On the difficulty of interpreting market behaviour in an uncertain world: the case of oil futures pricing between 2003 and 2016

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Abstract

Our results show that over the two cycles that characterize the 2003-2016 period a significant change in the working of oil markets occurs. Our pricing investigation, based on a three-agent model (hedgers, fundamentalist speculators and chartists), find that from 2009 onwards traditional analysis of supply and demand forecasts, loses its explanatory power and hence its credibility. The sharp and unexpected fluctuations in oil prices, compounded by unpredictable political factors and technological break-troughs (e.g. tight sands/shale oil) strongly raises uncertainty and reduces the effectiveness of customary forecasting techniques.

Keywords: Oil pricing, Speculation, Dynamic hedging, Logistic smooth transition, Multivariate GARCH

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1. Introduction

Between 2003 and 2016, oil prices witness unprecedented fluctuations that result in two major cycles, which straddle the 2009 global financial freeze. The first cycle begins in 2003, when prices – starting from a persistent low level (about 30 dollars per barrel on average) – increase continuously, driven by US economic expansion compounded by the rapid growth of demand from emerging market countries (especially India and China). The decline, which begins in mid-2006, due to mild weather conditions, heavy selling by financial funds and the first decline in twenty years of oil demand by OECD countries, is brought to abrupt halt, in the subsequent two years, by an extremely rapid and unexpected upswing variously attributed to portfolio considerations and/or to financial speculation.[1] This first cycle thus appears to be determined mostly by demand considerations in the context of growing financialization of commodity/oil markets, characterized by increasing involvement of financial agents (institutional investors, hedge funds, and ETFs). The second factor becomes more relevant in the final part of the cycle.

With the world economy plunged in the Great Recession and with major technological innovations (shale oil in particular) and geopolitical turmoil (Middle-East conflicts, Saudi Arabia energy policy shifts) affecting the global oil industry, a proper identification of oil price drivers, during the second cycle (2008 – 2016), becomes more difficult. Indeed the market witnesses unprecedented changes in demand, supply and industrial factors. A rapid recovery in oil prices in 2010, due to supply disruptions, such as the decline of Lybian and Iranian oil output, associated with a recovery in demand, as the US economy exited the crisis, is followed by a period of

[1] As to the origin of the 2008 oil/commodity prices upswing, debate is still open. Master (2008), among others, attributes it to financial speculation, Hamilton (2009) and Kesicki (2010) to fundamental variables (weak dollar combined with low elasticity of supply).

relatively stable and high prices. The Summer of 2014, however, witnesses a slowdown in demand, cyclical in nature in emerging market countries and structural in the major industrialized countries, due to the adoption of energy saving measures (see Babel and McGillicuddy 2015). This, combined with rapid growth of US shale oil output, brings about an unprecedented change in the oil production policies of Saudi Arabia and of the major OPEC countries. More precisely, Saudi Arabia, with the explicit objective of undercutting the booming US tight sands/shale oil industry, decided to abandon its policy of price stabilization, which traditionally implied that supply be adjusted to demand shifts.[2] The resilience of the US shale oil sector, which reduced its production costs, regrouped, and managed to maintain its share of global oil production, defeated this attempt. Faced by ballooning budget deficits, Saudi Arabia and its OPEC partners had to resume their policy of price stabilization.[3]

The growing financialization of commodity/oil markets mentioned above implies that a proper interpretation of oil pricing requires model structures that incorporate agents moved by purely financial considerations alongside traditional market players.

Frankel and Froot (1986) underline the importance of the interaction between chartists (or noise traders) and fundamentalist speculators, as a driver of an endogenous non-linear law of motion in foreign exchange rate dynamics. In the same vein, a large and booming literature on commodity/oil pricing, building on path-breaking contributions by Brock and Hommes (1997, 1998) and Westerhoff (2004), among many others, posits that agents react to differing information sets, resulting in market prices, which are weighted averages of their heterogeneous reactions.

[2] Canada too witnessed a rapid growth in production from 2006 onwards driven primarily by the development of oil sands production.

[3] See Santabárbara (2017) and the literature quoted therein for more details on the November 2014 and December 2015 OPEC oil supply policy decisions. On the oil supply and price stabilization policy of Saudia Arabia see Nakov and Nuño (2011) among others. For an alternative interpretation of the causes of the 2014 oil price slump, which emphasizes the role of demand factors, see Baumeister and Kilian (2015).

Drawing inspiration from this literature, Westerhoff and Reitz (2005), Reitz and Westerhoff (2007) and the classification of oil market participants set out in Tokic (2011), we build a model in which three categories of agents interact: noise traders, fundamentalist speculators and hedgers. Noise traders react to past price changes and can either stabilize or destabilize the market, according to whether they behave as contrarians (negative feedback traders) or trend followers (positive feedback traders). Fundamentalist speculators, among whom we include financial agents, as defined above respond to deviations of market returns from equilibrium. In this case, a destabilizing behavior is due to lack of confidence in the mean-reverting nature of market prices. Finally, we account for the presence of industry investors, producers and consumers, by including them in the category of hedgers who reduce risk by using futures contracts.

Studies by Morana (2001), Vo (2009) and Silvernnoinen and Thorp (2013), among others, find that oil prices time series have the properties of standard financial data series such as fat-tails and volatility clustering. In this line, the structure of our model combines typical financial market behaviour with dynamic hedging of commodity contracts.

As noted above, both the 2003-2009 and 2008-2016 cycles terminate abruptly, to the surprise of market participants. The end of the first cycle has the characteristics of a typical financial bubble collapse. The end of the second is related to diplomatic/political considerations, which were, *ex ante*, even less predictable for standard financial agents, as briefly discussed above. The paper captures the growing uncertainty of rational financial oil market participants (fundamentalists and hedgers), which raises both between the first and second sub-periods and with contract maturity, as they are reluctant to operate in the market, whenever it posts prices that they fail to understand. Feedback traders only are left, in a highly volatile and erratic context.

This paper introduces some relevant innovations in the extant literature on oil market pricing to the best of our knowledge. Three categories of traders are explicitly included in our model: feedback traders, fundamentalists and hedgers. This greatly expands the dynamics of the standard behavioural speculative pricing models, which followed the seminal work by De Long et al. (1990), and adapts them to the pricing of futures contracts. We impose no a priori restrictions on the signs of the parameters of the futures returns relationship and stabilizing or destabilizing reactions of economic agents are allowed for. In the same way, no restrictions are imposed on the sign of the speed of adjustment coefficient in the logistic functions which model the entry in (exit from) the market of these agents according to their trust in the reliability of market pricing. By modelling both the one-month and the three-month to expiry futures contracts, based on weekly data, we detect a tendency to short-termism by rational financial agents. In periods of turmoil and rising uncertainty, they tend to leave the three-month futures sector and focus on the one-month contract, as they are wary of taking positions based on three-month ahead expectations. Feedback traders only are left in the market. This last finding, in particular, captures the fact that, especially in recent years, "new players that don't necessarily possess the same depth of understanding are quickly moving in and out of the market, basing their trading decisions almost entirely on price momentum and volatility" (CommodityPoint, 2013, p.7).

This research is structured as follows. Section 1 provides a discussion of the main topics that are analyzed in the paper, along with a short survey of the major aspects of the literature. Section 2 analyses the theoretical and empirical characteristics of our three-agent model and provides a primer of the implied dynamics. Section 3 sets forth the empirical estimates over the two sub-periods. In Section 4, we discuss and interpret the dynamics implied by the significance, the signs and the absolute values of the coefficient estimates, taking carefully into account the historical market context in which oil traders had to operate. Section 5 concludes the paper.

2. The model

2.1 Theoretical considerations

Hedging transactions are intended to reduce the risk of unwanted future cash price changes. Spot market trades are often associated with trades of the opposite sign in the corresponding futures market. Since current cash and futures prices are mostly positively correlated the financial loss in one market will be compensated by gains in the other market. We define the return of cash position in the oil market as $r_{ct} = \Delta log C_t = \Delta c_t$ where C_t is the cash (spot) oil price. In the same way, the return of futures positions is $r_{ft} = \Delta log F_t = \Delta f_t$, where F_t is the price of the corresponding futures contract. An investor who takes short (long) position of one unit in the oil cash market will hedge by taking a long (short) position of β in the futures market. This hedge ratio can be regarded as the fraction of the short (long) position that is covered by futures purchases (sales).

Prices are set in an order-driven market. Every period traders revise their long/short positions; price changes from *t* to *t+1* are a function of their excess demands and can be parameterized by the following log-linear function

$$f_{t+1} = f_t + \alpha(D_t^C + D_t^F + D_t^H) + e_{t+1} \quad (1)$$

where *α* is a positive market reaction coefficient and D_t^C , D_t^F and D_t^H denote the demand of chartists (feedback traders), fundamentalists and hedgers. The residual e_{t+1}

accounts for additional factors that may impact on prices. The demand of feedback traders at time t is given by

$$D_t^C = a_1 S_{it}^C (f_t - f_{t-1}) \quad (2)$$

where coefficient a_1 is positive as feedback traders expect the existing price trend to persist in the subsequent time period. They will buy the commodity if Δf_t is positive and sell it if Δf_t is negative.[4] Their overall impact is nonlinear and given by $a_1 S_{it}^C$ where S_{it}^C is assumed to measure the fraction of the set of feedback traders entering the market at time t. This fraction depends upon market conditions and is parameterized by the following logistic function

$$S_{it}^C = \left[1 + exp\left\{-\gamma_C \left(\left|N - r_{ft-i}\right| / \sigma_{r_{ft-i}}^2\right)\right\}\right]^{-1} \qquad i = 0,1,\dots,l \quad (3)$$

N is the normal (equilibrium) return of oil futures contract, which is defined as the following n-periods moving average of current and past commodity futures returns $N = \sum_{k=0}^{n-1} r_{ft-k}/n$. We assume, in this way, that oil futures returns are the algebraic sum of two stochastic components: an equilibrium level N and a temporary deviation $(N - r_{ft-i})$. The value of the delay parameter i is determined empirically as it depends upon the physical and institutional characteristics of WTI oil pricing. The component $\left|N - r_{ft-i}\right| / \sigma_{r_{ft-i}}^2$ is a signal to noise ratio. The larger the deviation of r_{ft-i} from N, the stronger the perception of market disequilibrium and the larger the fraction of feedback traders that will post orders on the market. The denominator, $\sigma_{r_{ft-i}}^2$, is an index of futures price variability. It accounts for the impact of risk. A higher (lower)

[4] If a_1 is negative, negative feedback traders/contrarians stabilize the market.

risk associated with higher (lower) price volatility will reduce (increase), for a given perception of market disequilibrium, the willingness of speculators to enter the market. The term S_{it}^{C} can take any value in the [0;1] interval depending on the sign of coefficient γ_C as $|N - r_{ft-i}|$ ranges from 0 (when $N = r_{ft-i}$) to $+\infty$. Large deviations of r_{ft-i} from normal value will bring about a decline (increase) in the number of chartists when γ_C is negative (positive). The absolute value of γ_C matters too. The higher the synchronization of traders' reaction to price deviations from their normal level (a symptom of herding behaviour), the larger is the value of γ_C. On the contrary, a low absolute value of this coefficient will reflect idiosyncratic reactions of traders to price disequilibria, possibly due to differing degrees of risk aversion.

Alongside feedback traders, we posit the existence of professional (institutional) investors, labelled here fundamentalists, who exploit their oil market expertise for portfolio diversification purposes. As such, their behaviour is influenced by both futures and cash returns. Their demand of futures contracts at time t is given by

$$D_t^F = a_2 S_{jt}^F (N - r_{ft}) \quad (4)$$

Fundamentalists react to deviation of the futures return from its equilibrium value *N* as defined above. The coefficient a_2 indicates how fundamentalists' beliefs about market prices affect their behaviour. If the coefficient a_2 takes on a positive value, this indicates that the majority of fundamentalists believes that the price will revert to its equilibrium value. This will lead them to buy if $N > r_{ft}$ and to sell in the opposite case. If the coefficient a_2 takes on a negative value, fundamentalists, disbelieving in the mean-reverting nature of the price, will sell if $N > r_{ft}$ and buy in the opposite case.[5] In all cases, we posit that fundamentalists enter or exit the market depending

[5] See Chia et al. (2014).

on their perception of oil price misalignment in the spot market. Fundamentalists base their investment strategies on more sophisticated scenarios, which necessarily include the evaluation of cash oil markets and of their underlying fundamental drivers. Consequently, we model the transition function S_{jt}^{F} as follows

$$S_{jt}^{F} = \left[1 + exp\left\{-\gamma_F\left(\left|M - r_{ct-j}\right|/\sigma_{r_{ct-j}}^{2}\right)\right\}\right]^{-1} \qquad j = 0,1,\dots,p \quad (5)$$

Where M is the normal (equilibrium) return of oil cash contracts, which is defined as the following m-periods moving average of of current and past cash oil returns $M = \sum_{k=0}^{m-1} r_{ct-k}/m$.[6] The value of the delay parameter j is determined empirically. The component $\left|M - r_{ct-j}\right|/\sigma_{r_{ct-j}}^{2}$ is a signal to noise ratio, synthesizing the dynamics of the oil spot market. Here too, the term S_{jt}^{F} can take any value in the [0; 1] interval depending on the sign of coefficient γ_F as $\left|M - r_{ct-j}\right|$ ranges from 0 (when $M = r_{ct-j}$) to $+\infty$. Large deviations of r_{ct-j} from normal value will bring about a decline (increase) in the number of fundamentalists when γ_F is negative (positive).

Hedgers base their decisions on the return of the hedging position and on its variance. As equation (6) indicates, the return to the hedging position r_{Ht} is a linear combination of the returns of the cash and futures prices

$$r_{Ht} = r_{ct} - \beta r_{ft} = (c_t - c_{t-1}) - \beta(f_t - f_{t-1}) \quad (6)$$

Where β is the hedging ratio.

The variance of the portfolio revenue by unit of product is obtained:

[6] In our empirical analysis it is assumed that *m* = *n* = *12*.

$$\sigma_{r_{Ht}}^2 = \sigma_{r_{ct}}^2 + \beta^2\sigma_{r_{ft}}^2 - 2\beta\sigma_{r_{ct}}\sigma_{r_{ft}}\rho_{r_{ct}r_{ft}} \quad (7)$$

Where $\sigma_{r_{ct}}^2$ is the variance of the cash return, $\sigma_{r_{ft}}^2$ the variance of the futures return, $\rho_{r_{ct}r_{ft}}$ is the linear correlation coefficient between the two returns and is equal to $\left(\sigma_{r_{ct}r_{ft}}/\sigma_{r_{ct}}\,\sigma_{r_{ft}}\right)$. The optimum hedge ratio $\beta^*$is derived from the first order condition of the hedging position variance minimization and reads as

$$\beta^* = \frac{\sigma_{r_{ct}}\sigma_{r_{ft}}\rho_{r_{ct}r_{ft}}}{\sigma_{r_{ft}}^2} \quad (8)$$

Therefore, the optimum hedge ratio depends on the covariance between the changes in futures price and cash price and on the variance of the futures price. The hedging model is extended by introducing a dynamic component. The performance of a portfolio is measured by its variance reduction with respect to the optimal percentage of hedging. Substituting β^* in equation (7), we obtain

$$\sigma_{r_{Ht}}^2 = \sigma_{r_{ct}}^2 - \frac{\left(\sigma_{r_{ct}r_{ft}}\right)^2}{\sigma_{r_{ft}}^2} = \sigma_{r_{ct}}^2\left(1 - \rho_{r_{ct}r_{ft}}^2\right) \quad (9)$$

Equation (10) describes the demand of futures contracts of a trader wishing to minimize the variance of her optimally hedged position

$$D_t^H = a_3 S_{ht}^H \sigma_{r_{Ht}}^2 \quad (10)$$

An increase in the minimum portfolio variance (9) may be due to a rise in the variability of cash price changes and/or to a decrease in the correlation between the two returns. The overall impact of hedgers' trading is nonlinear and given by $a_3 S_{ht}^H$

where S_{ht}^{H} is assumed to measure the fraction of the set of hedgers entering the market at time t, fraction which, in turn, will depend upon market conditions. The structure of the hedgers transition function is analogous to that, which governs the behavior of fundamentalists. Indeed both categories of agents respond to deviations of cash prices from their perceived equilibrium value M, even if with different speeds and obviously with different goals. Based on these considerations, the transition function S_{ht}^{H} is parameterized by the following logistic function, whose properties mirror those of equation (5)

$$S_{ht}^{H} = \left[1 + exp\left\{-\gamma_H\left(|M - r_{ct-h}|/\sigma^2_{r_{ct-h}}\right)\right\}\right]^{-1} \qquad h = 0,1,\dots,k \quad (11)$$

Substituting equations (2), (4) and (10) in equation (1) we have the following futures prices relationship

$$r_{ft+1} = \theta_1 S_{it}^{C} r_{ft} + \theta_2 S_{jt}^{F}\left(N - r_{ft}\right) + \theta_3 S_{ht}^{H}\left(\sigma^2_{r_{ct}} - \frac{\left(\sigma_{r_{ct} r_{ft}}\right)^2}{\sigma^2_{r_{ft}}}\right) + e_{ft+1} \quad (12)$$

Where $\theta_1 = \alpha a_1$, $\theta_2 = \alpha a_2$ and $\theta_3 = \alpha a_3$

Equation (12) relates futures returns to their previous period values, to the deviation of these values from their long run equilibrium N, and to the past variability of the optimally hedged positions of oil traders and oil producers.

Economic theory posits that spot and futures prices are jointly determined for any given commodity (Stein 1961). Our investigation thus includes two equations accounting, respectively, for the behavior of spot and futures price returns together with their covariance. The conditional mean equation for r_{ct} is modelled as an error correction relationship (Equation 13), where spot prices adjust to futures prices, which play the price discovery role.[7] In the long run, indeed, a cointegration relationship between cash and futures prices holds and plays the role of attractor for the short-run cash price adjustments.

$$r_{ct+1} = b_0 + \sum_{z=0}^{n} b_{1z} r_{ct-z} + \sum_{w=0}^{m} b_{2w} r_{ft-w} + \theta(c_t - \lambda f_t) + e_{ct+1} \quad (13)$$

2.2. The empirical model

Futures and cash price rates of return are conditionally heteroskedastic when data are sampled with a weekly frequency – as we do in this paper – and a GARCH approach is used to model the second moments that enter equation (12). Equation (14), the empirical counterpart of equation (13) above, parameterizes the conditional mean of the cash returns whereas equation (15), the counterpart of equation (12), illustrates futures pricing by hedgers and speculators.

$$r_{ct} = d_0 + \sum_{z=1}^{n} d_{cz} r_{ct-z} + \sum_{w=1}^{m} d_{fw} r_{ft-w} + \zeta(f_{t-1} - \lambda_0 - \lambda_1 c_{t-1}) + \nu_{ct} \quad (14)$$

$$r_{ft} = g_0 + g_1 S_{it-1}^{C} r_{ft-1} + g_2 S_{jt-1}^{F}\left(N - r_{ft-1}\right) + g_3 S_{ht-1}^{H} h_{r_{Ht-1}}^{2} + \nu_{ft} \quad (15)$$

$$S_{it-1}^{C} = \left[1 + exp\left\{-\gamma_C\left(\left|N - r_{ft-1-i}\right| / h_{r_{ft-1-i}}^{2}\right)\right\}\right]^{-1} \quad (16)$$

$$S_{jt-1}^{F} = \left[1 + exp\left\{-\gamma_F\left(\left|M - r_{ct-1-j}\right| / h_{r_{ct-1-j}}^{2}\right)\right\}\right]^{-1} \quad (17)$$

$$S_{ht-1}^{H} = \left[1 + exp\{-\gamma_H(|M - r_{ct-1-h}| / h_{r_{ct-1-h}}^{2})\}\right]^{-1} \quad (18)$$

$$\nu_t = \begin{bmatrix} \nu_{ct} \\ \nu_{ft} \end{bmatrix} \quad (19)$$

$$\nu_t | \Omega_{t-1} \sim N(0, H_t) \quad (20)$$

$$H_t = \Delta_t R \Delta_t \quad (21)$$

$$R = \begin{bmatrix} 1 & \rho_{r_c r_f} \\ \rho_{r_c r_f} & 1 \end{bmatrix} \quad (22) \qquad \Delta_t = \begin{bmatrix} h_{r_c t} & 0 \\ 0 & h_{r_f t} \end{bmatrix} \quad (22')$$

[7] See Figuerola-Ferretti and Gonzalo (2010).

$$h^2_{r_ct} = \omega_c + \alpha_c v^2_{r_ct-1} + \beta_c h^2_{r_ct-1} \quad (23) \qquad h^2_{r_ft} = \omega_f + \alpha_f v^2_{r_ft-1} + \beta_f h^2_{r_ft-1} \quad (23')$$

$$h^2_{r_{Ht-1}} = \left(h^2_{r_{ct-1}} - \frac{\left(h_{r_{ct-1}r_{ft-1}}\right)^2}{h^2_{r_{ft-1}}} \right) \ (24)$$

Our empirical model allows for a complex characterization of the interaction among different categories of economic agents, who react to deviations of market prices from their equilibrium values, in ways, which can be stabilizing or destabilizing. Table 1 sets out a primer of the associated dynamics, focusing on the process of futures price determination.

Table 1. A primer on speculative and hedging dynamics

	Feedback traders g_1		Fundamentalists g_2		Hedgers g_3	
	> 0	< 0	> 0	< 0	> 0	< 0
$\gamma > 0$	Positive feedback traders (chartists) enter the market	Negative feedback traders (contrarians) enter the market	Stabilizing crude oil investors / fundamentalist speculators enter the market	Destabilizing crude oil investors / fundamentalist speculators enter the market	Growing number of hedgers stabilize (destabilize) the market if cash prices decline (rise)	Growing number of hedgers stabilize (destabilize) the market if cash prices rise (decline)
$\gamma < 0$	Positive feedback traders (chartists) exit the market	Negative feedback traders (contrarians) exit the market	Stabilizing crude oil investors / fundamentalist speculators exit the market	Destabilizing crude oil investors / fundamentalist speculators exit the market	Decreasing number of hedgers stabilize (destabilize) the market if cash prices decline (rise)	Decreasing number of hedgers stabilize (destabilize) the market if cash prices rise (decline)

The second and third column in Table 1 synthesize the behavior of feedback traders, taking into account both the sign of the coefficient g_1 that relates the current futures rate of return to its past values and the heterogeneity index γ. The signs of both coefficients have relevant implications. If g_1 is positive (negative), chartists (contrarians) destabilize (stabilize) the market, acting as positive (negative) feedback traders.[8] If γ (γ_C in equation 16) is positive (negative), the relative number of feedback traders, present in the market, grows (declines) with the deviation of r_{ft-1-i} from its moving average value N.

Turning to fundamentalist speculators (see Table 1, Columns 4 and 5), the negative value of g_2 deserves specific comment. Fundamentalists may indeed believe that the persistence in the misalignment between the equilibrium and the current rate of return on futures contracts will last for some time and persist to buy (sell) if $r_{ft} > N$ ($r_{ft} < N$). This is a symptom of the failure of the price signaling process during periods of turbulence and is consistent with fundamentalists destabilizing the market, their traditional stabilizing behaviour being associated with a positive value of g_2. As for the negative sign of γ (γ_F in Equation 17), Shleifer and Vishny (1997) explain it by the wariness of fundamentalists to enter the market if trades based on their own forecasts turn out to be persistently incorrect. In this case, a growing disequilibrium between the cash return and its equilibrium value will bring about a decline in the number of fundamentalists active in the market.

Coming to hedgers, the following considerations apply. As Cifarelli (2013, p.161) explains, an increase in $\sigma^2_{r_{ct}}$ can be produced either by an increase or a decrease in crude oil prices. As Equation (9) indicates the hedged portfolio variance $\sigma^2_{r_{Ht}}$ depends on the variance of cash prices $\sigma^2_{r_{ct}}$ and on the squared correlation coefficient between cash and futures prices $\rho^2_{r_{ct}r_{ft}}$. Whenever – as is the case in our estimates – correlation between the two prices is stable over time, hedgers will react to changes in cash prices only. Coefficient g_3 is expected to be negative if in the previous period(s) the cash price rate of change is positive and positive if in the previous period(s) the cash price rate of change is negative. Long positions in commodities (by producers) are

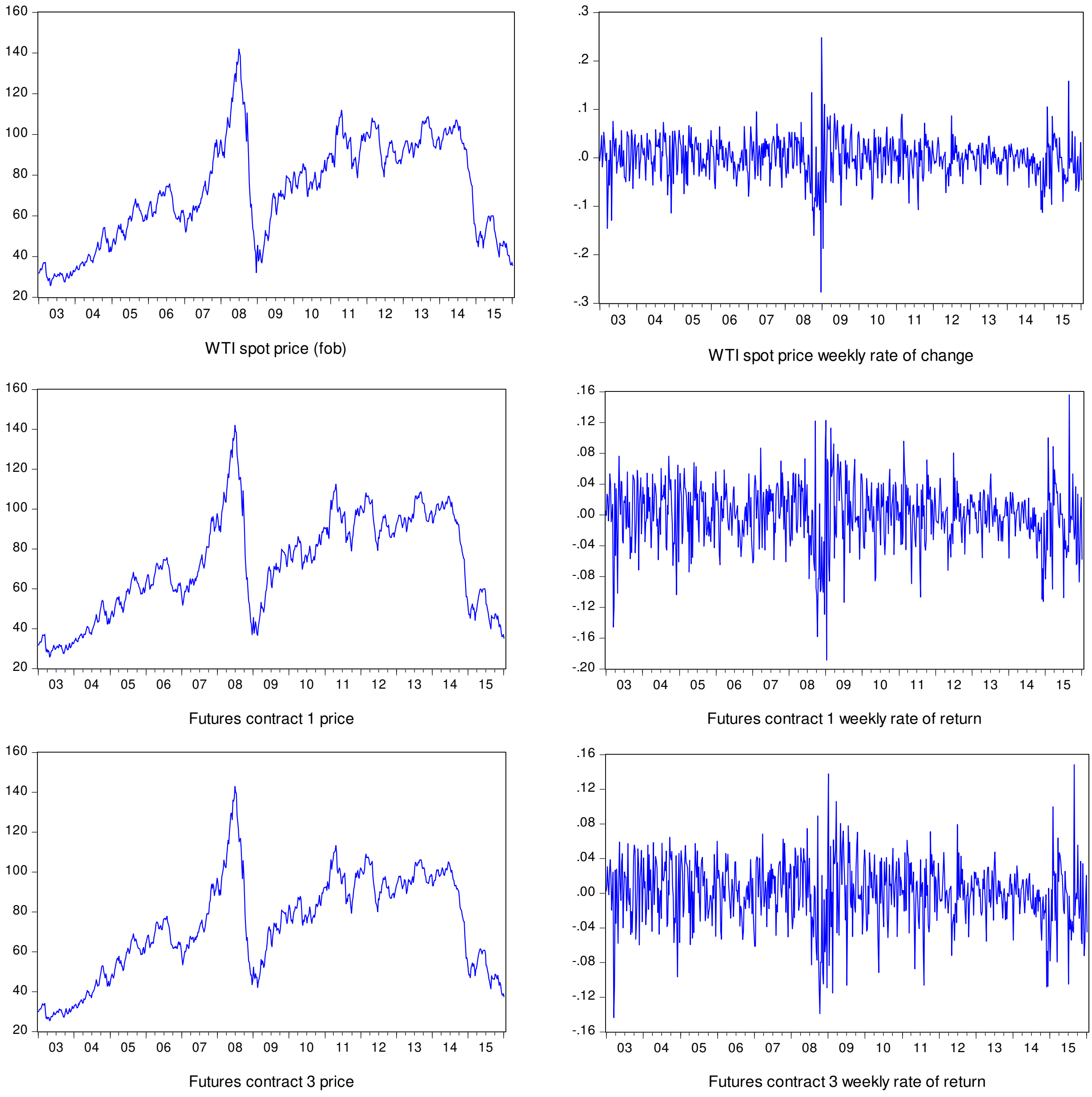
[8] The standard justification for the presence of contrarians is that some feedback traders may believe that prices have overshot a reasonable equilibrium value (Wan and Kao, 2009).

associated with short positions in futures contracts, whereas short positions in commodities (by e.g. traders or consumers) are associated with long positions in futures contracts. If the commodity cash price rises (falls), the producer is likely, in the subsequent time period, to increase (reduce) his planned future sales. In order to hedge against future spot price declines he is going to raise (decrease) his hedging position by selling more (less) futures contracts. The futures price will fall (rise) and the coefficient of the hedged position variability g_3 will be negative (positive). The behavior of either traders or consumers causes the same sign shifts. If the commodity price declines (rises) traders will face, in the following period, an increase (decrease) in demand and increase (reduce) their short positions commitments in the cash market, and in order to hedge against futures price rises, will raise (cut) their long positions in the futures market bringing about a futures price increase (decrease).

3. Empirical results

The paper uses weekly data in order to measure the impact of the financial crisis on the dynamics of futures oil pricing, in a period, which witnessed the transition from a relatively smooth price behavior to accelerating growth, abruptly interrupted by unprecedented gyrations. Our sample spans the time interval from 2 January 2003 to 12 January 2016 and is divided in two sub-periods, from 2 January 2003 to 30 December 2009 and from 2 September 2008 to 12 January 2016. The partial overlap of the two sub-samples is due to the difficulty of attributing the consequences of the Lehman crisis either to the first or to the second sub-period. The oil spot price C_t is the WTI spot price FOB (US dollars per barrel), the futures oil price F_t is provided by the EIA database.[9] Figure 1 exhibits the series themselves and summary statistics of the rates of returns over the two sub-samples are set out in Table 2.

Figure 1. Oil spot and futures prices and rates of return



[9] Futures contract 1 expires on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the 3rd business day prior to the business day preceding the 25th calendar day. Contract 3 corresponds to the second successive delivery month following contract 1.

Figure 1 depicts oil cash and futures prices in levels (left-hand panels) and in first log-differences (right-hand panels). Price levels provide visual insights into the puzzling price behaviour, which our analysis tries to explain. Leaving out the "Great Moderation", our sample period is characterized by two cycles. In the first cycle, a persistent price increase, from 2003 to 2007, was followed by a sharp bubble-like spike, between 2007 and 2008. The second cycle witnesses a rise in oil prices, from through reached in 2009 to peak in September 2014, which ends abruptly during the subsequent months.[10]

Table 2. Descriptive statistics

	02/01/2003 – 30/12/2009			02/09/2008 – 12/01/2016		
	Spot price return r_{ct}	Futures contract 1 return r_{f1t}	Futures contract 3 return r_{f3t}	Spot price return r_{ct}	Futures contract 1 return r_{f1t}	Futures contract 3 return r_{f3t}
Mean	0.0025	0.0025	0.0027	-0.0033	-0.0033	-0.0032
Std. dev.	0.0477	0.0443	0.0396	0.0471	0.0439	0.0392
Skewness	-0.6782	-0.6725	-0.5654	-0.7263	-0.4773	-0.3897
Kurtosis	8.2764	4.3423	4.0195	5.6423	2.2641	1.8172
JB	485.5200 [0.000]	101.2127 [0.000]	96.8535 [0.000]	544.5468 [0.000]	96.8535 [0.000]	62.7217 [0.000]
AR1	7.2583 [0.007]	14.645 [0.000]	16.087 [0.000]	12.242 [0.000]	12.978 [0.000]	14.493 [0.000]
AR5	18.441 [0.002]	22.022 [0.001]	23.647 [0.000]	14.392 [0.013]	15.148 [0.010]	16.243 [0.006]
ARCH1	70.479 [0.000]	46.214 [0.000]	30.342 [0.000]	8.1652 [0.004]	7.1610 [0.007]	4.9034 [0.027]
ARCH5	162.37 [0.000]	165.57 [0.000]	97.429 [0.000]	14.974 [0.010]	13.635 [0.018]	9.8834 [0.079]
ADF (c, n)	-10.234 (c, 2) [0.000]	-5.233 (c, 7) [0.000]	-6.961 (c, 4) [0.000]	-15.022 (c, 0) [0.000]	-5.564 (c, 7) [0.000]	-8.929 c, 2) [0.000]
BDS2	4.0244 [0.000]	4.7491 [0.000]	4.0749 [0.000]	7.4704 [0.000]	6.7449 [0.000]	6.2902 [0.000]

Notes. Probability values in square brackets; JB: Jarque-Bera normality test; ARk: Ljung-Box test statistic for k-th order serial correlation of the time series; ARCHk: Ljung-Box test statistic for k-th order serial correlation of the squared time series; ADF(c, n): Augmented Dickey Fuller unit root test statistic, with a constant term and n^{th} order autoregressive component; BDSk: test statistic, with embedding dimension k, of the null that the time series, filtered for a first order autoregressive structure, is independently and identically distributed.

[10] The dating of the breakpoint is corroborated by recursive residuals analyses of AR(1) OLS estimates of each of the return time series and corresponding CUSUM of squares tests. They are not reported here for the sake of parsimony and are available from the authors upon request.

As expected, the rates of return in Table 2 are strongly serially correlated and conditionally heteroskedastic, volatility clustering being extremely large between 2008 and 2009 and again at the end of the sample period. They are always stationary, as shown by ADF test statistics, non-normally distributed and affected by nonlinearities. Indeed, the BDS test statistics of Brock et al. (1987) strongly reject, with embedding dimension 2, the null hypothesis that the rates of returns, filtered for first order serial dependence are iid. (Analogous results are obtained for the unfiltered returns, with embedding dimensions varying from 2 to 6).

3.1 First period analysis

The first sub-sample estimates (02/01/2003 – 30/12/2009) of the model can be found in Table 3. The parameterization of equation (15) is justified by the strategy set out in Teräsvirta (1994). At first, the lag of the autoregressive futures log difference is selected using the Akaike Information Criterion: a one-week lag provides the best fit. A test of linearity against the non-linear parameterization of equation (15) is performed following the procedure of Luukkonen at al. (1988), as modified by Wan and Kao (2009). The transition functions (16), (17) and (18) are replaced in equation (15) by a third order Taylor series approximation. The following auxiliary equation is estimated

$$r_{ft} = \pi_0 + \pi_1 r_{ft-1} + \pi_2 r_{ft-1} y_{t-1-i} + \pi_3 r_{ft-1} y_{t-1-i}^2 + \pi_4 r_{ft-1} y_{t-1-i}^3 +$$

$$+\mu_1(N - r_{ft-1}) + \mu_2(N - r_{ft-1}) x_{t-1-j} + \mu_3(N - r_{ft-1}) x_{t-1-j}^2 + \mu_4(N - r_{ft-1}) x_{t-1-j}^3 +$$

$$+\delta_1 h_{r_{Ht-1}}^2 + \delta_2 h_{r_{Ht-1}}^2 x_{t-1-h} + \delta_3 h_{r_{Ht-1}}^2 x_{t-1-h}^2 + \delta_4 h_{r_{Ht-1}}^2 x_{t-1-h}^3 + \epsilon_t$$

where, $x_{it-k} = |M - r_{ct-1-k}|$, $k = j,\ h$ and $y_{t-i} = |N - r_{ft-1-i}|$

We test linearity against STAR modeling - for various values of *i, j* and *h* - performing LM tests of the null hypothesis H_0: $\pi_2 = \pi_3 = \pi_4 = \mu_2 = \mu_3 = \mu_4 = \delta_2 = \delta_3 = \delta_4 = 0$. We have also tested linearity against STAR modeling for chartists, fundamentalists and hedgers in isolation. That is, we have performed the following LM tests of the null hypotheses H_{0C}: $\pi_2 = \pi_3 = \pi_4 = 0$; H_{0F}: $\mu_2 = \mu_3 = \mu_4 = 0$; and H_{0H}: $\delta_2 = \delta_3 = \delta_4 = 0$. For the values of the delay parameters of the first row of Tables 3 and 4, the Teräsvirta Non-linearity Test (TNT) statistics uniformly reject H_0, H_{0C} and H_{0H} in the case of the first period estimates and fail to reject H_{0F} only, in the second period, in the case of the three month futures contract. Our non-linear parameterization is thus convincingly justified by the data and the time-varying fractions of chartists, fundamentalists and hedgers in equation (15) are parameterized using equations (16), (17) and (18).[11]

The overall quality of fit of the model is satisfactory. The estimated parameters are significantly different from zero and our GARCH model captures the conditional heteroskedasticity of the residuals.[12] The usual misspecification tests indicate that the standardized residuals η_t are always well behaved; for each system $E[\eta_t] = 0$, $E[\eta_t^2] = 1$ and η_t^2 is serially uncorrelated. The BDS2 tests, moreover, fail to reject the null that the standardized residuals are iid. The nonlinearities detected in the return time series of Table 2 are filtered away by the model. Surprisingly, the reaction of economic agents to return shifts is not homogeneous across the term-structure of the futures price. In the case of the more liquid one-month contract (Fut1), chartists behave as contrarians and enter the market, their number growing with the deviation

[11] The Taylor procedure allows us to reject the alternative ESTAR parameterization of the transition function. For the sake of parsimony these tests are not reported here. It should be noticed that rejection of the H_{0C}, H_{0F} and H_{0H} hypotheses implies also the rejection of the hypotheses that chartists, fundamentalists and hedgers fail to affect the behaviour of the futures contracts rates of change, justifying, in this way, the three-agent model parameterization of our paper.

[12] The t-ratios reported in the tables are based on the robust quasi-maximum likelihood estimation procedure of Bollerslev and Wooldridge (1992).

of observed returns from their normal (equilibrium) value, defined as the 12-periods moving average of the logarithms of current and past futures prices in first differences.

Table 3. First period estimates: 02/01/2003 – 30/12/2009

Fut1						Fut3				
m = 1, n = 3		i=0, j=0, h=0				m = 1, n = 3		i=0, j=7, h=5		
r_{ct}		r_{ft}				r_{ct}		r_{ft}		
d_0	1.326 (41.113)	g_0	0.732 (22.454)			d_0	0.954 (13.885)	g_0	0.437 (17.369)	
d_{c1}	0.0813 (10.522)	g_1	-0.099 (-11.510)			d_{c1}	-0.134 (-9.298)	g_1	0.209 (14.419)	
d_{c2}	-0.001 (-0.034)	g_2	-0.228 (-22.096)			d_{c2}	-0.012 [-0.883]	g_2	-0.297 (-4.359)	
d_{c3}	-0.036 (-3.959)	g_3	-0.639 (-3.105)			d_{c3}	-0.035 (-1.976)	g_3	0.293 (2.612)	
d_{f1}	-0.006 (-0.774)	γ_C $i = 0$	3.013 (1.303)			d_{f1}	0.362 (15.955)	γ_C $i = 0$	1.856 (2.411)	
ζ	0.887 (27.118)	γ_F $j = 0$	0.953 (4.827)			ζ	0.059 (15.933)	γ_F $j = 7$	-9.191 (-2.039)	
λ_0	0.003 (9.544)	γ_H $h = 0$	-2.081 (-1.721)			λ_0	0.009 (1.120)	γ_H $h = 0$	-3.387 (-2.603)	
λ_1	1.001 ((10929.7)					λ_1	1.020 (161.029)			
$\rho_{r_c r_f}$	0.986 (2594.630)	LLF	-401.498			$\rho_{r_c r_f}$	0.955 (215.150)	LLF	-1568.035	
ω_c	0.721 (22.707)	ω_f	0.898 (22.91)			ω_c	0.619 (7.879)	ω_f	0.479 (15.006)	
α_c	0.131 (94.493)	α_f	0.1450 (70.889)			α_c	0.136 (58.830)	α_f	0.102 (28.991)	
β_c	0.831 (513.487)	β_f	0.808 (349.957)			β_c	0.832 (352.982)	β_f	0.862 (164.179)	
T.N.T.	13.823 [0.000] C F H	23.754 [0.000] C	25.410 [0.000] F	15.393 [0.000] H		T.N.T.	3.715 [0.000] C F H	6.419 [0.000] C	1.920 [0.125] F	2.771 [0.041] H
$\eta_{ct} = \nu_{ct}/\sqrt{h^2_{r_c t}}$		$\eta_{ft} = \nu_{ft}/\sqrt{h^2_{r_f t}}$				$\eta_{ct} = \nu_{ct}/\sqrt{h^2_{r_c t}}$		$\eta_{ft} = \nu_{ft}/\sqrt{h^2_{r_f t}}$		
$E[\eta_{ct}]$	-0.080	$E[\eta_{ft}]$	-0.077			$E[\eta_{ct}]$	-0.066	$E[\eta_{ft}]$	-0.061	
$E[\eta^2_{ct}]$	1.007	$E[\eta^2_{ft}]$	1.008			$E[\eta^2_{ct}]$	1.028	$E[\eta^2_{ft}]$	1.031	
Sk.	-0.688	Sk.	-0.588			Sk.	-0.689	Sk.	-0.575	
Kurt.	0.528	Kurt.	0.225			Kurt.	0.765	Kurt.	0.385	
ARCH1	0.258 [0.612]	ARCH1	0.574 [0.449]			ARCH1	0.853 [0.356]	ARCH1	0.147 [0.702]	
ARCH2	0.447 [0.799]	ARCH2	0.636 [0.727]			ARCH2	1.737 [0.419]	ARCH2	0.224 [0.894]	
AR1	6.431 [0.011]	AR1	8.142 [0.004]			AR1	0.918 [0.338]	AR1	1.011 [0.315]	
AR2	6.671 [0.036]	AR2	8.601 [0.014]			AR2	3.094 [0.213]	AR2	3.879 [0.144]	
JB	33.037 [0.000]	JB	21.801 [0.000]			JB	37.763 [0.000]	JB	22.397 [0.000]	
BDS2	-0.3879 [0.698]	BDS2 0.6981	0.0610 [0.951]			BDS2	-1.0441 [0.296]	BDS2	-1.0708 [0.284]	

Notes. Probability values in square brackets; Sk.: Skewness; Kurt: Excess Kurtosis; JB: Jarque-Bera normality test; ARk: Ljung-Box test statistic for k-th order serial correlation of the time series; ARCHk: Ljung-Box test statistic for k-th order serial correlation of the squared time series; T.N.T.: Teräsvirta (1994) test of nonlinearity applied to the chartists' (C), fundamentalists' (F) and hedgers' (H) transition functions and to the three transition functions simultaneously (C F H). BDSk: test statistic, with embedding dimension k, of the null that the standardized residuals are independently and identically distributed.

This behaviour matches that defined in column 3, row 3 of Table 1. Fundamentalist speculators tend to destabilize the market, as the estimated coefficient g_2 is negative, in increasing numbers as spot price returns deviate from their equilibrium value (see Table 1, column 5, row 3). Finally, the negative value of g_3, combined with a negative γ_H and with a rate of change of cash prices, which on average is positive, suggests that hedgers play a stabilizing role in the 1-month futures market, even if their number declines as disequilibrium grows (Table 1, column 7, row 4). This points to a growing lack of confidence in the ability of the market to properly price these contracts.

In the case of the less liquid 3-month contract (Fut3), chartists destabilize the market, their number growing with the absolute value of the disequilibrium (Table 1, column 2, row 3). Fundamentalists too destabilize the market, even if their number decreases as price misalignment grows (Table 1, column 5, row 4). In the case of Fut3, the positive sign of g_3 suggests that hedgers destabilize the market, in a context where cash prices rising should induce producers to increase their hedging positions, with the effect of lowering futures prices rather than raising them as we observe. Their number declines as the cash returns deviate from their average values (Table 1, column 6, row 4). Overall, these results seem to capture the uneasiness of hedgers, whose presence in oil markets declines with the unprecedented price gyrations observed during the first sub-sample.

3.2 Second period analysis

Table 4 contains the estimates relative to the second sub-sample (02/09/2008 – 12/01/2016), which differ significantly from the first periods estimates, a finding, which upholds our partition of the overall data set. Results are satisfactory, as shown by standard misspecification tests. Starting with the one-month contract (Fut1), both chartists and fundamentalists destabilize the market, leaving it, however, for large deviations of futures and spot prices from their equilibrium values.

Table 4. Second period estimates: 02/09/2008 – 12/01/2016

Fut1						Fut3				
m = 1, n = 3		i=0, j=3, h=5				m = 1, n = 3		i=0, j=5,h=5		
r_{ct}		r_{ft}				r_{ct}		r_{ft}		
d_0	-0.902 (-34.213)	g_0	0.001 (0.025)			d_0	-2.778 (-53.870)	g_0	0.103 (2.794)	
d_{c1}	-0.076 (-8.297)	g_1	0.475 (25.209)			d_{c1}	-0.055 (-4.391)	g_1	0.231 (18.761)	
d_{c2}	-0.003 (-0.269)	g_2	-0.129 (-4.107)			d_{c2}	-0.011 (-0.693)	g_2	-0.020 (-1.537)	
d_{c3}	-0.025 -3.063)	g_3	0.954 (2.082)			d_{c3}	-0.010 (-1.201)	g_3	-0.020 (-0.589)	
d_{f1}	0.330 (35.825)	γ_C $i = 0$	-0.152 (-2.929)			d_{f1}	0.278 (21.287)	γ_C $i = 0$	2.229 (3.593)	
ζ	0.543 (34.340)	γ_F $j = 3$	-2.536 (-2.525)			ζ	0.063 (170.945)	γ_F $j = 5$	6.599 (4.369)	
λ_0	-0.000 (-0.245)	γ_H $h = 5$	-5.365 (-2.561)			λ_0	-0.123 -(22.911)	γ_H $h = 5$	2.214 (8.281)	
λ_1	0.996 (9138.965)					λ_1	0.928 (162.071)			
$\rho_{r_c r_f}$	0.988 (3251.962)	LLF	-1379.404			$\rho_{r_c r_f}$	0.966 (361.189)	LLF	-1556.834	
ω_c	1.010 (41.072)	ω_f	1.008 (53.938)			ω_c	0.774 (17.579)	ω_f	0.565 (26.971)	
α_c	0.182 (111.898)	α_f	0.154 (86.162)			α_c	0.164 (54.085)	α_f	0.124 (39.703)	
β_c	0.765 (428.090)	β_f	0.784 (470.650)			β_c	0.796 (285.621)	β_f	0.835 (296.251)	
T.N.T.	4.848 [0.000] C F H	5.422 [0.001] C	2.958 [0.032] F	6.086 [0.000] H		T.N.T.	3.139 [0.001] C F H	6.681 [0.000] C	0.949 [0.416] F	2.137 [0.095] H
$\eta_{ct} = \nu_{ct} / \sqrt{h^2_{r_c t}}$		$\eta_{ft} = \nu_{ft} / \sqrt{h^2_{r_f t}}$				$\eta_{ct} = \nu_{ct} / \sqrt{h^2_{r_c t}}$		$\eta_{ft} = \nu_{ft} / \sqrt{h^2_{r_f t}}$		
$E[\eta_{ct}]$	-0.087	$E[\eta_{ft}]$	-0.087			$E[\eta_{ct}]$	-0.107	$E[\eta_{ft}]$	-0.104	
$E[\eta^2_{ct}]$	1.001	$E[\eta^2_{ft}]$	1.001			$E[\eta^2_{ct}]$	1.010	$E[\eta^2_{ft}]$	1.013	
Sk.	-0.518	Sk.	-0.468			Sk.	-0.511	Sk.	-0.520	
Kurt.	1.749	Kurt.	1.539			Kurt.	1.639	Kurt.	1.538	
ARCH1	0.262 [0.608]	ARCH1	0.009 [0.761]			ARCH1	0.209 [0.647]	ARCH1	0.003 [0.847]	
ARCH2	0.796 [0.671]	ARCH2	0.334 [0.846]			ARCH2	1.336 [0.513]	ARCH2	0.896 [0.639]	
AR1	0.248 [0.618]	AR1	0.001 [0.920]			AR1	0.291 [0.590]	AR1	0.335 [0.562]	
AR2	1.039 [0.594]	AR2	1.113 [0.573]			AR2	0.872 [0.646]	AR2	1.397 [0.497]	
JB	66.338 [0.000]	JB	52.064 [0.000]			JB	59.935 [0.000]	JB	55.310 [0.000]	
BDS2	-0.6295 [0.529]	BDS2	-0.0183 [0.985]			BDS2	0.3577 [0.720]	BDS2	0.7274 [0.467]	

Notes. Probability values in square brackets; Sk.: Skewness; Kurt: Excess Kurtosis; JB: Jarque-Bera normality test; ARk: Ljung-Box test statistic for k-th order serial correlation of the time series; ARCHk: Ljung-Box test statistic for k-th order serial correlation of the squared time series; T.N.T.: Teräsvirta (1994) test of nonlinearity applied to the chartists' (C), fundamentalists' (F) and hedgers' (H) transition functions and to the three transition functions simultaneously (C F H). BDSk: test statistic, with embedding dimension k, of the null that the standardized residuals are independently and identically distributed.

Their behaviour corresponds to that described in Table 1, (column 2, row 4) and (column 5, row 4) respectively. The positive value of g_3, combined with a negative γ_H and with negative

cash returns on average suggests that, hedgers maintain the stabilizing role they played in sub-period 1, even if under different cash market conditions.

In this case too, the number of hedgers falls with market disequilibrium (Table 1, column 6, row 4), confirming the loss of confidence in market pricing, which results from the huge gyrations observed between 2008 and 2009 and the subsequent turmoil registered by the oil industry. The estimates relative to the three-month contract (Fut3) do not contradict these findings. Positive feedback trading seems to be the only activity capable of attracting market transactions. Indeed, the number of chartists increases as returns deviate from their equilibrium value (Table 1, column 2, row 3). Both fundamentalist speculators and hedgers, on the other hand, become marginally irrelevant; the coefficients relative to these two categories of agents are very small and, in one case, statistically insignificant.

4. Stabilizing vs. destabilizing impact of chartists, fundamentalists and hedgers: a comprehensive view

Following Cifarelli and Paladino (2011), we compute the following two "level of importance" ratios[13] in order to assess the relative impact of hedgers versus speculators in determining futures market behavior:

$$R_{CF} = \left|\frac{w_1\sigma^2_{r_f}}{w_2\sigma^2_{r_c}}\right| \quad (25)$$

[13] For a definition of this measure, see Achen (1982, p. 72-73).

$$R_{CFH} = \left| \frac{w_1 \sigma_{r_f}^2 + w_2 \sigma_{r_c}^2}{w_3 \sigma_{r_c}^2 \left(1 - \rho_{r_c r_f}^2\right)} \right| \quad (26)$$

Where $w_1 = g_1 \overline{S_{it-1}^C}$, , $w_2 = g_2 \overline{S_{Jt-1}^F}$ and $w_3 = g_3 \overline{S_{ht-1}^H}$. These coefficients quantify the average impact on prices of the different categories of economic agents active on the market, $\overline{S_{gt-1}^{C,F.H}}$, g = i, j, h, being the average values of the transitions functions.

Equation (25) provides an index R_{CF} , which quantifies the relative importance of noise trading versus fundamentalist speculation as determinants of futures rates of change. It does so by taking the absolute value of the respective g-coefficients, weighted by the average values of the corresponding transition function and the unconditional variances of futures and cash rates of change respectively. In the same way, Equation (26) measures the relative importance of speculation as a whole (that is chartists plus fundamentalists) relative to hedging (R_{CFH}). The results of this exercise can be found in Table 5.

Table 5. Average impact of chartists, fundamentalists and hedgers

	Noise traders	Fundamentalists	Hedgers	Noise traders vs. fundamentalists	Speculators vs. hedgers
	$w_1 = g_1 \overline{S_{it-1}^C}$	$w_2 = g_2 \overline{S_{Jt-1}^F}$	$w_3 = g_3 \overline{S_{ht-1}^H}$	R_{CF}	R_{CFH}
Fut1 Period 1	-0.0830	-0.1514	-0.0043	0.4728	52.3671
Fut3 Period 1	0.1603	-0.0190	0.0456	5.8147	2.0246
Fut1 Period 2	0.2240	-0.0268	0.1105	7.2611	1.5335
Fut3 Period 2	0.1757	-0.0178*	-0.0150*	6.8373*	6.9921*

Note. * The estimates of coefficients g_2 and g_3 entering these indexes are not significantly different from zero at the 5 percent level.

In the first sub-period, as discussed previously, both feedback traders and hedgers tend to stabilize the market for 1-month futures contracts (Fut1), whereas fundamentalists play a relevant opposite role. The coefficient R_{CF}, combined with these indications, points to a generally destabilizing role for speculation coming mainly from fundamentalist speculators, among which we include crude oil investors. The huge dimension of the R_{CFH} index significantly reinforces the impression that destabilizing speculation prevails over market stabilizing forces. Similar considerations apply to the case of the 3-month contract (Fut3), where however the main destabilizing push comes from noise traders. The lower value of the speculators vs. hedgers ratio, observed in the case of Fut3, does not contradict these conclusions. Overall, these findings clearly reflect the bubble-like behavior of oil markets observed in the last years of the first sub-sample.

In the second sub-period, feedback traders take the upper hand in determining futures rates of change, in the case of Fut1 particularly. Speculation continues to exert a destabilizing role, feedback trading replacing fundamentalist speculation as the main driver, as coefficient R_{CF} indicates. The general impact of speculation relative to hedging is, however, sensibly smaller with respect to what we observe in the first sub-sample. These findings are repeated for the 3-month contract, with the proviso however, that the coefficients that measure the impact of fundamentalists and hedgers on futures prices are not measured in a precise way.

Comparison of the two sub-periods suggests two key considerations. The first consideration relates to the fact that speculation plays a destabilizing role over the entire sample period, its effect being however weaker in the second sub-period, as shown by the data reported in the last column of Table 5. The second consideration refers to the weakness of the stabilizing role of hedgers, who moreover tend to either leave the market for large deviations of cash returns from their equilibrium values or have an insignificant impact as is the case for Fut3 in sub-period 2. We interpret this result as corroborating the main hypothesis set out in our paper, viz. the reduction in the informative content of fundamentals in the post-Lehman crisis period.

Table 5 is based on the average values of the weights coefficients w_1, w_2 and w_3. In Figures 2 to 5, we analyze the shifts in these coefficients as cash and futures rates of return deviate from their respective equilibrium values. Each graph contains a scatter plot of the impact of each group of agents on futures returns (regression coefficient multiplied by the value of the LSTAR transition function) and the deviations of the transition variable from its equilibrium value. We report the former on the vertical axis and the latter on the horizontal one. For the sake of clarity, we have interpolated the scatter plots using local first order polynomial regressions with bandwidth based on the nearest neighbor approach.[14]

As for the 1-month futures contract, in the pre-Lehman sub-period, we notice that 10 basis points deviations from equilibrium bring about a sharp increase in the stabilizing power of negative feedback traders (Figure 2, left panel), countered by a corresponding increase in the destabilizing effect of fundamentalist speculators (Figure 2, central panel). Hedgers, however, seem to leave the market as their influence on futures rates of change collapses to values close to zero (Figure 2, right panel). In the case of the 3-month contract, 10 basis point deviations from equilibrium cause a substantial rise in the destabilizing role of chartists, which is compensated however by the disappearance of destabilizing fundamentalists and hedgers.

[14] The local regressions are performed on a sub sample selected according to the Cleveland (1993) procedure and involves about 100 evaluation points. Tricube weights are used in the weighted regressions used to minimize the weighted sum of squared residuals. The bandwidth span of each local regression is set to 0.3.

Figure 2. Impact of speculators and hedgers on 1-month futures rates of return and deviations from long-term equilibrium (first sub-period)

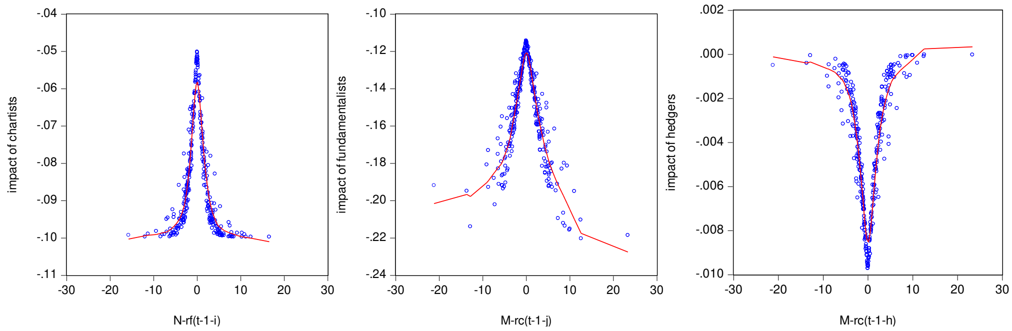


Figure 3. Impact of speculators and hedgers on 3-month futures rates of return and deviations from long-term equilibrium (first sub-period)

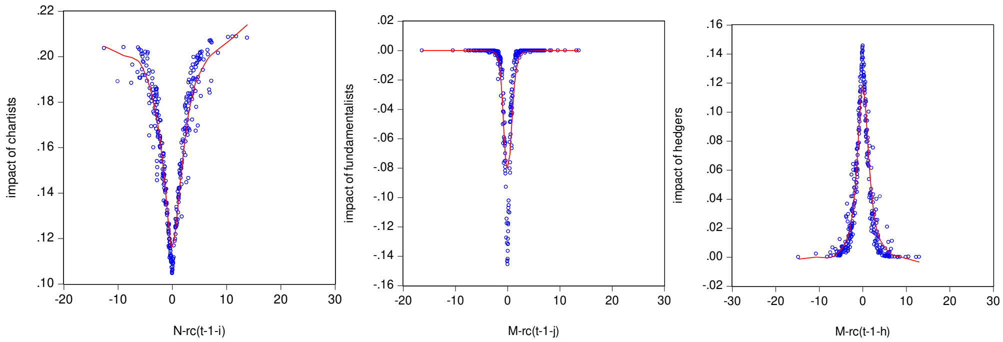


Figure 4. Impact of speculators and hedgers on 1-month futures rates of return and deviations from long-term equilibrium (second sub-period)

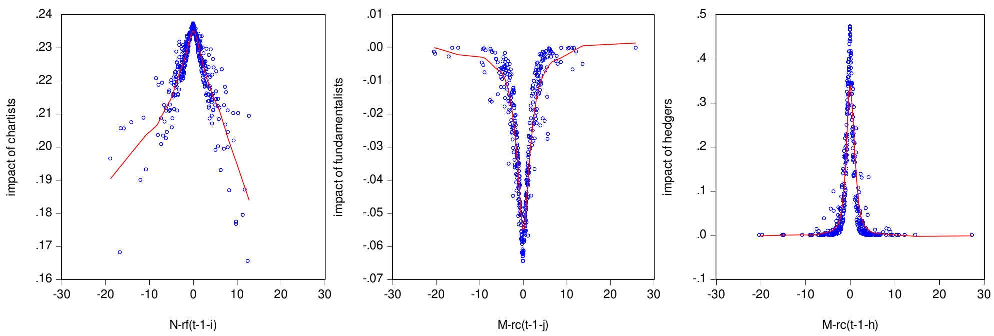
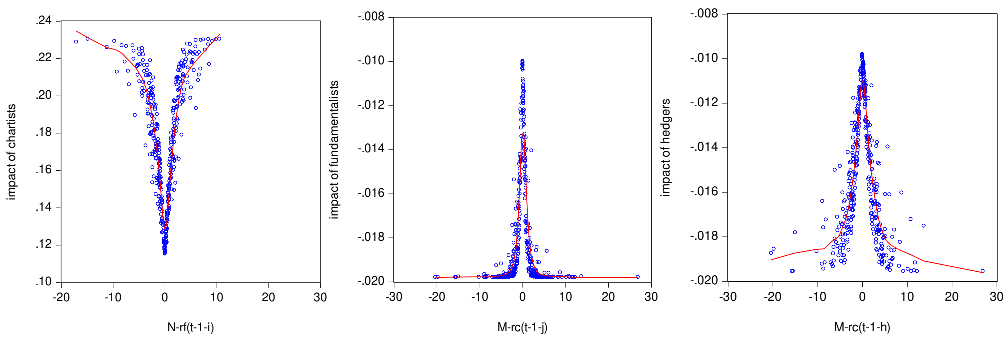


Figure 5. Impact of speculators and hedgers on 3-month futures rates of return and deviations from long-term equilibrium (second sub-period)



The post-Lehman period provides interesting additional insight. As for the 1-month contract, a 10 basis points deviation from equilibrium is reflected in a moderate decrease in the destabilizing role of chartists, reinforced by the disappearance of destabilization coming from both fundamentalists and hedgers. Finally, focusing on the role of chartists as the only significant driver of Fut3 rates of return in the post-Lehman period, we detect that their contribution to market destabilization increases with deviations from the equilibrium.

5. Conclusions

Our research addresses a controversial and hotly debated topic in commodity pricing viz. the effect of speculation vs. hedging in determining oil futures prices in a context of changing uncertainty. Our main results corroborate recent evidence by practitioners regarding withdrawal of rational agents (i.e. fundamentalists and hedgers) from oil futures markets whenever prices seem to be losing their informative content. Our first conclusion relates to the fact that speculation plays a clear-cut destabilizing role over the entire sample period, due to the joint reaction of chartists and fundamentalists. Of great interest is the fact that fundamentalist speculators, among which we include institutional investors, ETFs and Hedge funds, tend systematically to destabilize the market, with the exception of the three-month contract in the second sub-period, in which uncertainty hinders their decision taking. Our second conclusion refers to the weakness of the stabilizing role of hedgers, who moreover tend to either leave the market for large deviations of cash returns from their equilibrium values or have an insignificant impact as is the case of Fut3 in sub-period 2. We interpret this result as corroborating the main hypothesis set out in our paper, viz. the reduction in the informative content of fundamentals in the post-Lehman crisis period, characterized by unprecedented industrial and geopolitical shocks. Our third finding is that, during the second sub-period, most economic agents not only concentrate on the short end of the market (Fut1), distrusting longer maturities, but also tend to leave it as deviations from long-term returns equilibrium values rises.

References

Achen, C., 1982. Interpreting and using regression. Thousand Oaks, CA: Sage Publications.

Babel, A., McGillicuddy, J., 2015. Oil prices: is supply or demand behind the slump? Federal Reserve Bank of Saint Louis Economic Synopses, 8.

Baumeister, C., Kilian, L., 2015. Understanding the decline in price of oil since June 2015. CEPR Discussion Paper, 10404.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-maximum likelihood estimation and dynamic models with time-varying co-variances. Econometric Reviews, 11, 143-172.

Brock W.A., Dechert, W.D., Scheinkman, J.A., 1987. A test for independence based on the correlation dimension, Department of Economics, University of Winsconsin-Madison, SSRI Working Paper n. 8702.

Brock W.A., Hommes C.H., 1997. A Rational Route to Randomness, Econometrica, 65: 1059-1095.

Brock W.A., Hommes C.H., 1998. Heterogeneous Beliefs and Route to Chaos in a Simple Asset Pricing Model, Journal of Economic Dynamics and Control, 22: 1235-1274.

Chia, W.-M., Li, M., Zheng, H., 2014. Regime switching models in the foreign exchange market. In Dieci R., He X.-Z., Hommes C. (eds) Nonlinear economic dynamics and financial modelling. Springer, Heidelberg, 201-223.

Cifarelli, G., 2013. Smooth transition regime shifts and oil price dynamics. Energy Economics, 38, 160-167.

Cifarelli, G., Paladino, G. 2011. Hedging vs. speculative pressures on commodity futures returns, MPRA Paper n. 28229, online at https://mpra.ub.uni.muenchen.de/28229/

Cleveland W.S., 1993, Visualizing Data, Hobart Press: Summit, NJ.

CommodityPoint, 2013. Global oil markets – increasing uncertainty and risk. CommodityPoint White paper, January 2013.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise Trader Risk in Financial Markets. Journal of Political Economy, 98, 703-738.

Frankel J.A., Froot, K.A., 1986, Understanding the US Dollar in the Eighties: the Expectations of Chartists and Fundamentalists, The Economic Record, 62, 24-38.

Figuerola-Ferretti, I., Gonzalo, J. 2010. Modelling and measuring price discovery in commodity markets. Journal of Econometrics, 158, 95-107.

Hamilton, J., 2009. Understanding crude oil prices. Energy Journal, 30, 179-206.

Kesicki, F., 2010. The third oil surge – What's different this time? Energy Policy, 36, 1596 – 1606.

Luukkonen, R., Saikkonen, P., Teräsvirta, T., 1988. Testing linearity against smooth transition autoregressive models. Biometrika, 75, 491-499.

Master, M.E., 2008. Testimony before the Committee on Homeland Security and Government Affairs, United States Senate, May 20.

Morana, C., 2001. Semi-parametric approach to short-term oil price forecasting. Energy Economics, 23, 325–338.

Nakov, A., Nuño, G., 2011. Saudi ARAMCO and the oil market. ECB Working Paper, 1354.

Reitz S., Westerhoff, F.H., 2007. Commodity price cycles and heterogeneous speculators: A STAR-GARCH Model, Empirical Economics, 33: 231-244.

Santabárbara, D., 2017. The oil market: recent developments and outlook. Banco de España, Analytical Articles Economic Bulletin 3/2017.

Shleifer A., Vishny, R., 1997. The limits of arbitrage. Journal of Finance, 52, 35-55.

Silvennoinen, A., Thorp, S., 2013. Financialization, crisis and commodity correlation dynamics. Journal of International Financial Markets, Institutions and Money, 24, 42-65.

Stein, J.L., 1961. The simultaneous determination of spot and futures prices. American Economic Review, 51, 1012-1025.

Tang, K., Xiong, W. 2010. Index investment and the financialization of commodities. NBER Working Paper w16385, NBER, Cambridge, MA, Princeton NJ.

Teräsvirta, T., 1994. Specification, estimation, and evaluation of smooth transition autoregressive models. Journal of the American Statistical Association, 89, 208-218.

Tokic, D., 2011. Rational destabilizing speculation, positive feedback trading and the oil bubble of 2008. Energy Policy, 39, 2051-2061.

Vo, M.T., 2009. Regime-switching stochastic volatility: Evidence from the crude oil market. Energy Economics, 31, 779 – 788.

Wan, J.-Y., Kao, C.-W., 2009. Evidence on the contrarian trading in the foreign exchange markets, Economic Modelling, 26, 1420-1431.

Westerhoff F.H., 2004. Multiasset market dynamics. Macroeconomic Dynamics, 8: 596-616.

Westerhoff, F.H., Reitz, S., 2005. Commodity price dynamics and the non-linear Market Impact of Technical Traders: Empirical Evidence for the US Corn Market. Physica, A 349: 641-648.