University of Heidelberg

Department of Economics

Discussion Paper Series | No. 525

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Christian Conrad, Karin Loch and Daniel Rittler

March 2012

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Christian Conrad[†], Karin Loch[‡], and Daniel Rittler[§]

Heidelberg University, Germany

March 13, 2012

Abstract

Using a modified DCC-MIDAS specification, we endogenize the long-term correlation between crude oil and stock price returns with respect to the stance of the U.S. macroeconomy. We find that variables which contain information on current and future economic activity are helpful predictors for changes in the oil-stock correlation. For the period 1993-2011 there is strong evidence for a counter cyclical behavior of the long-term correlation. For prolonged periods with strong growth above trend our model predicts a negative long-term correlation, while before and during recessions the sign changes and remains positive throughout the economic recovery. Our results strongly suggest that crude oil prices cannot be viewed as being exogenous with respect to the U.S. macroeconomy and explain the controversial results concerning the oil-stock relationship in previous studies.

Keywords: Oil-stock relationship, long-term volatility, long-term correlation, GARCH-MIDAS, DCC-MIDAS

JEL Classification: C32, C58, Q43

*We would like to thank Thomas Eife and Sandra Schmidt for valuable comments and suggestions. Christian Conrad gratefully acknowledges financial support from the "Juniorprofessorenprogramm" of the state of Baden-Württemberg.

[†]Christian Conrad, Department of Economics, Heidelberg University, Bergheimer Strasse 58, 69115 Heidelberg, Germany, E-mail: christian.conrad@awi.uni-heidelberg.de; Phone: +49/6221/54/3173.

[‡]Karin Loch, Department of Economics, Heidelberg University, Bergheimer Strasse 58, 69115 Heidelberg, Germany, E-mail: karin.loch@awi.uni-heidelberg.de; Phone: +49/6221/54/2908.

[§]Daniel Rittler, Department of Economics, Heidelberg University, Bergheimer Strasse 58, 69115 Heidelberg, Germany, E-mail: daniel.rittler@awi.uni-heidelberg.de; Phone: +49/6221/54/2908.

1 Introduction

Given the empirical evidence in, e.g., Hamilton (1983, 1985, 2003) on the negative impact of oil price shocks on economic activity, it does not seem surprising that studies such as Jones and Kaul (1996) also find a negative relationship between oil prices and stock returns. In this article, we revisit the oil-stock market relationship by analyzing the dynamic correlations between crude oil prices and U.S. stock market returns during the period 1993–2011. The rolling window of yearly realized correlations in Figure 1 clearly reveals that there is considerable time-variation in the correlation between the two return series with extended periods of positive correlations. Using a two-component dynamic correlation model, we aim at explaining these variations by changes in the U.S. macroeconomic environment. Our specification allows us to separate day-to-day fluctuations (the dashed line in Figure 1) from gradual long-term movements (the bold line) which are related to the stance of the economy. The dynamic correlations plotted in Figure 1 are obtained from a specification which explains the long-term component by variations in the Chicago Fed national activity index (NAI). Figure 1 clearly shows the close link between the oil-stock correlation and the business cycle. In particular, note the positive oil-stock correlation during recessions and thereafter.

Figure 1 about here

Our econometric specification is based on the Dynamic Conditional Correlation - MIxed Data Sampling (DCC-MIDAS) model proposed in Colacito et al. (2011). The DCC-MIDAS model combines the Engle (2002) DCC specification with the GARCH-MIDAS framework of Engle et al. (2009). The GARCH-MIDAS framework extends the simple GARCH specification by modeling volatility as consisting of a short-term and a long-term component. Most importantly, the long-term component is specified as a function of the macroeconomic environment. In the original DCC specification with correlation targeting each quasi-correlation follows a 'GARCH type' process which is mean-reverting to the unconditional correlation of the volatility-adjusted residuals. The basic idea of Colacito et al. (2011) is to replace this unconditional correlation with a slowly time-varying long-term component. The quasi-correlation then fluctuates around this long-run trend. Hence, the new specification can be considered as a two component model for the dynamic correlations. In the spirit of Engle et al. (2009) the short-term component fluctuates at a daily frequency while the long-term component adjusts at the lower monthly frequency. Colacito et al. (2011) assume that the long-term component can be expressed as a weighted sum of the lagged monthly realized correlations between the volatility-adjusted residuals.

Using the GARCH-MIDAS framework, we first analyze whether the long-term oil market volatility is related to the U.S. macroeconomy and whether oil and stock volatility respond to the same macroeconomic information. Next, we extend the DCC-MIDAS model by directly incorporating information on the macroeconomic development in the long-term correlation component, i.e. we replace the realized correlations by monthly macroeconomic variables. Since the macroeconomic variables – unlike the realized correlations – are not restricted to the minus one to plus one interval, we suggest a new specification for the long-term component. Similar to Christodouklakis and Satchell (2002), we assume that the Fisher-z transformation of the long-term component can be written as a linear function of the weighted lagged macroeconomic variables. The weights are again determined using the MIDAS approach. We refer to this new specification which includes a macroeconomic explanatory variable as the DCC-MIDAS-X model.

In broad terms, our results can be summarized as follows. First, we find that the movements in long-term oil market volatility can be well predicted by various measures of U.S. macroeconomic activity. Our empirical results provide convincing evidence for a counter cyclical relationship between measures which either describe the current stance of the economy, e.g. industrial production, or provide forward looking information about the future state of the economy, e.g. the leading index for the U.S., and oil market volatility. Current and expected increases (decreases) in economic activity clearly anticipate downswings (upswings) in long-term oil volatility. This result strengthens the argument of Barsky and Kilian (2004) and Harris et al. (2009) that – in contrast to the 1970s – over the last decade the oil price development is very much synchronized with the business cycle and that there is indeed reverse causality from macroeconomic variables to the oil price.[1] Interestingly, we also find that long-term oil and stock market volatility respond to the same macroeconomic information. This observation challenges the view of Kilian and Vega (2011) who report that oil price returns do not respond instantaneously to macroeconomic news and, hence, claim that oil prices do not behave like asset prices. At least for the second moment of oil price returns, our results are conflicting with their

[1] Barsky and Kilian (2004) and Harris et al. (2009) argue that the relation between the oil price and macroeconomic developments has changed over time. While during the 1970s exogenous oil supply shocks were primarily responsible for the detrimental effect of oil price increases on growth, the oil price is mainly driven by and, hence, positively related to global demand since the mid-1990s.

argument.

Second, our empirical results show that changes in the long-term oil-stock correlation can be anticipated by the same macroeconomic factors which also affect the long-term volatilities. We provide strong evidence for a counter cyclical behavior of the long-term oil-stock correlation. The economic rationale behind is best explained by again looking at Figure 1 which exemplarily relates the oil-stock correlation to changes in the NAI. The phases with positive long-term oil-stock correlations correspond to values of the NAI which either indicate recessions or the beginning of expansions with growth still below or at trend. On the other hand, a negative long-run correlation emerges when the NAI signals strong growth above trend. Clearly, the positive correlation during recessions is driven by the simultaneous drop in oil and stock prices. The economic recovery during the early phase of an expansion then leads to increasing oil prices due to higher demand as well as to rising stock prices because of the improved outlook for corporate cash flows. The combination of these two effects causes the long-run oil-stock correlation to remain positive. This interpretation squares with the findings in Kilian and Park (2009) regarding the positive short-run effect of an unexpected increase in global demand on oil and stock prices. Finally, during boom phases with strong growth above trend both the further increasing oil prices as well as the expectation of rising interest rates have a depressing effect on the stock market. Hence, for these periods our model predicts a negative long-term correlation.

Third, the long-term correlation component can be interpreted as the predicted or expected correlation given a certain state of the economy. Since the macroeconomic variables which drive the long-term component represent aggregate demand, the deviations of the short-term from the long-term component should be driven by other factors related to the stock and/or the oil market. Typical examples would be either oil specific, i.e. precautionary, demand shocks or supply shocks. The fact that various measures of macroeconomic activity lead to a convincing and coherent fit of the long-term correlation suggests that aggregate demand is the most important factor for the oil-stock relationship. Our results can thus be understood as further empirical evidence for Kilian's (2009, p.1068) claim that "models of endogenous oil prices should focus on the aggregate demand side of the oil market".

Fourth, the fact that the sign of the oil-stock correlation critically depends on the state of the economy reinforces the argument by Kilian and Park (2009) that simple regressions of stock returns on oil price changes can be very misleading. This point may well explain the conflicting empirical evidence on the oil-stock relationship in Jones and Kaul (1996), Wei (2003) and others.

Fifth, as shown in Colacito et al. (2011) the explicit modeling of the long-term correlation component can be very beneficial when it comes to portfolio choice, hedging decisions or risk management. In the oil-stock context we expect the potential efficiency gains to be highly relevant, since the time-varying correlations are relatively large and – in contrast to backward looking models – the DCC-MIDAS-X specification allows us to anticipate changes in correlations.

Finally, several remarks are in order. The DCC-MIDAS-X specification remains a reduced form model. Hence, while we find that measures of economic activity are helpful predictors for the long-term oil-stock correlation, our estimates do not necessarily have a causal interpretation. Further, the model does not explicitly distinguish between different types of shocks to oil prices as in, e.g., Kilian and Park (2009) or Kilian (2009). However, we can interpret our long-term correlation component as the correlation that would be prevalent if the aggregate demand side dominates. Oil specific shocks due to precautionary demand or supply shocks are rather reflected by the short-term component and can be considered as a reason why the short-term component can deviate from the long-run trend. The behavior of the short-term component during the invasion of Kuwait in August 1990 and the second Gulf War in 2003 are in line with this interpretation. Finally, we focus on economic activity measures for the U.S. only, while the oil price is driven by global demand. Nevertheless, we believe that our U.S. activity measures are likely to be highly correlated with global demand for most of the time.

The remainder of the article is organized as follows. Section 2 reviews the related literature while Section 3 discusses the GARCH-MIDAS and DCC-MIDAS models. The data and empirical results are presented in Sections 4 and 5. Section 6 provides some robustness analysis and Section 7 concludes the article.

2 Related literature

Our analysis is based on two strands of literature. The first one is concerned with the modeling of long-term movements in volatilities and correlations, the second one with the relationship between oil, the macroeconomy and stock prices.

The idea of having short- and long-term component models of volatilities dates back to Ding and Granger (1996) and Engle and Lee (1999). In their specifications, both components simply follow 'GARCH-type' processes but with different degrees of persistence. Similarly, Davidson (2004) proposed the HYGARCH specification which can be considered as a two component model with the short-term component being a GARCH process while the long-term component follows a FIGARCH process (see also Conrad, 2010). While these specifications allow to separate the two volatility components, both components are assumed to be driven by the same shocks. In addition, the unconditional variance is still constant over time. Engle and Rangel (2008) and Engle et al. (2009) relax this assumption and propose specifications in which the long-term component can be considered a time-varying unconditional variance. While in the Engle and Rangel (2008) Spline-GARCH model both components fluctuate at the same frequency, Engle et al. (2009) assume that the long-term component evolves at a lower frequency than the short-term component. Using the MIDAS framework of Ghysels et al. (2005, 2007), they directly relate the long-term component to the evolution of macroeconomic time series such as industrial production or inflation. In line with the earlier findings in Schwert (1989), the GARCH-MIDAS model provides strong evidence for a counter cyclical behavior of financial volatility. Recently, Conrad and Loch (2011) extend the analysis of Engle et al. (2009) by using a broader set of macroeconomic variables including leading indicators and expectations data from the Survey of Professional Forecasters. The DCC-MIDAS model proposed in Colacito et al. (2011) simply extends the two component idea from volatilities to correlations. However, instead of relating the long-term correlation directly to its potential macroeconomic sources, Colacito et al. (2011) only consider lagged realized correlations as explanatory variables.

Since the seminal articles of Hamilton (1983, 1985, 2003) exogenous oil supply shocks were suspected to be causal for recessions and periods of low economic growth. Based on this presumption, several empirical studies have analyzed the relationship between oil prices and stock market returns. While Jones and Kaul (1996) or Nandha and Faff (2008) indeed find that oil price increases negatively affect stock prices, Huang et al. (1996) or Wei (2003) cannot establish a significant relationship. Recently, Miller and Ratti (2009) provide evidence for a time-varying relationship. For the period after 1999 they even report a positive connection. Hence, the empirical evidence is far from being uncontroversial. Kilian and Park (2009) provide two explanations for the conflicting results. First, although the oil price is often assumed to be exogenous with respect to the U.S. economy, there may be reverse causality at work (see also Barsky and Kilian, 2004). Similarly, Harris et al. (2009) argue that – in contrast to the 1970s when supply shocks were likely to be predominant – oil prices are mainly driven by high global aggregate demand since the mid-1990s. Thus, stock and oil price changes may be induced by the same macroeconomic factors and, hence, regressions of stock returns on oil price changes may be misleading due to endogeneity. The empirical results in Ewing and Thompson (2007) confirm the procyclical behavior of oil prices and specifically indicate that crude oil prices lag industrial production. Second, Kilian and Park (2009) argue that the sign of the effect of an oil price increase on the stock market depends on the type of the underlying shock and, hence, may change over time. While shocks due to an unanticipated economic expansion may have a positive impact, shocks related to precautionary demand are likely to have a negative impact. For several oil-importing and oil-exporting countries Filis et al. (2011) show that the oil-stock correlation is indeed time-varying. Although they informally relate phases of positive or negative correlations to demand and supply shocks, their simple DCC-GARCH model does not explicitly incorporate information on the state of the economy. In particular, their model does not allow to forecast changes in correlations in response to changes in the macro environment.

3 The DCC-MIDAS Model

In this section, we develop the econometric framework to analyze the impact of macroeconomic variables on long-term volatility and correlations. We consider the bivariate vector of asset returns $\mathbf{r}_t = (r_{1,t}, r_{2,t})'$, where $r_{1,t}$ refers to the stock and $r_{2,t}$ to the oil returns, and denote by $\mathcal{F}_{t-1} = \sigma(\mathbf{r}_{t-1}, \mathbf{r}_{t-2}, \ldots)$ the σ-field generated by the information available through time $t-1$. Let $\mathbf{E}[\mathbf{r}_t|\mathcal{F}_{t-1}] = \boldsymbol{\mu}_t = (\mu_{1,t}, \mu_{2,t})'$ and define the vector of residuals $\mathbf{r}_t - \boldsymbol{\mu}_t = \boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$. We assume that conditional on $\mathcal{F}_{t-1}$ the residuals are normally distributed with $\mathbf{Var}[\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}] = \mathbf{H}_t$, i.e. $\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1} \sim \mathcal{N}(\mathbf{0}, \mathbf{H}_t)$. Following Engle (2002), we decompose the conditional covariance matrix into $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$ where

$$\mathbf{R}_t = \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{12,t} & 1 \end{pmatrix} \qquad \text{and} \qquad \mathbf{D}_t = \begin{pmatrix} h_{1,t}^{1/2} & 0 \\ 0 & h_{2,t}^{1/2} \end{pmatrix}. \tag{1}$$

Finally, we define the standardized residuals $\boldsymbol{\eta}_t = (\eta_{1,t}, \eta_{2,t})'$ as $\boldsymbol{\eta}_t = \mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t$. Note that $\mathbf{Var}[\boldsymbol{\eta}_t|\mathcal{F}_{t-1}] = \mathbf{R}_t$. The DCC framework allows us to separately model the conditional variances and the conditional correlations.

3.1 Conditional Variances

To capture the impact of macroeconomic variables on return volatility, we adopt the GARCH-MIDAS framework of Engle et al. (2009). We assume a multiplicative component model for each conditional variance, i.e. we specify $h_{i,t} = g_{i,t} m_{i,\tau}$, where $g_{i,t}$ is the short-run and $m_{i,\tau}$ the long-run component. While the transitory volatility component changes at the daily frequency t, the long-run component changes at the monthly frequency τ only. We denote by $N^{(\tau)}$ the number of days within month τ. Specifically, we assume that the short-run volatility component follows a mean-reverting unit GARCH(1,1) process

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_{i,t-1})^2}{m_{i,\tau}} + \beta_i g_{i,t-1}, \tag{2}$$

with $\alpha_i > 0$, $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$. The long-term component is modeled as a slowly varying function of exogenous variables X_τ using the MIDAS specification

$$\log(m_{i,\tau}) = m_i + \theta_i \sum_{k=1}^{K_v} \varphi_k(\omega_i) X_{\tau-k}, \tag{3}$$

where the log transformation guarantees the non-negativity of the conditional variances when the exogenous variables can take negative values. The X_τ will be monthly macroeconomic variables. For the weighting scheme, we follow Engle et al. (2009) and adopt a restricted beta weighting scheme where the weights are computed according to

$$\varphi_k(\omega_i) = \frac{(1 - k/K_v)^{\omega_i - 1}}{\sum_{l=1}^{K_v} (1 - l/K_v)^{\omega_i - 1}}, \qquad k = 1, ..., K_v. \tag{4}$$

For all $\omega_i > 1$, the weighting scheme guarantees a decaying pattern, where the rate of decay is determined by ω_i. Large (small) values of ω_i generate a rapidly (slowly) decaying pattern. Given a maximum lag order K_v, the weighting scheme entails a data driven lag-length selection, depending on the scale of ω_i. K_v itself can be determined by the Akaike information criterion (AIC).

In the following, we will refer to the component model with explanatory variables as GARCH-MIDAS-X. Finally, note that when $\theta_i = 0$ the long-run component is simply a constant and $h_{i,t}$ follows a GARCH(1,1) process with unconditional variance $\sigma_i^2 = \exp(m_i)$.

3.2 Conditional Correlations

The DCC-MIDAS specification proposed by Colacito et al. (2011) provides a natural extension of the GARCH-MIDAS model to dynamic correlations. We first decompose the conditional correlation matrix as $\mathbf{R}_t = diag\{\mathbf{Q}_t\}^{-1/2}\mathbf{Q}_t diag\{\mathbf{Q}_t\}^{-1/2}$, with $\mathbf{Q}_t = [q_{ij,t}]_{i,j=1,2}$, and specify the quasi-correlations as

$$\mathbf{Q}_t = (1-a-b)\bar{\mathbf{R}}_t + a\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1} + b\mathbf{Q}_{t-1}, \tag{5}$$

with $a > 0$, $b \geq 0$, and $a + b < 1$. In the Engle (2002) DCC model with correlation targeting the matrix $\bar{\mathbf{R}}_t$ does not depend on time and equals the empirical correlation matrix of $\boldsymbol{\eta}_t$, i.e. has ones on the main diagonal while the off-diagonal elements are $\bar{\rho}_{12} = T^{-1}\sum_{t=1}^{T}\eta_{1,t}\eta_{2,t}$. In contrast, in the DCC-MIDAS framework introduced in Colacito et al. (2011) the off-diagonal elements are the long-term correlations $\bar{\rho}_{12,\tau}$. As in the GARCH-MIDAS equation the long-term correlation component does not vary at the daily frequency t but at the lower frequency τ. That is, the short-run quasi-correlations fluctuate around the time-varying long-run correlations:

$$q_{12,t} = \bar{\rho}_{12,\tau} + a(\eta_{1,t-1}\eta_{2,t-1} - \bar{\rho}_{12,\tau}) + b(q_{12,t-1} - \bar{\rho}_{12,\tau}). \tag{6}$$

Colacito et al. (2011) assume that $\bar{\rho}_{12,\tau}$ can be expressed as a weighted average of the K_c past realized correlations RC_τ:

$$\bar{\rho}_{12,\tau} = \sum_{k=1}^{K_c}\varphi_k(\omega_{12})RC_{\tau-k}, \tag{7}$$

with

$$RC_\tau = \frac{\sum_{t=(\tau-1)N^{(\tau)}+1}^{\tau N^{(\tau)}}\eta_{1,t}\eta_{2,t}}{\sqrt{\sum_{t=(\tau-1)N^{(\tau)}+1}^{\tau N^{(\tau)}}\eta_{1,t}^2}\sqrt{\sum_{t=(\tau-1)N^{(\tau)}+1}^{\tau N^{(\tau)}}\eta_{2,t}^2}}. \tag{8}$$

The weights are again given by equation (4) with ω_i and K_v replaced by ω_{12} and K_c, respectively. Since the weights $\varphi_k(\omega_{12})$ sum up to one and the RC_τ are correlations, the long-run correlation will itself lie within the $[-1, +1]$ interval.

We extend the DCC-MIDAS model by directly incorporating information on the macroeconomic development in the long-run component. Similarly as in the GARCH MIDAS setting – where the specification for $m_{i,\tau}$ has to ensure the non-negativity of the long-term volatility – our specification has to ensure that the long-run correlation lies within the $[-1, +1]$ interval although the macroeconomic explanatory variables do not. We follow Christodoulakis and Satchell (2002) and use the Fisher-z transformation of the correlation coefficient, i.e. we assume that

$$\bar{\rho}_{12,\tau} = \frac{\exp(2z_{12,\tau}) - 1}{\exp(2z_{12,\tau}) + 1}, \tag{9}$$

with

$$z_{12,\tau} = m_{12} + \theta_{12} \sum_{k=1}^{K_c} \varphi_k(\omega_{12}) X_{\tau-k}, \tag{10}$$

where X_τ denotes either a macroeconomic explanatory variable or the realized correlations. Note that in our non-linear specification, from θ we can only infer the sign but not directly the marginal effect of a macroeconomic variable on the long-term correlation.

Finally, in the DCC-MIDAS model - as in the standard DCC model - the short-run correlations are obtained by rescaling, i.e. $\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t} q_{22,t}}$. In the subsequent analysis we refer to the specifications with either macroeconomic explanatory variables or the realized correlations as DCC-MIDAS-X or DCC-MIDAS-RC models, respectively.

3.3 Estimation

Following Engle (2002) and Colacito et al. (2011) the model parameters can be estimated using a two-step procedure. This is feasible because the log likelihood function to be maximized

$$\mathcal{L} = -\sum_{t=1}^{T} \left(T\log(2\pi) + 2\log(|\mathbf{D}_t|) + \boldsymbol{\varepsilon}_t' \mathbf{D}_t^{-2} \boldsymbol{\varepsilon}_t \right) - \sum_{t=1}^{T} \left(\log(|\mathbf{R}_t|) + \boldsymbol{\eta}_t' \mathbf{R}_t^{-1} \boldsymbol{\eta}_t - \boldsymbol{\eta}_t' \boldsymbol{\eta}_t \right) \tag{11}$$

can be separated into two parts. The first sum in equation (11) contains the data and the variance parameters while the second sum depends on the volatility-adjusted residuals and the correlation parameters. Hence, in the first step we estimate the GARCH-MIDAS parameters individually for each return series and use the estimated volatility-adjusted residuals in the second step to obtain the correlation parameters.

4 Data

Since we apply the MIDAS approach, our data consists of observations at the daily as well as the monthly frequency. We combine daily stock market and crude oil price data with monthly observations on the macroeconomic variables. While the stock series was obtained from the Kenneth R. French data library, the oil prices and the macroeconomic data are taken from the FRED database at the Federal Reserve Bank of St. Louis. Our data covers the period from January 1993 to November 2011.

4.1 Oil and stock market data

For the stock series, we employ the daily returns on the CRSP value-weighted portfolio, which is based on all NYSE, AMEX and NASDAQ stocks and can be considered the best available proxy for 'the stock market'. In addition, the CRSP data facilitates comparison of our results with those of Engle et al. (2009) and Conrad and Loch (2011). As in Kilian and Vega (2011), the oil price returns are constructed from the West Texas Intermediate (WTI) crude oil spot price. Panel A of Table 1 provides summary statistics for the two return series. While the sample mean of the returns is positive for both markets, the table provides first evidence for stronger price fluctuations in the oil than in the stock market. The annualized unconditional standard deviation of the oil price returns is 39.18% and, hence, considerably higher than the 19.41% of the CRSP returns. Finally, the unconditional correlation between oil and stock returns is 0.15.

Table 1 about here

4.2 Macroeconomic data

We divide the monthly macroeconomic data into three categories. Those which measure the current stance of the economy, forward looking indicators and measures of inflation. The first category contains the following variables: industrial production (IP), nonfarm payrolls (NFP), and the unemployment rate (UR). The forward looking indicators are the national activity index (NAI)[2] and the leading index (LI)[3] for the U.S. They are supposed to reflect the role of market participants' expectations concerning the future economic development. The final category consists of the producer price index (PPI) and the consumer price index (CPI) and captures inflation dynamics.

[2]The NAI is standardized weighted average of 85 monthly indicators of national economic activity including figures that represent (i) production and income, (ii) employment, unemployment, and hours, (iii) personal consumption and housing, and (iv) sales, orders and inventories. The NAI is computed and published by the Federal Reserve Bank of Chicago. Positive realizations indicate growth above trend, while negative realizations indicate growth below trend. The variables IP, NFP, and UR are among the indicators used for the computation of the NAI.

[3]The LI predicts the six-month growth rate of the US coincident index based on variables that lead the economy including housing permits, unemployment insurance claims, delivery times from the ISM manufacturing survey, and the term spread. The LI is published by the Federal Reserve Bank of Philadelphia.

For the variables IP, PPI, and CPI we compute month-to-month growth rates according to $100 \cdot [\ln(X_\tau) - \ln(X_{\tau-1})]$, while in case of UR and NFP we use month-to-month changes. Finally, NAI and LI are included in levels. Panel B of Table 1 provides the summary statistics for the macroeconomic data. Figure 2 shows the dynamics of the macroeconomic variables for the period from January 1993 to November 2011.

Figure 2 about here

5 Empirical results

We first present the estimation results for the GARCH-MIDAS models which relate the long-term volatilities to the macroeconomic environment. Thereafter, the DCC-MIDAS specifications which focus on the long-run correlations are discussed.

5.1 Determinants of long-term volatilities

Tables 2 and 3 present the estimates for the various stock and oil GARCH-MIDAS models. In addition to the models which include the macroeconomic explanatory variables, we also consider the restricted version of equation (3) with $\theta_i = 0$. Recall, that in this benchmark specification the GARCH-MIDAS model reduces to a GARCH(1,1) with constant unconditional variance. Since this model is nested within the class of GARCH-MIDAS models, we can use likelihood-ratio tests (LRT) and the AIC to compare the fit of the models which are augmented by macroeconomic variables with the benchmark specification. Further, since the serial correlation in daily stock and oil returns is negligible, we choose $\mu_{i,t} = \mu_i$ in both conditional means. Based on the AIC we choose $K_v = 36$ for both markets, i.e. our specifications cover three MIDAS lag years. However, all results are robust to moderate changes in K_v. The constant μ_i is significant in all stock return models, but insignificant in the oil return specifications. In all cases the estimated α_i and β_i parameters are highly significant. Interestingly, while the α_i (β_i) parameters are estimated to be slightly higher (lower) in the stock than in the oil market, the sum $\alpha_i + \beta_i$ is almost identical in both markets and always less than one. That is, in all specifications the short-run volatility component is mean-reverting to the long-run volatility trend. Next, we discuss the estimated θ_i and ω_i parameters individually for the two markets.

Tables 2 and 3 about here

Table 2 shows that each variable in the two categories current stance of the economy and future economic outlook has a significant effect on long-term stock market volatility. For IP, NFP, NAI, and LI the estimated coefficient $\hat{\theta}_1$ is negative and highly significant, while it is positive and highly significant in case of UR. Since the sign of θ_1 measures whether an increase of the respective variable leads to an upswing or downswing in the long-run volatility, the estimates imply that higher (lower) levels of economic activity lead to a reduction (rise) in long-term stock market volatility. In stark contrast, both inflation measures do not significantly affect long-term stock market volatility. The LRT which compare the GARCH-MIDAS-X models with the restricted benchmark specification imply that we can reject the hypothesis that $\theta_1 = 0$ for all specifications with significant macroeconomic variables. This result is also confirmed by the AIC. Finally, the loglikelihood function, the LRT, and the AIC unambiguously identify the model including the unemployment rate as the one with the best fit.

Our results are consistent with the findings in Engle et al. (2009) and Conrad and Loch (2011). Engle et al. (2009) consider industrial production and producer price inflation as explanatory variables and report that industrial production strongly influences long-term U.S. stock market volatility. In line with our results, they find significant effects of inflation when it was high and volatile in the 1970s, but insignificant ones during the post-1985 period of the Great Moderation.[4] Conrad and Loch (2011) consider various other measures of economic activity including several leading indicators and find that variables which can predict the future state of the economy have explanatory power for long-run volatilities. This squares with our highly significant θ_1 estimates for LI and NAI. These variables are likely candidates to affect uncertainty concerning future cash flows and risk premia. In summary, our findings deliver further support for the view that long-term stock market volatility behaves counter cyclical.

In Table 3 we now turn to the analysis of the macroeconomic determinants of long-term oil market volatility. As in case of the stock market, the estimates for θ_2 suggest that long-term oil price volatility is closely linked to each of the macroeconomic variables describing the current stance of the economy as well as the future economic outlook. In particular, the results imply that downturns in U.S. economic activity, i.e. decreases in IP, NFP, NAI, and LI and increases in UR lead to higher levels of long-term oil market volatility. The empirical evidence implies that changes in variables which measure economic activity

[4] In addition to the levels, Engle et al. (2009) also investigate whether the uncertainties about IP and PPI affect stock volatility.

do precede changes in long-term oil market volatility. Although this result does not necessarily invalidate the assumption that "oil price changes cannot be predicted from earlier movements in macro variables" (see Hamilton, 2008), it challenges the view that oil price movements are exogenous with respect to the U.S. economy. We will return to this issue in the next subsection. The fact that measures of economic activity help to anticipate changes in oil price volatility also supports the argument of Hamilton (2009), Harris et al. (2009), and Kilian and Park (2009) that at least since the mid-1990s oil prices are mainly driven by aggregate demand and to a much lesser extend by oil supply shocks. Since then, an economic downturn can be viewed as a negative aggregate demand shock which increases long-term oil price volatility.[5] Similarly as for the stock returns, neither PPI nor CPI significantly affect oil price uncertainty. This, in turn, is consistent with the argument in Harris et al. (2009) that in contrast to the 1970s, the relationship between inflation and oil prices is muted during the 2000s. Similarly, Ewing und Thompson (2007) have shown that oil prices lag industrial production but lead consumer prices in the period 1982-2005. Lastly, the LRT and the AIC in Table 3 reveal that all GARCH-MIDAS-X specifications with significant macroeconomic variables achieve a better fit than the restricted GARCH(1,1). While the information criteria of the various GARCH-MIDAS-X specifications are pretty similar, it is interesting that UR and LI achieve the best fit which is in line with the stock market results.

Figure 3 shows the GARCH-MIDAS-UR estimates of the annualized long-term volatility components for the two markets. While the level of oil price volatility is about twice as high as the one of the stock prices, the evolution of the two components is very similar across markets. The observation that the macroeconomic environment affects long-term oil and stock volatility in almost the same way is very interesting. Recently, Kilian and Vega (2011) investigated whether oil prices can be viewed as asset prices. By regressing daily oil price changes on macroeconomic news they find that oil prices do not react to U.S. macroeconomic aggregates and, hence, conclude that oil prices behave very differently from asset prices. However, our results suggest that at least the second moments of oil and stock returns respond in a comparable fashion to macroeconomic news.

Figure 3 about here

[5] The finding is analogous to the leverage effect in the stock market. A positive (negative) demand shock leads to increasing (decreasing) oil prices and thereby decreases (increases) oil market uncertainty.

Based on the estimates $\hat{\omega}_i$ and $\hat{\theta}_i$, we now quantitatively compare the persistence and the magnitude of the effect of changes in the macro variables on long-term volatility in both markets. As can be seen from Tables 2 and 3, for each macroeconomic variable with significant θ_i, the corresponding estimate $\hat{\omega}_i$ is considerably larger in the oil than in the stock market. Hence, the effect of changes in macro variables on long-term volatility is less persistent in the oil market than in the stock market. Following Engle et al. (2009), we can compute the magnitude of an effect of a one percent (unit) change in the macroeconomic variable X_τ on the long-term volatility in month $\tau+1$ according to $exp(\hat{\theta}_i \cdot \varphi_1(\hat{\omega}_i))-1$. Even though we observe differences in the persistence of the effects across markets, we find that the magnitude of the effects in $\tau+1$ is pretty similar. In case of the GARCH-MIDAS-UR, a one percentage point increase in this variable is accompanied by an increase in long-term stock market volatility of 0.799%, while oil price volatility increases by 0.712%.

5.2 Determinants of long-term correlations

Next, we analyze the macroeconomic determinants of the long-term oil-stock correlation. Now we consider two benchmark specifications. The first natural benchmark is the DCC-GARCH model which is obtained from the DCC-MIDAS specification by replacing $\bar{\rho}_{12,\tau}$ with the unconditional correlation of the volatility-adjusted GARCH residuals. The second benchmark specification follows Colacito et al. (2011) and uses backward-looking monthly realized correlations as explanatory variables. We estimate two versions: one where m_{12} und θ_{12} vary freely (DCC-MIDAS-RC) and one where we restrict these parameters to $m_{12} = 0$ and $\theta_{12} = 1$ (DCC-MIDAS-RC restr). In the DCC-MIDAS-X specifications we replace the realized correlations with key macroeconomic figures. In order to facilitate comparison between the various DCC, DCC-MIDAS-RC and DCC-MIDAS-X models, the first step volatility-adjusted residuals for all models are taken from the benchmark GARCH(1,1) specification. As in case of the long-term volatilities, we find that the optimal lag length is equal to three MIDAS lag years, i.e. we choose $K_c = 36$.

Table 4 presents the estimation results. Clearly, in all specifications the estimated parameters a and b are highly significant and sum up to a value of less than one. That is, the quasi-correlations are mean-reverting either to the unconditional correlation in the DCC-GARCH case or to the long-term correlation in the various DCC-MIDAS-X specifications. The estimates of θ_{12} indicate that all variables which represent the current stance of the economy or the future economic outlook significantly affect the long-run oil-stock correlation. In line with our analysis in Section 5.1, we find negative θ_{12} coefficients on IP, NFP, NAI, and LI, while the coefficient on UR is positive. The estimates imply that a contraction of macroeconomic activity leads to an increase of the long-term correlation. Moreover, none of the two inflation measures can explain the long-run co-movements in stock and oil prices which again reinforces our findings from the long-term volatility analysis.

Table 4 about here

According to the LRT, all DCC-MIDAS-X specifications with significant θ_{12} estimates as well as the restricted DCC-MIDAS-RC model are preferred to the nested DCC-GARCH. Hence, there is convincing evidence in favor of the component models which allow for a time-varying long-term correlation. In addition, a comparison of the information criteria also confirms the superiority of the DCC-MIDAS-X models relative to the DCC-MIDAS-RC benchmark specification. Finally, according to the AIC the DCC-MIDAS-NAI model achieves the best fit among all specifications. We explain below that the forward looking properties of the NAI which gauges future economic activity as well as inflationary pressures (and thereby future monetary policy) are particularly relevant for anticipating changes in the oil-stock correlation. Note that the model which includes UR still performs second best.

Figure 1 shows the estimated dynamics of the short- and long-run correlations based on the DCC-MIDAS-NAI specification together with a rolling-window of yearly realized correlations. First, although the unconditional correlation between stock and oil returns was found to be 0.15, the figure shows that there is substantial time-variation in the realized correlations with prolonged periods of positive or negative correlations. While the short-run component closely follows the behavior of the realized correlations, the long-run correlation evolves much more smoothly. Both the realized correlations as well as the short-run correlations follow this long-run trend component. Figure 1 reveals a very interesting cyclical pattern in the evolution of the long-run correlation. At the beginning of the sample period in 1993 the correlation takes a value of 0.14 and then starts to decrease until it reaches a minimum of -0.12 in 1994. It stays in the negative territory until mid-2000. From mid-2000 onwards the long-term correlation starts to increase and turns positive before the recession of 2001 (first shaded area). The correlation further increases until it reaches a peak of 0.25 at the end of the recession. The figure shows that the long-term correlation remains above 0.2 for the two subsequent years, which are followed by a smooth decrease and a period of negative correlations during the years 2005 to 2006. Again, the long-term correlation starts to increase almost two years before the recession of 2007-2009 and becomes positive clearly before the beginning of the recession (second shaded area). At the end of this recession we observe a peak at 0.60. Finally, the correlation starts to decrease smoothly.

To provide an economic interpretation of the correlation dynamics we refer to Figure 4 which depicts the long-term correlation along with the NAI. First, the figure clearly shows the inverse relationship between the NAI and the long-term oil-stock correlation which was already evident from the negative θ_{12} estimate in Table 4. On average, the oil-stock correlation is positive (negative) when the NAI takes negative (positive) values, i.e. when the economy is expanding below (above) trend growth. Interestingly, when the NAI turns negative before and during the 2001 and 2007-2009 recessions the long-term correlation steeply increases, while it decreases more gradually when the NAI stays in the negative territory in the aftermath of the recessions. On the other hand, the long period of growth above trend from 1994 to 1999 is accompanied by a period of negative oil-stock correlations.[6] Our empirical evidence for a counter cyclical oil-stock correlation is again perfectly in line with the recent evidence in Harris et al. (2009) and Kilian (2009) in favor of a positive oil-growth relation. Similarly, the results in Section 5.1 support the view that good news on the macroeconomy are also good news for the oil price, i.e. reduce oil volatility. Increasing economic activity leads to higher oil demand and, consequently, higher oil prices. Further, Kilian and Park (2009) argue that in an early phase of an expansion increasing oil prices may not have negative effects on the stock market. This is because in the short-run the positive effect of higher economic activity on expected future cash flows dominates and, hence, the oil-stock correlation will be positive. However, in the long-run the negative effect of increasing oil prices on corporate cash flows will dominate and turn the oil-stock correlation negative.

Figure 4 about here

The long-term correlation in Figure 4 very much supports these views. Before and during both recessions bad news on the NAI lead to sharply decreasing stock and oil prices and, therefore, to a positive oil-stock correlation. The fact that the correlation turns positive well before both recessions is remarkable and suggests that the long-term

[6] Only during 1995 when the NAI takes a few negative values the long-term correlation temporarily increases but remains negative.

oil-stock correlation may itself be used as an early recession indicator. During the recovery phases in 2002-2003 and 2010-2011 the improvement in the NAI leads to increasing oil prices and at the same time to upward revisions concerning firms' expected dividends and cash flows. In these periods the oil-stock correlation remains positive, but smoothly decreases. The same rationale also applies to the first year of our sample, which falls into the recovery period after the recession of 1990/91 (see Section 6). Finally, during the years 1994-1999 and 2005-2006 the NAI grows above trend for a protracted period which again should positively affect oil prices. However, the (expected) oil price increases now dampen the outlook for future corporate cash flows, i.e. during these periods the good news on the macroeconomy – through the indirect effect via increasing oil prices – turn into bad news for the stock market. Alternatively, the negative effect might also work via interest rates. When the economy is already close to full employment, good news on the NAI should signal higher future interest rates and, hence, be bad news for the stock market. During these strong boom phases the negative effect dominates and leads to a negative long-run oil-stock correlation.

Since the evolution of the long-term correlation is purely driven by variables which represent U.S. aggregate demand, deviations of the short-term component from the long-run trend must be related to other factors which either affect stock and/or oil returns. Typical oil related factors would be oil supply shocks or oil specific, i.e. precautionary, demand. Specifically, the temporary deviation in 2003 may be due to precautionary demand provoked by the second Iraq war (see Figure 1). Another example would be the positive correlation signaled by the short-term component as well as the realized correlations around 1998/99. Following the Asian and Russian financial crises, this positive short-term correlation can be explained by simultaneously falling oil and stock prices. Nevertheless, the fact that these deviations occur only for relatively short periods suggests that the oil-stock correlation can be well explained by U.S. economic activity for most of the time. This result is very much in line with Kilian (2009, p.1068) who reasons that "models of endogenous oil prices should focus on the demand side of the oil market".

A particular interesting conclusion that can be drawn from the time-varying oil-stock correlation is that regressions of stock returns on oil price changes are likely to be misleading, since the result will depend on the state of the economy. This insight may explain the controversial empirical findings on the oil-stock relationship and squares with the arguments put forward in Kilian and Park (2009).

Next, we discuss the MIDAS lag structure and its implications more closely. Recall that the higher ω_{12} the more weight will be given to the more recent observations of the macro variable and, hence, the faster the weights will decline to zero. Table 4 reveals that the lowest ω_{12} is estimated for IP and the highest for NFP. Since the DCC-MIDAS-NAI model produced the best fit for the correlations, we plot in Figure 5 the corresponding weighting function. For comparison, we also plot the weighting functions for the GARCH-MIDAS-NAI models for the stock and oil market. The figure shows that the weighting function of the correlation model is nearly linear while the weighting functions of the volatility specifications are rapidly declining. This in turn implies that changes in the NAI have a much more persistent effect on the long-run correlation than on the long-run volatilities. We obtain similar results for each of the other significant macroeconomic variables.

Figure 5 about here

In the previous considerations we mainly focused on the DCC-MIDAS-NAI specification to explain the dynamic behavior of the slowly-moving long-run correlation component. However, Table 4 clearly reveals that the fit of the DCC-MIDAS-X specifications with IP, NFP, UR, and LI are only slightly inferior. Figure 6 displays the estimated long-run correlations from the corresponding specifications. The figure nicely illustrates that the long-term components of all specifications follow the same pattern and, hence, further support our argument that the long-term oil-stock correlation is counter cyclical. Note that the exceptional deviation in the long-term correlation component predicted by IP for October 2005 can be traced back to a significant contraction in industrial production one month earlier which is not reflected to such a strong intend in the other macroeconomic figures (compare Figure 2).

Figure 6 about here

6 Robustness

In this section we present evidence on the robustness of our results by considering alternative measures of the stock market and extending our sample period. We first make use of two alternative return series representing the stock market: the S&P 500 and the DJIA index (both were obtained from the FRED database). Second, we extend the initial sample to the period 1986-2011 and thus include the first Gulf War from 1990 to 1991.

6.1 S&P 500 and DJIA

Tables 5 and 6 refer to the specifications including the S&P 500 and the DJIA index, respectively. The coefficient estimates in both tables broadly confirm the results presented in Table 4. Again, all variables on the current economic stance as well as the future economic outlook significantly affect the long-term correlation between stock and oil prices. As for the CRSP, the DCC-MIDAS-NAI specification achieves the best fit in both cases.

Tables 5 and 6 about here

6.2 Extended Sample

The parameter estimates for the extended sample are qualitatively identical to the ones for the original sample and, hence, strongly confirm our previous interpretations.[7] Nevertheless, the extended sample allows for some further insights into the behavior of the long- and short-term correlation components. Both components are plotted in Figure 7 for the DCC-MIDAS-NAI model. While the behavior of the long-term correlation component during the recession of 1990/91 exhibits the same pattern as described above, the short-term correlation component sharply declines from 0.15 to −0.30 with the invasion of Kuwait on August 2. In line with Kilian (2009), we view the evolution of the short-term component as mainly triggered by precautionary demand. On January 18, the short-term component realized an all-time minimum of −0.47 as a consequence of the 40% oil price drop accompanied by a stock market recovery of more than 3%. This was caused by the decision of the Bush administration to compensate for shortfalls in oil supply by releasing the strategic crude oil reserves. Finally, at the beginning of 1993 the short-term correlation reverts to the long-term component.

Figure 7 about here

7 Conclusion

We investigate the effect of changes in the U.S. macroeconomic environment on the long-term co-movements between crude oil and stock price returns. For this, we extend the two-component DCC-MIDAS model of Colacito et al. (2011) by allowing the slowly-moving long-term correlation component to be determined endogenously by the variation of key

[7]The estimates are not reported but are of course available upon request to the authors.

macroeconomic figures. We show that changes in macroeconomic variables which reflect the current stance of the economy as well as the future economic outlook can anticipate counter cyclical fluctuations in the long-term correlation. More specifically, our model predicts a negative correlation during prolonged periods of strong economic expansions, while a positive correlation is observed during recessions and recoveries. The correlation pattern suggests that during recessions (expansions with growth below or at trend), bad (good) news on the macroeconomy are bad (good) news for the stock as well as for the oil market. However, during periods with strong growth above trend, good news on the macroeconomy are still good news for the oil market but become bad news for the stock market. This is because both the further increasing oil prices as well as the expectation of rising interest rates have a depressing effect on the stock market.

Our results provide further evidence for the argument put forward in Barsky and Kilian (2004) and Kilian (2009) that oil price changes should not be considered exogenous with respect to the U.S. economy. The counter cyclical behavior of the long-term oil-stock correlation squares with the recent evidence in Harris et al. (2009) and Kilian and Park (2009) that oil price developments have been synchronized with the business cycle since the mid-1990s. Moreover, the finding that the sign of the oil-stock correlation varies with the state of the economy, may explain the conflicting empirical evidence in previous studies on the oil-stock relationship when simple regressions of stock returns on oil price changes are employed.

Finally, we also assess the impact of macroeconomic developments on the long-term volatilities of crude oil and stock price returns. Our results show that the long-term volatilities in both markets are driven by the same macroeconomic factors. Hence, while Kilian and Vega (2011) report that oil prices in contrast to asset prices do not respond to U.S. macroeconomic news, at the least the second moments of oil price returns behave very much like those of asset prices.

References

[1] Barsky, R., and Kilian, L., 2004. Oil and the macroeconomy since the 1970s. *Journal of Economic Perspectives* 18, 115-134.

[2] Bollerslev, T., and Wooldridge, J., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews* 11, 143-172.

[3] Christodoulakis, G. and Satchell, S., 2002. Correlated ARCH (CorrARCH): Modelling the time-varying conditional correlation between financial asset returns. *European Journal of Operational Research* 139, 351-370.

[4] Colacito, R., Engle, R., and Ghysels, E., 2011. A component model for dynamic correlations. *Journal of Econometrics* 164, 45-59.

[5] Conrad, C., 2010. Non-negativity conditions for the hyperbolic GARCH model. *Journal of Econometrics* 157, 441-457.

[6] Conrad, C., and Loch, K., 2011. Anticipating long-term stock market volatility. Working paper. Heidelberg University.

[7] Davidson, J., 2004. Moment and memory properties of linear conditional heteroscedasticity models, and a new model. *Journal of Business and Economic Statistics* 22, 16-19.

[8] Ding, Z., and Granger, C., 1996. Modeling volatility persistence of speculative returns: A new approach. *Journal of Econometrics* 73, 185-215.

[9] Driesprong, G., Jacobsen, B., and Maat, B., 2008. Striking oil: Another puzzle? *Journal of Financial Economics* 89, 307-327.

[10] Engle, R., 2002. Dynamic conditional correlation - a simple class of multivariate GARCH models. *Journal of Business and Economic Statistics* 20, 339-350.

[11] Engle, R., Ghysels, E., and Sohn, B., 2009. Stock market volatility and macroeconomic fundamentals. (Former title: On the economic sources of stock market volatility). Working Paper. New York University.

[12] Engle, R., and Lee, G., 1999. A permanent and transitory component model of stock return volatility. In: Engle, R., White, H. (Eds.). Cointegration, Causality and Forecasting: A Festschrift in Honor of Clive W.J. Granger. Oxford University Press.

[13] Engle, R., Rangel, J., 2008. The spline GARCH model for unconditional volatility and its global macroeconomic causes. *Review of Financial Studies* 21, 1187-1222.

[14] Ewing, B., and Thompson, M., 2007. Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. *Energy Policy* 35, 5535-5540.

[15] Filis, G., Degiannakis, S., Floros, C., 2011. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis* 20, 152-164.

[16] Ghysels, E., Santa-Clara, P., and Valkanov, R., 2005. There is a risk-return trade-off after all. *Journal of Financial Economics* 76, 509-548.

[17] Ghysels, E., Sinko, A., and Valkanov, R., 2007. MIDAS regressions: Further results and new directions. *Econometric Reviews* 26, 53-90.

[18] Hamilton, J., 1983. Oil and the macroeconomy since World War II. *Journal of Political Economy* 91, 228-248.

[19] Hamilton, J., 1985. Historical causes of postwar oil shocks and recessions. *Energy Journal* 6, 97-116.

[20] Hamilton, J., 2003. What is an oil shock? *Journal of Econometrics* 113, 363-398.

[21] Hamilton, J., 2008. Oil and the macroeconomy. In: Durlauf, S., and Blume, L. (Eds.). New Palgrave Dictionary of Economics. 2nd edition. Palgrave McMillan Ltd.

[22] Hamilton, J., 2009. Understanding crude oil prices. *Energy Journal* 39, 179-206.

[23] Harris, E., Kasman, B., Shapiro, M. and West, K., 2009. Oil and the macroeconomy: Lessons for monetary policy. US Monetary Policy Forum Conference Paper.

[24] Huang, R., Masulis, R., and Stoll, H., 1996. Energy shocks and financial markets. *Journal of Futures Markets* 16, 1-27.

[25] Jones, C., and Kaul, G., 1996. Oil and the stock markets. *Journal of Finance* 51, 463-491.

[26] Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review* 99, 1053-1069.

[27] Kilian, L., and Park, C., 2009. The impact of oil price shocks on the U.S. stock market. *International Economic Review* 50, 1267-1287.

[28] Kilian, L., and Vega, C., 2011. Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. *Review of Economics and Statistics* 93, 660-671.

[29] Miller, J., and Ratti, R., 2009. Crude oil and stock markets: Stability, instability, and bubbles. *Energy Economics* 31, 559-568.

[30] Nandha, M., and Faff, R., 2008. Does oil move equity prices? A global view. *Energy Economics* 30, 986-997.

[31] Schwert, W., 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1153.

[32] Wei, C., 2003. Energy, the stock market, and the Putty-Clay investment model. *American Economic Review* 93, 311-323.

8 Appendix

8.1 Tables

Table 1: Descriptive Statistics (January 1993 - November 2011)

Variable	Obs	Min	Max	Mean	Std. Dev.*	Skewness	Kurtosis
Panel A (Daily return data)							
Oil	4744	-17.09	16.41	0.0332	39.18	-0.19	7.73
CRSP	4744	-9.00	11.52	0.0365	19.41	-0.15	11.07
Panel B (Monthly macro data)							
Current stance of the economy							
IP	227	-4.23	2.15	0.17	0.69	-1.73	11.30
NFP	227	-820	508	98.21	234	-1.46	5.93
UR	227	-0.50	0.60	0.01	0.18	0.62	4.37
Future economic outlook							
NAI	227	-4.46	1.55	-0.14	0.87	-1.92	8.71
LI	227	-3.82	2.84	1.17	1.20	-1.83	7.25
Inflation rates							
PPI	227	-5.48	2.94	0.24	1.11	-1.30	8.97
CPI	227	-1.83	1.37	0.21	0.28	-1.79	16.56

Notes: *The standard deviations are annualized for the daily return series.

Table 2: GARCH-MIDAS parameter estimates: CRSP

Variable	μ_1	α_1	β_1	m_1	θ_1	ω_1	LLF	LRT	AIC
Current stance of the economy									
IP	0.0678***	0.0843***	0.9056***	0.3873*	−0.9893**	2.7737**	-6520.74	4.48	2.7487
	(0.0119)	(0.0123)	(0.0137)	(0.2339)	(0.4961)	(1.2659)		[0.1065]	
NFP	0.0680***	0.0873***	0.8998***	0.3714*	−0.0019***	8.8520	-6518.19	9.58	2.7476
	(0.0119)	(0.0128)	(0.0147)	(0.2038)	(0.0005)	(5.6496)		[0.0083]	
UR	0.0688***	0.0863***	0.9010***	0.1403	3.9929***	5.5678*	-6515.07	15.82	**2.7463**
	(0.0117)	(0.0121)	(0.0138)	(0.2015)	(0.7600)	(2.9746)		[0.0004]	
Future economic outlook									
NAI	0.0682***	0.0864***	0.9010***	0.1036	−0.6120***	6.0568	-6517.63	10.7	2.7474
	(0.0118)	(0.0126)	(0.0144)	(0.2077)	(0.1382)	(4.1461)		[0.0047]	
LI	0.0681***	0.0867***	0.8999***	0.6557***	−0.4055***	5.8714	-6515.83	14.3	2.7466
	(0.0118)	(0.0125)	(0.0142)	(0.2117)	(0.0814)	(4.5227)		[0.0008]	
Inflation rates									
PPI	0.0666***	0.0823***	0.9098***	0.2506	−0.0895	15.8835	-6522.44	1.08	2.7494
	(0.0119)	(0.0120)	(0.0131)	(0.2658)	(0.1545)	(27.6558)		[0.5827]	
CPI	0.0664***	0.0815***	0.9106***	0.1806	0.1907	532.2708***	-6521.69	2.58	2.7491
	(0.0119)	(0.0117)	(0.0127)	(0.2566)	(0.1486)	(0.0188)		[0.2753]	
Benchmark model									
GARCH(1,1)	0.0665***	0.0822***	0.9099***	0.0112***	-	-	-6522.98	-	2.7488
	(0.0119)	(0.0119)	(0.0129)	(0.2281)					

Notes: The numbers in parentheses are Bollerslev-Wooldridge robust standard errors. ***, **, * indicate significance at the 1 %, 5 %, and 10 % level. LLF is the value of the maximized likelihood function and AIC is the Akaike information criterion. The numbers in bold letters indicate the model with the smallest value of the information criterion. LRT is the likelihood ratio test $LR = 2[L_{UR} - L_R]$, where L_{UR} is the likelihood of the unrestricted GARCH-MIDAS-X specification and L_R is the likelihood of the restricted benchmark model. The numbers in brackets are p-values.

Table 3: GARCH-MIDAS parameter estimates: Oil market

Variable	μ_2	α_2	β_2	m_2	θ_2	ω_2	LLF	LRT	AIC
Current stance of the economy									
IP	0.0486	0.0582***	0.9230***	1.8422***	-0.4641^{**}	6.9842***	-10589.1	5.2	4.4620
	(0.0331)	(0.0157)	(0.0221)	(0.1389)	(0.2353)	(2.2342)		[0.0743]	
NFP	0.0475	0.0597***	0.9225***	1.8526***	-0.0008^{**}	16.5369***	-10589.2	5.0	4.4621
	(0.0331)	(0.0158)	(0.0212)	(0.1485)	(0.0004)	(6.1789)		[0.0821]	
UR	0.0497	0.0579***	0.9230***	1.7406***	1.6849***	13.4396**	-10586.3	10.8	**4.4609**
	(0.0327)	(0.0146)	(0.0202)	(0.1310)	(0.6116)	(6.1886)		[0.0045]	
Future economic outlook									
NAI	0.0484	0.0571***	0.9251***	1.7239***	-0.2890^{**}	15.1178**	-10588	7.4	4.4616
	(0.0331)	(0.0156)	(0.0215)	(0.1378)	(0.1148)	(6.8522)		[0.0247]	
LI	0.0481	0.0573***	0.9239***	2.0059***	-0.2084^{***}	18.8496***	-10586.5	10.4	**4.4609**
	(0.0329)	(0.0154)	(0.0212)	(0.1542)	(0.0609)	(7.0180)		[0.0055]	
Inflation rates									
PPI	0.0461	0.0582***	0.9264***	1.8007***	-0.0881	16.0532*	-10591.1	1.2	4.4629
	(0.0333)	(0.0164)	(0.0209)	(0.1549)	(0.1196)	(9.3534)		[0.5488]	
CPI	0.0470	0.0599***	0.9248***	1.7799***	0.0291	5.9839	-10591.7	0.0	4.4631
	(0.0331)	(0.0156)	(0.0197)	(0.2252)	(0.7773)	(14.9089)		[1.0000]	
Benchmark model									
GARCH(1,1)	0.0470	0.0599***	0.9248***	1.7858***	-	-	-10591.7	-	4.4623
	(0.0332)	(0.0156)	(0.0196)	(0.1586)					

Notes: See Notes of Table 2.

Table 4: DCC-MIDAS parameter estimates: CRSP and oil market

Variable	a	b	m_{12}	θ_{12}	ω_{12}	LLF	LRT	AIC
Current stance of the economy								
IP	0.0189***	0.9713***	0.2143***	$-0.6888^{\star\star\star}$	1.5996*	-4665.09	13.1	1.9668
	(0.0063)	(0.0107)	(0.0594)	(0.1936)	(0.8845)		[0.0044]	
NFP	0.0190***	0.9706***	0.1982***	$-0.0010^{\star\star\star}$	3.8517	-4664.52	14.24	1.9665
	(0.0064)	(0.0118)	(0.0545)	(0.0003)	(3.3013)		[0.0026]	
UR	0.0204***	0.9636***	0.0582	2.6018***	1.7203**	-4663.00	17.28	1.9659
	(0.0058)	(0.0112)	(0.0360)	(0.6054)	(0.7918)		[0.0006]	
Future economic outlook								
NAI	0.0192***	0.9659***	0.0462	$-0.3502^{\star\star\star}$	2.0487**	-4662.10	19.08	**1.9655**
	(0.0057)	(0.0108)	(0.0368)	(0.0771)	(1.1143)		[0.0003]	
LI	0.0192***	0.9684***	0.3450***	$-0.2142^{\star\star\star}$	2.2960	-4663.71	15.86	1.9662
	(0.0059)	(0.0110)	(0.0800)	(0.0544)	(1.6828)		[0.0012]	
Inflation rates								
PPI	0.0190**	0.9774***	0.1669	-0.1590	7.7937	-4671.24	0.8	1.9694
	(0.0076)	(0.0105)	(0.1055)	(0.1990)	(10.2830)		[0.8495]	
CPI	0.0201***	0.9744***	0.4247*	-1.5224	3.7484*	-4670.59	2.1	1.9691
	(0.0074)	(0.0113)	(0.2352)	(1.1307)	(2.1652)		[0.5519]	
Benchmark models								
DCC-RC	0.0225***	0.9582***	0.0324	0.8704***	5.3086*	-4668.95	5.38	1.9684
	(0.0058)	(0.0108)	(0.0366)	(0.3202)	(2.7355)		[0.1460]	
DCC-RC restr	0.0228***	0.9574***	-	-	4.7764**	-4669.56	8.98	1.9678
	(0.0060)	(0.0101)			(2.3004)		[0.0414]	
DCC	0.0191***	0.9775***	-	-	-	-4671.64	-	1.9683
	(0.0035)	(0.0046)						

Notes: See Notes of Table 2. The LRT compares the unrestricted DCC-MIDAS-X models with the DCC-GARCH specification.

Table 5: DCC-MIDAS parameter estimates: S&P 500 and oil market

Variable	a	b	m_{12}	θ_{12}	ω_{12}	LLF	LRT	AIC
Current stance of the economy								
IP	0.0212*** (0.0065)	0.9680*** (0.0109)	0.1888*** (0.0585)	$-0.6734^{\star\star\star}$ (0.1877)	1.6217* (0.8294)	-4662.74	12.96 [0.0047]	1.9658
NFP	0.0214*** (0.0065)	0.9668*** (0.01162)	0.1737*** (0.0528)	$-0.0010^{\star\star\star}$ (0.0002)	4.0441 (3.1617)	-4661.84	14.76 [0.0020]	1.9654
UR	0.0229*** (0.0060)	0.9595*** (0.0114)	0.0354 (0.0354)	2.5942*** (0.5858)	1.7862** (0.7948)	-4659.96	18.52 [0.0003]	1.9646
Future economic outlook								
NAI	0.0215*** (0.0059)	0.9619*** (0.0110)	0.0233 (0.0362)	$-0.3485^{\star\star\star}$ (0.0744)	2.1222* (1.0954)	-4659.20	20.04 [0.0002]	**1.9643**
LI	0.0215*** (0.0061)	0.9648*** (0.0111)	0.3189*** (0.0769)	$-0.2114^{\star\star\star}$ (0.0516)	2.4474 (1.6603)	-4660.93	16.58 [0.0009]	1.9650
Inflation rates								
PPI	0.0212** (0.0079)	0.9745*** (0.0111)	0.1416 (0.0962)	-0.1549 (0.2013)	7.3416 (9.3929)	-4668.84	0.76 [0.8590]	1.9683
CPI	0.0227*** (0.0074)	0.9701*** (0.0114)	0.4476* (0.2585)	-1.7569 (1.2303)	3.2581 (2.3148)	-4667.84	2.76 [0.4301]	1.9679
Benchmark models								
DCC-RC	0.0251*** (0.0059)	0.9543*** (0.0116)	0.2739 (0.0346)	0.8521*** (0.3037)	5.5409** (2.6691)	-4666.33	5.78 [0.1228]	1.9673
DCC-RC restr	0.0254*** (0.0061)	0.9534*** (0.0109)	-	-	4.8424** (2.2679)	-4666.92	4.60 [0.0320]	1.9667
DCC	0.0211*** (0.0074)	0.9749*** (0.0102)	-	-	-	-4669.22	-	1.9672

Notes: See Notes of Table 4.

Table 6: DCC-MIDAS parameter estimates: DJIA and oil market

Variable	a	b	m_{12}	θ_{12}	ω_{12}	LLF	LRT	AIC
Current stance of the economy								
IP	0.0248*** (0.0068)	0.9628*** (0.0115)	0.1692*** (0.0558)	−0.6670*** (0.1806)	1.3994** (0.5774)	-4642.36	12.7 [0.0053]	1.9572
NFP	0.0252*** (0.0065)	0.9607*** (0.0116)	0.1552*** (0.0515)	−0.0010*** (0.0003)	3.0553 (2.2618)	-4641.41	14.6 [0.0022]	1.9568
UR	0.0264*** (0.0060)	0.9533*** (0.0116)	0.0153 (0.0345)	2.6614*** (0.5519)	1.5454*** (0.5393)	-4638.81	19.8 [0.0002]	1.9557
Future economic outlook								
NAI	0.0252*** (0.0060)	0.9552*** (0.0115)	0.0034 (0.0350)	−0.3542*** (0.0714)	1.8093** (0.7539)	-4638.19	21.04 [0.0001]	**1.9554**
LI	0.0252*** (0.0063)	0.9591*** (0.0114)	0.3020*** (0.0741)	−0.2126*** (0.0503)	2.0039* (1.0740)	-4640.40	16.62 [0.0008]	1.9564
Inflation rates								
PPI	0.0239** (0.0087)	0.9707*** (0.0127)	0.1216 (0.0868)	−0.1418 (0.2063)	6.4377 (9.4750)	-4648.21	1.00 [0.8013]	1.9597
CPI	0.0267*** (0.0072)	0.9630*** (0.0117)	0.5362* (0.3168)	−2.2800 (1.4860)	2.3720 (2.1948)	-4646.32	4.78 [0.1886]	1.9589
Benchmark models								
DCC-RC	0.0288*** (0.0059)	0.9460*** (0.0123)	0.0248 (0.0321)	0.9111*** (0.2532)	4.8276*** (1.7707)	-4643.71	10.00 [0.0186]	1.9578
DCC-RC restr	0.0289*** (0.0060)	0.9456*** (0.0116)	-	-	4.5605*** (1.6072)	-4644.13	9.16 [0.0025]	1.9571
DCC	0.0237*** (0.0081)	0.9713*** (0.0115)	-	-	-	-4648.71	-	1.9586

Notes: See Notes of Table 4.

8.2 Figures

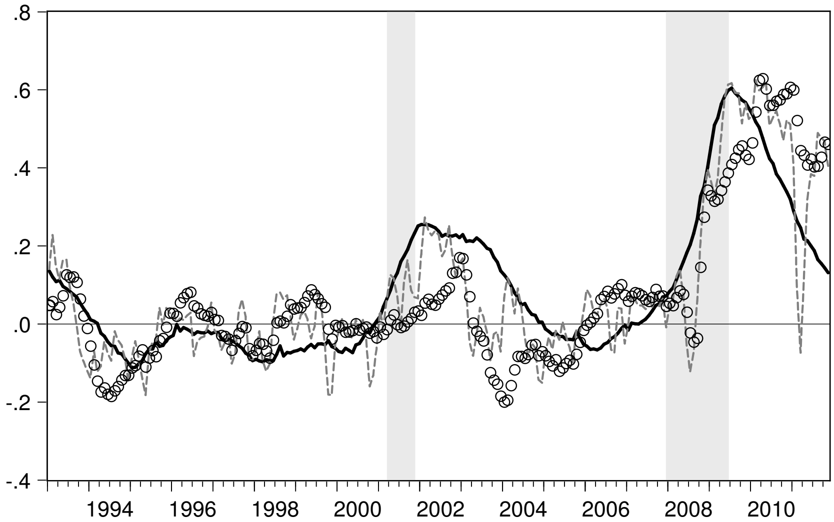

Figure 1: The figure shows the DCC-MIDAS-NAI estimates of the short-term (dashed line) and long-term (bold black line) oil-stock correlation. The circles correspond to one-year rolling window realized correlations. Each series is shown at a monthly frequency. Monthly realizations of the daily short-term and realized correlations are obtained by computing monthly averages. Shaded areas represent NBER recession periods.

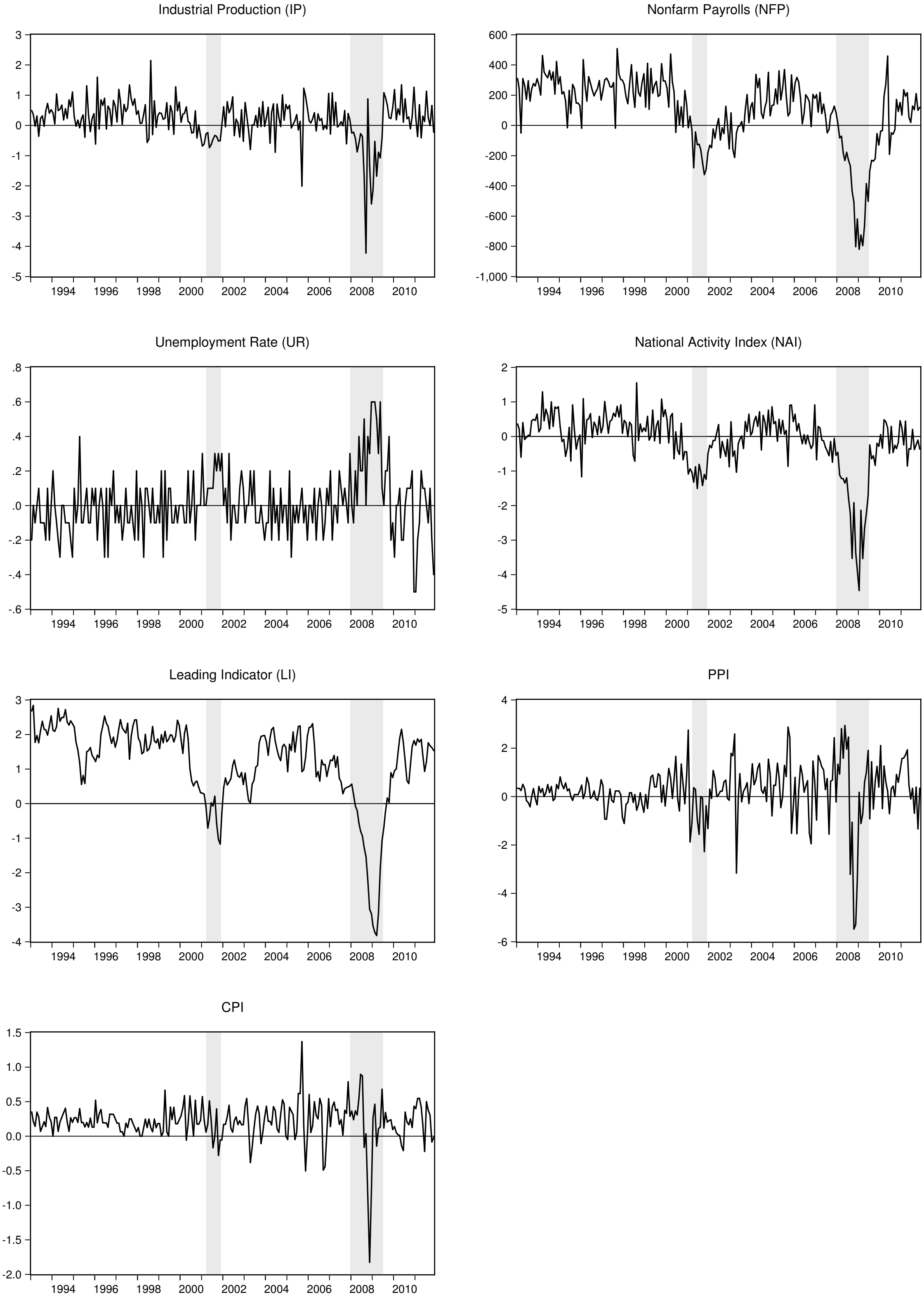

Figure 2: The figure shows the development of the macroeconomic explanatory variables. Shaded areas represent NBER recession periods.

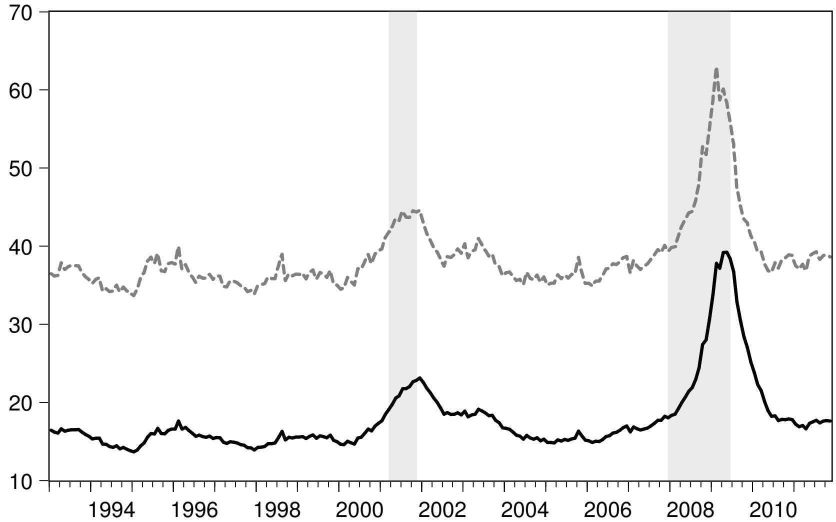

Figure 3: The figure shows the annualized long-term volatility components (standard deviations) obtained from the GARCH-MIDAS-UR specification. The bold line refers to the stock market, the dashed line to the oil market. Shaded areas represent NBER recession periods.

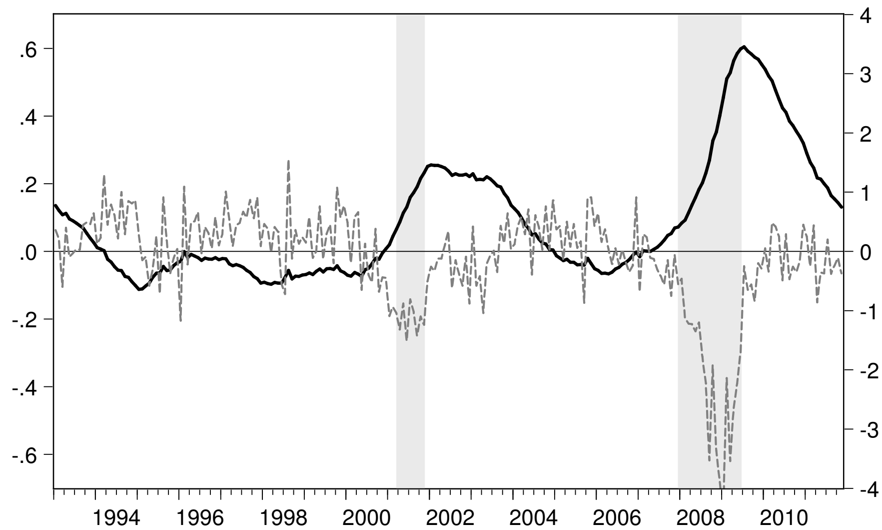

Figure 4: The bold black line (left scale) represents the DCC-MIDAS-NAI estimate of the long-term oil-stock correlation. The dashed line (right scale) corresponds to the NAI. Shaded areas represent NBER recession periods.

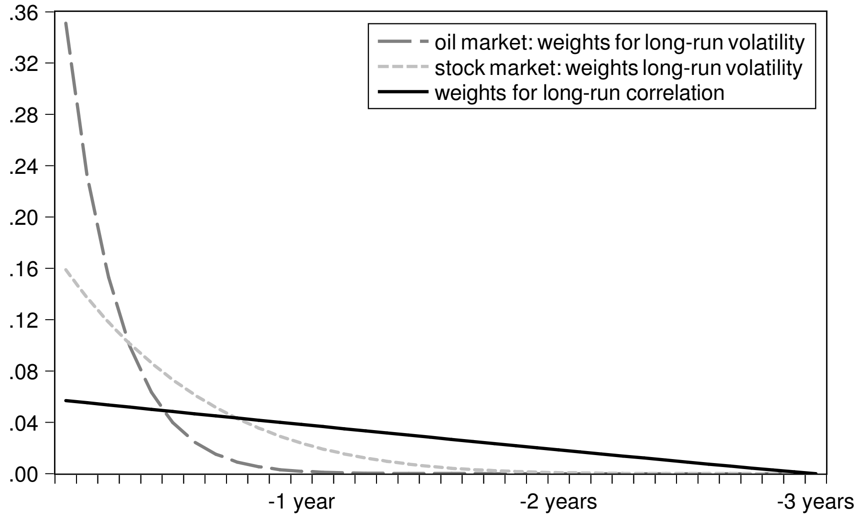

Figure 5: The figure shows the estimated weighting functions for the long-term volatilities based on the GARCH-MIDAS-NAI and for the long-term correlation based on the DCC-MIDAS-NAI. While the bold black line refers to the long-term correlation, the light-gray and the dark-gray dashed lines refer to the long-term volatilities of CRSP and of oil price returns, respectively.

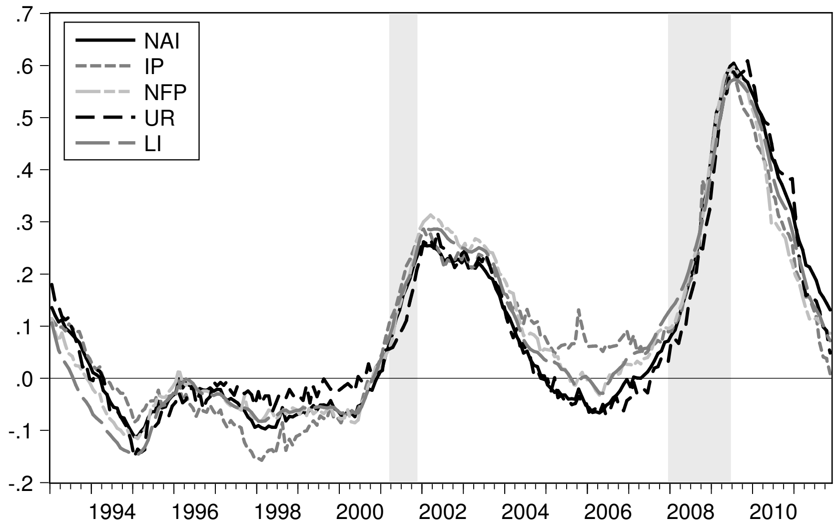

Figure 6: The figure shows the DCC-MIDAS-X estimates of the long-term oil-stock correlations for all significant macroeconomic variables. Shaded areas represent NBER recession periods.

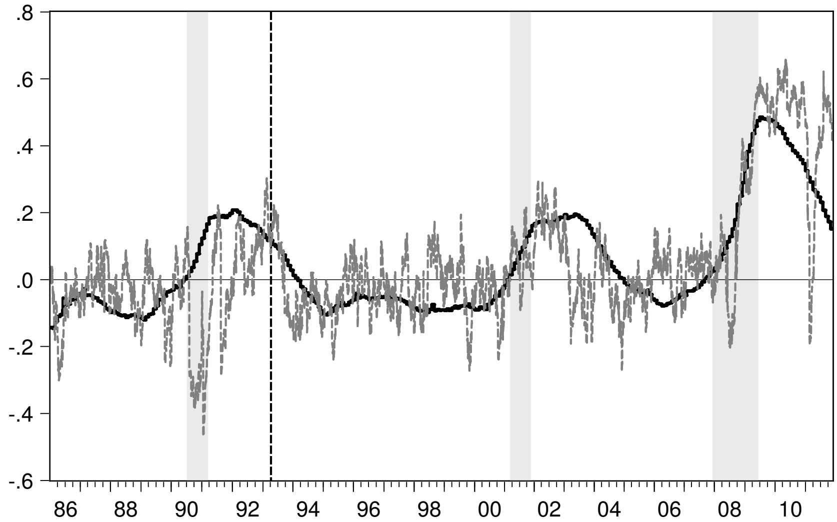

Figure 7: The figure shows the DCC-MIDAS-NAI estimates of the short-term (dashed dark-gray line) and long-term (bold black line) correlation for the extended sample (1986 - 2011). Each series is shown at a daily frequency. The vertical dashed line indicates the beginning of the shorter sample. Shaded areas represent NBER recession periods.