 0.10 level respectively.

Figures 5 and 6 show how weights change over time. Unlike the spot model both, both models exhibit positive γ values such that the dynamics of both resemble each other in large lines. Chartists dominate the market mostly, but there are clear fundamentalist spells that occur after a chartist trend reverses, and that coincide with the reversals visible in figure 2. An important difference is again the more volatile changes in the symmetric case.

Table 7 shows that for the one- month futures market, the switching mechanisms increases model fit significantly when compared to the static cases for both symmetric and asymmetric versions below a 0.01 significance level. Incorporating asymmetry in speculator responses yields improvements close to a 0.05 significance level, making the asymmetric switch model most likely to be the best model. The symmetric switch model provides the second best alternative.

M1	Asymmetric		Symmetric	
	Static	Switch	Static	Switch
Log-Likelihood	114.2297	119.2427	113.0664	116.3989
ΔLog(switch) 1DF	NA	10.0260*** (0.0015)	NA	6.665*** (0.0098)
ΔLog(symmetric) 2DF	2.3266 (0.3125)	5.6876* (0.0582)	NA	NA
ΔLog(both) 3DF	NA	12.3526*** (0.0063)	NA	NA

Table 7 This table presents the log-likelihood scores of the different HAM models for one-month futures. ΔLog notes the difference between compared models, with a significance value in brackets. DF stands for degree of freedom, and differs per model version. The colored cells show which models are compared (horizontally).

6.3 Two-month Futures

For two-month futures, the results in table 8 closely resemble the estimation results of one-month futures. Fundamentalists again lack a clear direction when confronted with undervaluation. Chartists have again a higher impact in up-ward trends when compared to down-ward trends. What stands out is the lack of power of adding the switching mechanism to the symmetric version, where adding γ in the asymmetric version is highly significant. This might be due to the fact that fundamentalist responses are aggregated and they do not provide an sufficiently different alternative to the chartist strategy. When inspecting the other speculator responses, one notices a fundamentalist response to overvaluation of -1.4. This suggests that the fundamentalist reaction to the discrepancy between fundamental futures price and observed futures price is overly “corrected”. One possible explanation is that trend-reversals are intense, and overshooting fundamentalist responses are the result of herding behaviour (Boswijk et al., 2007) that continues after the fundamental value has been reached. Furthermore, exogenous net market influences seem present, whereas price-sensitive functions are implicated but not significantly so.

M2	Asymmetric		Symmetric	
Fundamentalist	Static	Switch	Static	Switch
$\boldsymbol{\alpha_1}$	-0.372081***	-1.403694**	-0.123592	-0.201602*
	(0.0062)	(0.0196)	(0.1168)	(0.0778)
$\boldsymbol{\alpha_2}$	0.094657	0.226722		
	(0.5094)	(0.1483)		
Chartists				
$\boldsymbol{\beta_1}$	0.515663	0.689920***	0.629088***	0.674998***
	(0.1168)	(0.0007)	(0.0006)	(0.0002)
$\boldsymbol{\beta_2}$	0.816256**	0.540813**		
	(0.0274)	(0.0285)		
Real Demand/Supply				
$\boldsymbol{a}$	0.029398**	0.073842***	0.053820*	0.054416**
	(0.0140)	(0.0065)	(0.0575)	(0.0457)
$\boldsymbol{b}$	-0.025435	-0.020274	-0.033194*	-0.032360*
	(0.1588)	(0.2375)	(0.0649)	(0.0592)
Switching				
$\boldsymbol{\gamma}$	-	1.876992***	-	2.960200
		(0.0001)		(0.1100)
Log-Likelihood	**133.6988**	**140.0789**	**130.9354**	**134.8012**

Table 8 Estimation Results Two-Month Futures. *, **, *** Represent significant values at the 0.01, 0.05 and 0.10 level respectively.

The figures 7 and 8 shows again significant time-variation in strategies over time, with most speculators adhering to chartists' strategies. In general the figures and interpretation are reminiscent of those of the one-month futures market. Table 9 shows that the asymmetric switch model improves upon its nested competitors at high significance levels. Its closest competitor is the symmetric switching model. Introducing asymmetry to the symmetric switch model yields model improvements, and adding the switch mechanism to the static asymmetric model does as well. The asymmetric switch model performs significantly better others.

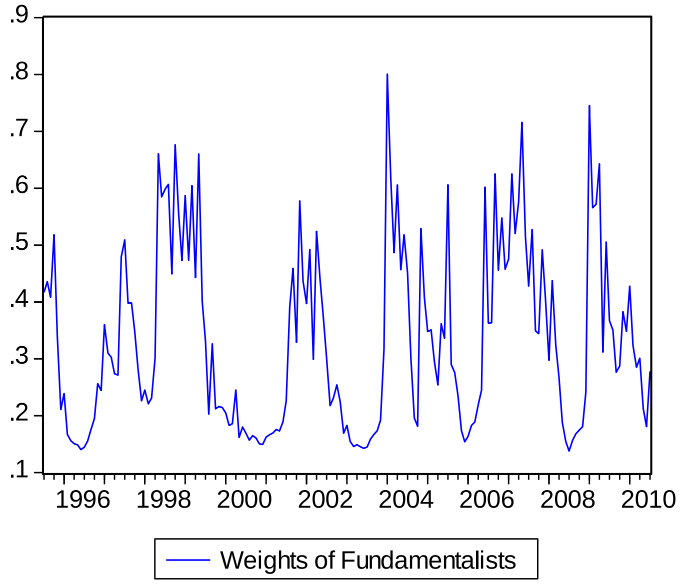

Figure 7 Natural Gas Asymmetric Two-Month Future

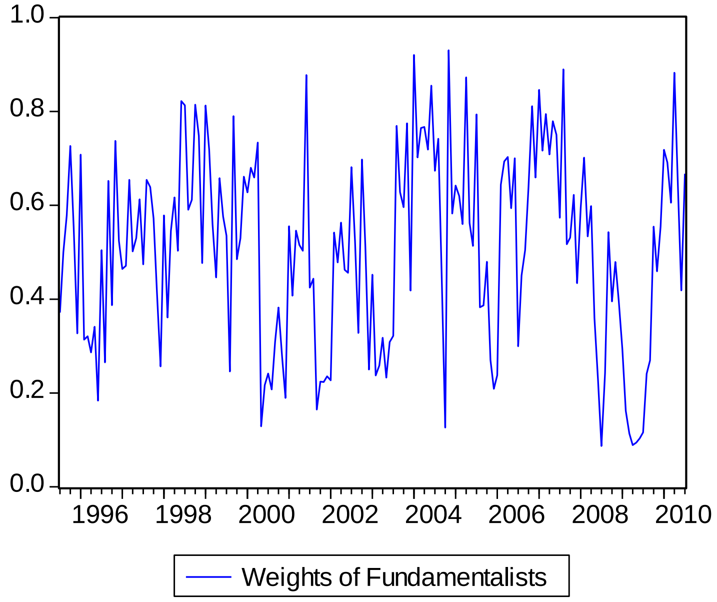

Figure 8 Natural Gas Symmetric Two-Month Future

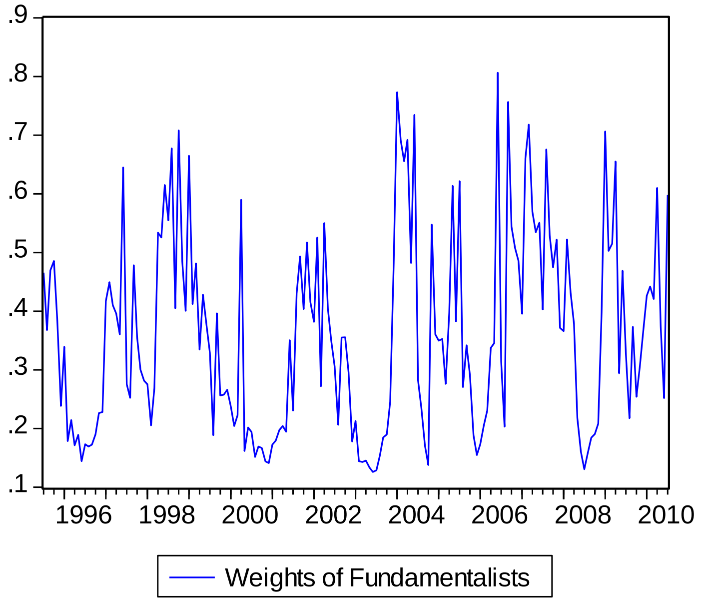

Figure 9 Natural Gas Asymmetric Three-Month future

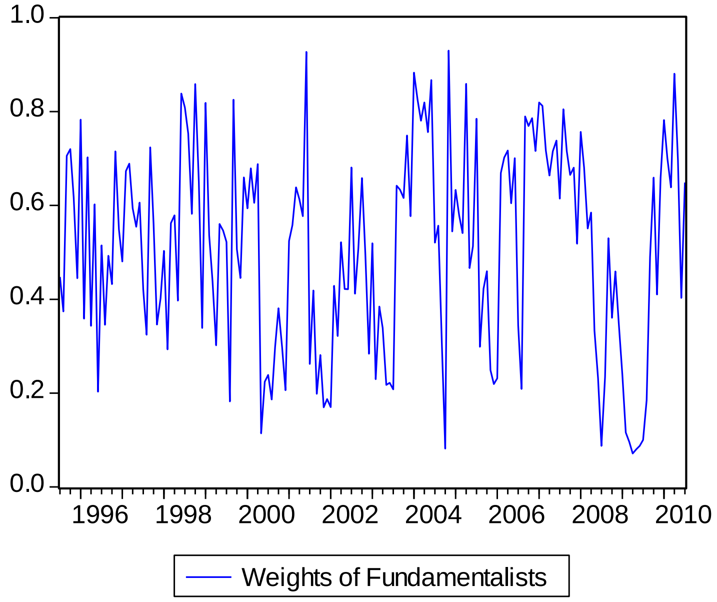

Figure 10 Natural Gas Symmetric Three-Month future

M2	Asymmetric		Symmetric	
	Static	Switch	Static	Switch
Log-Likelihood	133.6988	140.0789	130.9354	134.8012
ΔLog(switch) 1DF	NA	12.7602*** (0.0000)	NA	6.665*** (0.0098)
ΔLog(symmetric) 2DF	5.5268* (0.0630)	10.5554 *** (0.0051)	NA	NA
ΔLog(both) 3DF	NA	18.2870*** (0.0000)	NA	NA

Table 9 This table presents the log-likelihood scores of the different HAM models for two-month futures. ΔLog notes the difference between compared models, with a significance value in brackets. DF stands for degree of freedom, and differs per model version. The colored cells show which models are compared (horizontally).

6.4 Three-month futures

For three month futures, an interesting change from the one and two-month futures occurs. Here the presence of fundamentalists is implicated by the sign of parameters, but does not pass a significance test of at the 0.10 level in the asymmetric switch model.. It indicates a less convincing story of fundamentalist presence. Other values are all within reasonable bounds, with again no clear distinction between positive and negative trends for chartists. The switching mechanism is not significant for the symmetric version, but is highly significant in the asymmetric case.

M3	Asymmetric			Symmetric
Fundamentalist	Static	Switch	Static	Switch
$\boldsymbol{\alpha_1}$	-0.263013**	-0.889539	-0.100253	0.181957
	(0.0460)	(0.1157)	(0.1911)	(0.1448)
$\boldsymbol{\alpha_2}$	0.056545	0.217039		
	(0.6852)	(0.2238)		
Chartists				
$\boldsymbol{\beta_1}$	0.245397	0.540204***	0.539406***	0.619150***
	(0.3639)	(0.0042)	(0.0016)	(0.0002)
$\boldsymbol{\beta_2}$	0.881973**	0.487747*		
	(0.0157)	(0.0672)		

Real Demand/Supply				
a	0.063879**	0.064140**	0.047224*	0.051070**
	(0.0191)	(0.0121)	(0.0722)	(0.0422)
b	-0.020682	-0.021406*	-0.028466*	-0.029503*
	(0.2029)	(0.1706)	(0.0746)	(0.0508)
Switching				
γ	-	2.083529 ***	-	3.170366
		(0.0017)		(0.1047)
Log-Likelihood	**148.4540**	**151.7364**	**146.2326**	**149.7960**

Table 10 Estimation Results Three-Month Futures. *, **, *** Represent significant values at the 0.01, 0.05 and 0.10 level respectively.

Figures 9 and 10 show again a market dominated by chartists, and time-variation of speculator strategies is clearly present. The model comparison table 11 shows that introducing a switch mechanism improves the model when compared to the static version in asymmetric and symmetric versions at significance level close to 0.01. Looking from a different perspective, introducing asymmetry to the symmetric switching version does not yield significant improvements. Hence, the most important observations are that introducing γ yielded the hypothesized improvements, and differentiating expectations within fundamentalist classes is again difficult. As a result, the improvements from symmetry to asymmetry are not clearly present.

M3	**Asymmetric**		**Symmetric**	
	Static	**Switch**	**Static**	**Switch**
Log-Likelihood	148.4540	151.7364	146.2326	149.7960
ΔLog(switch) 1DF	NA	6.5648** (0.0104)	NA	7.1268 *** (0.0076)
ΔLog(symmetric) 2DF	4.4428 (0.1085)	3.8808 (0.1426)	NA	NA
ΔLog(both) 3DF	NA	11.0076 *** (0.0117)	NA	NA

Table 11 This table presents the log-likelihood scores of the different HAM models for one-month futures. ΔLog notes the difference between compared models, with a significance value in brackets. DF stands for degree of freedom, and differs per model version. The coloured cells show which models are compared (horizontally).

6.5 Changing Weights

The weights of speculators over time shows for all markets that the chartist' strategy is preferred in most periods. This is especially true for the futures market. This consistent finding implicates that most speculators have faith in a market in which each subsequent future is priced higher than the previous one. They believe the market is mostly trending. The fundamentalist strategy appeals mostly in periods that coincide with reversals after peaks in prices (figure 2).

The figures 11 -14 represent the impact of the status quo bias for the selected asymmetric switch models. The figures show how fundamentalist's weight changes when plotted against the relative difference in performance of the strategies. When chartist's performance is lower, AC+AF/AC+AF increases, and higher AC+AF/AC+AF increases fundamentalist weight. The higher values for γ in futures markets are reflected by a more vertical plot, since a vertical plot represents high speculator responsiveness to small differences in strategy performance. An S-shape is visible for futures market, and contrasts with the straight line for the spot market. This indicates that increasingly large differences in performance have diminishing effect on shifting of weights in futures market. The steepness of the plot around the 0.5 weight mark shows that investors are sensitive to which strategy performs best, but become relatively less sensitive when performance differences increase.

6.6 Benchmarking in the Spot Market

As discussed in the previous sections, introducing the switch parameter to either the asymmetric or symmetric version was an improvement for all models except for the spot market. Introducing asymmetry yielded improvements for the one and two-month futures at levels close to 0.05, but was a decisive improvement for three-month futures. Overall, the alleged superiority of incorporating prospect theory in speculator expectations is not proven. In general, the asymmetric switch model was the best performing model and is used for further comparison with benchmark models.

The log-likelihood estimation results of the random walks and VAR's are presented alongside the scores for the HAM models in table 12. The VAR model obtains higher log-likelihood scores in the spot market only, but for all other markets the asymmetric switch HAM appears to be best. As discussed in the methodology section, these models are non-nested, and ΔLog is not an appropriate method of comparison to evaluate the claim that the HAM model is indeed better. The AICc approach can help out, and the steps taken in the AICc tests are shown in table 13.

In the spot market, the VAR model outperforms the HAM. It seems that HAM has its best application in the futures market. Especially for two-month futures, given the confidence of 0,99 with which it is the better model. For one and three-month futures, the probability that the HAM is better is close to 0.95, which also constitutes strong support in favour of the HAM model.

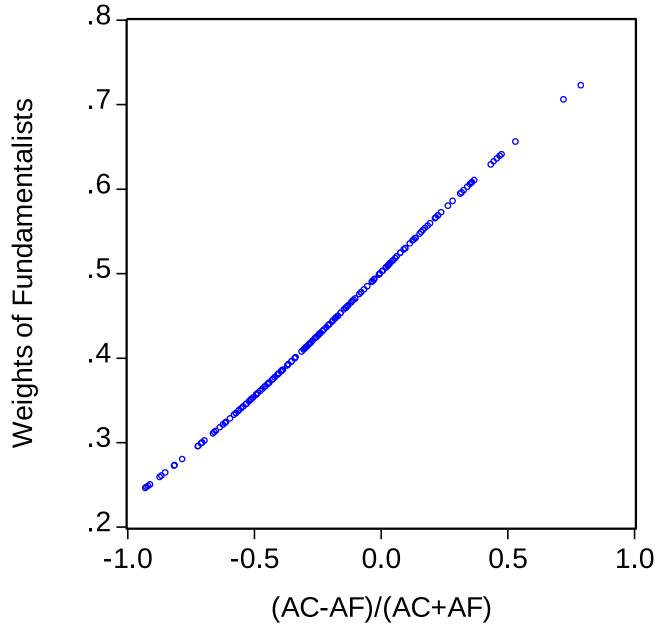

Figure 11 Spot Market strategy performance and weights

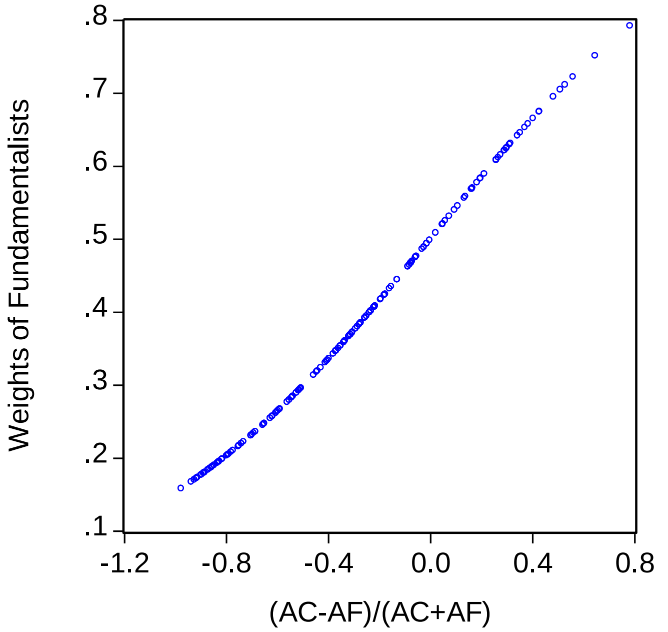

Figure 12 1-Month futures strategy performance and weights

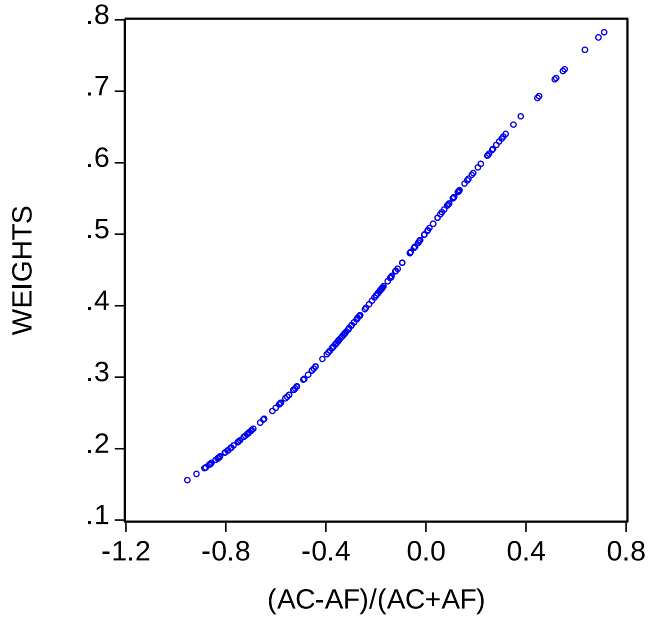

Figure 13 2-Month futures strategy performance and weights

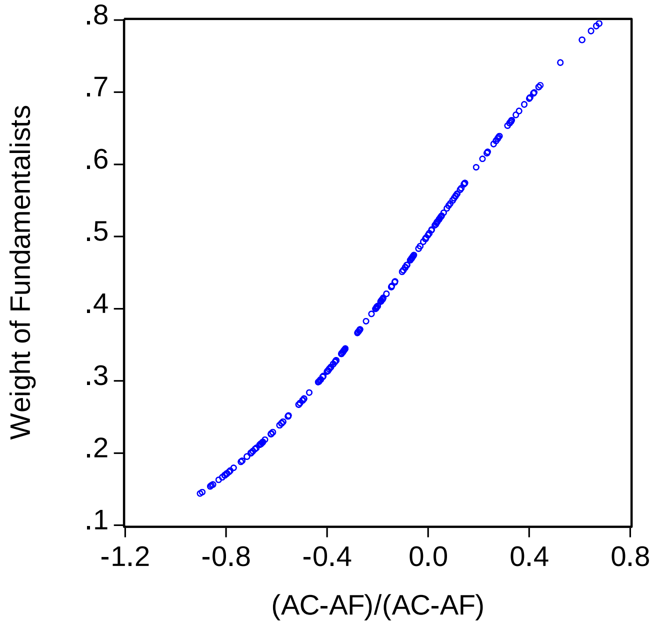

Figure 14 3-Month futures strategy performance and weights

	HAM	RW	VAR
Spot	133.1732	124.1727	132.69
	(-249,848)	(-246,093)	(-259,146)
M1	119.242	105.7180	122.0397
	(-222,336)	(-209,350)	(-216,067)
M2	140.0789	121.6200	138.1367
	(-263,061)	(-241,206)	(-249,029)
M3	151.7364	138.8978	151.7944
	(-287,496)	(--275,777)	(-281,522)

Table 2 Comparison of log-likelihood scores. This table shows the log-likelihood scores of the benchmark models and adjusted Akaike info criterion scores. The VAR model included for spot: 2 lags, for M1: 10 lags, M2: 8 lag, M3: 9 lags.

	HAM	RW	VAR
ΔAICc Spot	9,297937	13,0531	0
exp(-0.5*Δ)	(0,010)	(0,001)	(1)
AICc weights	[0,009]	[0,001]	[0,989]***
ΔAICc M1	0	12,986	6,269
exp(-0.5*Δ)	(1)	(0,002)	(0,043)
AICc weights	[0,957]**	[0,001]	[0,042]
ΔAIC M2)	0	21,856	14,032
exp(-0.5*Δ)	(1)	(1,8E-05)	(0,001)
AICc weights	[0,999]***	[1,79E-05]	[0,001]
ΔAIC M3	0	11,719	5,974
exp(-0.5*Δ)	(1)	(0,003)	(0,050)
AICc weights	[0,949]*	[0,003]	[0,048]

Table 13 Comparison of AICc weights. shows which model is most likely to be best. The. ΔAICc gives the difference in AICc scores with the best (lowest AICc score) model. Exp(-0.5*Δ) gives the relative likelihood of the model. This likelihood is normalized in AICc weights, which gives the chance that the considered model is actually the best model. *, **, *** Represent probabilities values greater than 0.99, 0.95 and 0.90 level respectively. Small values are rounded.

7 Conclusion

The media have become increasingly aware of speculators in commodity markets. Hedge funds such as Amaranth are known to have taken large positions and impact the market adversely. But the natural gas spot and futures market has shown tremendous growth and increased regulation throughout the years and a similar scenario is not likely. But aggregate trading of many smaller speculating investors might impact over price dynamics. Traditional approaches using a rational expectations framework are of limited use in modelling speculators, but behavioral finance is able to incorporate bounded rationality and heterogeneous expectations using biases. This papers Heterogeneous Agents Models tested whether heterogeneous influences explain the observed price variation in the natural gas market.

The first objective was to model the behaviour of natural gas prices using heterogeneous agents that switch strategies over time, and evaluate if adding ideas grounded in behavioural finance added value to the model. The second objective was to analyse if the best performing HAM models yields a higher fit with observed data than benchmark models do.

The results of this study sketch a clear picture of heterogeneous expectations in short-term futures market. Chartist extrapolative activity in the spot market is visible in all markets in both upwards and downwards trends, whereas their fundamentalist counterparts are only clearly present in situations where they find that spot prices are higher than fundamental values. The distinction between the two is accurately reflected in the signs of the parameters: negative for fundamentalists and positive for chartists and significantly different from zero. Chartist responses show for all models a higher coefficient in positive trend situation than in downward trends ($\alpha 1 > \alpha 2$). Testing whether these differences are significant is left for future studies. Such tests might support the notion that a slight distinction in heuristics is at work in positive and downward trends. The hypothesised responses for fundamentalist are not visible in all markets, but the difference in expectation between the fundamentalist class and speculator class is clear. At the very least, the fundamentalist strategy provides a conservative no-change forecasted strategy in over-valued markets.

The positive net exogenous demand impacts price formation is present in most markets, but is mostly countered by the negative impact of the price sensitivity function.

The switching mechanism clearly adds explanatory value in the futures market, but not so in the spot market. This finding can be attributed in part to the quality of the spot market data, which was found to be particularly non-normal and which is based on non-standard contracts that make it less attractive for aggregate data-analysis. Spot prices can reflect different delivery specifications and buyer-seller relationships in the spot market. In addition, the hypothesis of speculators trading on the spot markets is less convincing than the hypothesis of speculators active on futures market, as the spot market requires warehousing to actually profit from spot price movements. It seems that the characteristics of the natural gas spot market make it less likely that speculators impact prices, which is why the VAR performs so well when compared to the HAM model.

This paper presents supportive evidence of dynamic behaviour of speculators in natural gas futures markets. Observed returns in the futures market can be convincingly explained by a HAM model. The model is shown to out-perform a benchmark VAR. Subsequent research should focus on whether the assumptions hold, in particular the assumption that the expected profit forecasts can be proxied. But the reported high levels of correlation between futures suggest that it is a fair approximation, and results show that the model works well. The HAM approach should be explored more thoroughly, especially its applicability to futures markets, a market where speculators are known to be very active. Recommendations for further studies include using high frequency data to understand how speculators behave on shorter terms, modelling different expectation formations, and most importantly, out-sample forecasting comparison.

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Appendix

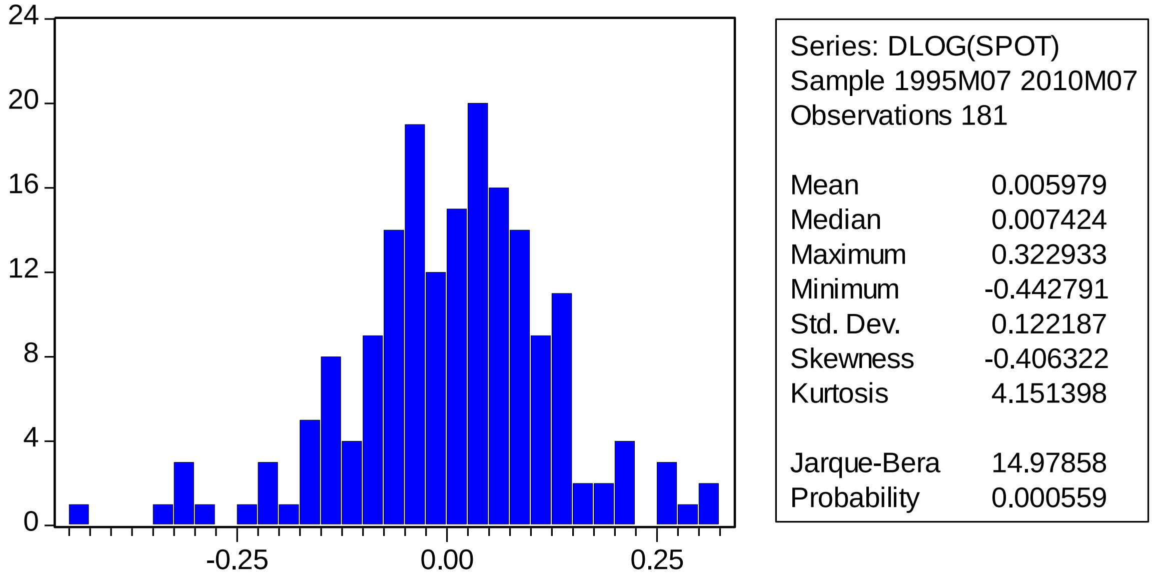

Figure 8 Histogram of log spot returns

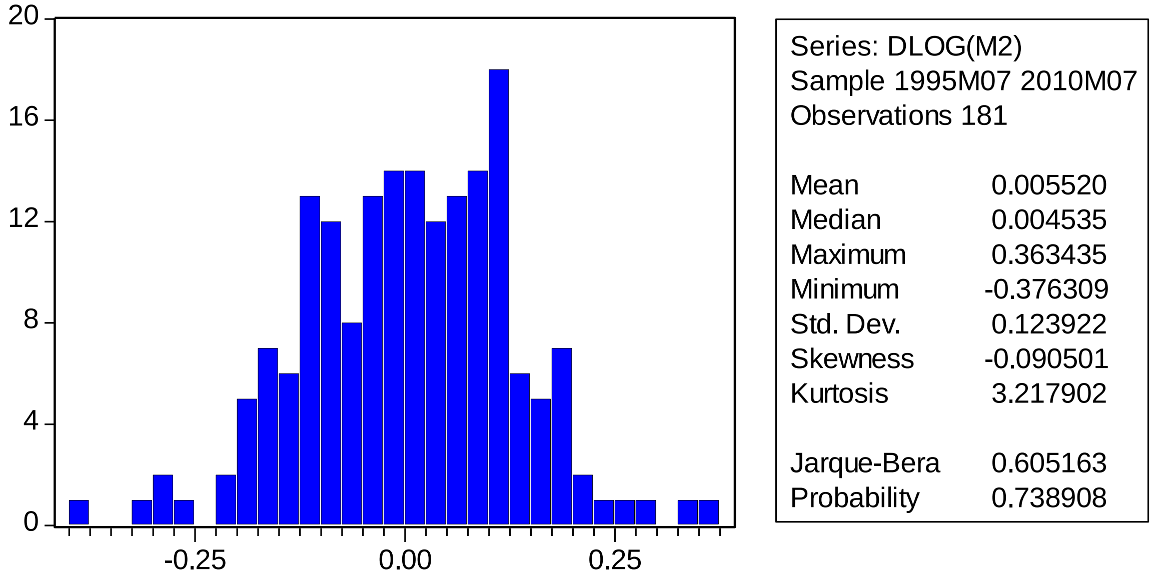

Figure 2 Histogram log-returns 2-month futures

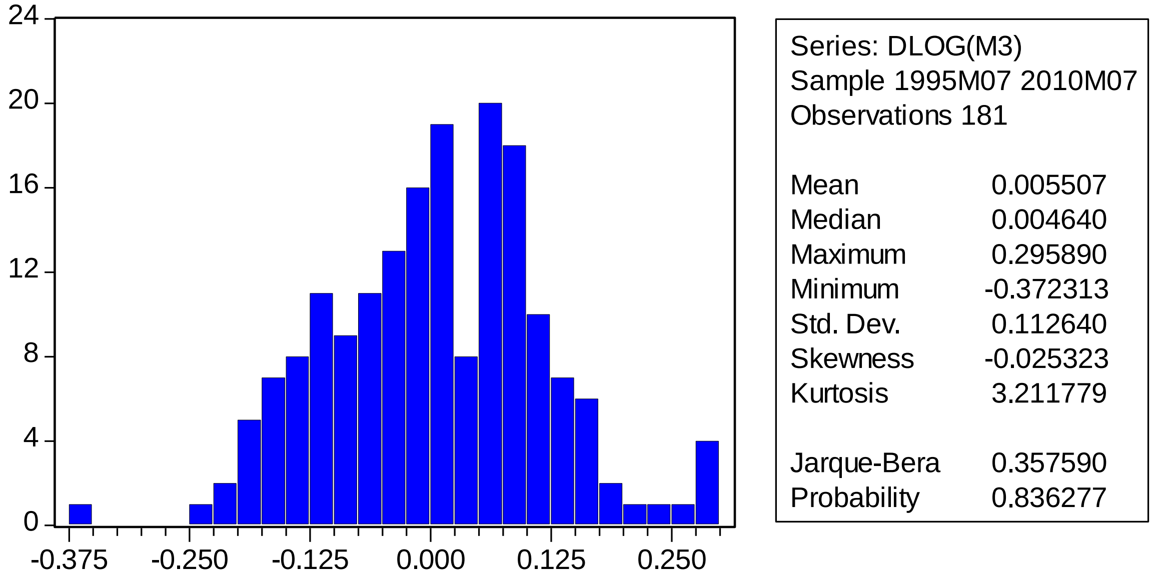

Figure 3 Histogram log-returns 3-month futures

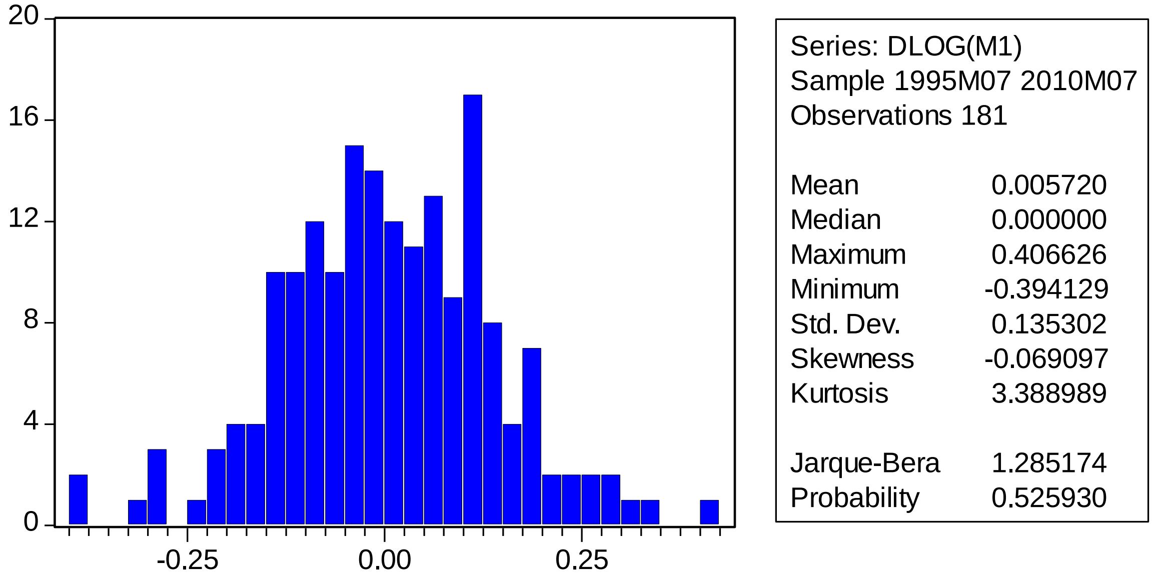

Figure4 Histogram log-returns 1-month futures