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

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Ancona, June 11, 2015
"4^{th} Conferenza dell' Associazione Italiana di Economia Agraria e Applicata"
(AIEAA 2015)

What is the aim?

Objective:

Investigating the impact of the U.S. Federal Reserve monetary policy on crude oil future price (COFP) volatility.

Why is investigating crude oil volatility important?

- 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);

- More risky crude oil market leads to economic instability for both energy net-exporter and net-importer countries (Narayan and Narayan, 2007).

Literature review

- Several authors have addressed the modeling of the volatility in crude oil markets using GARCH models (Agnolucci, 2009, Bernard et al., 2008, Efimova and Serletis, 2014, Sadorsky, 2006).

- According to Kilian (2009) and Gargano and Timmermann (2014), macroeconomic and financial variables are important determinants of crude oil price changes.

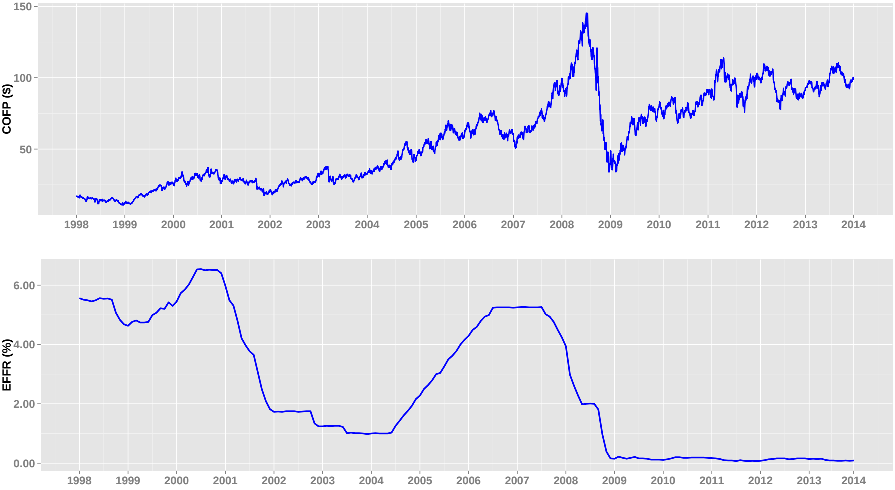
- Conrad et al. (2014) have recently investigated the impact of some macroeconomic variables on the COFP volatility. Using a **GARCH-MIDAS** model, they find that variables containing information on current and future economic activity are helpful predictors of COFP volatility.

Why is studying the relationship monetary policy - COFP volatility important?

- In order to shed light on the *proactive* vs *reactive* role of monetary policy (Bernanke and Gertler, 1999) $\Rightarrow$ If monetary policy affected crude oil price volatility, monetary authorities could effectively manage the fluctuations of the former in order to anticipate the fluctuations of the latter.
- During last years, both the U.S. monetary policy and the COFP have exhibited severe shocks.

A Cold Fact

Crude oil future prices and effective federal fund rates



Research questions

1. Does the U.S. monetary policy affect the crude oil future price (COFP) volatility?

2. Does including the U.S. monetary policy in the COFP volatility model improve the volatility predictions?

A general conditional heteroskedastic model

A general conditional heteroskedastic model can be defined as:

$$\begin{aligned} r_i &= \mu + h_i \epsilon_i \qquad i = 1, \cdots, I; \\ h_i^2 &= f(\Phi_{i-1}; \Theta), \end{aligned} \tag{1}$$

where

- μ is the (unconditional) mean;
- h_i^2 is the conditional variance at day i;
- ϵ_i is an iid process with zero mean and unit variance;
- Φ_i denotes the information set up to day i;
- Θ is the parametric space.

GARCH-MIDAS model

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

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}}\epsilon_{i,t}, \quad \forall i = 1, \cdots, N_t, \tag{2}$$

- $r_{i,t}$ represents the log-return for day i of the period t;
- μ is the (unconditional) mean;
- $\epsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$, where $\Phi_{i-1,t}$ denotes the information set up to day $i-1$ of period t.

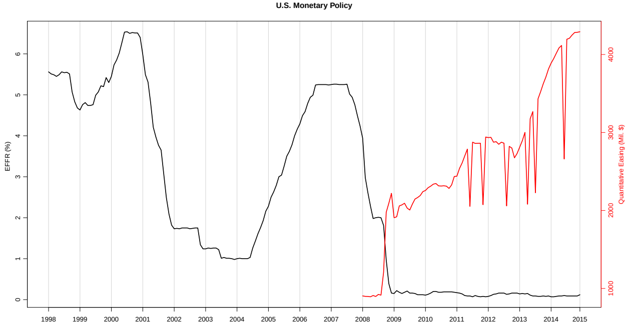
Our approach

- We plug a U.S. monetary policy proxy into the GARCH equation of crude oil volatility. Given that such a proxy is sampled monthly, we use a GARCH-MIDAS approach (Engle et al., 2013)
- Furthermore, according to (He et al., 2010, Krichene, 2006), we also control for the U.S. aggregate demand and the global crude oil supply as additional COFP volatility determinants.

An empirical issue

- In the aftermath of the financial crisis EFFR is flat and close to zero;
- From the end of the 2008 the Federal Reserve has purchased long-term assets in order to reduce real long-term interest rates.

Effective federal fund rates and Quantitative Easing



Empirical analysis

We consider the period from January 2, 1998 to December 31, 2014:

- Daily data for the dependent variable:
  - Data on COFP from Bloomberg;
- Monthly data on macroeconomic variables:
  - Data on Effective Federal Fund Rate (**EFFR**) from Federal Reserve Bank of St. Louis (FED);
  - Data on Quantitative Easing measures (**QE**) from (Fawley and Neely, 2013) and FED;
  - Data on the U.S. Industrial Production Index (**IndPro**) from FED;
  - Data on the Global Oil Production Index (**OilP**) from U.S. Energy Information Administration.

Estimations results

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.

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Forecasting accuracy

We compare the forecast accuracy of the GARCH-MIDAS model with respect to that of a GARCH(1,1) model using two tests $\Rightarrow$ the Diebold and Mariano (1995) (**DM**) and the Clark and West (2007) (**CW**) tests).

- 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 also for nested models.
- The loss function comparing the benchmark (the squared daily returns) to the prediction of each model is the mean squared error;
- The loss differential at time t is defined as

$$d_t = L\left(b_t, \hat{\sigma}^2_{G,t}\right) - L\left(b_t, \hat{\sigma}^2_{M,t}\right), \quad t = 1, \cdots, h. \tag{3}$$

Forecasting accuracy

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^{*}

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Answers to research questions

1. Does the U.S. monetary policy affect the crude oil future price volatility?
   - Yes, the U.S. monetary policy affects COFP volatility. In particular, an **expansionary** (restrictive) monetary policy anticipate a **positive** (negative) variation in COFP volatility.
2. Does the U.S. monetary policy help the COFP volatility predictions?
   - Yes, including the monetary policy proxy (as well as the other economic variables) in the COFP volatility model improves the predictions especially when such a proxy experienced a huge shock in a previous period.

Thank you for your attention

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We start from the GARCH (p,q) model (Bollerslev 1986), that when $p = q = 1$ becomes

$$h_t^2 = \psi + \sum_{i=1}^{p} \alpha_i \left(r_{t-i} - \mu\right)^2 + \sum_{i=1}^{q} \beta_i h_{t-i}^2, \tag{4}$$

with $\psi > 0$, $\alpha_i \geq 0$ and $\beta_i \geq 0$ sufficient conditions for ensuring the positiveness of the conditional variance.

We start from the GARCH (p,q) model (Bollerslev 1986), that when $p = q = 1$ becomes

$$h_t^2 = \psi + \alpha \left(r_{t-1} - \mu\right)^2 + \beta h_{t-1}{}^2, \tag{4}$$

GARCH-MIDAS model (ii)

Within the GARCH-MIDAS framework, the conditional variance is the product of two components $(\tau_t \times g_{i,t})$, is given by the product of two components:

- The short-run component $g_{i,t}$ follows a mean-reverting unit GARCH(1,1) process:

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

  with $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$.

- The long-run component τ_t is obtained as a filter of the J exogenous variables $X_{t,j}$:

$$\tau_t = exp\left(m + \theta_j \sum_{k=1}^{K_j} \delta_{k,j}(\omega) X_{t-k,j} \right), \quad \text{with} \quad j = 1, \cdots, J. \tag{6}$$

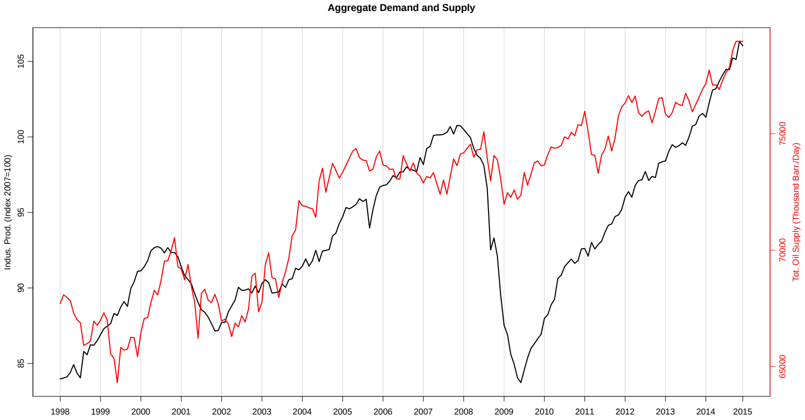
- The parametric space of the GARCH-MIDAS model is $\Theta = \{\mu, \alpha, \beta, m, \theta_j, \omega_{1,j}, \omega_{2,j}\}$ with $j = 1, \cdots, J$.

- The estimation of the unknown parameters is carried out by maximizing the following log-likelihood provided by Engle et al. (2013):

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

Other control variables

U.S. industrial production, oil global production



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^{***}

- The evaluation of out-of-sample performance is the "*ultimate test of a forecasting model*" (Stock and Watson, 2007);
- According to (Asgharian et al., 2013) we use a rolling forecasting scheme adopting a window length of 5 years and letting the estimate parameters be fixed for the following 6 months;
- We investigate both the short-term and the long term forecasting performance.

- Let us considering the first estimation period from January 1998 to December 2003.
- We estimate the parameters with the selected volatility model and then we keep them fixed from January 2004 to June 2004 to predict the volatility conditioned on the macro-variables;
- Afterwards, the window moves forward such that the estimation period goes from July 1998 to June 2004 while the evaluation period consists of the last 6 months of 2004.
- Thus, for M2 we have 6 years of volatility predictions, from 2003 to 2008. While for M3, we only have two volatility prediction in the timespan which goes from 2009 to 2014.

- In the short-run, we use the squared returns as benchmark In order to evaluate the forecast performance;

- As for the long-run prediction (monthly horizon), we compare the monthly variances obtained by summing the volatility predictions within each month with the monthly sum of the squared daily returns as benchmark.

- According to Giacomini and White (2006), the DM should not be applied to situations where the competing forecasts are obtained using two nested models;
- 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 grow, i.e. when the forecasting scheme is the rolling one.

As argued by Hansen (2005), when the aim of interest of the superior predictive ability of a model (GARCH-MIDAS) against a benchmark (GARCH(1,1)), the system of the hypotheses has to be formulated as follows:

$$\begin{cases} H_0: & \overline{d} = 0; \\ H_1: & \overline{d} > 0, \end{cases} \tag{8}$$

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

$$d_t = L\left(b_t, \hat{\sigma}^2_{G,t}\right) - L\left(b_t, \hat{\sigma}^2_{M,t}\right), \quad t = 1, \cdots, h. \tag{9}$$

In (9), $L(\cdot)$ 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 $\hat{\sigma}^2_{G,t}$ and the volatility prediction of the GARCH-MIDAS, indicated with $\hat{\sigma}^2_{M,t}$. Moreover, h represents the length of the evaluation period. Throughout the section, $L(\cdot)$ is the MSE.