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On the influence of the U.S. monetary policy on the crude oil price volatility

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Summary

Modeling crude oil volatility is of substantial interest for both energy researchers and policy makers. This paper aims to investigate the impact of the U.S. 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, a proxy of the U.S. monetary policy is included into the COFP volatility equation, alongside with other macroeconomic determinants. Strong evidence that an expansionary monetary policy is associated with an increase of the COFP volatility is found. In particular, an expansionary (restrictive) variation in monetary policy anticipates a positive (negative) variation in COFP volatility. Furthermore, an out of sample forecasting procedure shows that the estimated GARCH-MIDAS model has a superior predictive ability with respect to that of the GARCH(1,1), when the U.S. monetary policy exhibits severe changes in the run-up period.

Keywords: volatility, garch-midas, firecasting, crude oil

JEL Classification codes: c22, c58, e30, q43

1 INTRODUCTION

According to the consolidated literature, volatility is a central aspect in financial markets (Poon and Granger, 2003). Kroner et al. (1995) show that commodity prices have historically experienced periods of great variability. Within the vast universe of commodities, modeling 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).

In literature, the GARCH class of models has been extensively used for modelling commodities volatility in general (Nadarajah et al. (2014) and Efimova and Serletis (2014), for instance) and crude oil volatility in particular (Wei et al. (2010), Agnolucci (2009) and Sadorsky (2006), among others). However, the GARCH structure relies on the (squared log) daily returns, not taking into account the association between the volatility and additional (macroeconomic) variables sampled at different frequencies. Nevertheless, a number of authors shows that macroeconomic and financial information are important determinants of commodity prices (Gargano and Timmermann, 2014) and, in particular, of crude oil price (Zagaglia, 2010).

According to the previous literature (Krichene (2006); He et al. (2010)), the most important macroeconomic determinants of the crude oil price are the aggregate demand and the global supply. As regards to the crude oil volatility, Conrad et al. (2014) establish a counter-cyclical relationship with variables describing the current stance of the U.S. economy (e.g. the U.S. industrial production). To this extent, modeling crude oil volatility without taking into account its macroeconomic determinants could lead to less accurate estimates.

This paper aims to contribute to this debate by investigating the impact of the U.S. monetary policy on the COFP volatility. In general, the influence of monetary policy on asset volatility has been a controversial and much disputed subject (Bernanke and Gertler, 1999). The influence of crude oil price on the decisions of monetary authorities has been highlighted by a number of studies (Bernanke and Blinder, 1992; Kilian, 2009; Wei, 2014), while little attention has been devoted to the discussion of a possible reverse causality. Several authors (to name a few examples, 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. Therefore, further investigation of this topic could be extremely relevant for policy making. In fact, in terms of whether monetary policy affects COFP volatility, monetary authorities could effectively manage the fluctuations of the former in order to anticipate fluctuation of the latter.

In order to answer our research question, we consider the empirical relation between a proxy for the U.S. monetary policy and crude oil volatility controlling for the variation of the U.S. aggregate demand and the global crude oil supply. Given that we are interested in the daily COFP volatility, and the macro-variables are observed monthly, we use the GARCH-MIDAS model recently proposed by Engle et al. (2013) that allows for mixed data sampling in a GARCH framework.

Since central banks ordinarily conduct monetary policy by targeting short-term nominal interest rates, we use the Effective Federal Fund Rate (EFFR) as a proxy for the U.S. monetary policy. In a first specification, whose time span covers the whole period of interest, i.e. the interval 1998-2014, we include EFFR as well as the aggregate demand and global oil supply as additional COFP volatility determinants. Under this specification, strong evidences of an increase of COFP volatility after an expansionary monetary policy have been found.

However, in the aftermath of 2007 financial crisis, the nominal interest rate fell down practically close to zero and the Federal Reserve turned to unconventional monetary policies, such as the Quantitative Easing (QE), in order to alleviate financial distress and stimulate the economy. Accordingly with the change of the monetary policy instrument, we have repeated the analysis dividing the original full sample into two sub-periods using the proper monetary policy proxy for each ones. In particular, in the first period, from 1998 until 2008, we keep to use EFR. On the other hand, in the second sub-sample, we adopt QE to describe the monetary policy variations. By doing so, we also test the robustness of the empirical association between the monetary policy and the COFP volatility with respect to different periods and monetary policy proxies. Again, we find that an expansionary monetary policy determines an increase of the COFP volatility.

Finally, we focus on the forecast accuracy of our specifications for the data and period under consideration against that of a GARCH(1,1). By using a rolling forecasting scheme and the same procedure of Asgharian et al. (2013), the Diebold and Mariano (1995) and Clark and West (2007) tests show that in 2006, 2008 and in the period 2003-2008 our specifications have a superior predictive ability than the GARCH(1,1). Interestingly, on the eve of 2006 and 2008 EFR experienced severe shocks. This suggests that including macro-variables such as the monetary policy proxies improves COFP volatility forecasts, when the U.S. monetary policy exhibits severe changes in the run-up period.

The rest of the paper is structured as follows: Section 2 briefly introduces the GARCH-MIDAS model. Section 3 describes the data. Section 4 shows the results and provides some comments. Section 5 is devoted to the forecasting accuracy. Section 6 concludes.

2 METHODOLOGY

During the last decades, many different approaches have been proposed to model volatility. A general conditional heteroskedastic model can be defined as:

$$r_i = \mu + h_i \varepsilon_i \quad \text{with } i = 1, \dots, I; \quad (1)$$

where r_i represents the log-return for day i , with $i = 1, \dots, I$, μ the (unconditional) mean, h_i the conditional standard deviation and ε_i a *iid* process with zero mean and unit variance.

Among all the different approaches, a particular role is played by the GARCH (Bollerslev, 1986) models. Within this framework, the volatility depends on its past information, therefore the GARCH(p,q) model is given by

$$h_i^2 = \psi + \sum_{i=1}^p \alpha_i (r_{t-i} - \mu)^2 + \sum_{i=1}^q \beta_i h_{t-i}^2, \quad (2)$$

with $\psi > 0$, $\alpha_i \geq 0$ and $\beta_i \geq 0$ sufficient conditions for ensuring the positiveness of the conditional variance. Since we use a GARCH(1,1) as benchmark model, then we assume $p = q = 1$, such that eq. (2) becomes:

$$h_i^2 = \psi + \alpha (r_{t-1} - \mu)^2 + \beta h_{t-1}^2. \quad (3)$$

However, 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 shown 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:

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}} \varepsilon_{i,t}, \quad \forall i = 1, \dots, N_t, \quad (4)$$

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 by each period t and one by each day i . The former is considered the long-run component, the latter the 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:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}, \quad (5)$$

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 :

$$\tau_t = \exp \left(m + \theta \sum_{k=1}^K \delta_k(\omega) X_{t-k} \right), \quad (6)$$

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 (6) 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:

$$\delta_k(\omega) = \frac{(k/K)^{\omega_1-1} (1-k/K)^{\omega_2-1}}{\sum_{j=1}^K (j/K)^{\omega_1-1} (1-j/K)^{\omega_2-1}} \quad (7)$$

The Beta function is very flexible, allowing for equally, increasingly or decreasingly 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 :

$$E_{t-1} \left[(r_{i,t} - \mu)^2 \right] = \tau_t E_{t-1} (g_{i,t}) = \tau_t. \quad (8)$$

However, if $\theta = 0$ in equation (6), 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:

$$E_{t-1} \left[(r_{i,t} - \mu)^2 \right] = \exp(m) E_{t-1} (g_{i,t}) = \exp(m). \quad (9)$$

This formalization of the GARCH-MIDAS model considers the fixed estimator for the specification of the MIDAS filter (equation (6)), 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:

$$LLF = -\frac{1}{2} \sum_{t=1}^T \left[\sum_{i=1}^{N_t} \left[\log(2\pi) + \log(g_{i,t} \tau_t) + \frac{(r_{i,t} - \mu)^2}{g_{i,t} \tau_t} \right] \right]. \quad (10)$$

So far, the formulation of the GARCH-MIDAS model allows for the inclusion of only one exogenous variable in the long-run equation (equation 6). Nevertheless, it is easy to include other macroeconomic variables in the long-run equation. In fact, assuming an additive formulation for τ_t , the long-run volatility equation with J exogenous variables is:

$$\tau_t = \exp \left(m + \theta_j \sum_{k=1}^{K_j} \delta_{k,j}(\omega) X_{t-k,j} \right), \quad \text{with } j = 1, \dots, J. \quad (11)$$

It is worth noting that each additional variable increases the parametric space by three parameters (θ and the weights ω_1 and ω_2). Therefore, a high number of control variables could make the model computationally highly demanding. The rest of the model is the same, given that equation (11) returns an observation of τ per each time period that is then plugged into (5). Once got the short and long-run volatility components, the volatility can be obtained.

Note that the GARCH-MIDAS nests the GARCH(1,1). In fact, the former reduces to the latter if $m = \theta_1 = \dots = \theta_J = 0$ in equation (11). Therefore, the GARCH(1,1) specification can be viewed as a parsimonious model compared to the MIDAS one, which includes additional parameters.

3 DATA DESCRIPTION

This section describes data on COFP and the exogenous variables entering our volatility equation. Recall that the aim of this study is to investigate the impact of the U.S. monetary policy on the COFP volatility. We use daily data on crude oil and monthly data on the U.S. monetary policy, aggregate demand and global oil supply over the period 1998-2014. The sample period covers different events in the financial markets, such as the dot-com bubble and the crisis of 2007, for instance.

¹Engle 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.

3.1 Crude oil future price (COFP)

Since crude oil is the most actively traded physical commodity worldwide, crude oil futures allow traders and investors to take positions in relation to 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. The CME Light Sweet Crude Oil (WTI) futures contract is the benchmark contract for U.S. crude oil. We collected daily data on the prices in these contracts from the Bloomberg dataset. Many authors show that for most futures contracts, at any given time, one contract will be traded much more actively than others. Since the most traded volume is usually 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). It is worth highlighting 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. Figure 1 shows the uprising trend of COFP until mid-2008, when the asset price reaches its historical peak before to collapse by the end of the year. Afterwards, the price experiences a partial recovery, but again in mid-2014 it sharply fall down.

Figure 1: Crude oil future prices



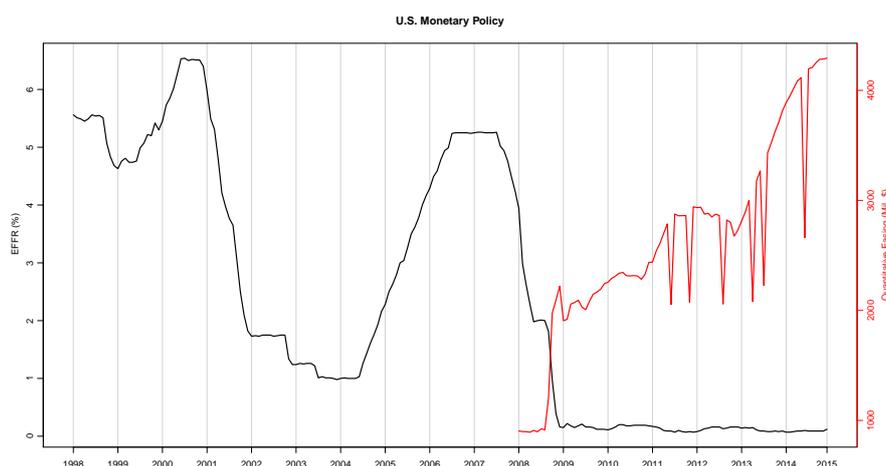
3.2 Monetary policy proxies

As said before, in this study, we consider two proxies for the U.S. monetary policy. The first one is EFFR, collected from the Federal Reserve Bank of St. Louis Economic Data. EFFR is traditionally considered the most important tool of U.S. monetary authorities, in order to manage the monetary policy in ordinary periods. As an example, 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 that 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. Conversely, when the Federal Reserve targets a higher and more restrictive monetary policy, it does the opposite.

However, when the short term nominal interest rate is near to zero, purchasing short-term securities cannot further stimulate the economic activity. In this case, monetary authorities are forced to implement unconventional monetary policies in order to stimulate the economy. This is what happened in the U.S. in the aftermath

of 2007 financial crisis. In fact, from November 2008 EFFR is flat and close to zero, and the Federal Reserve has purchased long-term assets in order to reduce real, long-term interest rates (*quantitative easing measures*). Therefore, by 2009, we replace the first proxy with QE. Data on QE are provided by Fawley and Neely (2013) but since the original series ended in October 2012, we have updated the dataset following their methodology. Figure 2 shows simultaneously the two series, highlighting the monetary policy instrument switch when EFFR went close to zero.

Figure 2: Effective federal fund rates and Quantitative Easing



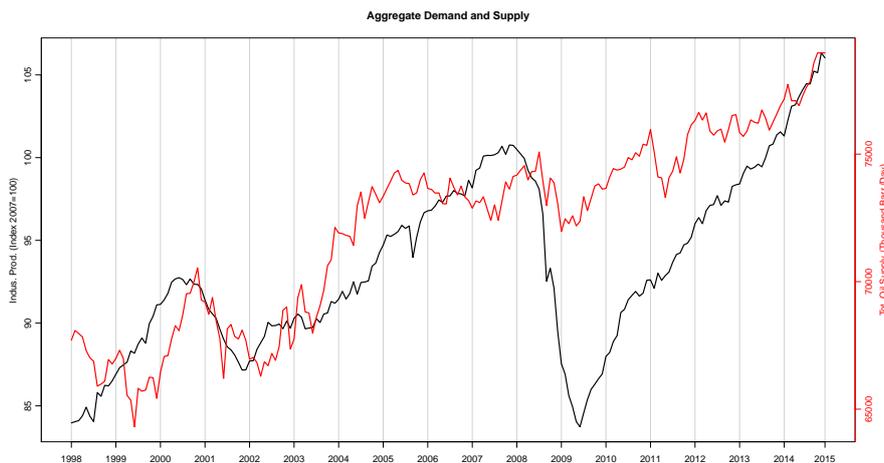
3.3 Other macroeconomic variables

The other macroeconomic variables plugged into the long-run equation of the GARCH-MIDAS model are the monthly U.S. industrial production index as a proxy of the aggregate demand (Conrad et al. (2014)) and the monthly global oil production as a proxy of the global oil supply.

The Industrial Production Index (IndPro), collected from the St. Louis Fed site, is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, electric, and gas utilities (Board of Governors of the Federal Reserve System, 2013). The index is compiled on a monthly basis in order to catch the short-term changes in industrial production. In what follows, a positive variation of IndPro from month to month is an indicator of growth in the industry and therefore could be a proxy for the increase in crude oil demand. In literature, the relationship between IndPro and crude oil price has been widely studied, and there is no consensus about the causality direction (Aguiar-Conraria and Soares (2011)). However, since in the volatility equation we include lagged IndPro data, only one causality direction is allowed.

As for the Global Oil Production Index (OilP), monthly data are provided as the average thousand barrels produced per day globally from the U.S. Energy Information Administration (EIA). In the empirical analysis we consider the global production's month-to-month variation in order to proxy change in crude oil supply. Figure 3 shows the patterns of the two series. IndPro clearly depends on the U.S. economic cycle. In fact, in the considered period its trend is increasing except for two huge falls, in correspondence with the two main crises occurred in mid-2000 and 2008. With reference to OilP, also in this case the trend is increasing but the series experiences a greater variability. However, while in mid-2000 OilP closely follows the U.S. aggregate demand, the 2008 crisis affects the global oil production only partially. This may be due to the increasing oil demand by the emerging economies.

Figure 3: U.S. industrial production, oil global production



3.4 Descriptive analysis

Table 1 summarizes the descriptive statistics of the variables presented above. In the table, there are illustrated the statistics related to the daily log-returns for the dependent variable (COFP) and monthly percentage variation for the macroeconomic variables.

Table 1: Descriptive statistics of the variables included in the models (percent variation)

| | ΔCOFP | ΔEFFR | ΔQE | ΔIndPro | ΔOilP |
|------------------|---------------------|---------------------|-------------------|-----------------------|---------------------|
| N. of obs. | 4266.000 | 204.000 | 72.000 | 204.000 | 204.000 |
| Minimum | -0.165 | -0.960 | -35.373 | -4.208 | -7.792 |
| Mean(%) | 0.026 | -2.637 | 215.484 | 11.926 | 4.064 |
| Median | 0.001 | 0.000 | 0.901 | 0.163 | 0.058 |
| Maximum | 0.164 | 0.280 | 57.715 | 2.080 | 2.929 |
| Standard dev.(%) | 2.396 | 17.818 | 1527.240 | 68.879 | 99.342 |
| Skewness | -0.127 | -2.031 | 1.205 | -1.825 | -2.320 |
| Excess kurtosis | 4.524 | 6.327 | 3.755 | 8.747 | 17.876 |
| Jarque Bera | 3653.336*** | 492.601*** | 14.818*** | 782.639*** | 2965.044*** |
| Ljung Box(20) | 1.598 | 97.754*** | 15.328*** | 9.438*** | 0.766 |
| ADF | -15.389** | -3.040 | -4.647 | -3.058 | -6.233** |
| Phillips Perron | -66.749** | -5.894*** | -17.755 | -12.020*** | -18.687*** |

For all the considered variables the sample means are quite small in comparison to the standard deviations. As regards to the test of normality, the variables display similar statistical characteristics. In fact, the Jarque Bera statistic always allows to reject the null hypothesis of normality at the 1% level of significance. This feature is also evidenced by a high excess kurtosis and negative skewness. The Ljung Box statistic for serial correlation shows that the null hypothesis of no autocorrelation up to the 20th order is rejected for ΔEFFR , ΔQE and ΔIndPro but not for ΔCOFP and ΔOilP . The augmented Dickey Fuller and Phillips Perron unit root tests both support the rejection of the null hypothesis of a unit root at the 5% significance level for ΔCOFP implying that the dependent variable is stationary and may be modeled directly without further transformation.

4 EMPIRICAL RESULTS

This section is devoted to the presentation of our model results. For comparison purposes, we also report the estimated GARCH(1,1), henceforth M0. Before maximizing the log-likelihood in (10), we needed to choose the initial values of Θ . The starting points of Θ and K in order to initialize the log-likelihood are chosen as follows. First of all, we set $K_1 = \dots = K_J = 12$ in order to include one year of observations for all the J macroeconomic variables 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_j . We let $\theta_1 = \dots = \theta_J = 0$ because we are interested in the sign together with the power of the exogenous variables explaining the volatility. Setting $\theta_j = 0$ without any constraints makes the parameter free to go in either a positive or negative domain. The initial values of the weights are fixed to their lower bound, that is $\omega_{1,j} = \omega_{2,j} = \dots = \omega_{1,J} = \omega_{2,J} = 1$. Finally, we put $m = -8$, a value that maximizes the log-likelihood, with the data and time period under consideration.²

As said before, we consider two different monetary proxies, that yield three different GARCH-MIDAS specifications. The first specification, namely M1, considers the full-sample period and use EFR as a proxy for the U.S. monetary policy. Afterwards, a second specification, namely M2, considers the period before the nominal interest rate goes to zero (i.e. 1998-2008) and keep to use EFR, while a third one, namely M3, considers the period 2009-2014 and use QE as the monetary policy proxy.

Table 2 summarizes all the estimated results, for the model M0 in the first column and for the three specifications of the GARCH-MIDAS in the second, third and fourth column. With reference to θ_{MP} , the proxy for the U.S. monetary policy is EFR in M1 and M2, while in M3 is QE. θ_{IndPro} denotes the parameter associated to the U.S. industrial production and θ_{OilP} the global oil production.

Table 2: Estimates of GARCH(1,1) and GARCH-MIDAS models

| | M0 (1998-2014) | M1 (1998-2014) | M2 (1998-2008) | M3 (2009-2014) |
|-------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| μ | $4.9 \cdot 10^{-4}$ | $4.3 \cdot 10^{-4}$ | $1.1 \cdot 10^{-3**}$ | $3.2 \cdot 10^{-4}$ |
| α | 0.053*** | 0.070*** | 0.078*** | 0.182*** |
| β | 0.944*** | 0.923*** | 0.874*** | 0.634*** |
| ψ | $2.7 \cdot 10^{-6**}$ | | | |
| m | | -7.376*** | -7.617*** | -8.350*** |
| θ_{MP} | | -0.806*** | -2.586*** | 0.019** |
| θ_{IndPro} | | 0.345*** | 0.970*** | -0.459*** |
| θ_{OilP} | | -0.054 | 0.333*** | 1.183*** |
| ω_{11} | | 1.019*** | 1.010*** | 39.526*** |
| ω_{12} | | 4.933*** | 1.499*** | 7.335*** |
| ω_{21} | | 4.571*** | 2.440*** | 12.216*** |
| ω_{22} | | 1.004*** | 6.259*** | 37.934*** |
| ω_{31} | | 10.748*** | 8.255*** | 5.420*** |
| ω_{32} | | 1.055*** | 3.745*** | 15.261*** |

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

²It is worth noting that in the GARCH-MIDAS framework the starting points of the parameters as well as the number of lags K quite affect the convergence of the BFGS algorithm (Shanno, 1985). Nevertheless, our results are robust to small variations of K .

We start with the interpretation of the M0 estimated coefficients. The unconditional mean μ is not statistically different from zero. According to the empirical evidences, the persistence in volatility, as given by the sum of α and β , is very close to one. This suggests a strong ARCH and GARCH effect. The parameter ψ , together with α and β , determines the unconditional volatility (that in the GARCH model, differently from the GARCH-MIDAS, is fixed over time). If $\psi/(1 - \alpha - \beta)$ is large, then the relative unconditional volatility is high. As in many other articles, the estimated ψ is small and statistically different from zero. With reference to our GARCH-MIDAS specifications, comparing α and β parameters of M1 to those of M0, their differences appear almost negligible.³ However, for the purpose of this study, the most relevant parameters are the θ s, detecting the direction and the magnitude of each macroeconomic variable impact on the COFP volatility. In particular, θ associated with EFFR is negative and statistically significant both in M1 and M2. This means that a negative (positive) variation in EFFR anticipated a positive (negative) variation in COFP volatility even controlling for other determinants. Given these results, we expect that the sign associated with monetary policy changes in the specification M3 switches from negative to positive. In fact, using QE as the monetary policy proxy, we find that an expansionary (restrictive) monetary policy anticipated an increase in COFP volatility.

Krichene (2006) argues that during a demand shock, falling interest rates cause oil prices to rise. Our results add new insights by identifying an impact of the monetary policy on oil price volatility. In particular, our findings suggest that when the Federal Reserve adopts an expansionary monetary policy, the COFP volatility increases. The reasons for which these results are crucial information for policy makers are twofold. On the one hand, they inform policy makers that the effect of an expansionary monetary policy could be offset by increasing COFP volatility. On the other hand, monetary authorities may properly manage their instruments in order to anticipate fluctuations in crude oil price, improving the macroeconomic stability. To this extent, these results are a further contribution in the heated debate about the proactive versus reactive role of the monetary policy on the asset price (Bernanke and Gertler, 1999, 2001; Cecchetti et al., 2000).

These results raise some issues related to the endogeneity of the monetary policy due to a possible reverse causality with COFP. Nevertheless, the structure of our model relaxes the endogeneity concerns. In fact, in the GARCH-MIDAS framework, the parameters influencing today's volatility rely on lagged macroeconomic variable realizations.

As for the other covariates, the findings of the current study do not completely support the results from the previous research. As an example, Conrad et al. (2014) establish a counter-cyclical relationship between crude oil volatility and variables describing the current stance of the U.S. economy.⁴ However, in their work, the authors include only one macro-variable per model. Nevertheless, we find that controlling for the monetary policy and global oil production, IndPro is positively associated with COFP volatility in M1 and M2 while only in M3 the association is negative. This suggests that in the long-run (M1) and during the expansion phases of business cycle (M2), COFP volatility behaves pro-cyclically. Conversely, it behaves counter-cyclically only after a recession period (M3).

As regards to the global oil production, the association with COFP volatility is positive and statistically significant only in M2 and M3. In particular, a positive (negative) variation of OilP anticipated an increase (decrease) in COFP volatility considering the periods 1998-2008 and 2009-2014.

To summarize, our results show that the empirical association between U.S. monetary policy and COFP volatility is robust, independently of the considered period and the monetary policy proxy.

³The two specifications share the same observation period.

⁴More precisely, Conrad et al. (2014) argue that a positive variation of IndPro is associated with a negative variation of the crude oil volatility, in the period 1993-2011.

5 FORECAST ACCURACY

As argued by Stock and Watson (2007), the evaluation of the out-of-sample performance is the “ultimate test of a forecasting model”. In the previous section, strong evidences of the U.S. monetary policy, as well as the aggregate demand and oil supply, influence on the COFP volatility have been found. Bearing this in mind, we are interested in controlling if the COFP volatility could be better predicted if these additional macro-variables are inserted in the volatility equation. Thus, this section aims to compare the COFP volatility predictions of the GARCH-MIDAS model with respect to those provided by the usual benchmark, namely the GARCH(1,1) model. In order to do that, we use a rolling forecasting scheme, following the same procedure of Asgharian et al. (2013). In particular, these authors use a window length of 2 years, due to the resultant smallest mean squared error (MSE) of the volatility predictions against the daily squared returns, considered as volatility proxy. As them, we use the same proxy but, contrary to them, we adopt a window length of 5 years, due to the smallest MSE that allows this configuration for our data and period. Afterwards, we let the estimated parameters be fixed for the following 6 months. In this evaluation period, we obtain the forecasted volatility predictions according to the estimated parameters and the observed values of the variables involved in the model. Subsequently, the estimation window is shifted forward of 6 months, in order to obtain new parameter estimates that will be kept fixed for, again, 6 months. Let us make an example. The first estimation period starts on January 1998 and ends on December 2003. The resulting estimated parameters are kept fixed from January 2004 to June 2004. In these 6 months, the observed values of the macro-variables are used together with the estimated parameters in order to obtain the volatility predictions. Afterwards, the window moves forward such that the estimation period goes from July 1998 to June 2004. This time, the evaluation period consists of the last 6 months of 2004. This procedure is repeated until December 2008 for M2. Thus, for this model we have 6 years of volatility predictions, from 2003 to 2008. After 2008, as already done in the previous section, we use M3. Therefore, in this case, we only have two estimation periods. The first goes from January 2009 to December 2013 and the second from July 2009 to June 2014. By doing so, we investigate the forecasting ability of the GARCH-MIDAS with respect to the short-term variance.

Moreover, we also investigate the forecasting performances of the GARCH-MIDAS related to a longer time span, namely at a monthly horizon. More precisely, we obtain the GARCH-MIDAS and GARCH(1,1) long-term variances by summing the relative volatility predictions within each month. As a benchmark, we use a realized monthly variance as a long-term volatility proxy, obtained from the summation of the squared daily returns per month.

In order to compare the predictive accuracy of the two models we use the DM (Diebold and Mariano, 1995) and CW (Clark and West, 2007) tests. According to Giacomini and White (2006), the DM should not be applied to situations where the competing forecasts are obtained using two nested models.⁵ However, Giacomini and Rossi (2013) argue the DM test remains asymptotically valid (under some regularity assumptions), even for nested models, when the size of the estimation sample remains finite as the size of the evaluation sample grows, i.e. when the forecasting scheme is the rolling one.

Instead, the CW test introduces a correction adjusting the point estimate of the difference between the MSEs of the two models for the noise associated with the larger model’s forecast. Thus, it properly works for nested models.

As argued by Hansen (2005), when the aim of interest of the superior predictive ability of a model (GARCH-

⁵In fact, with nested models, if the null hypothesis of equal predictive accuracy is true, then the forecast errors are perfectly correlated making the variance matrix of moment conditions singular.

MIDAS) against a benchmark (GARCH(1,1)), the system of the hypotheses has to be formulated as follows:

$$\begin{cases} H_0 : & \bar{d} = 0; \\ H_1 : & \bar{d} > 0, \end{cases} \quad (12)$$

where $\bar{d} = E(d_t)$, and d_t , the loss differential at time t is defined as

$$d_t = L(b_t, \hat{\sigma}_{G,t}^2) - L(b_t, \hat{\sigma}_{M,t}^2), \quad t = 1, \dots, h. \quad (13)$$

In (13), $L(\cdot)$ represents the chosen loss function used to evaluate the distance between the volatility proxy, b_t and the volatility prediction of the GARCH(1,1), denoted with $\hat{\sigma}_{G,t}^2$ and the volatility prediction of the GARCH-MIDAS, indicated with $\hat{\sigma}_{M,t}^2$. Moreover, h represents the length of the evaluation period. Throughout the section, $L(\cdot)$ is the MSE. Note that the same system of hypotheses has been followed by Awartani and Corradi (2005) for comparing the forecast accuracy of a larger model, such as the GARCH-MIDAS, that nests the parsimonious model, that is the GARCH(1,1).

Table 3 summarizes the results of the forecasting procedure, reporting the t statistics of the (right tailed) Diebold-Mariano (DM) and Clark-West (CW) tests. The forecasting procedure employs M2 up to 2008 and M3 for 2014. Therefore, for the short-term variance, the length of the evaluation period (h) is on average equal to 251 for the single years and 1506 for the period 2003-2008. For the long-term variance, instead, the length is 12 for the single years and 72 for the period 2003-2008. Recall that rejection of the null means that we fail to reject that the GARCH-MIDAS specification has a better forecasting performance than the GARCH(1,1).

Table 3: Forecasting ability comparative analysis: GARCH MIDAS vs GARCH (1,1)

| | Short-term variance | | Long-term variance | |
|------------------|---------------------|---------|--------------------|---------|
| | DM | CW | DM | CW |
| 2003 | -0.33 | 0.63 | -0.81 | -1.14 |
| 2004 | -0.74 | -1.13 | -0.73 | -1.47 |
| 2005 | -0.21 | 1.06 | -0.52 | 0.75 |
| 2006 | 0.48 | 3.80*** | 0.26 | 3.90*** |
| 2007 | -0.76 | -0.95 | -0.57 | -1.04 |
| 2008 | 1.10 | 3.49*** | 0.52 | 1.39* |
| 2014 | -0.44 | 0.68 | -0.25 | 1.02 |
| 2003-2008 | 1.00 | 3.54*** | 0.43 | 1.31* |

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Let us first consider the short-term variance comparison, reported in the first two columns of Table 3. Looking at the signs of the DM test, the GARCH-MIDAS model has a better forecasting performances only in 2006 and 2008. However, the associated p-values signal that the differences are not statistically significant. This is in line with Luger (2004), who shows that the MSE of the parsimonious model tends to be smaller than that of the larger one, when models are nested. In our case, this leads to under-reject the null hypothesis. On the other hand, when we consider the CW test, the GARCH-MIDAS has a statistically significant superior predictive ability in 2006 and 2008 and considering the whole period 2003-2008. We find identical results looking at the long-term variance comparison, as highlighted in the third and fourth columns of Table 3.

Interestingly, on the eve of 2006 and 2008, EFR experienced two huge shocks that lead the policy rate first to increase from 2.28% at the beginning of 2005 to 4.29% at the beginning to 2006 and then to decrease

from 5.25% in the mid-2007 to 2% in the mid-2008. These findings support the hypothesis that a shock in the monetary policy anticipated a change in COFP volatility. This also suggests that including this variable in the volatility model improves the forecast accuracy.

6 CONCLUSION

The aim of this paper has been to investigate the impact of monetary policy on the COFP volatility. By means of the GARCH-MIDAS model, we plugged a proxy for the U.S. monetary policy as a volatility determinant alongside with other COFP macroeconomic driving forces such as U.S. aggregate demand and global oil supply.

The results show that the U.S. monetary policy generally affects COFP volatility. In particular, an expansionary (restrictive) variation in monetary policy anticipated a positive (negative) variation in COFP volatility. The proactive role of EFFR on the COFP volatility is always confirmed, independently of the considered period and the variable used to describe the Federal Reserve monetary policy. These results provide crucial information for policy making. In fact, they suggest that monetary authorities may properly manage their tools in order to anticipate fluctuations in crude oil price improving the macroeconomic stability. The importance of including the monetary policy information in the volatility model is also supported by the forecast accuracy evaluation. In particular, the results of comparing the GARCH-MIDAS model with the more parsimonious GARCH(1,1) show that, for the data and the period considered, the former statistically significantly outperforms the latter when, in the run-up period, the monetary policy experienced a huge shock.

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