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Does U.S. monetary policy affect crude oil future price volatility? An empirical investigation‡

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Abstract

Modeling crude oil volatility is of substantial interest for both energy researchers and policy makers. Many authors emphasize the link between this volatility and some exogenous economic variables. This paper aims to investigate the impact of the U.S. Federal Reserve monetary policy on crude oil future price (COFP) volatility. By means of the recently proposed generalized autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS) model, the Effective Federal Fund Rate (EFFR) - as a proxy of the monetary policy - is plugged into the mean-reverting unit GARCH(1,1) model. Strong evidence of an inverse relation between the EFFR and COFP volatility is found. This means that an expansionary monetary policy is associated with an increase of the COFP volatility. Conjecturing that the unusual behavior of the COFP in 2007-2008 was driven by a monetary policy shock, we test the presence of mildly explosive behavior in the prices. The *sup Augmented Dickey-Fuller* test (SADF) confirms the presence of a bubble in the COFP series that started in October 2007 and ended in October 2008. We expect that the COFP-EFFR association could be affected by such a bubble. Therefore, we apply the same experimental set-up to two sub-samples - before and after October 2007. Interestingly, the results show that EFFR influence on COFP volatility is greater in the aftermath of the bubble.

Keywords: Volatility, GARCH-MIDAS, Bubbles, Futures, Crude Oil.
JEL classification: C22, C58, E30, Q43

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1. Introduction

According to the consolidated literature, volatility is a central aspect in financial markets (Poon and Granger, 2003). Kroner et al. (1995) argues that commodity prices have historically experienced periods of great volatility. Within the vast universe of commodities, modelling crude oil volatility is of substantial interest for both energy researchers and policy makers. In fact, persistent changes in crude oil volatility may affect the risk exposure of both producers and industrial consumers, altering the incentives to invest in inventories and facilities for production and transportation (Pindyck, 2004). Therefore, more risky markets lead to economic instability for both energy net-exporter and net-importer countries (Narayan and Narayan, 2007). Several authors, for instance Sadorsky (2006), Efimova and Serletis (2014) and Agnolucci (2009), have addressed the modelling of the volatility in these markets using generalized autoregressive conditional heteroskedasticity (GARCH) models. However, the classic GARCH structure relies on the (squared log) daily returns, not taking into account the association between the volatility and exogenous variables sampled at different frequencies. This could lead to less accurate volatility estimates, mainly when macroeconomic shocks affect financial stability.

This paper aims to investigate the impact of such a monetary policy on the crude oil future price (COFP) volatility. In general, the debate about the influence of monetary policy on asset volatility has been a controversial and much disputed subject (Bernanke and Gertler, 1999). The influence of the COFP on the monetary authorities' decisions has been highlighted by a number of studies (Bernanke and Blinder, 1992; Ferderer, 1997), while little attention has been devoted to the discussion of a possible reverse causality. Several authors (as few example Borio and White (2004), Bordo and Jeanne (2002)) point out that monetary policies could seriously influence asset price movements but, as far as we know, investigating whether the monetary policy affects COFP volatility is still an open issue. This study aims to offer some insights into this debate. By means of the GARCH-MIDAS model proposed by (Engle et al., 2013) it is possible to plug some exogenous economic variables into the GARCH equation. We choose the Effective Federal Fund Rate (EFFR) as a proxy for U.S. monetary policy. It is worth noting that the relevance of this topic has increased in recent years because the U.S. monetary authorities hugely cut the EFFR in order to face the latest crisis. Such an aggressive expansionary monetary policy coincided with an unusual surge in COFP followed by a sharp decrease. This pattern is consistent with mildly explosive behavior in the asset prices. In fact, the SADF test proposed by Phillips et al.

(2011) detects such behavior from October 2007 to October 2008. Thus, we carry out the same experimental set-up, dividing the full sample into two sub-samples, before and after-October 2007.

The rest of the paper is structured as follows. Section 2 briefly introduces the GARCH-MIDAS model and the SADF test. Section 3 describes the data used to implement the empirical analysis and illustrates the empirical results. Section 4 provides a discussion of the main findings and their policy implications. Section 5 concludes.

2. The methodology

The GARCH-MIDAS model

During the last decades, many different approaches have been proposed to model volatility. Among these, a particular role is played by the GARCH (Bollerslev, 1986) models. Within this framework, the volatility of an asset depends on its past information. The volatility may also be linked with some exogenous variables. For instance, Schwert (1989) has noted that the volatility of some economic variables (such as bond returns, inflation rates and so forth) varies through time together with that of the stock returns. Other studies have showed that the risk premiums are counter-cyclical (Fama and French, 1989). Endowed with this knowledge, new models specifying volatility as a product or a sum of different components have arisen. Engle and Lee (1993) consider a GARCH model with two components of volatility, a long- and a short-run one. More recently, Adrian and Rosenberg (2008) identify a short-run component, capturing a market skewness risk, interpreted by the authors as a measure of the tightness of financial constraints and a long-run component, related to business cycle risk. Although there are many models considering volatility driven by multiple components (see, among others, Ding and Granger (1996), Gallant et al. (1999), Alizadeh et al. (2002) and Chernov et al. (2003)), few are those that directly link these components with exogenous variables. The GARCH-MIDAS model, recently proposed by Engle et al. (2013), allows to explicitly consider these links in a one-step procedure. Such a model has been derived from the combination of the Spline-GARCH model (Engle and Rangel, 2008) with the mixed data sampling (MIDAS) framework (Ghysels et al., 2005).

In the GARCH-MIDAS context, the general conditional heteroskedastic model is defined as:

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \cdots, N_t, \tag{1}$$

where $r_{i,t}$ represents the log-return for day i of the period t, which has N_t days. The period t may be a week, a month, a quarter, and so forth, depending on frequency of the exogenous variable. Note that N_t may differ across the periods t. Moreover, μ stands for the (unconditional) mean of the $r_{i,t}$ process, and $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$, where $\Phi_{i-1,t}$ denotes the information set-up to day $i-1$ of period t.

Therefore, within the GARCH-MIDAS framework, the conditional variance, namely $(\tau_t \times g_{i,t})$, is given by the product of two components, one varying each period t and one each day i. The former can be considered a long-run component, the latter as a short-run one. The short-run component follows a mean-reverting unit GARCH(1,1) process, incorporating the effects of the long-run component as follows:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{2}$$

with $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The long-run component τ_t is obtained as a filter of the exogenous variable X_t:

$$\tau_t = exp\left(m + \theta \sum_{k=1}^{K} \delta_k(\omega) X_{t-k}\right), \tag{3}$$

where the exponential transformation is needed in order to have $\tau_t > 0$, given that the exogenous variable X_t can also assume negative values. Equation (3) says that the long-term component is a function of the K lagged observed variable X_t, where each lagged value is weighted according to the Beta function:

$$\delta_k(\omega) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}} \tag{4}$$

The Beta function is very flexible, allowing for equally, increasing or decreasing weighted schemes, provided that $\omega_n \geq 1$, with $n = 1,2$. For instance, $\omega_1 = \omega_2 = 1$ yields the equally weighted scheme, $\omega_1 > \omega_2$ the monotonically increasing weighted scheme (farther observations are weighted more) and $\omega_1 < \omega_2$ the monotonically decreasing weighted scheme (closer observations are weighted more). The number of lags K is normally determined by profiling the likelihood or a properly chosen information criteria.

Under this configuration, the unconditional variance of $r_{i,t}$ is not fixed but varies over periods t:

$$E_{t-1}\left[(r_{i,t}-\mu)^2\right] = \tau_t E_{t-1}(g_{i,t}) = \tau_t. \tag{5}$$

However, if $\theta = 0$ in equation (3), then the long-term component reduces to a constant $\forall t$, such that the unconditional variance of $r_{i,t}$ returns to be invariant through time:

$$E_{t-1}\left[(r_{i,t}-\mu)^2\right] = exp(m)E_{t-1}(g_{i,t}) = exp(m). \tag{6}$$

This formalization of the GARCH-MIDAS model considers the fixed estimator for the specification of the MIDAS filter (equation (3)), given that τ_t is constant within each period t while it varies across periods[1]

The parameter space of the GARCH-MIDAS model just presented is $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$. The estimation of the unknown parameters is carried out by maximizing the following log-likelihood:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\left[\sum_{i=1}^{N_t}\left[\log(2\pi) + \log(g_{i,t}\tau_t) + \frac{(r_{i,t}-\mu)^2}{g_{i,t}\tau_t}\right]\right] \tag{7}$$

The SADF test

According to Phillips et al. (2011), one of the most debated issues in macroeconomics and finance in recent years is the investigation of the unusual periodic surges and falls in asset prices. In this paper, we consider this kind of behaviors a rational bubble[2].

Gürkaynak (2008) provides an extensive review of the literature on bubble detection dating back to the early 1980s. In particular, the author highlights the theoretical limits and the econometric problems affecting the methodologies proposed at that time. Phillips et al. (2011) address these issues by proposing a recursive

[1] Engle et al. (2013) propose also a version of the MIDAS filter that allows for daily variation of the long-term τ_t, which would become $\tau_{i,t}$ (rolling estimator). However, as pointed out by the authors, there are negligible differences between the long-term component obtained by using a fixed or a rolling estimator.

[2] We consider as rational bubble a generic deviation (typically a huge surge followed by a sharp reverse correction) of the asset price from its fundamental value driven by rational expectation.

unit root test, namely the SADF test. The test is based on sequential implementation of a right-tail unit root test in a recursive sub-sample with a fixed starting point and an expanding window. The test statistic is the *sup value*[3] of the corresponding ADF statistic sequence. Therefore, the SADF test identifies period by period the presence of a unit root against the alternative of explosive behavior. Moreover, the recursive implementation allows to identify both the starting and the ending points of the explosive autoregressive process.

Formally, the asset price process p_t can be generalized as follows:

$$p_t = \mu + \delta p_{t-1} + \sum_{i=1}^{l} \phi_i \Delta p_{t-i} + \varepsilon_t, \qquad \text{with } t = 1, \cdots, T, \tag{8}$$

where $\varepsilon_t \overset{iid}{\sim} N(0, \sigma^2)$, μ is the intercept, l is the maximum number of lags, $\phi_i \Delta p_{t-i}$ with $i = 1 \cdots l$ are the different lag coefficients, and ε_t is the error term. Contrary to the notation of the GARCH-MIDAS model, here the time unit t represents a day.

According to Phillips et al. (2012b), since adding lag orders can potentially bias the estimation results, we set $l = 0$. The recursive formalization of the SADF test is:

$$p_t^P = dT^{-\eta} + \delta p_{t-1}^P + \varepsilon_t, \qquad \text{with } P = t + w, \cdots, T. \tag{9}$$

In equation (9), p_t^P denotes the price series from the period t throughout the period P. This formalization allows for the window to be enlarged. At the beginning, the window has a length of w, and at the end a length of $T - t$. Moreover, as done by Phillips et al. (2012b), the drift μ changes in $dT^{-\eta}$.

Following Phillips et al. (2012a), we assume that the intercept does not affect the limit distribution. This means that the implied drift in the process is negligible as it has a smaller order than the stochastic trend[4]. In other words, we assume the risk premium component is negligible, allowing us to consistently distinguish run-ups generated by the explosive behavior from a unit root process for a fixed and constant d.

Therefore, the null and alternative hypotheses are:

[3]That is, the *supremum* which corresponds to the highest value of the original test statistic.

[4]Phillips et al. (2012a) showed that when $\eta > 0.5$ the finite samples distribution moves toward the asymptotic ADF distribution as η increases i.e. the order of the drift decreases.

$$\begin{cases} H_0: & \delta = 1 \\ H_1: & \delta > 1 \end{cases}$$

Under the null hypothesis the regression model is consistent with a random walk process with an asymptotically negligible drift. Therefore, d and η and θ are equal to unity. However, under the alternative $\delta > 1$, the price sequence is diverted from a random walk process, providing evidence of explosive behavior in the series.

3. Data and empirical results

In this paper we use data on crude oil and the U.S. interest rate over the period 1998-2013.

Crude oil future price

Since crude oil is the most actively traded physical commodity worldwide, crude oil futures allow traders and investors to take positions in this key component of the global economy. In what follows, we consider light sweet crude oil futures traded on the New York Mercantile Exchange (NYMEX), a division of the CME Group, which is the most liquid global forum for the exchange of raw materials on the market, characterized by the greatest trading volume of the exchange of futures contracts for commodities. The CMEs Light Sweet Crude Oil (WTI) futures contract is the benchmark contract for U.S. crude oil. It is traded in units of 1,000 barrels and the delivery point is Cushing (Oklahoma); it is also accessible to the international spot markets via pipelines. We collected daily data on the price in these contracts from the Bloomberg dataset. Many authors show that for most futures contracts, at any given time, one contract will typically be traded much more actively than others. Since the most traded volume is typically concentrated in the front-month contract (i.e. the contract nearest to expiration), the price sequence is constructed considering the rolling nearby futures price (i.e. using prices until near the maturity date and then switching to the subsequent maturing contract prices). In other words, on each day t, we use the price of the shortest duration contract that could be purchased in the futures market[5]. It is

[5] In particular, we use data which reflect the price registered at the end of both the CME Globex (the electronic futures trading platform) and the Pit (a physical area of trading floor) sessions.

worth highlight that front month contracts are generally the most liquid of futures contracts, in addition to having the smallest spread between the futures price and the spot price for the underlying commodity.

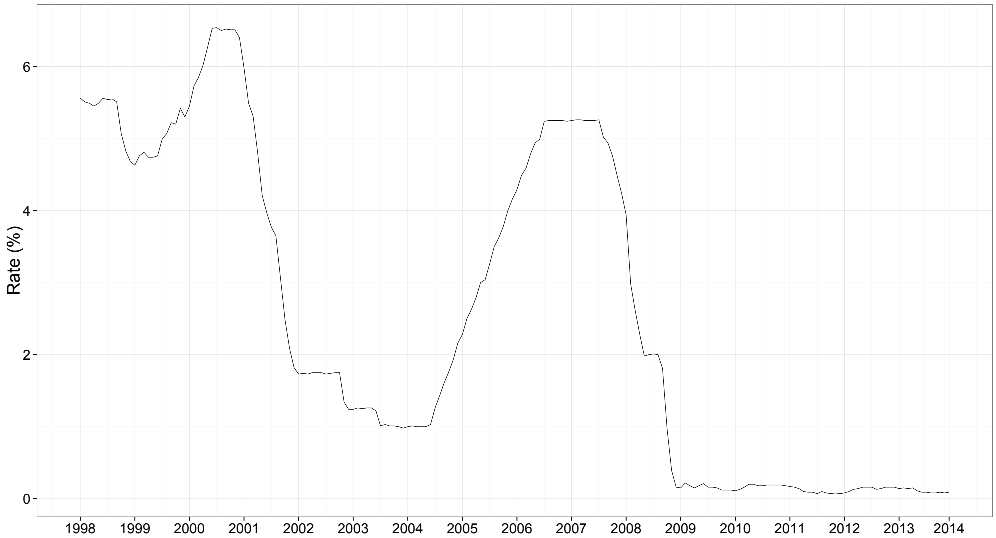
Effective Federal Fund Rate

As a proxy for the monetary policies implemented by the U.S. we use the monthly percent (not seasonally adjusted) series of EFFR collected from the Federal Reserve Bank of St. Louis Economic Data (FRED). Since each bank has an obligation to hold a certain percentage of deposits at its local Federal Reserve branch office each night to meet the reserve requirement, the Federal Fund rate is the rate that banks charge each other for overnight loans to meet this requirement. In particular, EFFR is the weighted average of all these interest rates. EFFR is traditionally considered the most important tool of U.S. monetary authorities, in order to manage the monetary policy. In fact, when the Federal Reserve decides on an expansionary monetary policy, it purchases securities (typically short-term government bonds) from its member banks. This operation increases the reserve of each bank pushing the institutions which have surplus balances in their reserve accounts (relative to the mandatory requirement) to lower the rate at which they lend out overnight the extra funds to other banks in need of larger balances. Obviously, when the Federal Reserve targets a higher and more restrictive monetary policy, it does the opposite. In what follows, we chose to use the EFFR monthly differences (rather than the level) in order to identify the monetary policy regime switches (expansionary or restrictive).

Descriptive analysis

The descriptive analysis of our data highlights that both the series present relevant shocks in the considered period. In particular, in mid-2007 the U.S. monetary authorities made a huge cut in the EFFR in order to face the incoming crisis (the EFFR level decreased from 5.26% in July 2007 to 0.16% in December 2008). Such an aggressive expansionary monetary policy anticipated a shock to the COFP which starting in the late 2007 experienced a rapid increases over its historical peak in July 2008 (reaching US$ 145 a barrel) and then fell (until US$ 33 a barrel) in December of the same year (see Figure1 below).

Figure 1: Monetary Policy and Crude Oil future prices from 1998 to 2013



(a) Effective Federal Fund Rate

(b) Crude Oil future prices

Empirical results[6]

Before introducing the results of the GARCH-MIDAS estimation, with reference to the maximization of the log-likelihood in (7), we remark that the starting points of the parameters as well as the number of lags K quite affect the convergence of the chosen algorithm, namely the Broyden, Fletcher, Goldfarb and Shanno (BFGS) method (Shanno, 1985). The following discussion concerns our choice about the starting points of Θ and K in order to initialize the log-likelihood. First of all, we set $K = 12$ in order to include one year of observations for the macroeconomic variable in the long-term component. Then, we set $\mu = 0$, $\alpha = 0.01$ and $\beta = 0.90$, according to widespread empirical evidence. The greatest variability of the starting log-likelihood values derives from the parameters m and θ. We let $\theta = 0$ because we are interested in the sign together with the power of the exogenous variable explaining the volatility. Setting $\theta = 0$ without any constraints makes the parameter free to go either in a positive or negative domain. With reference to the initial values of ω_1 and ω_2, these weight parameters are fixed to their lower bound, that is $\omega_1 = \omega_2 = 1$. Finally, given the just discussed initial values just discussed, m is fixed such that the starting log-likelihood value is maximum. With the data and time period under consideration, this happens setting $m = -8$.

The results from the GARCH-MIDAS model are summarized in Table 1. For comparison purposes, we also report the GARCH(1,1) estimated coefficients.

Table 1: Parameter Estimates of GARCH(1,1) and GARCH-MIDAS models

Sample	μ	α	β	m	θ	ω_1	ω_2
GARCH(1,1)	0.0007	0.0529	0.9404	-	-	-	-
	(2.24)	(4.00)	(62.27)	-	-	-	-
GARCH-MIDAS	0.0007	0.0725	0.9134	-7.4316	-0.5342	14.4893	4.5516
	(2.19)	(8.98)	(85.48)	(88.52)	(4.01)	(41.42)	(18.31)

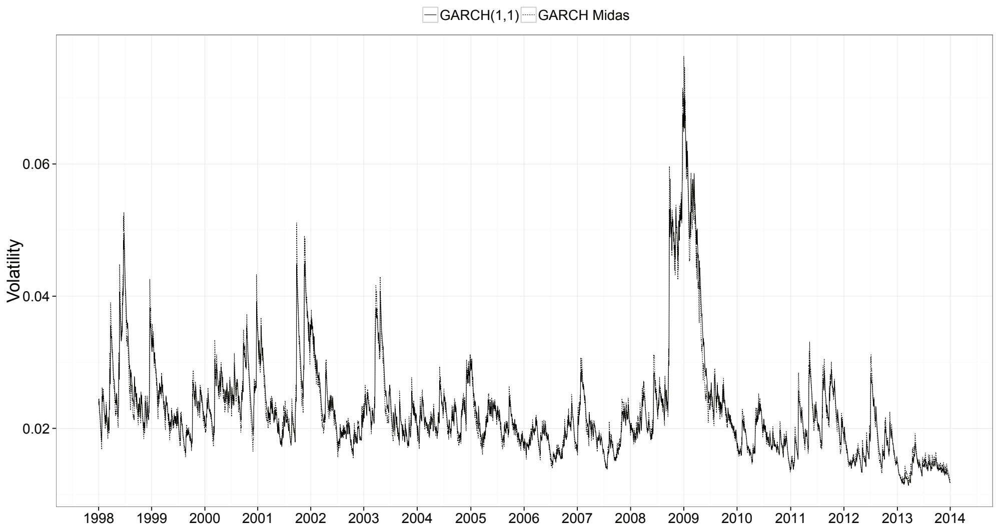
Notes: The numbers in parentheses are robust t-stats computed with HAC standard errors

First of all, we note that the common parameters of the two models are quite similar and highly significant. Figure 2 below shows graphically the differences

[6] The results of this work concerning the ADF test have been carried out by means of an Eviews Add-in developed by Itamar Caspi. All the remaining empirical applications have been implemented by R. The R code is available upon request.

between the volatility estimated through a GARCH(1,1) model (black line) and that estimated by means of the GARCH-MIDAS model. The two models follow the same pattern but, considering the contribution of the long-run component, the estimated volatilities diverged according to the period of greater instability.

Figure 2: GARCH (1,1) vs GARCH-MIDAS



With reference to the GARCH-MIDAS model, we are mainly interested in the significance, the sign and the magnitude of the coefficient θ. In fact, it determines how much the exogenous variable affects the asset volatility. In our case, θ is statistically different from zero and shows an inverse relation between EFFR and COFP volatility. Furthermore, the parameters ω_1 and ω_2 determine both the transmission lag and the elasticity of monetary policy on the COFP volatility. According to Engle et al. (2013), the elasticity is calculated as follows:

$$\varepsilon = \exp^{\theta \cdot \delta_k(\omega)} - 1, \tag{10}$$

In particular, the maximum weighted EFFR is the nine month lagged one. As a consequence, a 1% decrease of the EFFR today (expansionary monetary policy) would increase the COFP long-run volatility by 15.76% nine months later.

As discussed before, in mid-2007 the incoming crisis forced the monetary authorities to decide on an expansionary monetary policy. This shock anticipated an unusual surge of the COFP followed by a rapid sharp decrease. The SADF test is used in order to control if this unusual pattern of the COFP may be associated with a bubble. Effectively, the SADF test (Figure 3) confirms the presence of mildly explosive behavior in the COFP series from October 2007 to October 2008[7].

Figure 3: Results from SADF test and critical values

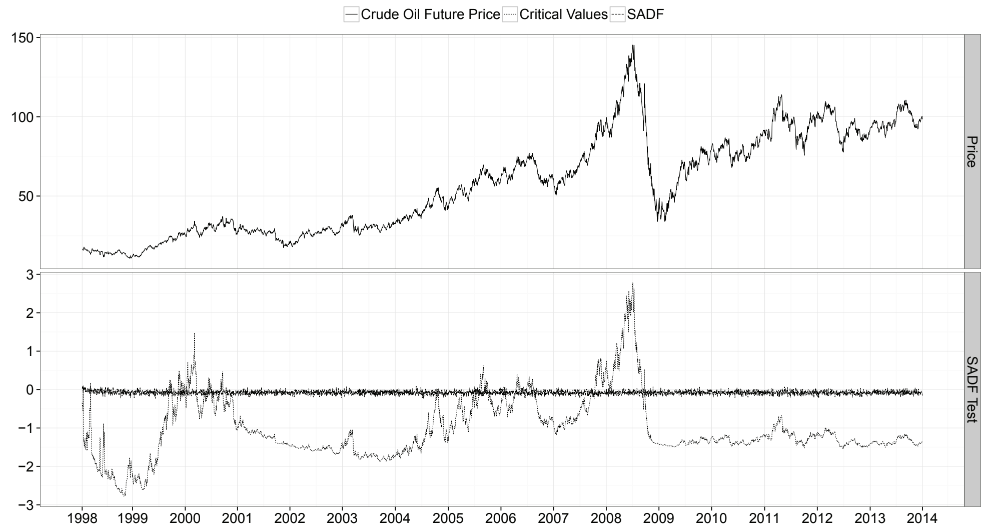


Figure 3 shows, at a glance, the presence and the timing of such a bubble in the COFP. In particular, the starting point of a bubble is the first chronological observation in which a value of ADF test sequence crosses the corresponding critical value from below. Instead, the ending point is the first chronological observation in which a value of the ADF test sequence crosses the corresponding critical value from above. This procedure signals the presence of multiple bubbles. However, the bubbles that burst before the 2008 are not considered as relevant because of the moderate intensity and/or the short time-span. Conversely, the latest bubble is very considerable because of the magnitude and the duration. According to the SADF results, it started in October 2007 and ended in October 2008.

[7] According to Gilbert (2010), the initial window w for the recursion test is set to 22 observations, which corresponds to about one month. The critical values necessary for the inference and data-stamp procedure are calculated with a significance level of 95% and derived as a by-product of 2000 recursive Monte Carlo simulations obtained using a finite sample size. The resulting SADF test statistic is 2.78 with a p-value of 0.0005

As a consequence, we expect that the COFP-EFFR association could be affected by such a bubble. Therefore, we aim to test whether the influence of the monetary policy changes in accordance with the bubble. In particular, we apply the same experimental set-up to two sub-samples - before and after October 2007.

The estimated coefficients of the full sample and first and second sub-samples are reported in Table 2.

Table 2: Parameter Estimates of GARCH-MIDAS model

Sample	μ	α	β	m	θ	ω_1	ω_2
Full sample	0.0007	0.0725	0.9134	-7.4316	-0.5342	14.4893	4.5516
	(2.19)	(8.98)	(85.48)	(88.52)	(4.01)	(41.42)	(18.31)
1^{st} sub-sample	0.0010	0.0677	0.8605	-7.5745	-0.8427	1.0062	7.6336
	(2.25)	(5.72)	(34.16)	(122.55)	(7.16)	(8.19)	(52.18)
2^{nd} sub-sample	0.0004	0.1649	0.8025	-7.5886	-1.8280	5.4596	2.4101
	(0.85)	(4.66)	(21.29)	(9.03)	(21.63)	(31.24)	(5.98)

Notes: The numbers in parentheses are robust t-stats computed with HAC standard errors

The results confirm the inverse relation between EFFR and COFP volatility in both sub-samples. However after October 2007, the impact of the monetary policy is much larger (θ is more than double the estimate for the full sample and the first sub-sample). As an example, in this case a 1% decrease of the EFFR today (expansionary monetary policy) would increase the COFP long-run volatility by 31.63% nine months later[8].

4. Discussion and policy implications

Results from the GARCH-MIDAS estimation show that EFFR is inversely associated with COFP volatility. This is not a brand new result. The proactive role of monetary policies on the asset prices (and the endogeneity of financial instability with respect to the monetary policies) has been a heavily debated economic issue in recent years (Bernanke and Gertler, 1999, 2001; Cecchetti et al., 2000). In addition, a number of empirical analyses (as an example Krichene (2006)) argue that during a demand shock, falling interest rates causes oil prices to rise. However,

[8] Interestingly, as happened for the full sample, a modification of the EFFR this month will produce the greatest volatility change in the next nine months.

as far as we know, for the first time these results arise from a one-step empirical estimation, i.e. by plugging the proxy for the monetary policy directly into the volatility equation. Furthermore, the results from the SADF test and those from GARCH-MIDAS on two sub-samples allow us to conjecture that the inverse relation between monetary policy and COFP volatility is much stronger when the cut of the interest rate causes mildly explosive behavior in the asset prices. The hypothesized mechanism is consistent with the literature on rational bubbles: first, prices increased in line with the beliefs of investors who expected that countercyclical monetary policy would be effective and the crisis would end soon with few consequences on the real economy. Then, when the persistence of the downturn changed investors' beliefs, the threat of a prolonged recession led the crude oil future prices to collapse and the COFP volatility to increase as a consequence. This paper provides some warnings to policy makers aiming to stimulate demand by means of an expansionary monetary shock. In fact, the results suggest that an unexpected increase of COFP volatility should offset (at least partially) the stimulus package.

5. Conclusion

The aim of this paper has been to investigate the impact of monetary policy on COFP volatility. The considered data cover the period from January 1998 up to December 2013. By means of the GARCH-MIDAS model we plugged EFFR (as a proxy for U.S. monetary policy) as a volatility determinant into the GARCH equation. In particular, GARCH-MIDAS allows to split the volatility into two components: the short-run and the long-run ones. The long-run component filters the macroeconomic variable through a weight function. This long-run component varies monthly and affects the short-run one. The latter component, in turn, follows a mean-reverting unit GARCH(1,1) process varying daily.

The main findings of this paper can be summarized as follows. The full sample results show that monetary policy affects COFP volatility. Furthermore, the weighting function casts light on the transmission lag of monetary policy on COFP volatility. In particular, the maximum weighted EFFR is the nine month lagged one. As a consequence, a 1% decrease of the EFFR today (expansionary monetary policy) would increase the COFP long-run volatility by 15.76% nine months later. Since the SADF test signals the presence of a bubble in the asset prices (starting in October 2007), we repeat the analysis considering two sub-samples. The results confirm the inverse relation between EFFR and COFP volatility in both sub-samples. However after October 2007, the impact of the monetary policy is much larger (θ is more than double the estimate for the full sample and the first sub-sample). As an example, in this case a 1% decrease of the EFFR today (expansionary monetary policy) would increase the COFP long-run volatility by 31.63% nine months later. Given these results, we conjecture that the negative association between monetary policy and COFP volatility is much stronger when the interest rate cut determines mildly explosive behavior in the asset prices. The hypothesized mechanism is consistent with a rational bubble: First, the bubble inflated according to the belief of some investors that counter-cyclical monetary policy would be effective and the crisis would end soon with few consequences on the real economy. Then, when the persistence of the downturn changed investors' beliefs, the bubble burst and the threat of a prolonged recession led future prices to collapse.

This research has thrown up many questions in need of further investigation. A number of possible future studies using GARCH-MIDAS models are apparent. To give just one example, further research might investigate the contribution of additional macroeconomic variables to volatility. Moreover, not only the levels of the macroeconomic variable but also the variance could be taken into consideration. Any further contribution in this direction will be relevant to improving commodity prices forecasts, providing effective guidance for policy makers' decisions.

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