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Summary

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Keywords: Energy Forward Prices, Financialization, Heterogeneous Agents, Uncertainty Aversion, Regret

JEL Classification: Q43, G15, G02, D81

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Heterogeneous beliefs, regret, and uncertainty: The role of speculation in energy price dynamics*

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Abstract

This paper proposes to investigate the impact of financialization on energy markets (oil, gas, coal, and electricity European forward prices) during both normal times and periods of extreme fluctuation through an original behavioral and emotional approach. With this aim, we propose a new theoretical and empirical framework based on a heterogeneous agents model in which fundamentalists and chartists co-exist and are subject to regret and uncertainty. We find significant evidence that energy markets are composed of heterogeneous traders who behave differently, depending on the intensity of the price fluctuations and the uncertainty context. In particular, energy prices are mainly governed by fundamental and chartist neutral agents during normal times, whereas they face irrational chartist averse investors during periods of extreme fluctuations. In this context, the recent surge in energy prices can be viewed as the consequence of irrational exhuberance. Our new theoretical model outperforms the random walk in out-of-sample predictive ability.

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1 Introduction

The recent and unprecedented surge observed in energy prices, and especially in the price of crude oil, from 2003 to 2008 has given rise to heated public and academic debates about the true nature of these shocks. Due to the potential impact of these huge movements on most economies (Sadorsky, 1999; Hamilton, 2003; Edelstein and Kilian, 2007; Kilian, 2008, among others), the effectiveness of economic policies strongly depends on the identification of the major causes of energy prices movements. Since Greenspan's (2004) intervention regarding the existence of speculators in oil market, a popular view of the origins of the price surge has been that these movements cannot be attributed to economic fundamentals (such as changes in the conditions of supply and demand), but were caused by the increasing financialization of commodities. This financialization should in turn cause volatility clustering phenomena, extreme movements, higher comovements between oil, financial assets, and commodity prices, as well as an increased impact of financial investors' decisions (such as hedge funds, swap dealers, . . .). The question as to the influence of financial investors on energy prices is of primary importance from both the economic and the political point of view. Economically, the role of speculation in energy markets raises the question of the trade-off between private and public interests, since financialization is often defined as being benefical from the private perspective without any benefical considerations from a social planner's point of view. Politically, the debate is even more relevant since it lends credibility to the regulation of the markets for commodity derivatives in the same way that the G20 governments try to regulate financial markets by limiting speculative behavior.[1]

Therefore, there has been a renewal of interest in the academic literature in this topic, even if no clear-cut conclusion has emerged. Indeed, the question about the role of speculation in commodity markets is not trivial; identifying and quantifying this phenomenon is a difficult task because trader positions are relatively opaque. As we will see in Section 2, some studies have defined the phenomenon as the consequence of increased comovements between markets, while some others consider markets as composed of different shocks which affect price dynamics. However, these approaches mainly focus on the oil market, without considering other energy prices, whereas the same movements also occur in these markets. More importantly, they assume that the market is efficient in the sense that investors are rational

[1] In 2010, the U.S. government initiated the Dodd–Frank Wall Street Reform and Consumer Protection Act, regarding commodity markets, to limit speculative behavior by mandating centralized clearing of OTC standard contracts and automation of the Securities and Exchange Commission.

and representative, and the oil price fully reflects all the available information. Oil market efficiency was however rejected by GjØlberg (1985) and by Moosa and Al-Loughani (1994). Moreover, according to Kirman (1992), aggregation arguments under rational behavior are insufficient to reduce markets to a single representative agent. Indeed, following Townsend (1983) and Singleton (1987), it seems reasonable to assume heterogeneous expectations, and it appears optimal for each agent to forecast the forecasts of others. Fundamentals are important but a variety of different models may be relevant to explaining behavior in energy markets. The purpose of this paper is precisely to bring new theoretical elements to understand who and what drive the markets.

Another important limitation in the existing literature is that it has been based on an analysis of risk as opposed to uncertainty.[2] Therefore, previous studies have supposed that agents do not allow for any uncertainty in their models, their priors, or the future evolution of prices, although allowing uncertainty could be relevant to account for some of the "anomalies" and stylised facts of markets.

Previous analyses have thus evolved in a constrained world, where agents are rational and where uncertainty does not exist. To deal with these limitations we propose a new theoretical and empirical framework to investigate what drives energy price fluctuations. Our theoretical model overcomes the restrictive assumption of rationality by allowing for the possibility that heterogeneous expectations could be the cause of recent price movements. We propose to extend the traditional heterogeneous agent model (HAM) of Brock and Hommes (1997, 1998) in the same way as Kozhan and Salmon (2009) to account for uncertainty in the markets. We therefore assume that investors are faced with forming energy price expectations and consider the worst outcome within the set of different models in some interval, where the size of the interval is a subjective choice of the agents, which allows capturing different degrees of uncertainty aversion. In traditional HAM, agents are supposed to switch between different strategies characterizing heterogeneous specifications according to a cognitive learning process. We propose to extend this rule to a more realistic one which accounts for both cognitive and emotional dimensions by a regret criterion *à la* Bell (1982) and Loomes and Sugden (1982).[3]

We also estimate our model empirically using nonlinear least squares (NLS) methods to investigate whether heterogeneous expectations and uncertainty exist in the markets and can lead to strong fluctuations in energy prices. The estimations are done for both normal times and periods of extreme

[2] By risk we mean that agents know the probability distribution of a random variable, as opposed to uncertainty, when agents have no knowledge of this.

[3] According to the seminal work of Damasio (1994), emotion can also affect behavior and play a crucial role in the decision process, where lack of feelings leads to suboptimal choices.

movements[4] in order to see if the behavior of prices depends on the intensity of the markets.[5] The theoretical model is then compared to a random walk (RW) in terms of its predictive ability. To our best knowledge, investigating the relative impact of financialization on energy price fluctuations through behavioral and emotional aspects under uncertainty during normal and extreme situations has never been done before.

The present paper is organised as follows. The next section provides a review of the literature on the role of speculation in energy markets. Section 3 describes our theoretical framework, and Section 4 outlines the specification and estimation procedure of the model. Section 5 contains in-sample and out-of-sample estimation results, and Section 6 concludes the paper.

2 The role of speculation in energy markets: What have we learned so far?

This section reviews the literature related to the impact of speculation on energy markets, and more specifically on oil future prices.[6] We discuss the relative conceptualization of "commodity speculation" and how it can impact price dynamics. We identify four strands in this literature. One strand links the participation of financial investors in the oil markets to the evidence of increased comovements between oil, commodity, and stock prices. Another strand looks at the causal relation between the positions taken by index fund managers and oil prices. The third approach uses structural VAR models to investigate the impact of speculation. Finally, the fourth approach assumes that the existence of heterogeneous traders in the markets, namely fundamentalists and chartists, can impact the fluctuations of prices.[7]

In this heated debate about the financialization of the oil market, and more generally of commodity markets, the key question is how to define what we call "commodity speculation". According to Kilian and Murphy (2013), a general definition of speculation in the oil market refers to a situation of "anyone buying crude oil not for current consumption, but for future use." Following this definition, speculative investors can have two options,

[4]Normal times are approximated by price movements in the mean of the distribution, while extreme fluctuation periods are those in the quantiles.

[5]By *intensity of the markets*, we consider price movements during normal times and periods of extreme price fluctuations.

[6]This debate mainly focuses on the oil market due to its potential impact on the real economy (c.f. Hooker, 1996; Rotember and Woodford, 1996; Hamilton, 2003; Sauter and Awerbuch, 2003;...).

[7]Unlike Fattouh et al. (2012), we do not talk about either the relation between oil futures and spot prices, or the role of time-varying risk premia in oil futures markets.

buying physical oil now and storing it to accumulate oil inventories, or buying crude oil futures contracts. Therefore, according to Alquist and Kilian's (2010) analysis, speculation in one of these markets will be necessarily reflected in speculation in other markets. In this sense, speculation would not be economically "irrational" because it seems reasonable that oil producers, considered as physical traders, will stock up on crude oil to smooth the production of refined products. Speculation would be essential for the oil market to function, because it provides liquidity and assists the price discovery process. However, speculation in the public debate has a negative connotation because it is often viewed as an excessive phenomenon. This excessive phenomenon would be the consequence of private interests, increasing price movements and affecting the social welfare. Determining excessive speculative behavior is a difficult task because it do not necessarily come from the positions taken by traders. Commercial traders generally act as hedgers to protect their physical interests, while noncommercials traders are often considered to be speculators. However, as documented by Büyüksahin and Harris (2011), we can have situations where commercial investors take a speculative position in the sense that they take a stance on the commodity price without hedging it in the futures market.

2.1 Comovements between commodity and financial prices

Since 2003, without explicit mention of financialization, there has been clear evidence of an increased proportion of financial investors in the oil futures market (see Alquist and Kilian, 2010; Büyüksahin et al., 2009; Tang and Xiong, 2011; Hamilton and Wu, 2011; among others). The first strand of literature on this topic focuses on comovements between commodity prices, mainly oil prices, and stock markets, as well as volatility spillover effects. Hammoudeh et al. (2004), using cointegration techniques as well as ARCH-type specifications among five daily S&P oil sector stock indices and five daily oil prices for the US oil markets from July 1995 to October 2001, find volatility spillover effects from the oil futures market to the stocks of some oil sectors. Chiou and Lee (2009), focusing on the asymmetric effects of WTI daily oil prices on S&P 500 stock returns from January 1992 to November 2006, investigate the structure changes in this dependency relation. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected, and negative unexpected oil price fluctuations, they find that high fluctuations in oil prices have asymmetric unexpected effects on stock returns. Filis et al. (2011) analyze time-varying correlations between oil prices and stock markets by differentiating between oil-importing (USA, Germany, and the Netherlands) and oil-exporting (Canada, Mexico, and Brazil) countries. They find that the conditional variances of oil and stock prices do not differ for each group. Büyüksahin et al. (2010), Silvennoinen and Thorp (2010), Choi and Hammoudeh (2010), and Cretì et al. (2013) show that conditional correlations between commodity returns and stock indexes have increased recently, especially in periods of high volatility. Büyüksahin and Robe (2011) further document that the increase in price comovements is related to the entry of hedge funds into both markets. Different general conclusions can emerge from these studies. Indeed, some studies argue that increased comovements between markets lead to decreased potential diversification (Silvennoinen and Thorp, 2010), while some others suggest that these comovements between prices develop transmissions from a wide range of commodity and financial markets (Tang and Xiong, 2011). However, this literature does not imply that the recent surge in commodity prices was caused by "commodity speculators". It could be due to many macroeconomic fundamental factors others than financial speculation.

2.2 Index fund positions and commodity prices

Some other studies have focused on the question of whether index funds positions can create higher commodity returns. Master (2008, 2010), and Singleton (2012), using highly aggregated Commodity Futures Trading Commission (CFTC) data on positions of index funds concluded that financial investments affect crude oil returns. However, Büyüksahin et al. (2009, 2010a,b, 2011a,b) show that heavily aggregated data are not suitable for studying the impact of speculation. By considering specific categories of traders (such as hedge funds and swap dealers), Büyüksahin and Harris (2011) and Brunetti et al. (2011) investigate the impact of positions in oil futures prices and volatility. They find a relevant causality from market conditions to speculators, as well as the fact that speculators provide liquidity to the market.

2.3 Structural models

A third strand of the literature is concerned with strucural economic models of oil markets. Kilian and Murphy (2013) are among the first to quantify the effect of speculative demand shocks on the real price of oil. In the same line as Kilian (2009a,b), Kilian and Murphy (2012), and Baumeister and Peersman (2012), they use structural vector autoregressive (VAR) models to disentangle demand and supply shocks in oil markets. They consider four strucural shocks: (i) an unanticipated disruption in the flow of supply of oil, (ii) an unanticipated increase in the flow of the demand of oil associated with an unexpected change in the business cycle, (iii) a positive speculative demand shock, and (iv) a residual oil demand shock.[8] Using data back to 1973, the model finds no evidence for speculation's having caused the price surge, price changes having been caused by fundamental characteristics, such as supply and demand conditions. More recently, Juvenal and Petrella (2011), and Lombardi and Van Robays (2011) propose extending Kilian and Murphy's model by introducing an additional shock (viz., speculation by oil producers for the former, and a 'non-fundamental' financial speculation shock for the latter) and find evidence of an impact of financial speculation on oil markets.

2.4 Heterogeneous agents and price fluctuations

All the previously mentioned studies are based on the representative agent paradigm and assume intuitively that agents in commodity markets are fully rational. It appears that results about the impact of speculation regarding the recent energy price surge are not so clear. Some of them attest the existence of "commodity speculation", while some others reject this explanation. Since the work of Simon (1957), the representative agent assumption seems to be too restrictive, in the sense that there is only one way of behaving rationally while there is an infinite number of ways of behaving boundedly rationally. A possible cause of the large price volatility of commodity markets could be therefore the existence of heterogeneous speculators in the markets. Originally focusing on financial and exchange rate markets, this literature turned to commodity markets to investigate potential anomalies in price fluctuations. He and Westerhoff (2005), Westerhoff and Reitz (2005), Reitz and Westerhoff (2007), and Reitz and Slopek (2009), are among the first to introduce models with heterogeneous agents for commodity markets and find significant evidence of trader heterogeneity and switching behavior in price fluctuations. More recently, Ellen and Zwinkels (2010) rely on the HAM of Brock and Hommes (1997, 1998) to study the impact of heterogeneous traders in Brent and WTI crude oil prices. They find that oil prices are mainly governed by fundamental factors (such as political and economic issues, ...) but find also that speculators are present in the markets and usually have destabilizing effects on the price of oil. These studies are mainly concerned about spot prices, where the oil companies are pretty much the same. More importantly, they cannot drive up the price without increasing inventories (unless the elasticity of demand is literally zero).

[8]For more details, see Kilian and Murphy (2012).

2.5 Extending the previous literature

The literature explaining the potential reasons for the recent commodity price surge does not go in the same way so that we do not really understand what causes these markets to be so volatile. It seems clear that the dynamics of commodities, and especially of energy prices, has increased significantly since 2003, and it appears also relevant that the properties of these prices tend to be close to those of traditional financial assets (such as volatility clustering and autocorrelation, to name a few (see Joëts, 2012)). What really causes these specific types of behavior?

Our paper proposes to investigate these specific characteristics by considering a less restrictive approach than previous methodologies. Because quantifying the problem of excessive speculation is not trivial, we will not really talk about the speculative phenomenon in its economic sense but rather try to understand whether "irrational" expectations[9] can cause abnormal fluctuations in the markets. More formally, we propose relaxing the rational agent paradigm by considering a model with heterogeneous beliefs (Brock and Hommes, 1997; 1998) where agents are allowed to switch between "rational" and "irrational" behavior depending on an emotional regret process. Moreover, we introduce a new circumstance in which energy prices can experience strong fluctuations. Indeed, as suggested by Knight (1921) and Keynes (1921), the reason why the standard approach, based on expected utility theory, fails to explain "abnormal" behavior may be because agents in the markets are facing uncertainty rather than risk.[10] In our context, investors may simply face uncertainty when they have no prior about their future energy price expectations. Uncertainty averse agents are therefore supposed to interact with uncertainty neutral ones, which can cause even more significant energy price movements. The purpose of this paper is therefore to investigate theoretically and empirically the proportion of each trader in energy markets (oil, gas, coal, and electricity) during both normal times and periods of extreme fluctuations, to see whether the weight of the irrational agents can exceed that of the rational ones and lead to excessive energy price movements (*i.e.*, which do not reflect fundamentals of each market).

[9] By "irrational", we include, for example, naïve behavior and noisy investors.

[10] According to Bewley (2002), the distinction between risk and uncertainty is defined by the fact that a random variable is risky if its probability distribution is known, but uncertain if its distribution is unknown.

3 The theoretical model

In this section, we develop a simple and stylized HAM that will be used to evaluate the effect of heterogeneous speculators on energy prices. The model is based on the model introduced by Brock and Hommes (1997, 1998) and extended by Kozhan and Salmon (2009). We propose a new specification of the HAM by integrating Bell (1982) and Loomes and Sugden's (1982) regret approaches, where agents are allowed to switch between strategies through an emotional learning process. More formally, there are different types of agents in the market, forming heterogeneous expectations in an uncertain universe, which interact by a regret learning specification.

The dynamics of prices can be expressed by

$$\Delta p_t^{(i)} = \zeta + \kappa D_t^{(i)} + \varepsilon_t, \tag{1}$$

where $\Delta p_t^{(i)}$ denotes the dynamics of the prices of energy i between t and $t-1$, with i indicating either oil, gas, coal, or electricity. $D_t^{(i)}$ is the aggregate demand function for each type i at time t, and ε_t is an error term $\varepsilon_t \sim (0; \sigma_\varepsilon^2)$. The aggregate demand function is the consequence of the disaggregated demands of each different type of trader.

In our economy, we assume that each agent can invest in both risk-free and and risky assets. An agent's wealth at time t is determined by his trading activity and is equal to[11]

$$W_t = (1 + r_{t-1})W_{t-1} + (P_t + y_t - (1 + r_{t-1})P_{t-1})d_{t-1}, \tag{2}$$

where W_t, respectively, W_{t-1}, is the wealth of each agent at time t, respectively, $t-1$; P_t is the price (ex-dividend) of the risky asset at time t; y_t is the dividend of the risky asset; and d_{t-1} is the demand for the risky asset at $t-1$. r_t is the risk-free rate.

As in the traditional Brock and Hommes (1997) model, there are two types of investors which interact in the market: fundamentalists and chartists. The former group believe that there exists an equilibrium price (the fundamental value) around which the price will always fluctuate. Fundamentalists' expectations of the energy price dynamics are therefore proportional to the observed difference between the fundamental value and the price at $t-1$ according to the equation

[11] From now on, for simplicity, we omit the exponent i.

$$E_t\left(P_{t+1}/F\right) = P_{t-1} + \alpha\left(\overline{P}_t - P_{t-1}\right), \quad (3)$$

with $0 \leq \alpha \leq 1$. $\overline{P}_t$ is the fundamental price of the energy market considered. F denotes the fundamentalist behavior at time t. E_t denotes the conditional expectation at time t.

In parallel, we assume that to predict future price evolution, chartist investors use a simple long–short moving average rule, given by

$$E_t\left(P_{t+1}/C\right) = P_{t-1} + \alpha^{'}\left(\frac{1}{MA^s}\sum_{j=1}^{MA^s} P_{t-j} - \frac{1}{MA^l}\sum_{j=1}^{MA^l} P_{t-j}\right), \quad (4)$$

with $\alpha^{'} > 0$, MA^s, and MA^l the respective lengths of the short and long moving average windows. C denotes chartist behavior at time t. E_t denotes the conditional expectation at time t.

The fact that the market can be summarized by these two types of beliefs is well established in the financial and exchange rate literatures (see, Taylor and Allen, 1992; Cheung et al., 2004; Broswijk et al., 2007; de Jong et al., 2010; to name a few). Because energy markets can, depending on the context, behave as traditional financial assets (see Joëts, 2012), we assume that these two types of traders can also be present in these markets. Reitz and Slopek (2009), Ellen and Zwinkels (2010), and Büyüksahin and Harris (2011), among others, have shown that in the oil market, participants act as "trend followers", where retroactive effects influence the positions taken by stakeholders. In our model, the information available to both types of traders at time t is the past level of prices, and past and present values of fundamental variables. Following Brock and Hommes (1998), Boswijk et al. (2007), and Kozhan and Salmon (2009), we assume for analytical tractability that investors have homogeneous expectations about the conditional second moment of price movements.[12]

3.1 Demand functions

Following Kozhan and Salmon (2009), we have four distinct individual demand functions depending on the strategy used and the uncertainty context (*i.e.*, uncertainty neutral/averse demand from fundamentalist/chartist traders). In the sequel, we write $d_t^u(B)$ and $d_t^n(B)$ for the individual demands from uncertainty averse and neutral traders, with $B = F, C$.

[12] $E_t\left(P_t^2/B\right) = E_t\left(P_t^2\right)$, where $B = F, C$.

3.1.1 Uncertainty neutral agents

In this case, we are in the situation where both fundamentalist and chartist investors are considered to be neutral to uncertainty. In other words, they are indifferent between their ignorance about an uncertain prospect or a situation in which they have no prior experience. Their risk preferences are characterized by a myopic mean-variance utility function, and agents maximize their expected utility functions as follows

$$E_t\left(U\left(W_{t+1}^n\right)/B\right) = E_t\left(W_{t+1}^n/B\right) - \frac{\gamma}{2}V_t\left(W_{t+1}^n/B\right) \underset{d_t^n}{\rightarrow} \max, \tag{5}$$

where U and V denote, respectively, the utility and the conditional variance, and γ is the risk aversion parameter, assumed to be the same across individuals. The wealth of an uncertainty neutral agent at $t+1$ is given by

$$W_{t+1}^n = (1+r_t)\,W_t^n + (P_{t+1} + y_{t+1} - (1+r_t)\,P_t)\,d_t^n. \tag{6}$$

Maximizing the mean-variance expected utility with respect to d_t^n gives us the following expression[13]

$$d_t^n = \frac{E_t\left[(P_{t+1} + y_{t+1} - (1+r_t)\,P_t)/B\right]}{\gamma V_t\left[(P_{t+1} + y_{t+1} - (1+r_t)\,P_t)/B\right]}. \tag{7}$$

Beliefs about future dividends are assumed to be the same for all types of traders, and to be equal to the true conditional expectation $E_t\left(y_{t+1}/B\right) = E_t\left(y_{t+1}\right)$. We also assume that in a special case, the dividend follows an i.i.d process, such as $E_t\left(y_{t+1}\right) = \overline{y}$.[14] For analytical tractability, the conditional variance is assumed to be equal and constant for all types of investors, so $V_t = \sigma^2$. Equation (7) can be simplified as follows

$$d_t^n = \frac{E_t\left(P_{t+1}/B\right) + \overline{y} - (1+r_t)\,P_t}{\gamma\sigma^2}. \tag{8}$$

[13] See Kozhan and Salmon (2009) for a proof.

[14] $\overline{y}$ being a constant term.

3.1.2 Uncertainty averse agents

Because the assumption of neutral uncertainty appears to be too restrictive in our case, we allow the existence of uncertainty averse agents in the energy markets. Unlike the neutral category, uncertainty averse agents are attentive to the misreading and potential unmeasurability of their models or associated probability distributions. They maximize their maxmin myopic mean-variance utility function of future wealth.[15] As in Kozhan and Salmon (2009), the preferences of uncertainty averse fundamentals/chartists are expressed by the set of possible expectations of future energy price evolutions. In turn, the set of different possibilities is determined by a symmetric bandwidth ϑ around the base of uncertainty neutral expectations. Therefore, the future energy price movements expected by the uncertainty averse agents are assumed to fluctuate in the interval $\Lambda = [E_t\left(P_{t+1}/B\right) - \vartheta; E_t\left(P_{t+1}/B\right) + \vartheta]$.

$$E_t\left(U\left(W^u_{t+1}\right)/B\right) = \min_{\theta\in\Lambda} E_t\left(W^u_{t+1}(\theta)/B\right) - \frac{\gamma}{2} V_t\left(W^u_{t+1}\left(\theta\right)/B\right) \underset{d^u_t}{\rightarrow} \max, \quad (9)$$

where θ is the anticipated price in the interval Λ. The wealth of the averse agents at $t+1$ is given by

$$W^u_{t+1}\left(\theta\right) = \left(1+r_t\right) W^u_t\left(\theta\right) + \left(P_{t+1} + y_{t+1} - \left(1+r_t\right) P_t\right) d^u_t. \quad (10)$$

When averse agents maximize their maxmin expected utilities with respect to d^u_t, they are able to determine three optimal demand functions depending on the interval Λ, namely $S(B)$, $S_{\max}\left(B\right)$, and $S_{\min}\left(B\right)$

$$S(B) = \frac{E_t(P_{t+1}/B) + \overline{y} - (1+r_t)P_t}{\gamma\sigma^2}$$

$$S_{\max}\left(B\right) = \frac{(E_t(P_{t+1}/B) + \vartheta) + \overline{y} - (1+r_t)P_t}{\gamma\sigma^2}$$

$$S_{\min}\left(B\right) = \frac{(E_t(P_{t+1}/B) - \vartheta) + \overline{y} - (1+r_t)P_t}{\gamma\sigma^2}$$

According to Kozhan and Salmon (2009), given the level of energy prices P_t, the optimal strategy in Λ for uncertainty averse investors is to keep d^u_t units of energy according to the following rules[16]

[15] For more details see Gilboa and Schmeidler (1989) and Garlappi et al. (2007).

[16] See Kozhan and Salmon (2009) for more details.

$$d_t^u = \begin{cases} S_{\min}(B) \text{ if } P_t < E_t(P_{t+1}/B) - \vartheta \\ 0 \text{ if } E_t(P_{t+1}/B) - \vartheta < P_t < E_t(P_{t+1}/B) + \vartheta \\ S_{\max}(B) \text{ if } E_t(P_{t+1}/B) + \vartheta < P_t \end{cases} \tag{11}$$

3.2 A learning process through an emotional regret interaction

In traditional HAMs, agents may change their strategies at any period of time (they choose to become fundamentalists or chartists). The learning process is generally similar to case-based reasoning scenarios, where agents evaluate the market and choose their investment strategies based on a comparison of the cumulative past performances of each forecasting rule (see Kirman, 1993; De Grauwe and Grimaldi, 2006; Kirman et al., 2007; Boswijk et al., 2007; Kozhan and Salmon, 2009; Ellen and Zwinkels, 2010; among others). However, these learning processes are cognitively oriented, while psychological studies have shown that investors' decision processes are the conjunction of both cognitive and emotional factors (see Zajonc, 1980; Schwarz, 1990; Damasio, 1994; Forgas, 1995; Isen, 2000; Loewenstein et al., 2001; among others).[17] To account for the potential impact of feelings on the behavior of agents, we propose introducing a learning emotional switching process based on anticipated emotions, defined as emotions that are expected to be experienced by investors given a certain outcome level. Intuitively, the switching mechanism is based on the regret theory of Loomes and Sugden (1982) and Bell (1982). More formally, at the beginning of period t, agents anticipate the regret they could experience if they were to choose the fundamental strategy rather than the other one. Agents are allowed to switch between different strategies (fundamental vs chartist), and also between their reaction to uncertainty in the market (averse vs neutral) according to this regret criterion. Regret appears to be a cognitively-based emotion of pain and anger when agents observe that they made a bad decision in the past and could have taken one with better outcome. In our case, agents will experience regret when their investment (based for example on fundamental strategy) yields, ex-post, a lower performance than an obvious alternative strategy (chartist strategy) they could haven chosen.[18]

[17] The impact of feelings in the decision process has been widely confirmed empirically in stock market fluctuations (Saunders, 1993; Cao and Wei, 2002; Kamstra et al., 2000; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Dowling and Lucey, 2005 and 2008), and more recently in energy price dynamics (Joëts, 2012).

[18] Unlike disappointment, which is experienced when an outcome happens which is negative in terms of prior expectations, regret is strongly associated with a feeling of responsibility for the choice that has been made.

Within this framework, suppose that $\pi_{t+1}(F,C)$ denotes the probability of a trader's adopting fundamentalist behavior at time $t+1$ by the following multinomial logistic expression

$$\pi_{t+1}(F,C) = \frac{e^{\beta H_t^n(F,C)}}{e^{\beta H_t^n(F,C)} + e^{\beta H_t^n(C,F)}}, \tag{12}$$

where $\pi_{t+1}(F,C) \in < 0,1 >$ denotes the fraction of fundamentalists in the market (*i.e.*, the probability of becoming a fundamentalist rather than a chartist at $t+1$), so that $\pi_{t+1}(C,F) = 1 - \pi_{t+1}(F,C)$, the fraction of chartists at time $t+1$. The parameter β is the intensity of choice, and represents the matter to which the regret/rejoice feelings relative to a certain strategy at t determine whether it is adopted at $t+1$. More explicitly, β measures the extent to which investors hold their believe even though the other option might be more attractive. $H_t^n(F,C)$ and $H_t^n(C,F)$ are both based on the following regret expression

$$H_t^n(F,C) = V^n(F) + f\left(V^n(F) - E\left[V^n(C)\right]\right)$$

$$H_t^n(C,F) = V^n(C) + f\left(V^n(C) - E\left[V^n(F)\right]\right),$$

with $f(.)$ the regret function. $V^n(F)$ is the utility of being F and not C, and $V^n(C)$ is the utility of being C and not F. Each utility is the discounted sum of the one-period utilities of the respective uncertainty neutral fundamentalist and chartist investors in the general form

$$V^n(B) = \sum_{k=1}^{K} \omega^{k-1} U\left(h_{t-k+1}^n(B)\right) \tag{13}$$

ω being the discount factor, $h_t^n(B) = (1+r_{t-1})W_{t-1}^n(B) + (P_t + y_t - (1+r_{t-1})P_{t-1})d_{t-1}^n(B)$. Anticipation of $V^n(B)$, is expressed as $E\left[V^n(B)\right] = V^n(B) + \varepsilon_t$, with ε_t an error term $\varepsilon_t \sim \left(0; \sigma_\varepsilon^2\right)$.

Our regret function is given by the following rule:

- if $V^n(F) > E\left[V^n(C)\right] \Rightarrow \Delta V^{n,F} > 0$, the group of fundamentalists rejoices and the probability of becoming F at time $t+1$ increases (the same analysis holds for the chartist group);

- if $V^n(F) < E\left[V^n\left(C\right)\right] \Rightarrow \Delta V^{n,F} < 0$, the group of fundamentalists feels regret and the probability of becoming F at time $t+1$ decreases (the same analysis holds for the chartist group).

Simultaneously with the fundamental/chartist switching mechanism, an agent can also change his reaction according to the level of uncertainty present in the market. An agent can be neutral to uncertainty if he considers the information available in the market as certain and has no doubt about his model or potential prior. He will be more willing to choose the expected utility strategy. However, a neutral agent is allowed to switch to uncertainty averse behavior. As discussed by Kozhan and Salmon (2009), under severe uncertainty about the conditions and the future evolution of the market, the agent will use the maxmin strategy, whereas under weak uncertainty, he will earn some positive utility and will be less sensitive to bad outcomes. In the same manner, the probability of becoming uncertainty neutral is given by

$$\pi_{t+1}\left(n,B\right) = \frac{e^{\beta' H_t^n(B)}}{e^{\beta' H_t^n(B)} + e^{\beta' H_t^u(B)}} \tag{14}$$

$H_t^u\left(B\right)$ is the regret expression of averse uncertainty agent with

$$H_t^u\left(F,C\right) = V^u\left(C\right) + f\left(V^u\left(F\right) - E\left[V^u\left(C\right)\right]\right)$$

$$H_t^u\left(C,F\right) = V^u\left(F\right) + f\left(V^u\left(C\right) - E\left[V^u\left(F\right)\right]\right)$$

and

$$V^u\left(B\right) = \sum_{k=1}^{K} \omega^{k-1} U\left(h_{t-k+1}^u\left(B\right)\right), \tag{15}$$

where $h_t^u\left(B\right) = (1+r_{t-1})W_{t-1}^u\left(B\right) + (P_t + y_t - \left(1+r_{t-1}\right)P_{t-1})d_{t-1}^u\left(B\right)$.

3.3 The aggregate demand function

The aggregate demand function is determined by the four disaggregated demands of each trader. z_t denotes the proportion of fundamentalists in the market and $(1-z_t)$ the proportion of chartists. W_t is the proportion of uncertainty neutral investors while $(1-W_t)$ represents the proportion of uncertainty averse agents. Finally N is the total number of agents. The general form of the aggregate demand function is

$$D_t = N\left[\underbrace{\left(z_t W_t^F d_t^{F,n} + z_t\left(1 - W_t^F\right) d_t^{F,u}\right)}_{fundamentalist\ group} + \underbrace{\left(\left(1 - z_t\right) W_t^C d_t^{C,n} + \left(1 - z_t\right) W_t^C d_t^{C,u}\right)}_{chartist\ group}\right]. \tag{16}$$

Equation (16) is then inserted into the relation (1) to investigate the impact of each category of investors on the dynamics of energy prices.

4 Specification and estimation

Due to the complex nonlinear specification of the model, HAMs have not often been estimated, but rather simulated. Boswijk et al. (2007), de Jong et al. (2009), Reitz and Slopek (2009), and more recently Ellen and Zwinkels (2010) are among the first to estimate HAMs with switching mechanism on the S&P500, the option market, and the oil market, respectively. In our empirical section, we consider daily data over the period January 3, 2005 to December 31, 2010. The sample has the property of covering the strong dynamics that we have recently observed in the energy market. In order to allow for both fundamental and speculative pressures, we rely on European forward prices at one month for oil, gas, coal, and electricity. Energy prices are quoted in US dollars per tonne of oil equivalent ($/toe) and are extracted from the Platt's Information Energy Agency.

As mentioned in Section 3, our model is characterized by the interaction of fundamentalist and chartist agents. Therefore for the model to function, it is necessary to set a stabilizing group against a destabilizing one. The fundamentalist group bases expectations around the fundamental value $\overline{P}_t$. To compute the fundamental value of each energy market, we use the moving average of each price over a period of 60 days.[19] One might argue that the moving average rule cannot constitute a true theoretical fundamental value. For instance, Reitz and Slopek (2009) generate the fundamental value of oil price based on Chinese oil imports. However, as discussed by Ellen and Zwinkels (2010), this type of fundamental value causes an informational advantage, making this method inappropriate in practice. Moreover, our moving average rule allows us to consider fundamentalists somewhat more broadly. The chartist agents, for their part, use a simple 1-50 moving average rule. Figure 6 in the Appendix depicts the energy prices and their respective fundamental values (in logarithms) and shows the relevance of our fundamental prices.

[19] The results are robust to the choice of the window length. They are available upon request to the author.

Table 1 in the Appendix reports the descriptive statistics of energy price returns and the misalignment between prices and fundamentals. They reveal that the kurtosis of each energy return series is largely above three, which means that the distribution is peaked with fat tails, indicating strong uncertainty in the markets. The specific properties of the electricity market (*i.e.*, its non-storablility, the inelasticity of the supply,. . .) cause thicker tails than for the other series. Skewness shows that oil, gas, and electricity returns are generally right skewed, while coal returns are left skewed. These confirm our view of large fluctuations in energy prices. Regarding the misalignment between prices and fundamental values, the positive mean for oil and gas signifies that prices are generally overvalued, while the negative mean for coal and electricity suggests an undervaluation.

Our model, characterized by the general form of eq. (1), is estimated using NLS. As we mentioned, the proportion of each agent in the markets follows a multinomial logistic rule. The optimal values for K in eqs. (13) and (15) are determined by the Akaike criterion.[20]

5 Empirical results

This section is devoted to testing whether the different types of traders we specified are active in the energy markets, and to determine their relative weights in explaining price fluctuations. We also propose an out-of-sample analysis to compare the predictive ability of our theoretical model against a simple random walk.

5.1 In-sample analysis

In order to investigate whether heterogeneous beliefs, and especially uncertainty, can dictate energy price dynamics, we propose to estimate different specifications of our model (*i.e.*, with and without ambiguity). Moreover, as documented by Joëts (2012), the dynamics of energy prices can be considerably different, depending on the intensity of the market.[21] Therefore, we also intend to estimate our model during extreme fluctuations periods to investigate whether investors' behavior is more severe in this circumstance.

Our model is estimated for each energy market. Tables 2, 3, 4, and 5 report the in-sample estimation results during normal times, for oil, gas, coal,

[20] $K = 6$ for oil, $K = 3$ for gas, $K = 3$ for coal, and $K = 2$ for electricity.

[21] Using a new test of Granger causality in risk, Joëts (2012) finds that interactions between energy prices can be more intense during extreme periods.

and electricity, respectively. First regarding the neutral case (*i.e.*, without uncertainty), only fundamental traders impact the energy markets. Indeed, although there is a significant switching phenomenon[22] between fundamental and chartist expectations, the role of "trend followers" appears to be irrelevant. In the neutral restrictive case scenario, fundamental considerations, such as changes in the supply and demand conditions (for example OPEC decisions, refining capacity, humanitarian unrest, increasing energy demand from Asian emerging countries,...), would drive the evolution of future energy prices.
Let us now turn to a less restrictive case by considering that uncertainty can exist in the markets and can cause future price fluctuations even more ambiguous for the participants. In this context, the influence of uncertainty in the decision-making process could create large gaps between prices and fundamental values, leading non-commercial investors to be more motivated to enter into the market. As we can see, neutral and averse fundamentalists coexist with averse chartists for almost all prices, whereas averse fundamentalists appear to be rationally bounded and more prone to switch toward a chartist strategy. The switching mechanisms between fundamental/chartist and between neutral/averse are significant and positive, indicating that a double change of attitude exists. Fundamentalist and chartist traders are not sure about their respective beliefs on the market so they perpetually switch between strategies following "the way of largest number", making price movements even more important, creating in turn more uncertainty. This market phenomenology tends to favor "trend followers" against fundamental traders.
Figure 1 reports the trader weights in mean for each market with respect to their significance impact. For each market, chartist agents seem to be dominant. While this dominance is weak for the gas market, it is clearer for the other series. Indeed, considering that the oil market is mainly composed of fundamentalist and chartist neutral and uncertain traders, the role of the chartists' behavior is largely ascendant. Turning to the coal market, this superiority is even more important, where fundamentalist uncertain agents seem to prefer to switch to the "trend follower" attitude than to keep to a fundamental strategy. Regarding electricity prices, two types of traders are mainly present in the market (*i.e.*, uncertain fundamentalists and chartists). As for the gas market, the preponderance of one group (uncertain chartists) against another (fundamentalists) is not immoderate in this market. This similarity between gas and electricity prices could be the consequence of existing input–output relations between both markets.[23]
The specific nature of the gas market compared to oil can be attributed to the recent European liberalization process making long-term gas contracts no

[22] The intensity of choice β is positive and highly significant for each market.
[23] Usually, the natural gas is used as an input to the electricity production process.

longer indexed to the oil market, but to spot and futures prices.[24] This fact leads gas prices to submit to fundamental and financial pressures in almost the same proportion. Moreover, unlike oil prices, which are internationally organized through liquid markets, gas prices are regionally managed and less subject to international macroeconomic uncertainty.

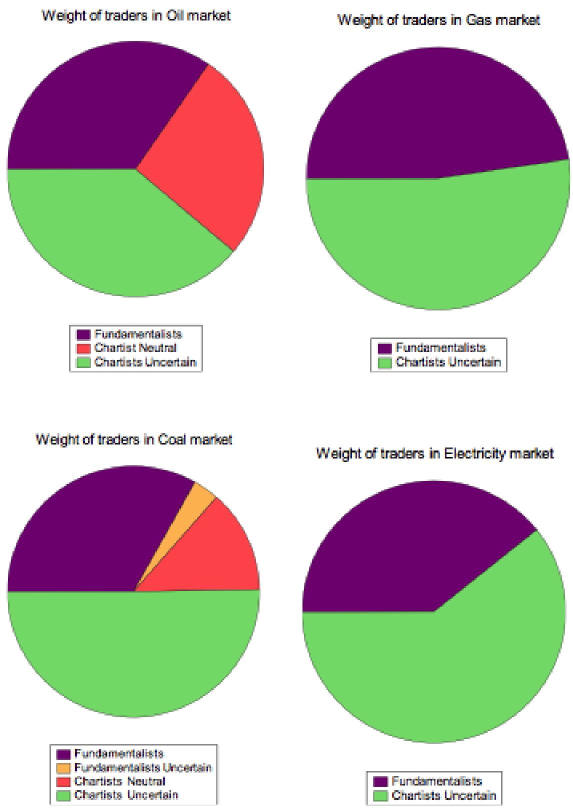

Figure 1: Trader weights in energy markets during normal times

As previously mentioned, the dynamics of prices can be considerably different if we look at extreme price movements. We propose to investigate the proportion of each type of trader during periods of extreme fluctuations by using a quantile regression approach.[25] This method allows us to distinguish between extreme downward and upward movements. As before, we

[24] Unlike futures prices, which are the most prone to be influenced by financial investors, spot prices usually reflect market fundamentals.

[25] For simplicity we suppose that the switching parameters are the same as those estimated during normal times.

propose restrictive and unrestrictive forms of our model (*i.e.*, neutral and uncertain specifications). Tables 6, 7, 8, and 9 report the estimation results of neutral HAM for oil, gas, coal, and electricity markets, respectively, under both downside and upside circumstances. The proportion of each agent is not constant in the markets; it depends on which side of the distribution one is on. Indeed, for all series, fundamentalists and chartists interact during downward extreme price fluctuations, while during upward movements only fundamentalist behavior are determinant (except for oil where both agents coexist). In other words, if we assume no uncertainty in the decision-making process, fundamental considerations would be the main consequence of a price increase, while both fundamental and speculative pressures would follow from a price decrease. However, because no ambiguity is a restrictive assumption, we propose to extend our analysis to the case of uncertainty to investigate whether averse behavior is more important during extreme movements than than normal times.

Tables 10, 11, 12, and 13 show the estimation results of the uncertain HAM for oil, gas, coal, and electricity prices, respectively, (downside and upside). We can see that compared to normal times, the composition of each market has changed significantly. Energy market movements are characterized by the interaction of both neutral and averse agents, however the weight of the averse traders seems to be higher than in normal times. As before, the proportion of each trader in the markets is different and depends on which side of the distribution one is on. Regarding the downside context, uncertainty causes chartist behavior to be more present in the market, making prices decrease extremely rapidly through self-fulfilling prophecy. This phenomenon has been recently observed empirically in energy markets. For instance, oil Brent price has increased sharply between mid-2007 and mid-2008, to a level of almost \$140 per barrel, and decreased to less than \$40 per barrel at the end of 2008. With less intensity, the same movements have been observed in the gas, coal, and electricity markets, showing potential herd behavior in prices. Turning to the upside context, unlike during normal periods, extreme upward movements are not only characterized by fundamental expectations, but also by speculators probably not related to physical interests. Generally speaking, the fundamental nature of energy prices seems to fade, in deference to "irrational exuberance", as the fluctuations become more intense.

Figures 2, 3, 4, and 5 show the weight of the types of traders in each market during extreme downward and upward movements, and confirm this fact. Indeed, during extreme price decreasaes, energy markets are clearly dominated by uncertain chartist agents, supporting our intuition about the fact that uncertainty increases and in turn leads to "cascading behavior". During an extreme price increase, the oil and electricity markets are dominated by both uncertain fundamentalists and chartists in the same proportion, whereas the latter are more important for the coal market, and less significant for the gas market. However, the difference between each market appears to be less pronounced than during normal times.[26] This phenomenon can be explained by the existing interconnections between energy prices, which are exacerbated during extreme fluctuation periods by diversified commodity index investors who have large diversified multi-asset investment strategies.

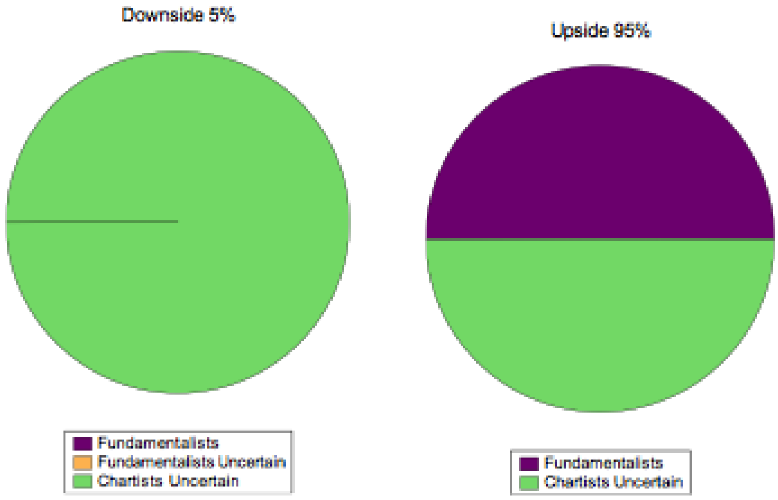

Figure 2: Trader weights in the oil market during extreme movements

5.2 Out-of-sample diagnostics

In this section, we investigate the forecasting ability of our HAM regret model against the RW model. Forecasts are created using an expanding window of observations. More precisely, both models are estimated from January 3, 2005 to December 31, 2007, then out-of-sample estimations are computed until December 31, 2010. The relative performance of the two forecast alternatives is evaluated by using the conditional Giacomini–White (2006) approach. Giacomini and White (2006) propose a test of Conditional Predictive Ability which allows comparing the forecasting properties of two models, given a general loss function.[27] This test allows directly understanding the effect of estimation uncertainty on relative forecasting performance.

[26] This finding goes in the same way as that of Joëts (2012) about the asymmetric behavior of energy markets during upside and downside movements.

[27] This literature was initiated by Diebold and Mariano (1995), West (1996), McCracken (2000), Corradi et al. (2001), and Chao et al. (2001), to name a few.

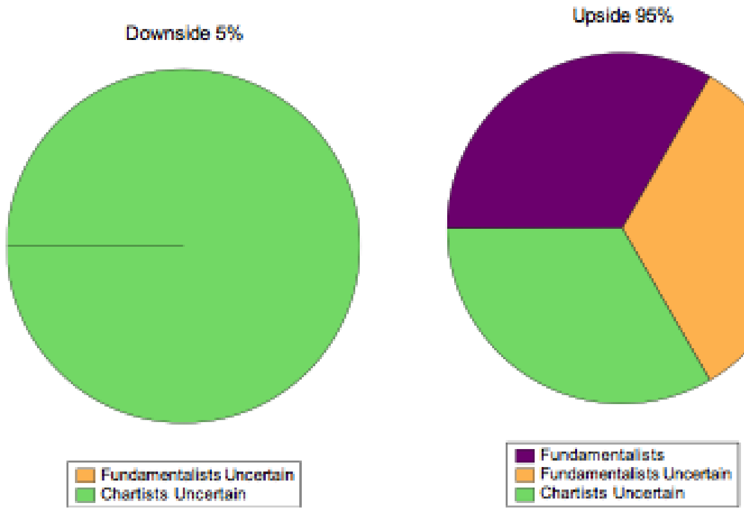

Figure 3: Trader weights in the gas market during extreme movements

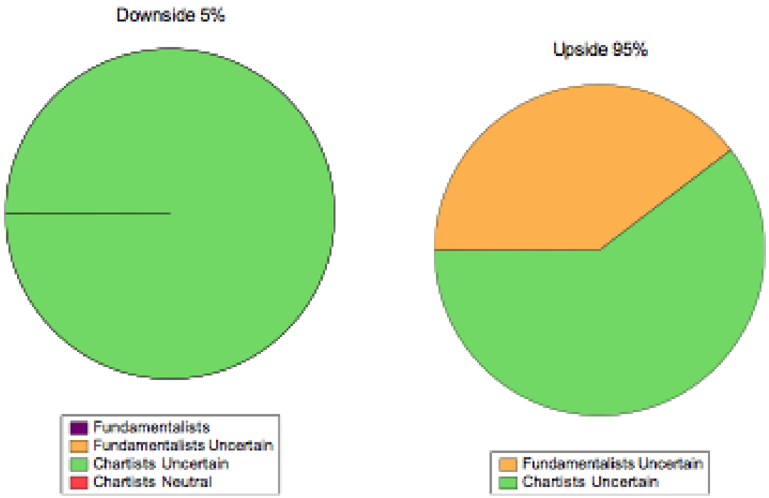

Figure 4: Trader weights in the coal market during extreme movements

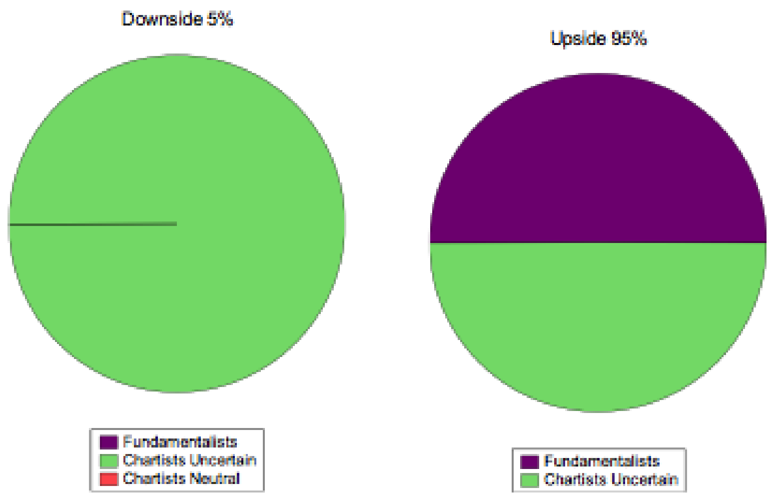

Figure 5: Trader weights in the electricity market during extreme movements

Moreover, it uses a less restrictive framework than previous methods, since it permits a unified treatment of nested and nonnested models and also can accommodate more general estimation procedures in the derivation of the forecasts. As discussed by Giacomini and White (2006), in order to choose the best forecasting model, we use a two-step decision rule. The first one allows us to see whether there is a different predictive ability between the two competing models, then the second step procedure lets us to decide which model is the best.[28] This method is applied to each energy market to see whether HAM is the best model.

Table 14 reports the results of the two-step test procedure for each energy market. The first step is characterized by the rejection of the null hypothesis of equal performance, meaning that the HAM and RW models are not equally accurate on average. In other words, it means that one model outperforms the other one in terms of predictive ability. The second step of the Giacomini–White procedure reveals that for each energy prices, the HAM outperforms the RW in terms of forecasting performance. Our HAM is therefore more adequate for understanding the dynamics of energy prices, reinforcing the fact that heterogeneous beliefs, regret, and uncertainty could be the causes of the high volatility of energy prices.

[28]For more details see Giacomini and White (2006).

6 Conclusion

In this paper we provide an original behavioral and emotional analysis of the impact of financialization on energy markets under uncertainty. For this purpose, we suppose that energy price fluctuations can be caused by heterogeneous expectations, as well as by uncertainty in the decision-making process. Our stylized heterogeneous agent model allows investors to switch between different strategies according to market circumstances.
Turning to the empirical analysis of the oil, gas, coal, and electricity markets over period from January 2005 to December 2010, our results indicate that the proportion of each type of trader in the markets varies, depending on the degree of uncertainty assumed, as well as on the intensity of the fluctuations. Energy price fluctuations are mainly governed by fundamentalist expectations when agents in the markets evolve in the context of certainty, while both fundamentalist behvaior and speculative behavior are the source of price movements in an uncertain world. We have also shown that the weights of the types of traders could be different if we look at extreme situations. The proportion of uncertainty averse agents increases during extreme downward movements, leading to situations where the fundamental nature of the markets fades, in favor of irrational fluctuations, such as "cascade behavior". The conclusion is more parsimonious regarding extreme upward movements, since price increases are the consequence of both fundamental and chartist traders. All in all, our paper shows the limitations of the previous literature assuming a too restrictive framework. We see that if we extend the analytical framework, we could have a better perception and understanding of what drives the energy markets.

Our model has obviously some limitations. Chartists have usually a more complex behavior than a simple trend follower specification, and fundamentalist behavior could be also more sophisticated, taking into account the specific nature of each energy market. Despite these limitations, the model outperforms standard benchmarks, and provides a first step toward the analysis of behavioral and emotional attitudes of energy investors facing uncertainty. Further work should be done to give a concise definition of what we call excessive "commodity speculation", as well as to explore more precisely if it can be costly in terms of social welfare.

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Appendix

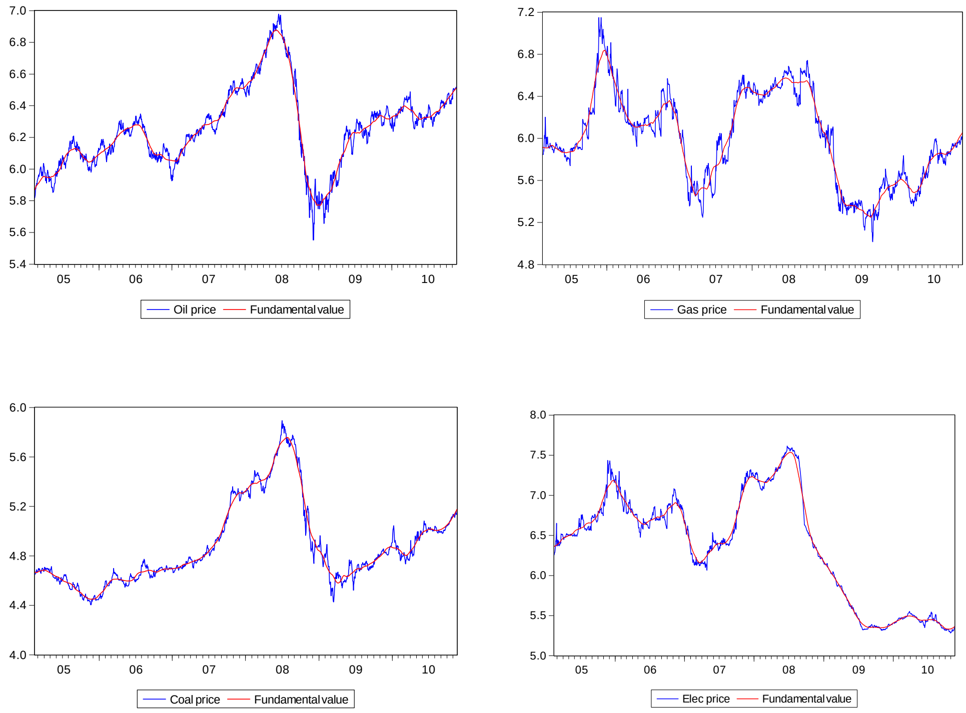

Figure 6: Energy prices and fundamental values at 1 month (in logarithms)

Table 1: Descriptive statistics

	Oil		Gas		Coal		Electricity	
	Δp	$p - \overline{p}$	Δp	$p - \overline{p}$	Δp	$p - \overline{p}$	Δp	$p - \overline{p}$
Mean	0.0004	0.003	0.0001	−0.0001	0.0003	−0.0002	−0.0006	0.0002
Std. Dev	0.023	0.047	0.047	0.099	0.018	0.045	0.030	0.063
Skewness	0.144	−0.455	2.029	0.127	−0.573	−0.099	1.81	0.419
Kurtosis	8.92	4.80	19.31	3.94	10.08	5.62	25.17	5.98

Notes: Δp denote price returns, and $p - \overline{p}$ the price deviation from the fundamental value of the energy considered.

Table 2: In-sample estimation results for the oil market during normal times

	Oil	
	neutral	uncertainty
ζ	0.0007 (0.99)	0.0006 (0.85)
κ_1	$6.30E-06^{**}$ (2.34)	$-5.42E-06^{**}$ (−2.27)
κ_2	NA	$9.49E-05^{***}$ (1.76)
κ_4	$2.40E-05$ (1.27)	$-2.90E-05$ (−1.01)
κ_5	NA	$8.07E-05^{*}$ (2.80)
Switching		
β_1	0.139^{*} (6.89)	0.140^{*} (12.32)
β_2	NA	0.043^{*} (13.29)

Notes: ζ is for the constant term, κ denotes the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists, β is the parameter for the intensity of choice. *,**,*** denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics in parentheses.

Table 3: In-sample estimation results for the gas market during normal times

	Gas	
	neutral	uncertainty
ζ	-0.0007 (−0.58)	−0.0003 (−0.25)
κ_1	-0.0001^{**} (−2.07)	$4.47E-05^{**}$ (2.29)
κ_2	NA	−0.0004 (−1.49)
κ_4	$-2.85E-05$ (−0.26)	−0.0001 (−0.77)
κ_5	NA	0.0003^{**} (1.98)
Switching		
β_1	0.150^{*} (10.14)	0.076^{*} (11.92)
β_2	NA	0.446^{*} (12.14)

Notes: Same as for previous table.

Table 4: In-sample estimation results for the coal market during normal times

	Coal	
	neutral	uncertainty
ζ	0.0004 (0.73)	0.0003 (0.51)
κ_1	$-1.68E-05^{**}$ (−2.55)	$-2.24E-05^{***}$ (−1.74)
κ_2	NA	0.0003^{**} (2.29)
κ_4	$6.68E-05$ (1.13)	-0.0002^{**} (−2.83)
κ_5	NA	0.0001^{*} (4.51)
Switching		
β_1	0.472^{*} (9.05)	1.06^{*} (4.29)
β_2	NA	0.028^{*} (12.13)

Notes: Same as for previous table.

Table 5: In-sample estimation results for the electricity market during normal times

	Electricity	
	neutral	uncertainty
ζ	-0.0005 (-0.58)	-0.0003 (-0.32)
κ_1	-0.0003^{**} (-2.00)	-0.0002^{***} (-1.84)
κ_2	NA	NA
κ_4	0.0004^{*} (2.80)	-0.0001 (-0.34)
κ_5	NA	0.0006^{*} (3.82)
Switching		
β_1	2.702^{*} (5.95)	2.13^{*} (3.47)
β_2	NA	0.090^{*} (11.95)

Notes: Same as for previous table.

Table 6: In-sample estimation results for the oil market during extreme movements (without uncertainty)

	Oil	
	neutral	
	Downside $\theta = 5\%$	Upside $\theta = 95\%$
ζ	-0.036^{*} (-16.07)	0.033^{*} (18.72)
κ_1	$-3.40E-05^{***}$ (-1.71)	$2.78E-05^{*}$ (2.63)
κ_2	NA	NA
κ_4	0.0002^{*} (4.08)	$-9.77E-05^{**}$ (-1.77)
κ_5	NA	NA

Notes: θ denotes the 5% quantile level for the downside, and the 95% quantile for the upside. Otherwise, same as for previous table.

Table 7: In-sample estimation results for the gas market during extreme movements (without uncertainty)

	Gas	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.059^{*} (−16.50)	0.063^{*} (18.89)
κ_1	-0.0001^{**} (−2.27)	-0.0001^{**} (−2.40)
κ_2	NA	NA
κ_4	0.0005^{***} (1.80)	$-2.70E-05$ (−0.70)
κ_5	NA	NA

Notes: Same as for previous table.

Table 8: In-sample estimation results for the coal market during extreme movements (without uncertainty)

	Coal	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.030^{*} (−12.98)	0.027^{*} (18.60)
κ_1	-0.0002^{**} (−2.51)	4.06^{**} (2.47)
κ_2	NA	NA
κ_4	0.0003^{*} (5.52)	$-6.47E-05$ (−0.99)
κ_5	NA	NA

Notes: Same as for previous table.

Table 9: In-sample estimation results for the electricity market during extreme movements (without uncertainty)

	Electricity	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.024^{*}	0.024^{*}
	(-20.22)	(16.20)
κ_1	0.0018^{*}	-0.0026^{*}
	(4.81)	(-8.52)
κ_2	NA	NA
κ_4	0.0019^{*}	-0.0012
	(11.32)	(-1.42)
κ_5	NA	NA

Notes: Same as for previous table.

Table 10: In-sample estimation results for the oil market during extreme movements (with uncertainty)

	Oil	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.036^{*}	0.033^{*}
	(-21.80)	(21.40)
κ_1	$-8.12E-05^{**}$	$2.68E-05^{**}$
	(-2.08)	(2.55)
κ_2	0.0002^{**}	$-2.03E-05$
	(2.01)	(-0.14)
κ_4	$-6.49E-06$	$-8.98E-05$
	(-0.09)	(-1.13)
κ_5	0.0003^{*}	-0.0001^{**}
	(7.54)	(-2.22)

Notes: Same as for the previous table.

Table 11: In-sample estimation results for the gas market during extreme movements (with uncertainty)

	Gas	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.061^{*} (−17.17)	0.063^{*} (14.79)
κ_1	0.0002 (0.66)	$-9.73E-05^{**}$ (−2.20)
κ_2	-0.001^{**} (−2.20)	-0.0004^{**} (−2.30)
κ_4	0.0005 (1.08)	-0.0009 (−0.77)
κ_5	0.0007^{**} (2.09)	0.0002^{**} (−2.29)

Notes: Same as for the previous table.

Table 12: In-sample estimation results for the coal market during extreme movements (with uncertainty)

	Coal	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.033^{*} (−10.75)	0.027^{*} (17.84)
κ_1	-0.0002^{*} (2.72)	$3.51E-05$ (0.42)
κ_2	0.001^{***} (1.66)	0.0005^{*} (8.81)
κ_4	-0.0006^{*} (−3.12)	-0.0006 (−0.40)
κ_5	0.0006^{*} (4.77)	$5.73E-05^{*}$ (2.79)

Notes: Same as for the previous table.

Table 13: In-sample estimation results for the electricity market during extreme movements (with uncertainty)

	Electricity uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.023^{*} (-19.95)	0.025^{*} (15.39)
κ_1	0.0018^{*} (5.35)	-0.0026^{*} (-7.75)
κ_2	NA	NA
κ_4	0.0013^{***} (1.65)	-0.0010 (-1.20)
κ_5	0.0021^{*} (11.17)	-0.0011^{*} (-2.58)

Notes: Same as for the previous table.

Table 14: Conditional Predictive Ability Test

Model strategy	RW			
	Oil	Gas	Coal	Electricity
HAM model	200.83 (0.00*) [0.70+]	180.90 (0.00*) [0.85+]	270.92 (0.00*) [0.98+]	196.87 (0.00*) [0.60+]

Notes: p-values in parentheses. * denotes rejection of the null hypothesis at 1% significance level. Between brackets the proportion of times the method in the column outperforms the method in the row over the out-of-sample period, according to the Giacomini and White (2006) decision rule. $^{+}$ indicates that the HAM outperforms the RW model more than 50% of the time.

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