Macroeconomic and Financial Effects of Oil Price Shocks: Evidence for the Euro Area*

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February 2017

Abstract

The paper investigates the macroeconomic and financial effects of oil price shocks for the euro area, with a special focus on post-2009 oil price dynamics and the recent slump. The analysis is carried out episode by episode, by means of a large-scale time-varying parameter model. We find that recessionary effects are triggered by oil price hikes and, in some cases, also by oil price slumps. In this respect, the post-2009 run-up likely contributed to sluggish growth, while uncertainty and real interest rate effects are the potential channels through which the 2014 slump has depressed aggregate demand and worsened financial conditions. Also in light of the zero interest rate policy carried out by the ECB, in so far as the Quantitative Easing policy failed to generate inflationary expectations, a more expansionary fiscal policy might be required to counteract the deflationary and recessionary threat within the expected environment of soft oil prices.

Keywords: oil price shocks, oil price-macroeconomy relationship, risk factors, semiparametric dynamic conditional correlation model, time-varying parameter models.
JEL classification: E30, E50, C32

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*This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 3202782013-2015. The paper was presented at the 48th Money, Macro and Finance Annual Conference and the 1st AIEE Energy Symposium. The author is grateful to the Editor, two anonymous reviewers, conference participants and M. Hartmann for their constructive comments.

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1 Introduction

Crude oil price dynamics since the mid-2000s have surely raised new interest on the oil price-macroeconomy relationship, particularly the 2008 boom-bust episode, comparable in real terms with the early 1980s shock (US$ 140 July 2008; US$ 40 December 2008). The oil price has persisted at rather high levels for about five years thereafter (90 US$), until the recent oil price slump, which has lead to a swift 50% oil price contraction since June/October 2014 (40 US$).

Despite the potentially sizable real effects for oil importing countries of recent oil price dynamics, we are unaware of any empirical assessment carried out using post-2009 data for the euro area (EA). The latter issue is particularly relevant since the EA has so far only partially recovered from the subprime financial crisis, newly falling in recession in July 2011 -through February 2013- as the sovereign debt crisis deepened. Hence, the unfavorable and long lasting oil price developments since late 2009 might have contributed to its scattered and sluggish recovery. It is also unclear whether the recent oil price slump will enhance economic growth in the EA. On the one hand, it might be expected to support economic recovery through reducing energy bills and input costs, increasing total factor productivity and through monetary policy accommodation (Mohaddes and Pesaran, 2016; see also Morana, 2013b). On the other hand, by occurring in an environment of weak economic growth, high deflation risk, and where the policy interest rate is already at the zero lower bound, the oil price slump might exercise recessionary effects through deepening deflationary dynamics, raising real interest rates and macroeconomic and financial uncertainty.[1]

In light of the above issues, in this paper we assess the macroeconomic and financial effects of oil price shocks for the EA since its creation, with a special focus on post-2009 oil price dynamics and the recent oil price slump. Overall the available evidence at the EA-wide level is rather thin and, by neglecting recent economic developments, might not yield accurate guidance concerning the expected effects of the slump. For instance, Jiménez-Rodríguez and Sánchez (2005) estimate a small-scale structural vector autoregressive model (SVAR) over the period 1972 through 2001. Consistent with the "reallocation effect" (Hamilton, 2011), they point to a non-linear impact of oil price shocks on real GDP, as oil price increases lead to stagflation, while oil price declines do not have a statistically significant impact.[2] Peersman and van Robays (2009) also estimate a small-scale constant parameter SVAR model over the period 1986 through 2008. They find that the macroeconomic effects of oil price shocks crucially depend on their source, i.e. on whether they are oil supply disturbances, shocks to flow oil demand, or precautionary oil demand shocks. In particular, all of the three types of shocks are inflationary already in the short-run, yet recessionary at different horizons: flow oil supply and demand shocks in the medium-term only; precautionary oil demand disturbances also in the short-term. Similar evidence is provided by Forni et al. (2012), who estimate a small open economy DSGE model over the period 1995-2007. On the other hand, Hahn and Mestre (2011) estimate a small-scale time-varying parameter SVAR model with stochastic volatility over

[1] The weak and scattered recovery from the sovereign debt crisis and the recent contraction in energy and food prices have put price stability at risk in the EA, inducing deflationary dynamics from December 2014 through March 2015, in September 2015, and then again from February through May 2016, despite the sizable depreciation of the currency and the implementation of the Quantitative Easing policy (*Q.E.*) since January 2015.

[2] See also Cuñado and Pérez de Gracia (2003) and Cologni and Manera (2009) for evidence on the asymmetric effects of oil price shocks for European economies, yet at the single-country level.

the period 1970 through 2009. They point to weaker stagflationary effects of both supply and demand oil shocks since the mid-1990s than over the three previous decades (see also ECB, 2010, for similar evidence), yet an unchanged relative contribution of both shocks to the determination of oil price fluctuations.

Differently from previous work in the literature, in this paper we assess the transmission of oil price shocks in the EA by means of a new large-scale time-varying parameter framework, based on the semiparametric dynamic conditional correlation model (SP-DCC) of Morana (2015). Relatively to standard time-varying parameter SVAR models, i.e. Hahn and Mestre (2011), the proposed modeling strategy is not subject to the curse of dimensionality and, by allowing for a large and comprehensive information set, should yield more accurate and robust results. In particular, our information set includes, in addition to standard macroeconomic variables, a new financial conditions index for the euro area (Morana, 2016) and the European *market*, *size*, *value* and *momentum* risk factors (Fama and French, 1993; Charart, 1999). We believe the inclusion of the latter variables is well justified in light of the progressive "financialization" of commodity markets since the early 2000s (Gkanoutas-Leventis and Nesvetailova, 2015) and the sizable contribution of oil market shocks to the determination of risk factor fluctuations themselves (Morana, 2014).

Consistent with the asymmetric response of the EA economy to positive and negative oil price shocks (Jiménez-Rodríguez and Sánchez, 2005; Cuñado and Pérez de Gracia, 2003; Cologni and Manera, 2009), we then separately assess the macroeconomic and financial effects of various episodes of persistent price changes. While we do not attempt to categorize the original source of oil price shocks, by evaluating their effects episode-by-episode our analysis is however fully consistent with the view that "not all the oil price shocks are alike" (Kilian, 2009), yet with the advantage of not imposing any identification assumption.

Overall, our findings yield new insights on the macro-financial impact of oil price disturbances for the euro area. For instance, we find strong evidence of asymmetric real effects of oil price shocks, as net oil price increases determined a contraction in industrial production over the whole sample investigated, while net price decreases were expansionary only in the early and mid-2000s. Moreover, real effects appear to increase with the magnitude of the shock and the level achieved by the oil price itself: the 2008 oil price shock was surely peculiar for both the size of its real effects and inflationary impact, as deflationary dynamics can be in general observed following both oil price hikes and slumps. The post-2009 oil price run-up also likely contributed to sluggish growth, while real interest rate and uncertainty effects are the potential channels through which the current slump has depressed aggregated demand and worsened financial conditions. Also in light of the zero interest rate policy carried out by the ECB, our findings have then a clear-cut policy implication: In so far as the Quantitative Easing ($Q.E.$) policy failed to generate inflationary expectations, a more expansionary fiscal policy might be required to counteract the deflationary and recessionary threat within the expected environment of soft oil prices.

The rest of the paper is organized as follows. In Section 2 we introduce the econometric methodology and in Section 3 we present the data. In Sections 4 and 5 we discuss the empirical results. Finally, Section 6 concludes.

2 Econometric Methodology

The semiparametric dynamic conditional correlation model (SP-DCC; Morana, 2015) is defined by the following equations

$$\mathbf{y}_t = \boldsymbol{\mu}_t(\boldsymbol{\delta}) + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}(\boldsymbol{\delta})\mathbf{z}_t \tag{2}$$

where $\mathbf{y}_t$ is the $N \times 1$ column vector of the variables of interest, $\boldsymbol{\mu}_t(\boldsymbol{\delta})$ is the $N \times 1$ conditional mean vector $E\left(\mathbf{y}_t|I_{t-1}\right)$, $\boldsymbol{\delta}$ is a vector of parameters, I_{t-1} is the sigma field; $\mathbf{H}_t(\boldsymbol{\delta})$ is the $N \times N$ conditional variance-covariance matrix $Var\left(\mathbf{y}_t|I_{t-1}\right)$. Moreover, the random vector $\mathbf{z}_t$ is of dimension $N \times 1$ and assumed to be *i.i.d.* with first two moments $E\left(\mathbf{z}_t\right) = \mathbf{0}$ and $Var\left(\mathbf{z}_t\right) = \mathbf{I}_N$. Concerning the specification of the conditional variance-covariance matrix $\mathbf{H}_t(\boldsymbol{\delta})$, we assume that the elements along its main diagonal, i.e., the conditional variances $Var\left(y_{i,t}|I_{t-1}\right) \equiv h_{i,t}$ follow a GARCH(1,1) process

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \qquad i = 1, ..., N \tag{3}$$

subject to the usual restrictions to ensure that the conditional variances are positive almost surely at any point in time.

Concerning the definition of the conditional covariances, a nonparametric specification is posited, grounded on the *polarization* identity

$$Cov(A, B) \equiv \frac{1}{4}\left[Var(A + B) - Var(A - B)\right] \tag{4}$$

given that $Var(A \pm B) = Var(A) + Var(B) \pm 2Cov(A, B)$, for any two random variables A and B.

Accordingly, the off-diagonal elements of $\mathbf{H}_t$, $Cov(y_{i,t}, y_{j,t}|I_{t-1}) \equiv h_{ij,t}$, are

$$h_{ij,t} = \frac{1}{4}\left[Var_{t-1}(y_{i,t} + y_{j,t}) - Var_{t-1}(y_{i,t} - y_{j,t})\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{5}$$

By defining the aggregate variables $y_{ij,t}^{+} \equiv y_{i,t} + y_{j,t}$ and $y_{ij,t}^{-} \equiv y_{i,t} - y_{j,t}$, and assuming a GARCH(1,1) specification for their conditional variance processes $Var_{t-1}(y_{ij,t}^{+}|I_{t-1}) \equiv h_{ij,t}^{+}$ and $Var_{t-1}(y_{ij,t}^{-}|I_{t-1}) \equiv h_{ij,t}^{-}$ as well, we then have

$$h_{ij,t}^{+} = \omega_{ij}^{+} + \alpha_{ij}^{+}\varepsilon_{ij,t-1}^{+2} + \beta_{ij}^{+}h_{ij,t-1}^{+} \qquad i, j = 1, ..., N \qquad i \neq j \tag{6}$$

$$h_{ij,t}^{-} = \omega_{ij}^{-} + \alpha_{ij}^{-}\varepsilon_{ij,t-1}^{-2} + \beta_{ij}^{-}h_{ij,t-1}^{-} \qquad i, j = 1, ..., N \qquad i \neq j \tag{7}$$

where $\varepsilon_{ij,t}^{+} = \varepsilon_{i,t} + \varepsilon_{j,t}$ and $\varepsilon_{ij,t-1}^{-} = \varepsilon_{i,t} - \varepsilon_{j,t}$.

The implied parametric structure for the generic conditional covariance can be worked out by substituting (6) and (7) into (5); one then has

$$\begin{aligned} h_{ij,t} &= \frac{1}{4}\left[\omega_{ij}^{+} + \alpha_{ij}^{+}\varepsilon_{ij,t-1}^{+2} + \beta_{ij}^{+}h_{ij,t-1}^{+} - \omega_{ij}^{-} - \alpha_{ij}^{-}\varepsilon_{ij,t-1}^{-2} - \beta_{ij}^{-}h_{ij,t-1}^{-}\right] && (8) \\ &= \omega_{ij} + \frac{1}{4}\left(\alpha_{ij}^{+}\left(\varepsilon_{i,t-1} + \varepsilon_{j,t-1}\right)^2 - \alpha_{ij}^{-}\left(\varepsilon_{i,t-1} - \varepsilon_{j,t-1}\right)^2\right) + \frac{1}{4}\left(\beta_{ij}^{+}h_{ij,t-1}^{+} - \beta_{ij}^{-}h_{ij,t-1}^{-}\right) && (9) \end{aligned}$$

where $\omega_{ij} = \frac{1}{4}\left(\omega_{ij}^{+} - \omega_{ij}^{-}\right)$. By assuming constant GARCH parameters across aggregate series, i.e. $\alpha_{ij}^{+} = \alpha_{ij}^{-} = \alpha$ and $\beta_{ij}^{+} = \beta_{ij}^{-} = \beta$, after rearranging one has

$$h_{ij,t} = \omega_{ij} + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta h_{ij,t-1} \tag{10}$$

Hence, assuming a GARCH(1,1) model for the conditional covariance is consistent with the assumption of GARCH(1,1) model for the conditional variance of the aggregate series only if the parametric structure is identical across processes. SP-DCC then appears to allow for more flexible parameterizations than competing approaches, such as Ledoit et al. (2003) or Engle (2002) DCC model.

2.1 Estimation of the SP-DCC model

Consistent and asymptotically Normal estimation is obtained by QML, following a two-step procedure similar to Engle (2002). Consider the Gaussian log-likelihood for the model in (2)

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(N\log(2\pi) + \log|\mathbf{H}_t| + \boldsymbol{\varepsilon}_t'\mathbf{H}_t^{-1}\boldsymbol{\varepsilon}_t\right). \tag{11}$$

Following Engle (2002), the latter can be written as

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(N\log(2\pi) + 2\log|\mathbf{D}_t| + \boldsymbol{\varepsilon}_t'\mathbf{D}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t\right) + \left(-\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t + \log|\mathbf{R}_t| + \boldsymbol{\varepsilon}_t'\mathbf{R}_t^{-1}\boldsymbol{\varepsilon}_t\right) \tag{12}$$

where

$$\mathbf{D}_t = diag\left(h_{1,t}^{1/2}, ..., h_{N,t}^{1/2}\right)$$

and the conditional correlation matrix $\mathbf{R}_t$ is defined as

$$\mathbf{R}_t = \mathbf{D}_t^{-1}\mathbf{H}_t\mathbf{D}_t^{-1}.$$

The log-likelihood function in (12) is the sum of a *volatility part*

$$L_v(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left(N\log(2\pi) + 2\log|\mathbf{D}_t| + \boldsymbol{\varepsilon}_t'\mathbf{D}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t\right) \tag{13}$$

and a *correlation part*

$$L_C(\boldsymbol{\theta}, \boldsymbol{\phi}) = -\frac{1}{2}\sum_{t=1}^{T}\left(-\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t + \log|\mathbf{R}_t| + \boldsymbol{\varepsilon}_t'\mathbf{R}_t^{-1}\boldsymbol{\varepsilon}_t\right). \tag{14}$$

The volatility part in (13) is the sum of individual GARCH likelihoods

$$L_v(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\log(2\pi) + \log h_{i,t} + \frac{\varepsilon_{i,t}^2}{h_{i,t}} \tag{15}$$

which is then jointly maximized by separately maximizing each term. The conditional variances $h_{i,t}$, $i = 1, ..., N$, i.e. the elements along the main diagonal of $\mathbf{H}_t$, are therefore estimated equation by equation by means of QML, using the conditional mean residuals $\varepsilon_{i,t}$, $i = 1, ..., N$.

Differently from DCC, SP-DCC does not maximize the correlation part in (14) directly, but rather the sum of individual GARCH likelihoods for the aggregate series $y^{+}_{ij,t}$ and $y^{-}_{ij,t}$, i.e.

$$\begin{aligned} L_{SP}(\boldsymbol{\phi}) &= \left(-\frac{1}{2}\sum_{t=1}^{T} 2\sum_{i=1}^{N}\sum_{j>i}^{N} \log(2\pi) + \log h^{+}_{ij,t} + \frac{\varepsilon^{+2}_{ij,t}}{h^{+}_{ij,t}}\right) \\ &\quad + \left(-\frac{1}{2}\sum_{t=1}^{T} 2\sum_{i=1}^{N}\sum_{j>i}^{N} \log(2\pi) + \log h^{-}_{ij,t} + \frac{\varepsilon^{-2}_{ij,t}}{h^{-}_{ij,t}}\right) \end{aligned} \tag{16}$$

which is jointly maximized by separately maximizing each term. Hence, the conditional variances for the aggregates $h^{+}_{ij,t}$, $h^{-}_{ij,t}$, $i, j = 1, ..., N$, $i \neq j$, are estimated equation by equation by means of QML, using the aggregated conditional mean residuals $\varepsilon^{+}_{ij,t} = \varepsilon_{i,t} + \varepsilon_{j,t}$ and $\varepsilon^{-}_{ij,t-1} = \varepsilon_{i,t} - \varepsilon_{j,t}$.

Through the polarization identity the conditional covariances are then computed, i.e. the off-diagonal elements of $\mathbf{H}_t$, $h_{ij,t}$, $i, j = 1, ..., N$, $i \neq j$, are estimated nonparametrically by computing

$$\hat{h}_{ij,t} = \frac{1}{4}\left[\hat{h}^{+}_{ij,t} - \hat{h}^{-}_{ij,t}\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{17}$$

The conditional correlation matrix $\mathbf{R}_t$ is then estimated as

$$\hat{\mathbf{R}}_t = \hat{\mathbf{D}}_t^{-1}\hat{\mathbf{H}}_t\hat{\mathbf{D}}_t^{-1} \tag{18}$$

where

$$\hat{\mathbf{D}}_t = diag\left(\hat{h}^{1/2}_{1,t}, ..., \hat{h}^{1/2}_{N,t}\right) \tag{19}$$

and the correlation part in (14) can be evaluated provided $\hat{\mathbf{R}}_t$ is positive definite at each point in time (see Morana (2015) for the correction to be applied in the case of a non positive definite correlation matrix). Hence the proposed two-step approach to maximize the log-likelihood function is to find

$$\hat{\boldsymbol{\theta}} = \arg\max\left\{L_v(\boldsymbol{\theta})\right\} \tag{20}$$

$$\hat{\boldsymbol{\phi}} = \arg\max\left\{L_{SP}(\boldsymbol{\phi})\right\} \tag{21}$$

and then use these values to evaluate $L_C(\boldsymbol{\theta}, \boldsymbol{\phi})$.

Then, under standard regularity conditions, the asymptotic distribution of the QML estimator is

$$T^{1/2}\left(\hat{\boldsymbol{\vartheta}} - \boldsymbol{\vartheta}_0\right) \rightarrow N\{\mathbf{0}, \mathbf{A}(\boldsymbol{\vartheta}_0)^{-1}\mathbf{B}(\boldsymbol{\vartheta}_0)\mathbf{A}(\boldsymbol{\vartheta}_0)^{-1}\} \tag{22}$$

where $\boldsymbol{\vartheta}_0 = \boldsymbol{\theta}_0, \boldsymbol{\phi}_0$ denotes the true value of the vector of parameters, $\mathbf{A}(\boldsymbol{\vartheta}_0)$ is the Hessian and $\mathbf{B}(\boldsymbol{\vartheta}_0)$ is the outer product gradient evaluated at the true parameter values. While the procedure does not necessarily grant the maximization of the correlation part in (14), and therefore of the joint log-likelihood in (12), consistent and asymptotically Normal estimation of the conditional covariance and correlation matrices is however granted by the proposed procedure. On the other hand, SP-DCC does not suffer from the inconsistency problem due to the use of the standardized residuals cross-product matrix in the derivation of the conditional correlations, to which the Engle (2002) DCC two-step procedure is potentially subject (Aielli, 2013). Also note that a third step could be added to the proposed procedure, as the correlation matrix estimated by SP-DCC, $\hat{\mathbf{R}}_t$, could be used as starting value in the correlation part in (14), and a suitably parameterized $L_C(\boldsymbol{\theta}, \boldsymbol{\phi}; \boldsymbol{\varphi})$ function successively maximized with respect to $\boldsymbol{\varphi}$, conditional to previous steps estimates $\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\phi}}$. The three-step estimation strategy would then require, in addition to (20) and (21), the additional step

$$\hat{\boldsymbol{\varphi}} = \arg\max \left\{ L_C \left(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\phi}}; \boldsymbol{\varphi} \right) \right\}, \tag{23}$$

yielding, jointly with (20), the joint maximization of the log-likelihood function in (12). We leave this final issue for further research. Available Monte Carlo results reported in Morana and Sbrana (2017) strongly support two-step SP-DCC estimation, which is shown to perform similarly to Engle (2002) DCC and even outperforming it for various parameterizations.

2.2 Conditional cross-correlations and dynamic multipliers

The conditional s-order cross-covariance at time t between any two variables i,j, $Cov(y_{i,t}, y_{j,t+s}|I_{t-1}) \equiv h_{ij,ts}$, can be computed as

$$h_{ij,ts} = \frac{1}{4}\left[Var_{t-1}(y_{i,t} + y_{j,t+s}) - Var_{t-1}(y_{i,t} - y_{j,t+s})\right] \qquad i,j = 1,...,N \qquad i \neq j,\ s\ > 0 \tag{24}$$

and therefore the s-order conditional cross-correlation at time t is

$$\rho_{ij,ts} = \frac{h_{ij,t,t+s}}{h_{i,t}^{1/2} h_{j,t+s}^{1/2}} \tag{25}$$

which can be estimated by

$$\hat{\rho}_{ij,ts} = \frac{\hat{h}_{ij,t,t+s}}{\hat{h}_{i,t}^{1/2} \hat{h}_{j,t+s}^{1/2}}. \tag{26}$$

From (24) conditional slope parameters or time-varying dynamic multipliers $\gamma_{ij,ts} \equiv \dfrac{Cov(y_{i,t}, y_{j,t+s}|I_{t-1})}{Var(y_{i,t}|I_{t-1})}$ can be computed as

$$\gamma_{ij,ts} = \frac{h_{ij,t,t+s}}{h_{i,t}} \equiv \rho_{ij,ts} \times \frac{h_{j,t+s}^{1/2}}{h_{i,t}^{1/2}} \tag{27}$$

and estimated by

$$\hat{\gamma}_{ij,ts} = \frac{\hat{h}_{ij,t,t+s}}{\hat{h}_{i,t}} \equiv \hat{\rho}_{ij,ts} \times \frac{\hat{h}_{j,t+s}^{1/2}}{\hat{h}_{i,t}^{1/2}}. \tag{28}$$

See Engle (2016) for similar results. Under general conditions $\gamma_{ij,ts}$ bears the interpretation of time-varying (reduced form) impulse response function of variable j relative to variable i; it therefore measures the revision in expectation for variable j at time period $t+s$, due to a unitary increase in variable i at time period t, i.e.

$$\gamma_{ij,ts} = \frac{\Delta E\left[y_{j,t+s}|I_{t-1}\right]}{\Delta y_{i,t}} = E\left[y_{j,t+s}|\Delta y_{i,t} = 1; I_{t-1}\right] - E\left[y_{j,t+s}|\Delta y_{i,t} = 0; I_{t-1}\right]. \tag{29}$$

See below for details.

2.2.1 Interpretation of the time-varying dynamic multipliers

Consider the time-varying parameter VAR(p) representation for the real valued discrete time $N \times 1$ process $\mathbf{y}_t$

$$\mathbf{y}_t = \Pi_{1,t}\mathbf{y}_{t-1} + ... + \Pi_{p,t}\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{30}$$

where $\boldsymbol{\varepsilon}_t$ is a martingale difference sequence with reference to the information set I_{t-1}.

Generalizing results available for constant parameter VAR models (Hamilton, 1994), time-varying impulse response functions can be obtained from the VAR(1) companion form

$$\mathbf{W}_t = \mathbf{F}_t\mathbf{W}_{t-1} + \mathbf{V}_t$$

where

$$\mathbf{W}_t \equiv \begin{bmatrix} \mathbf{y}_t \\ \mathbf{y}_{t-1} \\ \vdots \\ \mathbf{y}_{t-p} \end{bmatrix};\ \mathbf{F}_t \equiv \begin{bmatrix} \Pi_{1,t} & \Pi_{2,t} & \dots & \Pi_{p-1,t} & \Pi_{p,t} \\ \mathbf{I} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I} & \mathbf{0} \end{bmatrix};\ \mathbf{V}_t \equiv \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.$$

If all the roots of the matrix $\mathbf{F}_t$ are outside the unit circle, the time-varying parameter VMA representation at time period t can be obtained by inverting the VAR(1) in companion form

$$\begin{aligned} \mathbf{W}_t &= (\mathbf{I} - \mathbf{F}_t L)^{-1}\mathbf{V}_t \\ &= \mathbf{V}_t + \mathbf{F}_t\mathbf{V}_{t-1} + \mathbf{F}_t^2\mathbf{V}_{t-2} + ... \end{aligned}$$

and therefore

$$\mathbf{y}_t = \boldsymbol{\varepsilon}_t + \mathbf{F}_{1,t}\boldsymbol{\varepsilon}_{t-1} + ... + \mathbf{F}_{1,t}^s\boldsymbol{\varepsilon}_{t-s} + ...$$

where $\mathbf{F}_{i,t}^s$ is the ith upper, $N \times N$ block of the matrix $\mathbf{F}_t^s$. The reduced form impulse response function is then

$$\frac{\Delta\mathbf{y}_{t+s}}{\Delta\mathbf{v}_t} = \mathbf{F}_{1,t}^s \qquad s = 0, 1, ... \tag{31}$$

Moreover, the s-step ahead forecasts can be computed as

$$\begin{aligned} \mathbf{W}_{t+s} &= \mathbf{F}_t^s\mathbf{W}_t \\ &= \mathbf{V}_{t+s} + \mathbf{F}_t\mathbf{V}_{t+s-1} + ... + \mathbf{F}_t^s\mathbf{V}_t + \mathbf{F}_t^{s+1}\mathbf{W}_{t-1} \end{aligned} \tag{32}$$

and therefore

$$\mathbf{y}_{t+s} = \boldsymbol{\varepsilon}_{t+s} + \mathbf{F}_{1,t}\boldsymbol{\varepsilon}_{t+s-1} + ... + \mathbf{F}_{1,t}^s\boldsymbol{\varepsilon}_t + \mathbf{F}_{1,t}^{s+1}\mathbf{y}_{t-1} + ... + \mathbf{F}_{p,t}^{s+1}\mathbf{y}_{t-p}. \tag{33}$$

By rearranging one has

$$\mathbf{y}_{t+s} = \mathbf{F}_{1,t}^{s+1}\mathbf{y}_{t-1} + ... + \mathbf{F}_{p,t}^{s+1}\mathbf{y}_{t-p} + (\boldsymbol{\varepsilon}_{t+s} + \mathbf{F}_{1,t}\boldsymbol{\varepsilon}_{t+s-1} + ... + \mathbf{F}_{1,t}^s\boldsymbol{\varepsilon}_t) \tag{34}$$

which can be compared to the local projection for $\mathbf{y}_{t+s}$

$$\mathbf{y}_{t+s}= \mathbf{B}_{1,t}^{(s+1)}\mathbf{y}_{t-1} + ... + \mathbf{B}_{p,t}^{(s+1)}\mathbf{y}_{t-p} + \mathbf{u}_{t+s}^{(s)} \tag{35}$$

i.e. the projection of $\mathbf{y}_{t+s}$ on $\mathbf{W}_{t-1}$, which is computed for each horizon s, rather than the typical VAR, which is the projection of $\mathbf{y}_t$ on $\mathbf{W}_{t-1}$. Note that in (35) the exponent $(s+1)$ denotes only the order of the projection, different from the exponent $s+1$ in (34) which denotes the power of the matrix $\mathbf{F}_{1,t}$.

By comparing the two equations (34) and (35), it is obvious that

$$\begin{aligned} \mathbf{B}_1^{(s+1)} &= \mathbf{F}_1^{s+1} \\ \mathbf{u}_{t+s}^{(s)} &= (\boldsymbol{\varepsilon}_{t+s} + \mathbf{F}_{1,t}\boldsymbol{\varepsilon}_{t+s-1} + ... + \mathbf{F}_{1,t}^{s}\boldsymbol{\varepsilon}_t). \end{aligned}$$

Hence, when the DGP is the VAR in (30) the local projections in expression (35) yield the impulse responses in (31), i.e.

$$\frac{\Delta \mathbf{y}_{t+s}}{\Delta \boldsymbol{\varepsilon}_t} = \mathbf{F}_{1,t}^{s} = \frac{\Delta \mathbf{y}_{t+s}}{\Delta \mathbf{y}_t} = \mathbf{B}_1^{(s)} \qquad s = 0, 1, ... \tag{36}$$

with the normalization $\mathbf{B}_1^{(0)} = \mathbf{I}$.

The dynamic multipliers in (27) therefore bear the interpretation of time-varying reduced form impulse responses. As for standard constant parameter VAR specifications, structuralization of the shocks could also be performed.

2.2.2 Estimation of the time-varying dynamic multipliers

Consider the VAR(p) model in (30) in compact form

$$\begin{aligned} \mathbf{y}_t &= \boldsymbol{\mu}_t(\boldsymbol{\theta}) + \boldsymbol{\varepsilon}_t & (37) \\ \boldsymbol{\varepsilon}_t &\sim \mathbf{H}_t^{1/2}(\boldsymbol{\theta})\mathbf{z}_t & (38) \\ \mathbf{z}_t &\sim N.I.D.(\mathbf{0}, \mathbf{I}_N) & (39) \end{aligned}$$

where $\boldsymbol{\mu}_t(\boldsymbol{\theta}) = \Pi_t'\mathbf{x}_t$ is the $N \times 1$ conditional mean vector, $\mathbf{H}_t(\boldsymbol{\theta})$ is the $N \times N$ conditional variance-covariance matrix, $\mathbf{x}_t$ is the $[Np \times 1]$ vector containing the p lags of each of the elements of $\mathbf{y}$ and Π_t' is the $[N \times Np]$ matrix of coefficients. i.e.

$$\mathbf{x}_t \equiv \begin{bmatrix} \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \\ \vdots \\ \mathbf{y}_{t-p} \end{bmatrix} ; \Pi_t' \equiv \begin{bmatrix} \Pi_{1,t} & \Pi_{2,t} & ... & \Pi_{p,t} \end{bmatrix},$$

The ML estimate of the conditional mean parameters is

$$\hat{\Pi}_t' = \left[\sum_{t=1}^{T} \mathbf{y}_t\mathbf{x}_t'\right] \left[\sum_{t=1}^{T} \mathbf{x}_t\mathbf{x}_t'\right]^{-1}$$

where the generic jth row of $\hat{\Pi}_t'$ is

$$\hat{\boldsymbol{\pi}}_{j,t}' = \left[\sum_{t=1}^{T} y_{j,t}\mathbf{x}_t'\right] \left[\sum_{t=1}^{T} \mathbf{x}_t\mathbf{x}_t'\right]^{-1}$$

or equivalently in matrix notation

$$\hat{\boldsymbol{\pi}}'_{j,t} = \mathbf{H}(\hat{\boldsymbol{\theta}})^{-1}_{xx,t}\mathbf{H}(\hat{\boldsymbol{\theta}})_{xy_j,t}$$

with

$$\mathbf{H}(\hat{\boldsymbol{\theta}})^{-1}_{xx,t} = \begin{bmatrix} \hat{\mathbf{H}}_{11,t} & \hat{\mathbf{H}}_{12,t} & \dots & \hat{\mathbf{H}}_{1p,t} \\ \hat{\mathbf{H}}_{12,t} & \hat{\mathbf{H}}_{22,t} & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \hat{\mathbf{H}}_{1p,t} & \dots & \dots & \hat{\mathbf{H}}_{pp,t} \end{bmatrix}^{-1} ; \ \mathbf{H}(\hat{\boldsymbol{\theta}})_{xy_j,t} = \begin{bmatrix} \hat{\mathbf{H}}_{j1,t} \\ \hat{\mathbf{H}}_{j2,t} \\ \vdots \\ \hat{\mathbf{H}}_{jp,t} \end{bmatrix}.$$

Following Engle (2016), under general conditions the ML estimator is consistent and asymptotically Normal

$$\sqrt{T}\left(\hat{\Pi}'_t - \Pi'_{0t}\right) \xrightarrow{d} N\left(0, \mathbf{G}_t\mathbf{A}^{-1}\mathbf{G}_t\right),$$

where $\mathbf{A}$ is the information matrix under Gaussianity or a robust covariance matrix of the sandwich form if Gaussianity does not hold; $\mathbf{G}_t(\bar{\boldsymbol{\theta}}_t) = \frac{\partial\left[\mathbf{H}(\boldsymbol{\theta})^{-1}_{xx,t}\mathbf{H}(\boldsymbol{\theta})_{xy_j,t}\right]}{\partial\boldsymbol{\theta}'}|_{\boldsymbol{\theta}=\bar{\boldsymbol{\theta}}_t}$, $\bar{\boldsymbol{\theta}}_t \in \left(\boldsymbol{\theta}, \hat{\boldsymbol{\theta}}\right)$, and can be estimated as $\mathbf{G}_t(\hat{\boldsymbol{\theta}})$.

For illustrative purposes, consider the bivariate case with $p = 1$; then

$$\mathbf{H}(\hat{\boldsymbol{\theta}})^{-1}_{xx,t} = \begin{bmatrix} \hat{h}_{i,t-1} & \hat{h}_{ij,t-1} \\ \hat{h}_{ij,t-1} & \hat{h}_{j,t-1} \end{bmatrix}^{-1} ; \ \mathbf{H}(\hat{\boldsymbol{\theta}})_{xy_j,t} = \begin{bmatrix} \hat{h}_{ji,t,t-1} \\ \hat{h}_{j,t,t-1} \end{bmatrix}. \tag{40}$$

Therefore

$$\begin{aligned} \hat{\boldsymbol{\pi}}'_{j,t} &= \frac{1}{\hat{h}_{i,t-1}\hat{h}_{j,t-1} - \hat{h}^2_{ij,t-1}} \begin{bmatrix} \hat{h}_{j,t-1} & -\hat{h}_{ij,t-1} \\ -\hat{h}_{ij,t-1} & \hat{h}_{i,t-1} \end{bmatrix} \begin{bmatrix} \hat{h}_{ji,t,t-1} \\ \hat{h}_{j,t,t-1} \end{bmatrix} \\ &= \begin{bmatrix} \dfrac{\hat{h}_{j,t-1}\hat{h}_{ji,t,t-1} - \hat{h}_{ij,t-1}\hat{h}_{j,t,t-1}}{\hat{h}_{i,t-1}\hat{h}_{j,t-1} - \hat{h}^2_{ij,t-1}} \\ \dfrac{\hat{h}_{i,t-1}\hat{h}_{j,t,t-1} - \hat{h}_{ij,t-1}\hat{h}_{ji,t,t-1}}{\hat{h}_{i,t-1}\hat{h}_{j,t-1} - \hat{h}^2_{ij,t-1}} \end{bmatrix} \end{aligned} \tag{41}$$

which yields the dynamic multiplier $\hat{\gamma}_{ij,t-1,t}$ reported in (28)

$$\hat{\boldsymbol{\pi}}'_{ij,t-1,t} = \frac{\hat{h}_{ji,t,t-1}}{\hat{h}_{i,t-1}} \tag{42}$$

if $\hat{h}_{ij,t-1} = 0$, i.e. if conditional contemporaneous orthogonality at time period $t-1$ of the regressors applies. Moreover, by shifting forward one period the dependent variable $y_{j,t}$ one has

$$\hat{\boldsymbol{\pi}}'_{ij,t-1,t+1} = \frac{\hat{h}_{ji,t+1,t-1}}{\hat{h}_{i,t-1}}, \tag{43}$$

subject to the same condition of contemporaneous conditional orthogonality at time period $t-1$.

Notice that the above results hold for any N, still subject to the same orthogonality conditions ($\hat{h}_{ij,t-1} = 0$, $j = 1, ...N$, $i \neq j$). Yet, if the DGP is a higher order time-varying parameter VAR(p), i.e. $p > 1$, the above formula require modifications, in order to account for dynamic interactions. For instance, considering the bivariate case with $p = 2$, one has

$$\mathbf{H}(\hat{\boldsymbol{\theta}})^{-1}_{xx,t} = \begin{bmatrix} \hat{h}_{i,t-1} & \hat{h}_{ij,t-1} & \hat{h}_{i,t-1,t-2} & \hat{h}_{ij,t-1,t-2} \\ \hat{h}_{ij,t-1} & \hat{h}_{j,t-1} & \hat{h}_{ij,t-1,t-2} & \hat{h}_{j,t-1,t-2} \\ \hat{h}_{i,t-1,t-2} & \hat{h}_{ij,t-1,t-2} & \hat{h}_{i,t-2} & \hat{h}_{ij,t-2} \\ \hat{h}_{ij,t-1,t-2} & \hat{h}_{j,t-1,t-2} & \hat{h}_{ij,t-2} & \hat{h}_{j,t-2} \end{bmatrix}^{-1} ; \mathbf{H}(\hat{\boldsymbol{\theta}})_{xy_j,t} = \begin{bmatrix} \hat{h}_{ji,t,t-1} \\ \hat{h}_{j,t,t-1} \\ \hat{h}_{ji,t,t-2} \\ \hat{h}_{j,t,t-2} \end{bmatrix} \tag{44}$$

Assuming contemporaneous conditional orthogonality, i.e. $\hat{h}_{ij,t-1} = \hat{h}_{ij,t-2} = 0$ and conditional Granger non-causality from variable j to variable i, i.e. $\hat{h}_{ij,t-1,t-2} = 0$, one has

$$\begin{aligned} \hat{\boldsymbol{\pi}}'_{j,t} &= \begin{bmatrix} \hat{h}_{i,t-1} & 0 & \hat{h}_{i,t-1,t-2} & 0 \\ 0 & \hat{h}_{j,t-1} & 0 & \hat{h}_{j,t-1,t-2} \\ \hat{h}_{i,t-1,t-2} & 0 & \hat{h}_{i,t-2} & 0 \\ 0 & \hat{h}_{j,t-1,t-2} & 0 & \hat{h}_{j,t-2} \end{bmatrix}^{-1} \begin{bmatrix} \hat{h}_{ji,t,t-1} \\ \hat{h}_{j,t,t-1} \\ \hat{h}_{ji,t,t-2} \\ \hat{h}_{j,t,t-2} \end{bmatrix} \\ &= \frac{1}{\hat{h}_{i,t-1}\hat{h}_{i,t-2} - \hat{h}^2_{i,t-1,t-2}} \begin{bmatrix} \hat{h}_{i,t-2} & 0 & -\hat{h}_{i,t-1,t-2} & 0 \\ 0 & \hat{h}_{j,t-2} & 0 & -\hat{h}_{j,t-1,t-2} \\ -\hat{h}_{i,t-1,t-2} & 0 & \hat{h}_{i,t-1} & 0 \\ 0 & -\hat{h}_{j,t-1,t-2} & 0 & \hat{h}_{j,t-1} \end{bmatrix} \begin{bmatrix} \hat{h}_{ji,t,t-1} \\ \hat{h}_{j,t,t-1} \\ \hat{h}_{ji,t,t-2} \\ \hat{h}_{j,t,t-2} \end{bmatrix} \end{aligned}$$

Therefore

$$\begin{aligned} \hat{\boldsymbol{\pi}}'_{ij,t-1,t} &= \left[\frac{1}{\hat{h}_{i,t-1}\hat{h}_{i,t-2} - \hat{h}^2_{i,t-1,t-2}} \hat{h}_{i,t-2}\hat{h}_{ji,t,t-1} - \frac{1}{\hat{h}_{i,t-1}\hat{h}_{i,t-2} - \hat{h}^2_{i,t-1,t-2}} \hat{h}_{i,t-1,t-2}\hat{h}_{ji,t,t-2} \right] \\ &\neq \left[\hat{h}_{ji,t,t-1}/\hat{h}_{i,t-1} \right] \end{aligned}$$

unless $\hat{h}_{i,t-1,t-2} = 0$.

With this caveats in mind, time-varying impulse response functions can then be estimated using $\hat{\gamma}_{ij,ts}$ in (28) and comparisons with available empirical results carried out.

3 The Data

Our information set is monthly and spans the period 1999:1 through 2015:6. In addition to the real WTI oil price return (o; in € per Barrel), a comprehensive set of macroeconomic and financial variables is employed. In particular, real activity is measured by the industrial production growth rate (g); nominal conditions by the harmonized CPI index inflation rate (π); monetary policy stance conditions by the real Eonia interest rate (s) and the rate of growth of real M3 (m). Moreover, the real effective € exchange rate return (e), the EA current account balance (ca) in changes, the return on the real IMF non-energy commodities price index (c) in €, and the Morana (2016) EA financial condition index (fc) are included. The latter subsumes information contained in various interest rate spreads and measures of uncertainty/risk, well tracking the phases of the euro area business and financial cycles. In particular, an increase in the latter indicator points to worsening financial conditions. Revisions in market expectations about the economic outlook have been finally included using the Fama-French (1993) European size (smb), value (hml) and market (mkt) factors, plus the Charart (1997) European momentum factor (mom). Available evidence for the US shows that positive innovations to size and value factors reveal expectations of favorable changes in macroeconomic prospects, while the opposite holds for positive innovations to momentum (Morana, 2014).

3.1 Oil price episodes

In Figure 2 we contrast the real WTI oil price level series with its net changes computed according to Hamilton (1996, 2003). The latter are grounded on the rationale that the real effects of price changes depend on how current oil prices compare with their historical path. High costs of monitoring energy expenditures and frictions with regard to adjusting consumption might account for the reluctance of economic agents to respond to small oil price changes, and therefore only sizable fluctuations might be expected to affect economic activity. In particular, a *net oil price increase* is then defined as the amount by which the log real oil price in month t exceeds its maximum over the previous year (i.e., the last twelve months) and oil price increases less than this benchmark are assumed to have no effect. Similarly, a *net oil price decrease* can be defined as the amount by which the log real oil price in month t falls below its minimum over the previous year and oil price decreases less (in absolute value) than this benchmark do not have effects.

As shown in Figure 2, over the time span considered both sizable net price increases and contractions have occurred. Apart from the early 2000s episode (5.1%), sizable net price increases can be detected near the end of year 2002 and in early 2003 (3.4%; 2002:9-2003:2), concurrent with the oil supply disruptions caused by strikes in Venezuela and the US intervention in Iraq. Yet, global oil supply was not significantly affected by both events (Hamilton, 2013), and oil market supply side conditions, consequently, were not a major determinant of oil price fluctuations in 2003 (Morana, 2012). Moreover, the 2003 oil price shock episode was not long lasting, actually resolved within the same year (-2.4% 2003:4-2003:5), and the ensuing global real effects were also weak (Morana, 2013b).

Then, over the period 2004 through 2006, the real oil price almost doubled, from 25€ to 50€ per barrel on average. Five sizable net price changes can be detected, yielding an overall 18% net price increase over the period 2004:4 trough 2006:7, followed by a -4.3% net oil price contraction in 2006:10-2007:1. The real oil price has kept increasing thereafter, peaking at about 86€ per barrel in June 2008, following an 11% net price increase over the period 2007:9 through 2008:6, to swiftly plunge to about 30€ per barrel, within five months, in December 2008. Evidence reported in Morana (2013a) show that the 2004-2008 oil price swing was mostly driven by macro-financial factors, consistent with rapid global economic growth and an upsurge in financial speculation in the oil futures market driving oil demand upward initially (while oil supply was stagnating), and then downward as the Great Recession set in.[3] The overall contribution of the *third oil price shock* to the depth of the Great Recession was however moderate, oil market shocks jointly accounting for about 10% of the contraction in global real activity over the

[3]See also Kilian and Hicks (2012) on the role of economic growth in the determination of the 2008 oil price shock.

period 2008:2-2008:4 (-1.3% out of -15%; Morana, 2013b).

Since late 2009 a new run-up in real oil prices can be noted, concurrent with the recovery of the global economy from the Great Recession, shifting flow oil demand upward, and some episodes of oil supply disruption caused by social and political distress in the Middle-East (Arab spring; IS conflict). The latter lasted for about five years, until the reversal in the oil supply-demand imbalance led to the recent price slump (World Bank, 2015).[4] As shown in the plot, six sizable net price changes can then be noted over the period 2009-2015, yielding an overall 12.1% net price increase initially (2009:11 through 2013:8) and then a -13.5% net oil price contraction eventually (2014:10 through 2015:1). From an average value of about 70€ per barrel, persisting over a period of almost four years, a swift 50% plunge to about 40€ per barrel was then scored within four months, from October 2014 through January 2015. Since then, the real oil price has mostly stagnated.

In light of the above evidence, five periods of positive net oil price changes and five periods of negative net oil price changes can be selected. Of particular interest for our study are then the last six episodes, covering the sustained mid-2000s real oil price run-up, the 2008 boom-bust episode, and the post-Great Recession dynamics through the recent oil price slump.

4 Estimation results

As described in the methodological section, the estimation of the SP-DCC model is performed using conditional mean residuals. The latter are computed from univariate autoregressive (AR) models with lag length selected according the BIC information criterion and serial correlation tests. GARCH(1,1) models are then estimated using the whitened residuals.

Hence, concerning the conditional mean model in (1), $\mathbf{y}_t = \begin{bmatrix} o_t & g_t & \pi_t & e_t & \ldots & mom_t \end{bmatrix}'$, $N = 13$, and the generic ith element in $\boldsymbol{\mu}_t(\boldsymbol{\delta})$ is $\mu_{i,t}(\boldsymbol{\delta}) = \boldsymbol{\delta}_{i0} + \boldsymbol{\delta}_{i1}y_{i,t-1} + \boldsymbol{\delta}_{i2}y_{i,t-2} + \ldots + \boldsymbol{\delta}_{ip}y_{i,t-p}$, $i = 1, \ldots, N$. OLS estimation of the conditional mean model yields the residuals $\hat{\boldsymbol{\varepsilon}}_t = \mathbf{y}_t - \boldsymbol{\mu}_t(\hat{\boldsymbol{\delta}})$, which are then employed for the estimation of the conditional variance model. The elements along the main diagonal of the conditional variance-covariance matrix $\mathbf{H}_t(\boldsymbol{\delta})$ are posited to follow a GARCH(1,1) specification as in (3), and similarly for each of the 78 $N \times (N-1)/2$ distinct composite processes $h^{+}_{ij,t}$ and $h^{-}_{ij,t}$, as in (6) and in (7).

In all cases an IGARCH(1,1) specification was eventually selected and estimated by cross-validation, using the exponential smoothing form of the model for computational easiness.[5] The results show that all the models are well specified and yield standardized residuals consistent with white noise properties. In Table 1 we report details for the

[4] Since 2011, U.S. shale oil production has persistently surprised on the upside while expectations of global oil demand have been revised downward several times. Moreover, the failure to agree on production cuts for about eight years, until November 2016, and maintaining unchanged production levels in the face of increased US production, point to a change in the OPEC cartel's policy objective, from targeting an oil price band to preserving market share. Finally, since the second half of 2014 the U.S. dollar has sizably appreciated against major currencies, possibly contributing to the oil price decrese by depressing its demand in countries that have experienced an erosion in the purchasing power of their currency. See also Baumeister and Kilian (2015) for further evidence on the role of excess supply and oil market specific factors.

[5] Hence, equation (3) is estimated under the restrictions $\omega_i = 0$, $\alpha_i + \beta_i = 1$; notice the equivalent representation of the IGARCH model in terms of the exponential smoother once the mean reversion

estimated AR-IGARCH models for the original variables included in the vector $\mathbf{y}_t$. For reasons of space, we do not report details for each of 156 IGARCH(1,1) models estimated for the composite variables. We provide a summary of the findings in Figure 1, which shows the frequencies and the cumulated frequencies of the estimated IGARCH parameters and the p-value of the tests for serial correlation and conditional heteroskedasticity for the standardized residuals. As shown in Table 1 and Figure 1, the estimated lagged conditional variance parameter β falls in the range 0.70-0.95 for the original series, and 0.65-0.95 for the composite variables, with mean value close to 0.9 for both set of series.

Very accurate is also the estimation of the conditional correlation processes. In fact, by comparing the original and (ex-post) transformed conditional correlations, we find that the average Theil's U index, across the sample of 78 conditional correlation processes, is just 0.09, with standard deviation equal to 0.05 (not reported). This implies that the original and transformed (well-behaved) correlation processes are very close, i.e. the transformation required to make well-behaved the sequence of conditional correlation matrices leaves largely unchanged their original values, consistent with accurate estimation of second moments delivered by the SP-DCC model.[6]

4.1 Contemporaneous conditional correlations

In Figures 2-3 we plot the estimated (contemporaneous) conditional correlations relating the WTI real oil price return o with each of the macroeconomic (g, π, e, c, m, s, c, ca) and financial (mkt, smb, hml, mom, fc) variables considered. The latter are denoted as g/o, π/o, e/o, c/o, m/o, s/o, c/o, ca/o, mkt/o, smb/o, hml/o, mom/o, fc/o. In the Figures we also report the selected net oil price increases and decreases (H), scaled to range in the $[-1; 1]$ interval for graphical convenience. Shaded areas correspond to periods of economic recession for the EA economy, as measured by the OECD chronology.[7] Some descriptive statistics are reported in Table 2.

As shown in Figures 3-4, the estimated conditional correlations are sizable and often outside the 95% confidence band yield by the Constant Conditional Correlation model (Bollerslev, 1990), supporting our time-varying modeling strategy. For inflation (Figure 3) the linkage is in general positive (0.34 on average), pointing to a sizable transmission of oil price changes to consumer prices already within the same month.[8] On the other hand, for industrial production (Figure 3) the linkage is rather unstable, almost null on average (0.07) as conditional correlations take both sizable positive and negative values over time. The alternating regime feature of g/o can then possibly account for the delayed impact of oil price changes on real economic activity usually found by means of constant parameter specifications.[9] Hence, the transmission of oil price changes to the economy

parameter ω_i is omitted, i.e. $h_{i,t} = (1 - \beta_i) \sum_{s=1}^{\infty} \beta_i^{s-1} \varepsilon_{i,t-s}^2$. Similarly for equations (6) and (7). See Alexander (2008) for an introduction to exponential smoothing for variance estimation.

[6] A full set of results is available upon request from the author.

[7] The timeline is as follows. For the early 2000s recession: February 2001 (start) and July 2003 (end). For the late 2000s (Great) recession: March 2008 (start) and June 2009 (end). For the early 2010s recession: July 2011 (start) and February 2013 (end).

[8] This is consistent with previous evidence pointing to a direct pass-through of oil prices into pre-tax prices of liquid fuels accomplished within two to three weeks (ECB, 2010). See also Jiménez-Rodríguez and Sánchez (2005), Peersman and van Robays (2009), Forni et al. (2012), Hahn and Mestre (2011).

[9] For instance, Peersman and van Robays (2009) and Forni et al. (2012) find a delayed response of real activity to both oil demand and supply shocks (about three years), while a quicker impact is found

appears to be much faster than usually held.

Moreover, g/o tends to be negative at the beginning of recessions and positive toward their end. This is consistent with the finding that oil price hikes usually lead recessions (Hamilton, 2013).[10] It also suggests that a fall in the oil price at the end of a recession is not expansionary, consistent with asymmetries in the mechanism of job creation and destruction (Hamilton, 2011).[11] Also, for the early and late 2000s recessions the largest positive values for π/o occur at the end and all through the recession, pointing to stagflationary effects of oil price shocks.

Negative is also the average linkage between real oil price dynamics and real money balances (-0.11), real short-term rate (-0.31), real effective exchange rate (-0.13) and current account (-0.31) changes (Figure 3), consistent with a scenario where real oil price hikes lead to *i*) a contemporaneous worsening in the current account due to the increase in the price of imported energy goods; *ii*) a monetary policy accommodation, leading to a reduction in the real short-term rate; *iii*) a reduction in real money balances due to the inflationary effect of the shock (dominating the monetary accommodation); *iv*) a depreciation of the real effective exchange rate, consistent with the monetary policy response to the shock and the concurrent nominal depreciation of the euro currency (see Morana, 2016). Average figures however hide important properties of the data. For instance, since 2006 e/o has been persistently positive, rather than negative, almost through the end of the Great Recession; similarly, ca/o turns positive toward the end of the Great Recession. The same pattern can also be noted toward the end of the investigated sample, in correspondence of the oil price slump (October 2014) and the implementation of $Q.E$ by the ECB since January 2015.

On the other hand, the conditional correlations for commodity prices (0.22) and the financial condition index (0.11) are positive on average (Figure 4). The former finding is consistent with an increase in the real oil price leading to higher real commodity prices through *i*) higher production costs of commodities due to the associated increase in the price of chemical and petroleum derived inputs; *ii*) the expectation of a linkage between energy and commodity markets, as agricultural commodities have been increasingly used to produce energy over time; *iii*) the nominal depreciation of the euro currency; iv) increased financialization of commodity markets leading to a stronger comovement in their prices. Moreover, the latter finding is consistent with higher real oil prices leading to financial stress. Interestingly, both c/o and fc/o turn negative at the end of sample, as well as during the transition to the Great Recession (since 2006 for c/o and mid-2007 for fc/o) and during the crisis itself.

Relevant insights are also yield by the conditional correlations computed for the risk factors (Figure 4). On average, the conditional correlations are positive for the size (0.18) and momentum (0.27) factors, while null for the market (0.05) and value (0.02) factors due to sign compensations over the sample investigated. Similar behavior is shown by smb/o, hml/o and mkt/o turning negative since 2006 during the transition to the crisis, the Great Recession itself and the recent oil price slump; on the other hand, mom/o turns negative only during the Great Recession and the recent oil price slump, i.e. in correspondence of the two largest oil price drops. This is consistent with the expected

for precautionary/speculative demand shocks.

[10] Indeed, figures from Hamilton (2013) show that this has been the case in ten out of eleven postwar US recessions to date.

[11] A positive g/o correlation during expansions might also reflect the influence of the state of the business cycle on both the oil price and industrial production, which would be jointly driven upward.

signalling properties of risk factors (Morana, 2014), since *smb* and *hml* might be expected to increase (decrease) in the expectation and during an expansion (recession);[12] *mom* to increase in the expectation and during a recession.[13] In particular, the positive *mom/o* correlation over most of the sample is coherent with the recessionary bias exercised by oil market shocks since late 1990s (Morana, 2013b).

4.1.1 Robustness issues

In order to assess the robustness of the findings to the selection of the decay parameters $\hat{\beta}_i$, $\hat{\beta}^+_{ij}$, $\hat{\beta}^-_{ij}$, in Figures A1 and A2 in the Appendix, we contrast the above conditional correlations with their corresponding thick modeling estimates (Granger and Shin, 2004). In our framework, the latter are obtained by averaging upper and lower band estimates, as yield by setting $\hat{\beta}_i \pm 1.96 \times \hat{\sigma}_{\hat{\beta}_i}$, $\hat{\beta}^+_{ij} \pm 1.96 \times \hat{\sigma}_{\hat{\beta}^+_{ij}}$, $\hat{\beta}^-_{ij} \pm 1.96 \times \hat{\sigma}_{\hat{\beta}^-_{ij}}$. As shown in the plots, the estimated conditional correlations are strongly robust to the selection of the decaying parameters, since in all cases *point* and *thick* estimates are numerically very close. By assessing their distance using the Theil's U statistic, we find a median value of 0.30, with interquartile range of 0.08 (not reported); similar figures are obtained when considering the whole set of 78 distinct conditional correlation processes ($U = 0.27$; $IQR = 0.09$; not reported).

5 Dynamic effects of oil price shocks

From (27) the sequence of time-varying dynamic multipliers can be computed as

$$\hat{\beta}_{oj,ts} = \frac{\hat{h}_{oj,ts}}{\hat{h}_{o,t}} \equiv \hat{\rho}_{oj,ts} \times \frac{\hat{h}^{1/2}_{j,t+s}}{\hat{h}^{1/2}_{o,t}} \quad s = 1, 2, ...M \tag{45}$$

allowing to trace the dynamic (reduced form) responses of the selected macroeconomic and financial variables ($j = g$, π, s,m, e, ca, c, fc, smb, hml, mkt, mom) to real oil price changes (o). The latter bears the interpretation of time-varying impulse response functions, subject to the caveat discussed in the methodological section.

In our application median dynamic responses of the various macroeconomic variables for each of the ten episode of interest are computed (five periods of positive net oil price changes and five periods of negative net oil price changes), which are scaled by the size of the corresponding median net price change in order to make them comparable across episodes. Moreover, $M = 12$, i.e. the (cumulated) response of the various macroeconomic and financial variables is computed from one-month up to the following twelve months. Due to sample size limitations, the analysis for the 2014 oil price slump episode is carried

[12]The rationale is that small firms have limited access to external capital markets and are more vulnerable than large firms to adverse changes in credit conditions. Improved credit and, in general, macroeconomic prospects may then be associated with a rise in the profitability of small stocks, resulting in a higher size factor. Similarly, firms with high book-to-market ratios are likely to suffer more from a higher debt burden and are more vulnerable to adverse changes in monetary policy and interest rates. Improved economic conditions may then be associated with higher profitability of value stocks, resulting in a larger value factor.

[13]If firms with stronger fundamentals outperform firms with weaker fundamentals during economic downturns and fundamentals are persistent and reflected in stock returns, positive momentum should be observed during recessions.

out using a smaller forecasting horizon ($M = 6$). Confidence intervals ($\pm 1 S.E.$; 68%) for median responses have been computed by means of a bootstrap procedure (1000 replications). Results for selected variables and episodes are reported in Figures 5-7.[14]

5.1 Industrial production and inflation

As shown in Figure 5, net oil price increases determine a decrease in industrial production in all of the episodes investigated. The median contraction is fairly similar across episodes, in the range -0.1% to -0.3%, within 1 year, apart from the 2008 oil price boom, which triggers a stronger contraction (-0.65%). On the contrary, net price decreases exercise some expansionary effects only in the early (not reported) and mid-2000s: a 1% net oil price contraction leads to a 0.1% industrial production increase within 1 year; a median negative short-lived response can be noted for the other episodes (up to -0.05%), including the current oil price slump, consistent with uncertainty and deflationary effects (see below).[15]

The asymmetric response to positive and negative oil price shocks is consistent with previous evidence of Jiménez-Rodríguez and Sánchez (2005) for the EA-wide economy; Cuñado and Pérez de Gracia (2003) and Cologni and Manera (2009) for selected European countries. However, we also find that the contraction in industrial production deepens with the magnitude of the shock and the level achieved by the oil price itself, having been twice as large during the third oil price shock than for any of the other four episodes in the sample. Also, sizable real effects of oil price increases can be noted at much shorter horizons than documented by standard constant parameter specifications. For instance, Peersman and van Robays (2009) and Forni et al. (2012) find a delayed response of GDP growth to both oil supply and demand shocks (about three years), while a quicker response is found for precautionary/speculative demand shocks.[16]

Concerning the response of the consumer price index (CPI) level to net oil price increases, a weak inflationary response can be noted at the outset in all cases, followed by some sizable deflation apart from the 2008 oil price boom (0.05% within four months). Moreover, the response of CPI to net oil price contractions is in general (weakly) deflationary at the outset, as well as at longer horizons, apart from the 2006 episode. Our findings are therefore somewhat in contrast with earlier evidence of Peersman and van Robays (2009), pointing to short- to long-term inflationary effects of oil price shocks.[17]

[14] A full set of results is available upon request from the author.

[15] Kang and Ratti (2013) show that oil price shocks account for up to 20% of economic policy uncertainty at business cycle horizons in Europe. This is consistent with the view that oil price shocks might affect real and financial markets also through an uncertainty channel.

[16] Comparison with their estimates is not straightforward due to the different response variables used, i.e. industrial production rather than GDP, and the unity of measure of the shocks, i.e. *net* oil price changes rather than actual changes. With this caveat in mind, Peersman and van Robays (2009) point to a -0.3% real GDP contraction within four (twenty) quarters following a 10% real oil price hike generated by a precautionary oil demand shock (flow oil supply shock); the response to a global flow oil demand shock of the same magnitude is weaker (-0.10 % within twenty quarters) and even positive within four quarters (0.2%).

[17] Peersman and van Robays (2009) point to a 0.1% CPI increase within four quarters following a 10% oil price increase triggered by a precautionary oil demand shock; a 0.3% increase within twelve quarters following either a flow oil demand or supply shock of the same magnitude.

5.2 Monetary policy variables

Concerning the monetary policy response to oil price shocks (Figure 5), a weak real short-term rate contraction can be noted following any of the net oil price increase episodes, pointing to some monetary policy accommodation of their inflationary effects. As previously noted, apart from the 2008 boom episodes, at longer horizons net oil price increases tend to be deflationary; the reduction in the nominal short-term rate, implied by the contraction in the real short-term rate during deflation, is then consistent with monetary policy counteracting the deflation threat. The concurrent contraction in real money balances points to a new money market equilibrium characterized by a lower nominal interest rate and lower real money supply and demand (due to recessionary effects). Also, the 2008 boom episode would have been fully accommodated, given its inflationary impact and the observed reduction in the real short-term rate; this is also in light of real money balances remaining almost unchanged, implying an increase in the nominal money supply, given the rise in the price index level. Similar interactions can be noted during the mid-2000s oil price run-up. On the other hand, a small real short-term rate increase, without monetary tightening, can be noted following any of the net oil price decrease episodes.

Of particular interest is the ECB response to the 2014 oil price slump. In light of its deflationary effects (Figure 4), the increase in the real short term rate is consistent with an accommodation of the shock; coherently, real money balances increase following the deepening of the expansionary monetary policy stance during 2014, eventually culminated with the introduction of $Q.E.$ in January 2015. As nominal interest rates are currently at the zero lower-bound, the real short term rate increase determined by the deflationary effects of the oil price slump, jointly with uncertainty effects, might account for its (weak) recessionary impact. Hence, in so far as $Q.E.$ failed to generate recovery and inflationary effects, a more expansionary fiscal policy might be required to counteract the deflationary and recessionary threat within the expected environment of persistently weak oil prices. The latter insight is fully consistent with the persistent decrease in the common long-run level of inflation expectations detected by Gimeno and Ortega (2016) for the euro area since late 2014, which the implementation of $Q.E.$ does not seem to have reverted so far. It is also consistent with Mallick et al. (2017), showing that both before and after the 2008 financial crisis a monetary policy stimulus tends to reduce the term premium. But, post-crisis, the fall in the term premium does not appear to boost economic activity, unlike in the pre-crisis period. While this evidence is for the US, it is also coherent with the weak recovery observed in the euro area, despite the introduction of $Q.E.$

Comparison with available evidence in the literature is not straightforward, as previous contributions are based on data extending through the 1970s, when there was neither a euro area nor a single monetary policy; moreover, they do not consider post-2008 oil price developments. With this caveat in mind, available results point to a somewhat accommodative or neutral response to oil price shocks, as no sizable effects on the real short-term rate are detected by Jiménez-Rodríguez and Sánchez (2005) and little contribution of oil price disturbances to the determination of the shock of the interest rate equation is found by Hahn and Mestre (2011). Similar conclusions can be drawn from Peersman and van Robays (2009), pointing to a nominal short-term interest rate increase following an oil price hike determined by either flow oil supply or global oil demand shocks, while a nominal short-term interest rate contraction would follow a precautionary oil demand shock. Yet, the real interest rate is mostly unchanged in the former two cases, despite the nominal interest rate hike, while it contracts in the latter case. Extrapolation of the results of Peersman and van Robays (2009) would then imply that the current oil price slump, while being deflationary, would not be recessionary in the short-term, actually being expansionary in the medium-term; we do not regard the latter implications as reliable, neglecting that ECB monetary policy is currently managed at the zero lower-bound and the asymmetric feature of the oil price-macroeconomy relationship.

5.3 Real effective exchange rate, commodity prices and current account

As shown in Figure 6, net real oil price changes exercise mostly symmetric effects on the real effective exchange rate. Consistent with previous evidence of Jiménez-Rodríguez and Sánchez (2005), the euro depreciates (appreciates) following a net real oil price increase (decrease) in four out of five episodes. With reference to the recent oil price slump, the anomalous (relatively to the past) real depreciation of the euro is consistent with the concurrent implementation of $Q.E.$

Moreover, an inverse relation with non-energy commodity prices can be noted for almost all price hikes and for some oil price contractions, consistent with their recessionary effects and consequential decrease in the demand for non-energy inputs.

Also symmetric is the response of the current account to net oil price changes, worsening (improving) following a net oil price increase (contraction) for all the episodes in the sample; in this respect, particularly sizable is the response of the current account to the third oil price shock (about -2% within 12 months) as well as for the 2002:9-2003:2 episode (-1% within twelve months). Interestingly, the current account improvement associated with the recent oil price slump also yields an indirect measure of its negative aggregate demand impact, as reflected in the associated increase in national savings.

5.4 Financial conditions

Concerning overall financial conditions (Figure 6), among price hikes, only the early 2000s and 2008 boom episodes had a destabilizing impact, as detected by the sizable increase in the financial condition index; on the other hand, higher instability can be associated with the oil price contraction episodes, particularly since the mid-2000s.

Moreover, similarities can be noted concerning the response of risk factors to oil price developments (Figure 7). In fact, concerning the early 2000s episodes, net oil price increases in general determined a persistent decline in all risk factors (apart from hml for the 2000:8-2000:11 episode; not reported). Moreover, little response is shown by all risk factors to the mid-2000s oil price increase, while their contraction during the third oil price shock is very sizable. In this respect, only mom proves to be resilient to oil price developments, as a positive momentum is expected to lead recessions, as well as to persist at least through their early phase (Morana, 2014).

On the other hand, concerning net oil price decreases, a positive response of mkt, smb and hml can always be noted, apart from the 2008 bust episode for mkt. Overall, the symmetric response of mkt to oil price shocks is consistent with previous evidence of Park and Ratti (2008), Cuñado and Pérez de Gracia (2014) and Scholten and Yursever (2012).[18] Also, mom was negative during the early 2000s oil price contractions, yet positive for the

[18] See also Arouri (2011) for additional evidence on sectors'response.

other episodes, including the 2008 oil price bust within six months, signalling financial and economic distress. The positive response of *mom* to the most recent oil price contraction further corroborates the evidence of rising recession and deflation risk and worsening overall financial conditions, also consistent with the simulations reported in Kaabia et al. (2016).

6 Conclusions

The paper yields new insights on the macroeconomic and financial effects of oil price shocks for the euro area, with a special focus on post-2009 oil price dynamics and the recent oil price slump. Differently from previous work in the literature, we estimate a large-scale time-varying parameter model for the EA, based on the semiparametric dynamic conditional correlation model (SP-DCC) of Morana (2015). The proposed modeling strategy is not subject to the curse of dimensionality and, by allowing for a large and comprehensive macroeconomic and financial information set, should yield more accurate and robust results.

We find strong evidence of asymmetric real effects of oil price shocks for the EA, as net oil price increases have led to a contraction in industrial production over the whole sample, while net price decreases have yield some expansionary effects only in the early and mid-2000s. Evidence of recessionary effects of oil price slumps are also detected, as for the most recent episode.

Moreover, the real effects of oil price shocks appear to increase with their magnitude and the level achieved by the oil price itself. In this respect, the 2008 boom was surely peculiar for the size of its effects, twice as large than for any other episode since the 2000s; it was also peculiar for its larger inflationary impact, as deflationary rather than inflationary dynamics can be observed in the other cases. In light of its recessionary and deflationary effects, it is also likely that the post-2009 oil price run-up contributed to slowing down recovery in the euro area.

Deflationary effects also follow from net oil price contractions. In this respect, the current oil price slump has imparted both a recessionary and deflationary bias, through higher real interest rate and macroeconomic uncertainty effects. Ensuing financial distress is also signalled by the financial condition index and momentum risk factor. Overall, our findings have a key policy implication. In so far as $Q.E.$ failed to generate recovery and inflationary effects, a more expansionary fiscal policy might be required to counteract the deflationary and recessionary threat within the expected environment of soft oil prices. Recent evidence of Gimeno and Ortega (2016), pointing to a failure of $Q.E.$ in reverting a persistent decrease in the level of inflation expectations since late 2014, make the latter insight even more timely and compelling.

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Table 1: Conditional mean and variance models for original series

Panel A: macroeconomic variables								
Variables	o	g	π	e	c	m	s	ca
δ_0	0.5053 (0.6161)	0.0199 (0.0699)	0.1171 (0.0179)	-0.0495 (0.1101)	0.1096 (0.2061)	0.1388 (0.0389)	0.0063 (0.0123)	0.1862 (0.2539)
δ_1	0.2395 (0.1004)		0.2471 (0.0821)	0.2244 (0.0770)	0.2551 (0.0978)		0.3262 (0.0786)	-0.5801 (0.0760)
δ_2		0.2376 (0.0825)					0.1671 (0.0643)	-0.2314 (0.0834)
δ_3		0.3180 (0.0694)				0.2294 (0.0615)		
δ_6						0.2664 (0.0639)		
α	0.3000	0.1500	0.1000	0.0500	0.1000	0.0500	0.1000	0.0500
β	0.7000 (0.0850)	0.8500 (0.0590)	0.9000 (0.0389)	0.9500 (0.0244)	0.9000 (0.0328)	0.9500 (0.0108)	0.9000 (0.0345)	0.9500 (0.0289)
Q	0.7536	0.1410	0.0138	0.8374	0.9463	0.0742	0.0139	0.7897
Q_2	0.2597	0.2282	0.5592	0.5618	0.3411	0.9818	0.7015	0.0028
$S\&B$	0.0404	0.2537	0.9745	0.1231	0.7310	0.2751	0.7380	0.2674
BJ	0.0374	0.0018	0.0719	0.0000	0.0001	0.0000	0.3386	0.0000
Panel B: financial variables								
Variables	mkt	smb	hml	mom	fc			
δ_0	0.4451 (0.3588)	0.2218 (0.2217)	0.2992 (0.0888)	0.6619 (0.3686)	0.0040 (0.0158)			
δ_1			0.3188 (0.2176)	0.3243 (0.1058)	0.2153 (0.0804)			
δ_2				-0.2133 (0.0851)				
δ_3				0.1733 (0.0774)				
α	0.1000	0.1000	0.0500	0.1000	0.1500			
β	0.9000 (0.0419)	0.9000 (0.0326)	0.9500 (0.0439)	0.9000 (0.0470)	0.8500 (0.0257)			
Q	0.9081	0.9100	0.7937	0.5511	0.4597			
Q_2	0.5123	0.1708	0.0760	0.0806	0.9320			
$S\&B$	0.2446	0.8630	0.7960	0.1884	0.0677			
BJ	0.0019	0.5928	0.6269	0.0000	0.0000			

In the Table we report the estimated parameters for the AR-IGARCH models, with standard error in round brackets. We also report the p-value for the Bera-Jarque normality test (BJ), the Box-Ljung test for serial correlation in standardized (Q) and squared standardized (Q_2) residuals up to the 20th order, the joint Engle-Ng sign and size bias test ($S\&B$). The variables are the real oil price return (o), the industrial production growth rate (g), the inflation rate (π), the real effective exchange rate return (e), the non-energy commodity price index return (c), the real money growth rate (m), the real Eonia overnight interest rate (s), the EA current account in changes (ca), the Fama-French Euopean market (mkt), size (smb) and value (hml) factors, Charart momentum factor (mom) for Europe, and the EA financial condition index (fc).

Table 2: Descriptive statistics for contemporaneous conditional correlations.

	g/o	π/o	e/o	ca/o	m/o	s/o	c/o	fc/o	smb/o	mkt/o	hml/o	mom/o
mean	0.07	0.34	-0.13	-0.31	-0.11	-0.31	0.22	0.11	0.18	0.05	0.02	0.27
stdc	0.34	0.28	0.37	0.37	0.41	0.30	0.30	0.54	0.37	0.31	0.31	0.35

The table reports sample means (*mean*) and standard deviations (*stdc*) for the estimated conditional correlations of the various macroeconomic and financial variables relatively to the real oil price return (*o*). The variables are the industrial production growth rate (g), the inflation rate (π), the real effective exchange rate return (e), the non-energy commodity price index return (c), the real money growth rate (m), the real Eonia overnight interest rate (s), the EA current account in changes (ca), the Fama-French Euopean market (mkt), size (smb) and value (hml) factors, Charart momentum factor (mom) for Europe, and the EA financial condition index (fc).

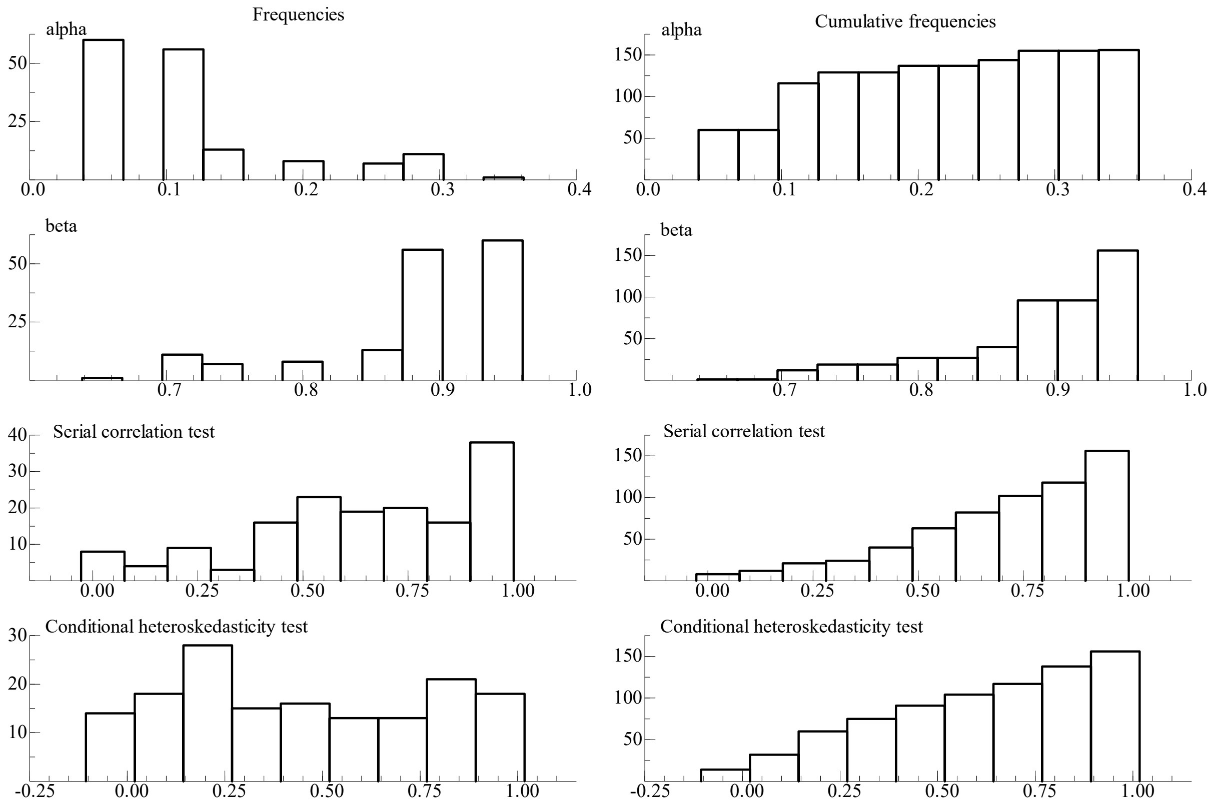

Figure 1: In the figure the cross-sectional distribution for the IGARCH (1,1) estimated parameters for the composite variables is reported. In particular, α is the squared lagged innovation parameter and β is the lagged conditional variance parameter. In the plot, also the cross-sectional distribution of the p-value of the Box-Ljung test for serial correlation in the standardized and squared standardized residuals (up to the 20th order) is reported. For all the statistics right-hand side plots refer to frequencies and left-hand side plots to cumulative frequencies.

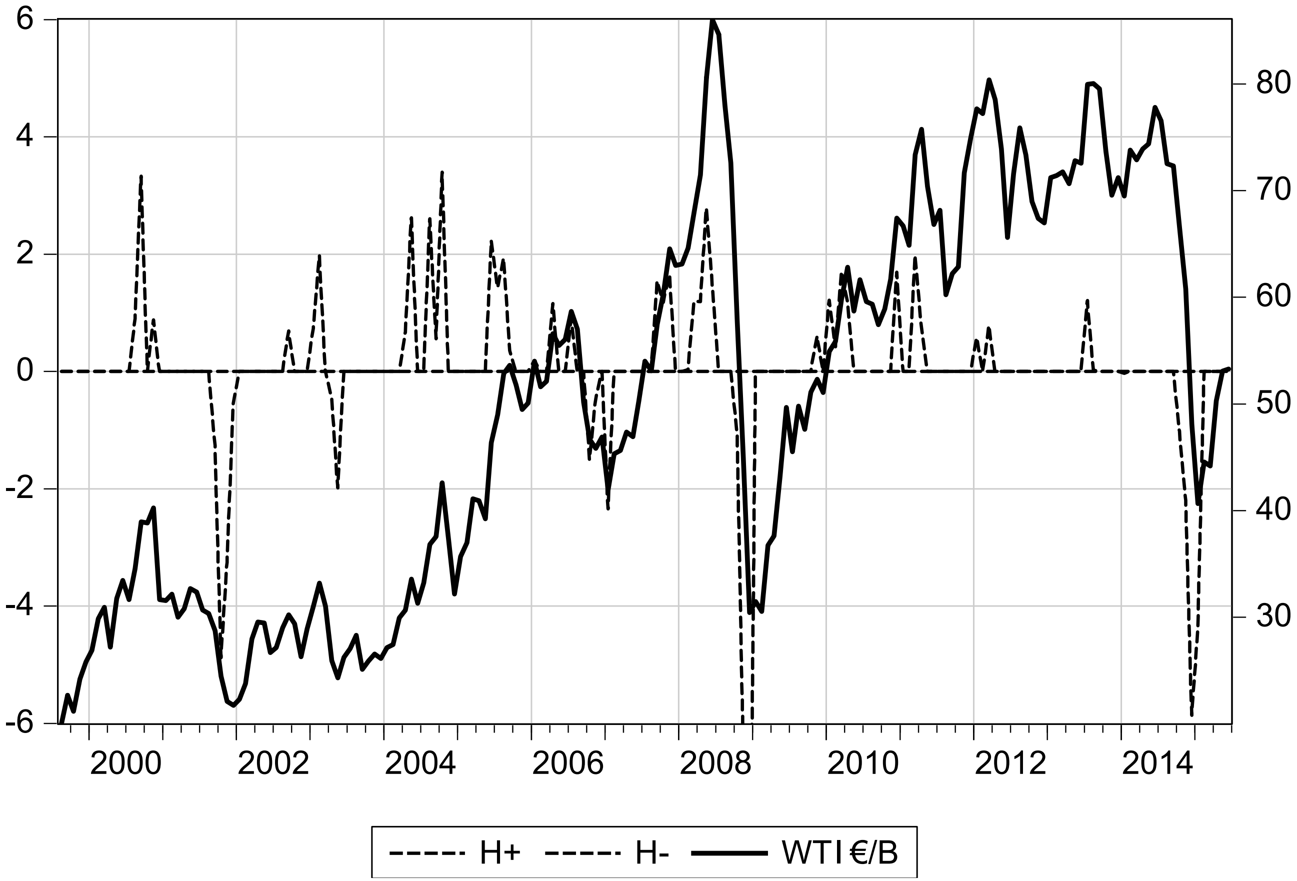

Figure 2: Real oil price (€/barrel) and Hamilton shock (net price increase H+ and net price decrease H-).

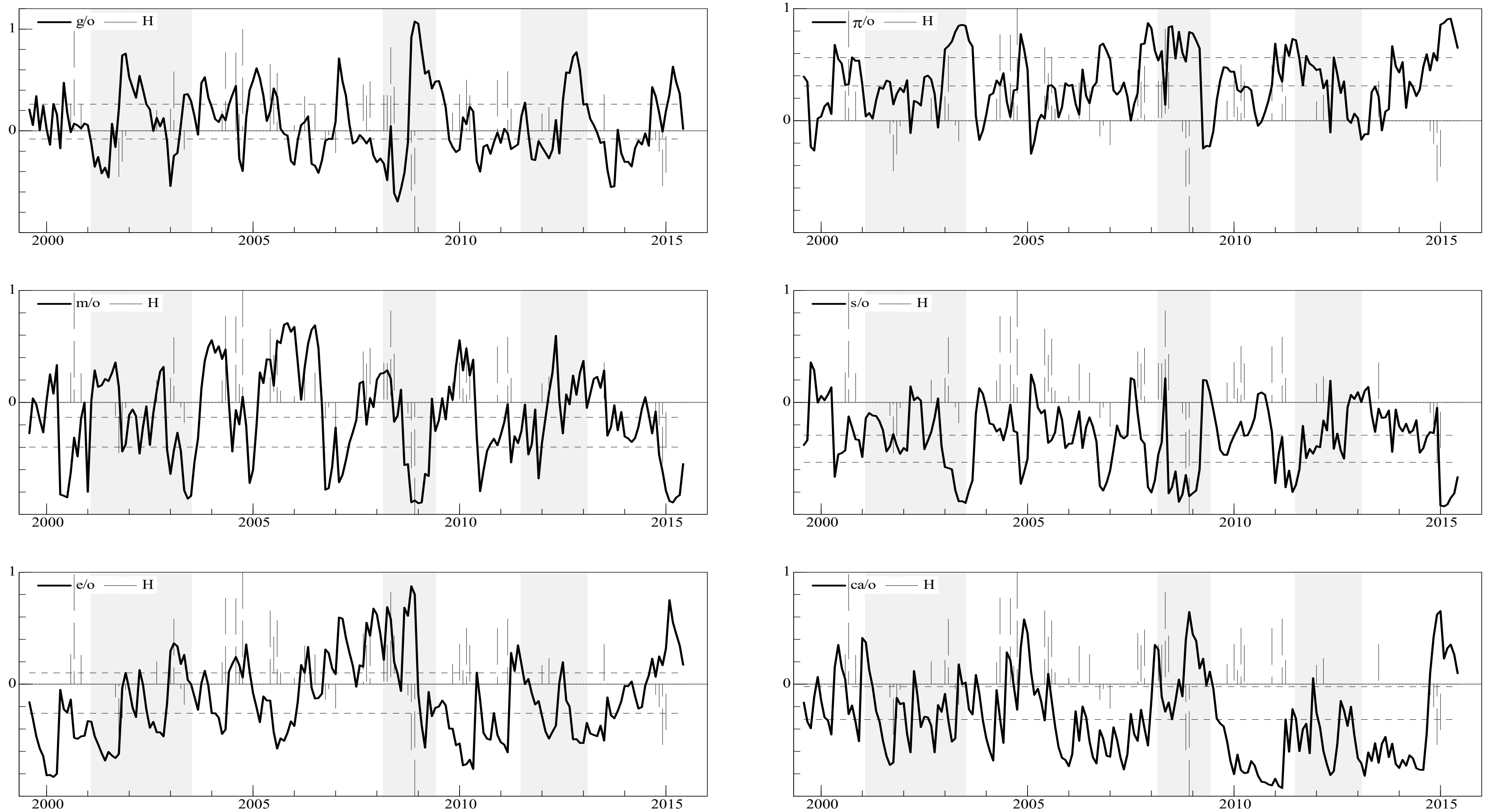

Figure 3: The figure shows the estimated conditional correlations for the various macro-financial variables relatively to the real oil price (o). The dotted horizontal lines refer to the estimated 95% significance bounds about the estimates yield by the CCC model (Bollerslev, 1990). The variables are: industrial production growth (g), CPI inflation (π), real Eonia interest rate (s), real M3 growth (m), real effective € exchange rate return (e), EA current account balance (ca) in changes. The dashed vertical line refers to the normalized Hamilton net price change variable (H). Shaded areas refer to recession periods for the EA . The timing is: February 2001 (start) and July 2003 (end); January 2008 (start) and June 2009 (end); July 2011 (start) and February 2013 (end).

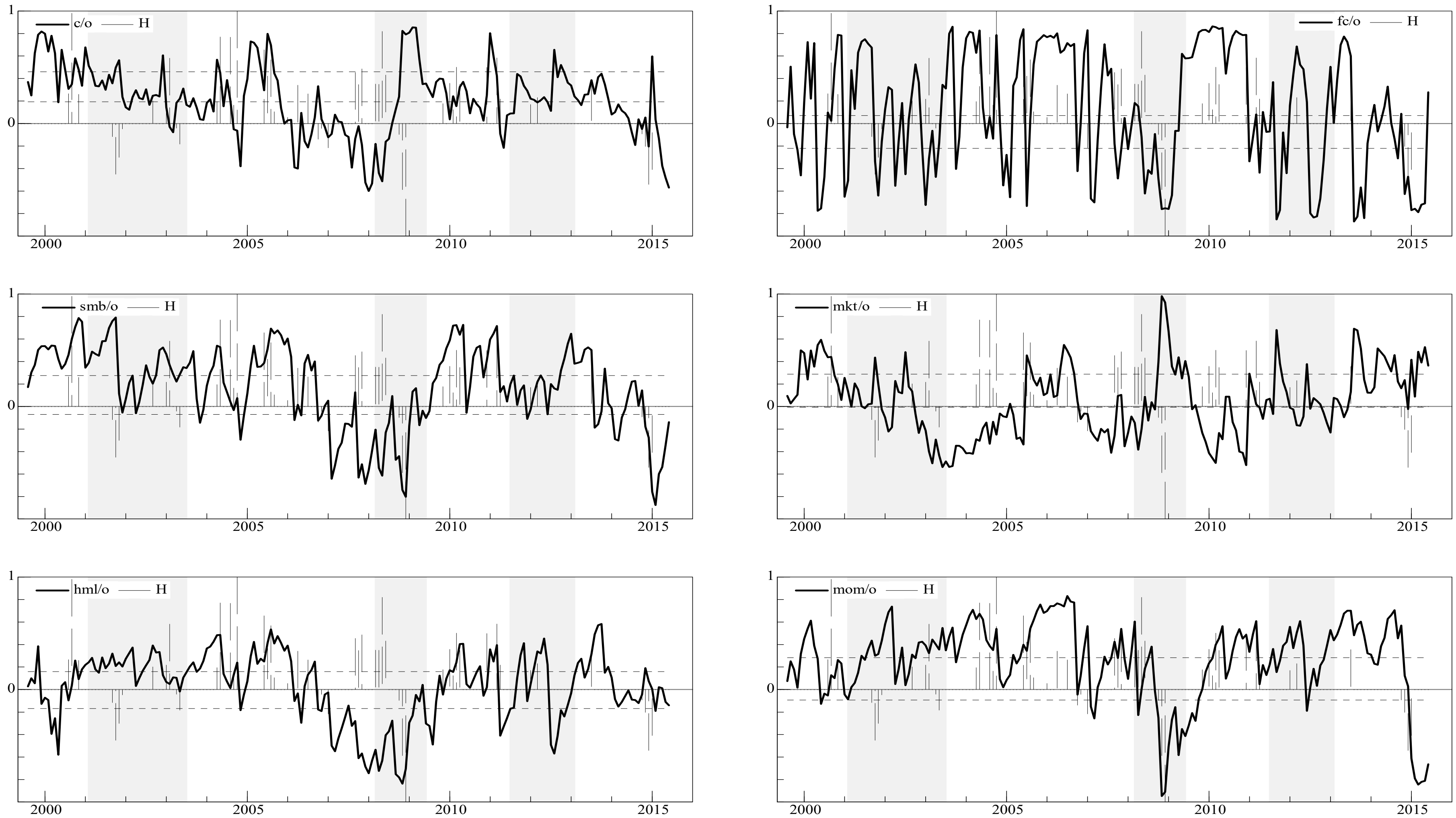

Figure 4: The figure shows the estimated conditional correlations for the various macro-financial variables relatively to the real oil price (o). The dotted horizontal lines refer to the estimated 95% significance bounds about the estimates yield by the CCC model (Bollerslev, 1990). The variables are: IMF real non-energy commodities price index return (c) in €, the Morana (2015a) EA financial condition index (fc), the Fama-French (1993, 2015) size (smb), value (hml) and market (mkt) factor returns for Europe, plus Charart (1997) momentum factor return (mom) for Europe. The dashed vertical line refers to the normalized Hamilton net price change variable (H). Shaded areas refer to recession periods for the EA . The timing is: February 2001 (start) and July 2003 (end); January 2008 (start) and June 2009 (end); July 2011 (start) and February 2013 (end).

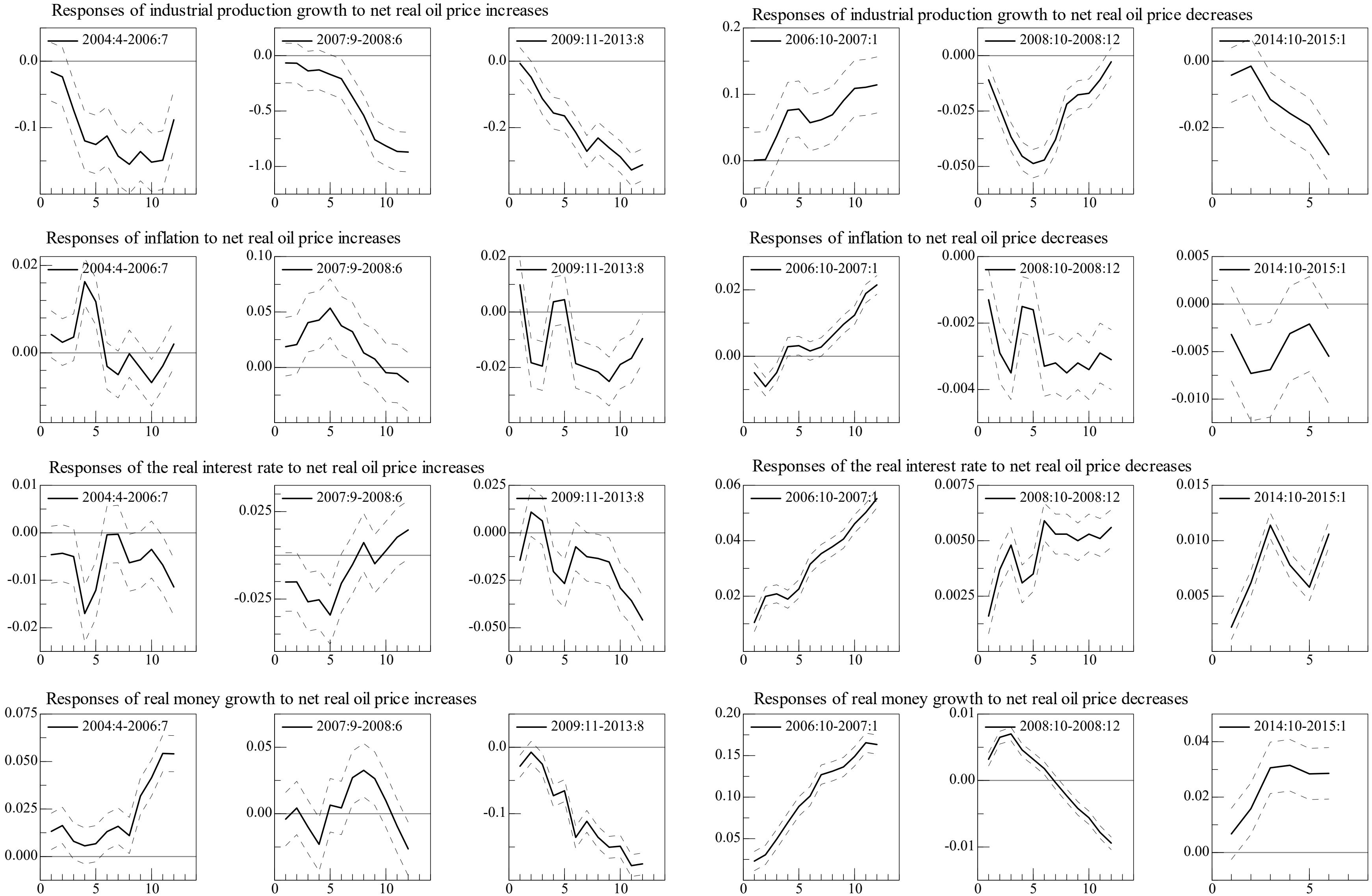

Figure 5: The Figure shows the cumulated (scaled) median response to net real oil price changes for the various episodes of interest.

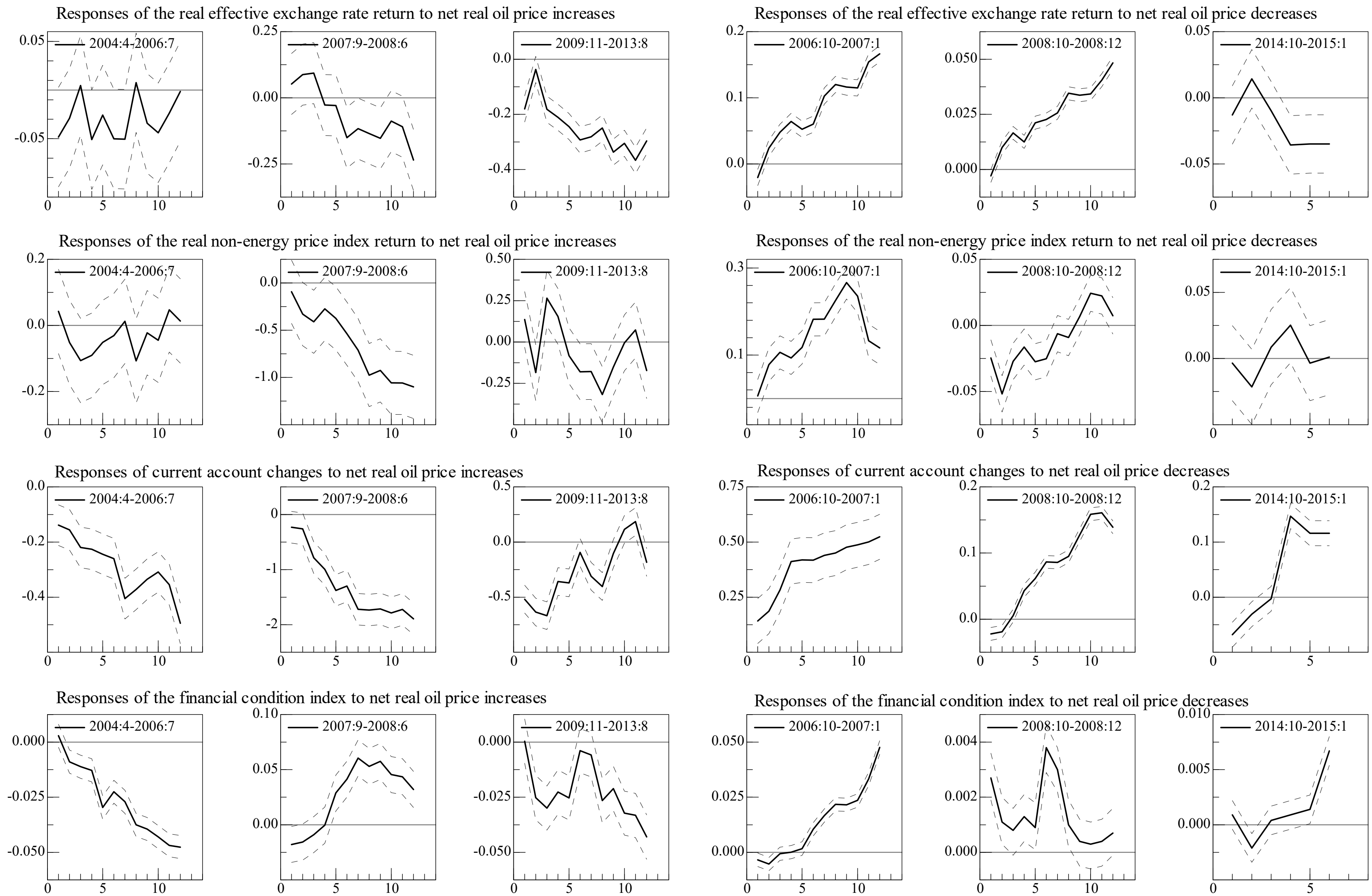

Figure 6: The Figure shows the cumulated (scaled) median response to net real oil price changes for the various episodes of interest.

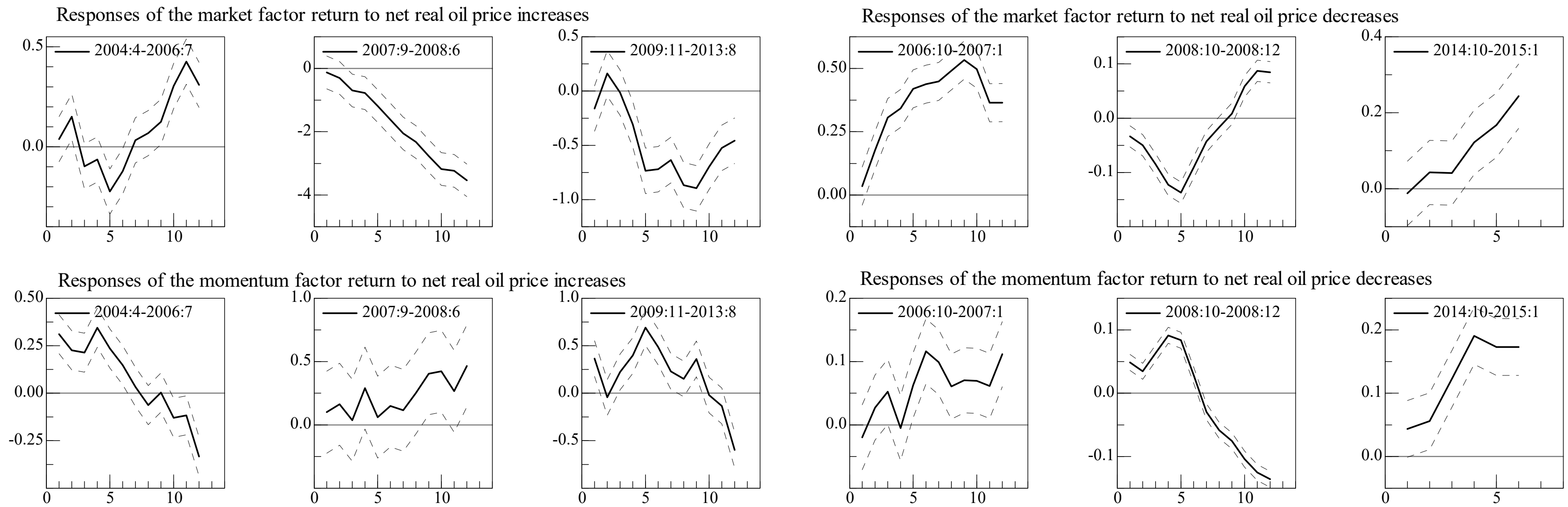

Figure 7: The Figure shows the cumulated (scaled) median response to net real oil price changes for the various episodes of interest.

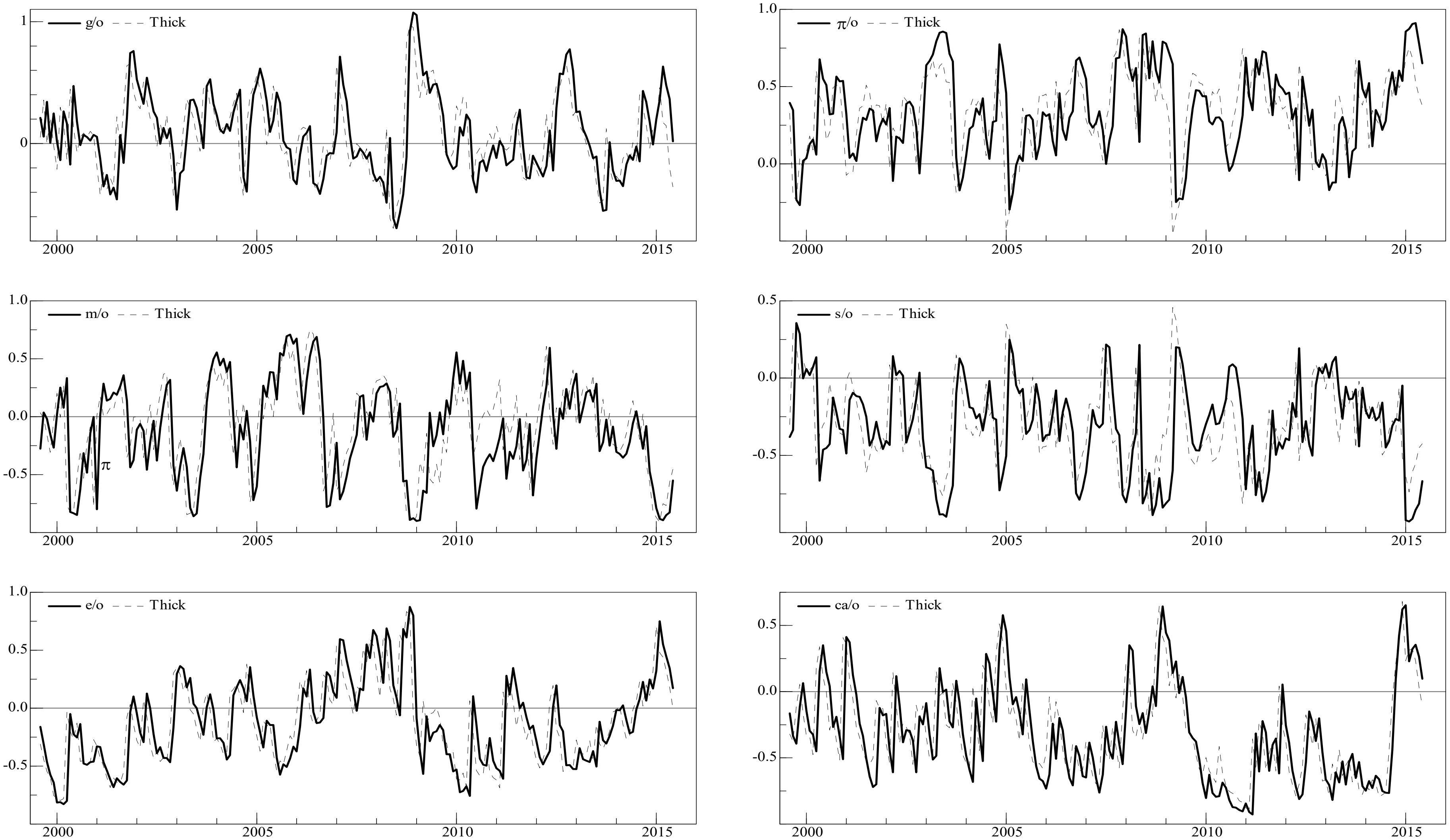

Figure 1A: The Figure shows the estimated conditional correlations for the various macro-financial variables, relatively to the real oil price (o), contrasted with their corresponding thick modeling estimates (Granger and Jeon, 2004). The variables are: industrial production growth (g), CPI inflation (π), real Eonia interest rate (s), real M3 growth (m), real effective € exchange rate return (e), EA current account balance (ca) in changes.

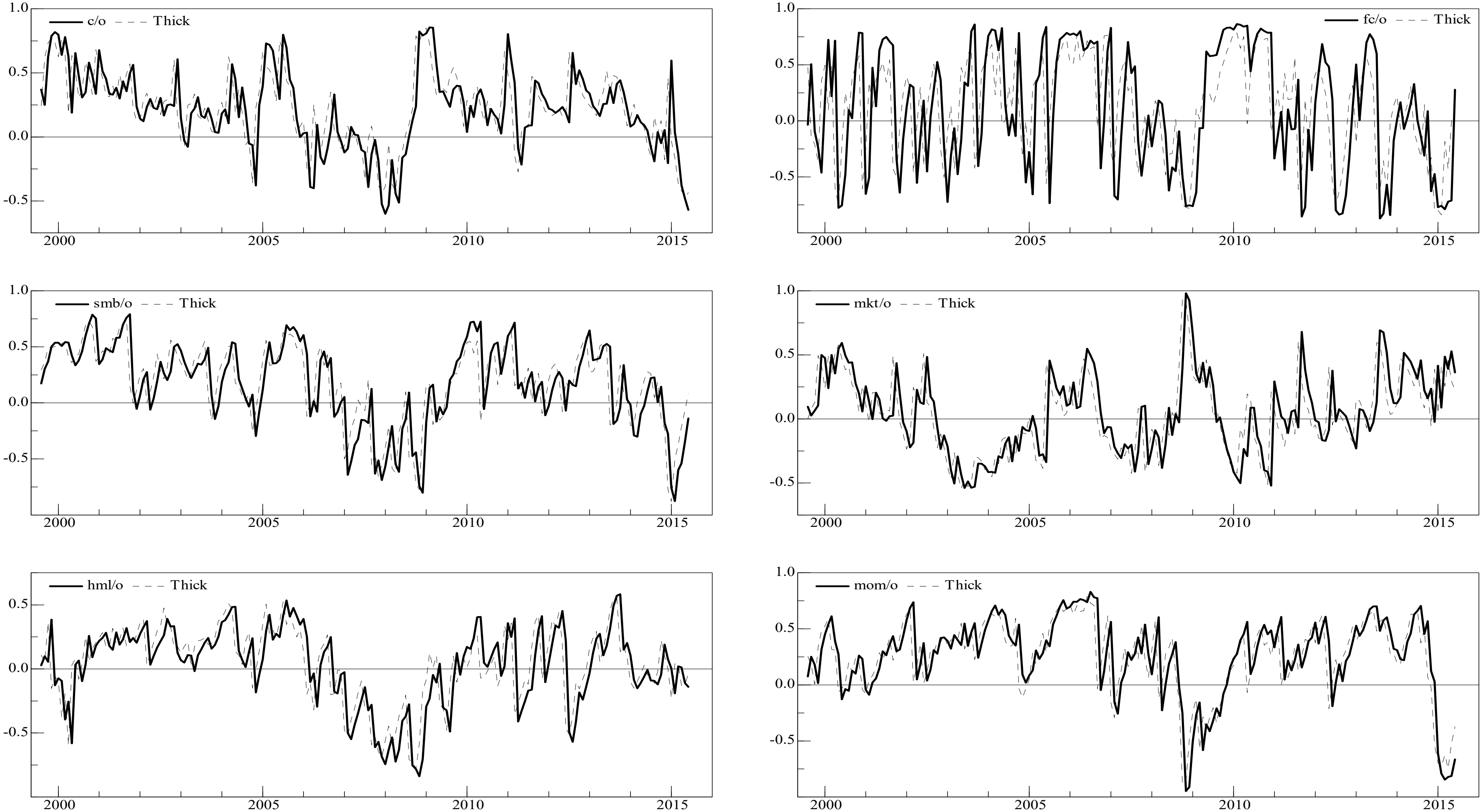

Figure 2A: The Figure shows the estimated conditional correlations for the various macro-financial variables, relatively to the real oil price (o), contrasted with their corresponding thick modeling estimates (Granger and Jeon, 2004). The variables are: IMF real non-energy commodities price index return (c) in €, the Morana (2015a) EA financial condition index (fc), the Fama-French (1993, 2015) size (smb), value (hml) and market (mkt) factor returns for Europe, plus Charart (1997) momentum factor return (mom) for Europe.