What affects the relationship between oil prices and the U.S. stock market? A mixed-data sampling copula approach

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Abstract

The relationship between oil prices and stocks is an important issue for portfolio selection and risk management. Understanding the economic factors affecting the interaction between oil prices and stocks allows investors to improve their portfolio performance. This paper proposes a mixed frequency data sampling copula model with explanatory variables (copula-MIDAS-X) that incorporates low frequency explanatory variables into a high frequency dynamic copula model. The new model enables us to investigate the impacts of economic factors on the relationship between oil and stock returns, regardless of their marginal distributions. In an application to Brent oil prices and S&P 500 indices, we find that the dependence of oil and stock markets is influenced by aggregate demand and stock specific negative news. The impact of aggregate demand lasts for two years, while the impact of stock specific bad news lasts for one quarter. The implication for market regulators and investors is that changes in aggregate demand have influential and long-lasting effects on both oil prices and stock markets. Besides, investors who rebalance portfolios daily or weekly should use the information on both monthly economic indicators and daily returns in portfolio management.

Keywords: Crude oil, stock, dependence, mixed frequency, copula

1. Introduction

Oil plays an essential role in the world's economy and financial markets. The relationship between oil prices and stock markets has attracted considerable attention in the past years because of its implications for portfolio selection and risk management. One important feature of the relationship between oil prices and stocks is its nonlinearity; oil and stock prices are more correlated in market downturns than in upturns, as documented by Aloui et al. (2013), Pan (2014), and Zhu et al. (2014). Another well recognized feature of the relationship is that it varies with time and depends on macroeconomic activity. There have been several studies that explore the impact of macroeconomic activity on the dependence between oil and stock markets, such as Huang et al. (1996), Sadorsky (1999), Park and Ratti (2008), Kilian and Park (2009), Mollick and Assefa (2013), and Sukcharoen et al. (2014). Portfolio investors and risk managers can use the information on the economic factors influencing the relationship between oil and stock prices, especially the tail dependence under extreme market conditions, to improve forecasts of the joint distribution of oil and stock returns. To this end, this paper investigates the economic factors that modify the relationship between oil and stock prices and their economic significance in portfolio management.

The literature on the dependence between oil and stock prices has focused on three groups of economic factors. The first group of factors concerns global supply and demand. Many studies evaluate the impacts of global oil supply and demand on the dependence between oil and stock prices. Examples include Kilian and Park (2009), Filis et al. (2011), Wang et al. (2013), and Fang and You (2014). These papers conclude that global oil supply is less important for understanding changes in oil and stock prices than aggregate demand. The second group of factors concerns the country's specific demand for oil. Kilian and Park (2009) interpret it as a country's precautionary demand for oil arising from the uncertainty about oil shortfalls (e.g. wars). Apergis and Miller (2009) show that oil market idiosyncratic demand shocks contribute to explaining stock returns for the most developed countries, while Fayyad and Daly (2011) and Naifar and Dohaiman (2013) find similar results for Gulf Cooperation Council (GCC) countries. The third type of factors is the stock specific shocks originating from the stock market, such as the global financial crisis, as financial crises usually start with a crash in the stock market. Aloui et al. (2012), Mollick and Assefa (2013), Aloui et al. (2013), Pan (2014), and Zhu et al. (2014) all document that oil and stock prices were more positively correlated during the 2008 global financial crisis than in more normal times.

Most economic indicators useful for understanding oil and stock prices have a lower sampling frequency than oil and stock prices do. Economic indicators are usually reported monthly, while oil and stock prices can be observed daily or even more frequently. The literature handles this problem in two ways. Some studies use daily returns to describe the relationship between oil and stocks and then just qualitatively explain the impacts of low frequency economic indicators, while others aggregate daily returns into monthly returns and build a regression model using monthly data. The second approach ignores the intra-month information lost by aggregation and, because the model is updated monthly, it may not provide enough information for investors who rebalance their oil and stock portfolios more frequently.

We address these limitations by proposing a copula model with explanatory variables based on the idea of mixed frequency data sampling (copula-MIDAS-X). The mixed frequency sampling scheme utilizes both monthly economic indicators and daily returns information. The copula approach enables us to examine the economic determinants of the oil and stock relationship independent of the marginal distributions. This new model allows for daily forecasting of the oil and stock relationship, which is more attractive for investors with frequent rebalancing strategies. Using the new model, this paper answers the following two questions. First, what are the most influential economic factors affecting the dependence between oil market and the U.S. stock market? Second, does understanding the economic factors influencing the dependence between oil and stock prices bring economic profits to investors?

The copula-MIDAS-X model extends earlier mixed frequency data sampling (MIDAS) models by incorporating low frequency explanatory variables into the dynamic dependence structure. Since the seminal work of Ghysels et al. (2004), several MIDAS models have been proposed to extract the long-run and short-run components in returns, volatilities, correlations, and copula-based dependence structures. Examples can be found in Ghysels et al. (2005), Clements and Galvao (2008), Colacito et al. (2011), Engle et al. (2013), Conrad et al. (2014), and Gong et al. (2018). Among them, Gong et al. (2018) use a mixed frequency data sampling copula model without any explanatory variables (copula-MIDAS) to analyze the dependence between returns and bid-ask spreads in stock index futures. We modify their model by adding low frequency explanatory variables that may affect the dependence structure into the copula model. The new model with explanatory variables enables us to find the most influential factors in the dependence structure, in particular to find out the factors affecting the tail dependence structure in extreme cases.

Our empirical findings about the economic determinants of the oil and stock dependence complement the literature on the contemporaneous dependence between oil and stock markets. Existing literature find that the dependence between oil and stock returns is linked with some macroeconomic variables. Our analysis using the copula-MIDAS-X model goes one step further by investigating the most influential economic factors affecting the oil and stock dependence. It is found that aggregate demand and stock specific negative news are more important than other factors. The impact of aggregate demand lasts for two years, while the impact of stock specific negative news lasts for one quarter. Furthermore, most existing studies only perform in-sample analysis. We provide both in-sample and out-of-sample results. The out-of-sample portfolio performance reveals that investors who rebalance their portfolios daily or weekly should use information from monthly economic indicators and daily returns in their portfolio optimization.

The remainder of this paper is organized as follows. Section 2 presents the copula-MIDAS-X model and its estimation. Section 3 explains the data, provides descriptive statistics, and justifies the variable selection. Section 4 contains the main results on the economic factors affecting the dependence between oil and stock returns. Section 5 is some robustness analysis. Section 6 concludes the paper.

2. Econometric methodology

The copula-MIDAS-X model is a natural extension of the copula-MIDAS model without any explanatory variables of Gong et al. (2018). We incorporate low frequency explanatory variables into their copula-MIDAS model to explain the evolution of the dynamic dependence structure.

2.1 Copula-MIDAS-X model

Suppose there are bivariate daily (high frequency) time series (r_{1t}, r_{2t}), $t = 1, \cdots, T$ and S monthly (low frequency) economic variables $X_\tau = (X_{1,\tau}, \cdots, X_{S,\tau})'$, $\tau = 1, \cdots, [T/N]$ (N days in a month). We want to examine how X_τ affects the long-run dependence between (r_{1t}, r_{2t}). Let F_1 and F_2 represent the marginal cumulative distribution functions (CDF) of r_{1t} and r_{2t} on day t. By the probability integral transformation, $u_{it} = F(r_{it})$ for $i = 1, 2$.

The copula-MIDAS-X model is written as

$$(u_{1t}, u_{2t}) \sim C(u_{1t}, u_{2t}; \theta_t, \varsigma), \; \theta_t = \Lambda(\lambda_t), \tag{1}$$

$$\lambda_t = \lambda_\tau + \alpha\, \Phi^{-1}(u_{1,t-1}) \Phi^{-1}(u_{2,t-1}) + \beta \lambda_{t-1}. \tag{2}$$

$$\lambda_\tau = c + \sum_{s=1}^{S} \gamma_s \left[\sum_{k=1}^{K} \varphi_k(\omega_s) X_{s,\tau-k} \right], s = 1, \cdots, S. \tag{3}$$

Equation (1) shows that the copula-MIDAS model belongs to the time-varying copula family. θ_t is a time-varying parameter and ς is a time-invariant parameter. θ_t is assumed to be driven by an unobserved dynamic process λ_t such that $\theta_t = \Lambda(\lambda_t)$, where $\Lambda(\cdot)$ is an increasing transformation to ensure that θ_t remains in its domain as in Patton (2006).

Equation (2) decomposes the dynamic dependence λ_t into two parts: the long-run component (monthly) λ_τ and the short-run component (daily) $\alpha\, \Phi^{-1}(u_{1,t-1}) \Phi^{-1}(u_{2,t-1}) + \beta \lambda_{t-1}$. λ_τ takes a different value each month (every N days). The specification of short-run component follows Patton (2006) and the short-lived effects are captured by an autoregressive lag λ_{t-1} and a data-driven term $\Phi^{-1}(u_{1,t-1}) \Phi^{-1}(u_{2,t-1})$, where $\Phi^{-1}(\cdot)$ is the inverse of standard normal CDF . Hence, α and β are the coefficients measuring the short-run components of the dependence.

Equation (3) is different from the copula-MIDAS model. λ_τ represents the fundamental or secular causes of time variation in the dependence, and is assumed to be affected by an intercept c and S monthly economic variables $X_\tau = (X_{1,\tau}, \cdots, X_{S,\tau})'$. For $s = 1, \cdots, S$, γ_s measures the impacts $X_{s,\tau}$ has on λ_τ and ω_s measures how long the impacts last. $\varphi_k(\omega_s)$ is the Beta weight function in Colacito et al. (2011), which gives progressively lower weights to $X_{s,\tau-1}, \cdots, X_{s,\tau-K}$, and it is given as follows.

$$\varphi_k(\omega_s) = (1-k/K)^{\omega_s - 1} \Big/ \sum_{k=1}^{K} (1-k/K)^{\omega_s - 1}, \; s = 1, \cdots, S. \tag{4}$$

Hence, c and (γ_s, ω_s) are the coefficients measuring the long-run components of the dependence; in particular, (γ_s, ω_s) measures the size and length of the impacts of economic indicator $X_{s,\tau}$ on the dependence.

The copula-MIDAS-X model differs from extant models by introducing explanatory variables X_τ into the long-run component λ_τ of dependence measured by copula. The model is flexible enough to describe the dynamics of linear or nonlinear dependence structure and its determinants, in particular the determinants of tail dependence. To be specific, the copula-MIDAS-X model with SJC copula (Symmetrized Joe-Clayton), which is to be discussed in section 2.2, can model the short-run and long-run components in the lower and upper tail dependence simultaneously. It also enables us to examine the determinants of the long-run tail dependence. However, most existing models focus on linear correlation rather than nonlinear tail dependence. For example, Colacito et al. (2011) incorporate the MIDAS scheme into the dynamic conditional correlation model in Engle et al. (2002), and Conrad et al. (2014) further introduce explanatory variables into the long-run component of correlation.

2.2 Examples: Gaussian and SJC copula-MIDAS-X

The Gaussian copula-MIDAS-X model has one time-varying correlation θ_t and has no time-invariant parameter ς in equation (1). $\Lambda(\cdot)$ is the Fisher transformation $\Lambda(\lambda_t) = [1-\exp(-\lambda_t)] / [1+\exp(-\lambda_t)]$ that ensures θ_t is in the domain $(-1,1)$. The dynamics of λ_t are given in equations (2) and (3).

The SJC copula-MIDAS-X model $C^{SJC}(u_{1t}, u_{2t}; \theta_t)$ has two time-varying tail dependence coefficients $\theta_t = (\kappa_t^L, \kappa_t^U)'$ and has no time-invariant parameter ς in equation (1).[①] The lower-tail dependence κ_t^L and the upper-tail dependence κ_t^U follow the dynamics in equations (5) and (6). For $j = L, U$, $\kappa_t^j = \Lambda(\lambda_t^j)$ is the logistic transformation $\Lambda(\lambda_t^j) = 1 / [1+\exp(-\lambda_t^j)]$ that ensures each κ_t^j is in the domain $(0,1)$.

$$\lambda_t^j = \lambda_\tau^j + \alpha^j \, \Phi^{-1}(u_{1,t-1}) \Phi^{-1}(u_{2,t-1}) + \beta^j \lambda_{t-1}^j, \tag{5}$$

① There is no time-invariant parameter ς in our examples of Gaussian and SJC copula-MIDAS-X models. But in student's t copula-MIDAS-X model, θ_t is the time-varying correlation and ς is the degree of freedom.

$$\lambda_\tau^j = c^j + \sum_{s=1}^{S} \gamma_s^j \left[\sum_{k=1}^{K} \varphi_k \left(\omega_s^j \right) X_{s,\tau-k} \right], s = 1, \cdots, S. \tag{6}$$

2.3 Estimation

The model is estimated by the two-step maximization likelihood method (MLE) as in Joe (1997) and Gong et al. (2018). The only difference is that the long-run component in our copula-MIDAS-X model is a linear combination of weighted lagged explanatory variables, while the long-run component in copula-MIDAS by Gong et al. (2018) is a weighted sum of past realized correlations.

The two-step procedure is as follows. First, estimate the marginal models of daily oil returns and stock returns and transform the standardized residuals into marginal CDFs by a probability integral transformation, denoted by $\left(\hat{u}_{1t}, \hat{u}_{2t}\right)$, $t = 1, \cdots, T$. The details of marginal models are to be explained in Section 4.1. Second, plug $\left(\hat{u}_{1t}, \hat{u}_{2t}\right)$ into the copula log-likelihood function and estimate the copula-MIDAS-X parameters by MLE. The optimal MIDAS lag K is determined by selecting the smallest number of MIDAS lags after which the log-likelihood values reach the plateau. Under certain regularity conditions, the asymptotic properties of the two-step estimator are normally distributed. The variance-covariance matrix is estimated by the block bootstrapping procedure with block length $\sqrt{T}$.

3. Data and variables

This paper investigates the dependence between daily oil returns and stock returns and the potential monthly economic factors that affect the dependence. The sample is from January 1, 1997 to February 28, 2018. We divide the sample into two sub-periods, such that the observations from 1997 to 2016 are used for the in-sample estimation and the remaining observations in 2017 and 2018 are reserved to check the accuracy of the out-of-sample forecast.

3.1 Data

The daily closing prices of Brent crude oil expressed in dollars per barrel are used to represent the oil market. Brent oil is chosen as it is a reference for determining the price of other light crudes in Europe and is closely related to other crude oil markets, such as those for West Texas Intermediate, Maya, and Dubai (Ciner et al., 2013; Reboredo and Rivera-Castro, 2014; Sukcharoen et al., 2014). Brent oil prices are collected from the U.S. Energy Information Administrate (EIA) website.

The daily S&P 500 index is used to represent the U.S. stock market. The data are collected from Bloomberg. Let $P_{i,t}$ be the daily price of oil ($i = OIL$) or stock ($i = STK$) on day t. The daily return is calculated as $r_{i,t} = 100 \times \left(\ln P_{i,t} - \ln P_{i,t\text{-}1} \right)$.

For the monthly data, we follow the related literature and consider four economic variables: (1) global oil production in thousands of barrels per day GOP_τ, (2) a global index of dry cargo single voyage freight rates KI_{τ} constructed by Kilian (2009), (3) the monthly closing prices of Brent crude oil $P_{OIL,\tau}$, and (4) the monthly S&P 500 index $P_{STK,\tau}$. Among them, global oil production and the Kilian index represent global oil supply and demand. $P_{OIL,\tau}$ is used to extract oil specific shocks besides oil supply and demand for certain econometric models (to be discussed in section 3.3). The oil specific shocks are taken to be precautionary demand arising from the uncertainty about oil shortfalls. Similarly, $P_{STK,\tau}$ is used to extract stock specific shocks besides the influence from the oil market. The global oil production data are collected from the U.S. EIA website. The global demand index is collected from Kilian's website.[2] The monthly oil and stock prices are collected from Bloomberg.

3.2 Descriptive statistics

Figure 1 plots the daily Brent oil returns and U.S. stock returns. Oil returns and stock returns tend to co-move in turmoil periods, such as 1999-2001, 2008-2009, and 2015-2017. It is also obvious that oil returns fluctuate much more than stock returns.

Figure 2 plots the monthly global oil production, Kilian index, Brent oil price, and S&P 500 index. Panel (a) with four sub-figures (the first row of Figure 2) shows the levels of the above four variables. From panel (a), global oil supply (GOP_{τ}) has increased steadily in the past twenty years outside of a few declines in 1999, 2003, and 2008, years when the Organization of Petroleum Exporting Countries (OPEC) cut quotas. Aggregate demand, represented by the Kilian index (KI_{τ}), peaked in 2000 and in early 2008, but dropped dramatically during the subprime crisis. From 2015 to 2017, aggregate demand fell and then rose due to the increasing demand from large emerging countries like China and India, as mentioned in Fang and You (2014). The monthly oil price ($P_{OIL,\tau}$) and stock index ($P_{STK,\tau}$) reached a peak and then declined together due to the 9-11 attacks between 1999 and 2001. A similar pattern can be observed between 2008 and 2009, when both oil and stock prices experienced an extremely bearish performance and recovered afterwards, as discussed in Reboredo and Rivera-Castro (2014). After the subprime crisis, the stock index did not always move in the same directions as oil prices, but from 2016 to 2017 the two markets were booming together. The co-movement patterns observed here coincide with the daily oil and stock returns in Figure 1.

Table 1 reports the summary statistics of daily oil returns and stock returns. For the full sample, oil has a slightly lower return than stock, but its standard deviation is almost twice as much as stock's, which is also observed in Figure 1. This implies that Brent oil is riskier than stocks. Both oil and stock returns exhibit non-normal features like negative skewness and heavy tails, and they exhibit serial correlation and volatility clustering. Similar features of oil and stock returns are found by Fayyad and Daly

[2] The personal website of Kilian is http://www-personal.umich.edu/~lkilian.

(2011), Mollick and Assefa (2013), and Sukcharoen et al. (2014).

Overall, the preliminary analysis tells us that oil and stock tend to boom or crash together and that the co-movement can be linked to some macroeconomic shocks, such as global oil supply, aggregate demand, and the subprime crisis. This provides us some hints of how to use the copula-MIDAS-X model to further investigate the economic factors influencing the dependence between oil and stock.

3.3 Variables

We focus on the four monthly economic variables that may affect the oil and stock dependence: GOP_τ, KI_τ, $P_{OIL,\tau}$ and $P_{STK,\tau}$. They are chosen because they contain a lot of information from other macroeconomic indicators. For example, the aggregate demand index that measures real economic activity shares information with industrial production and employment rate. But the four variables themselves cannot be used directly as explanatory variables X in the copula-MIDAS-X model in equation (3), as they have unit roots and are highly correlated. To avoid multi-collinearity in regression, we decompose them into four orthogonal shocks with economic meanings, as shown by Kilian and Park's (2009) structural vector autoregressive (SVAR) model. If additional macroeconomic indicators were used, such as industrial production, interest rates, employment rate, or consumer price index, it would be difficult to evaluate their individual contributions to the oil and stock dependence due to multi-collinearity.

We follow Kilian and Park (2009) and take log differences (except KI_τ) of the four variables and decompose these differences into four orthogonal innovations using the SVAR model specified in equation (7).

$$Ay_\tau = A_0 + \sum_{j=1}^{J} B_j y_{\tau-j} + \xi_\tau, \tag{7}$$

where $y_\tau = \left(\Delta \ln GOP_\tau, \Delta KI_\tau, \Delta \ln P_{OIL,\tau}, \Delta \ln P_{STK,\tau}\right)'$ is the vector of monthly changes in log global oil production, the Kilian index, log Brent oil price, and log S&P 500 index. $A = \begin{pmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix}$ is a full rank lower triangular matrix, A_0 is the intercept vector, and B_j is the autoregressive matrix with the maximum lag length $J = 6$ as in Wang et al. (2013). Panel (b) of Figure 2 with four sub-figures (the second row) shows the variables in y_τ.

In Killian and Park (2009), the ordering of y_τ and the identifiying restrictions are based on the following assumptions. First, oil supply will not respond to oil demand shocks within the month, given the costs of adjusting oil production and the uncertainty about the state of the oil market. Second, real economic activity measured by the Killian index will not respond to changes in oil price within the month, given the sluggishness of global real activity. Third, shocks to oil price that cannot be explained by oil supply and aggregate demand reflect the precautionary oil demand driven by uncertainty about the availability of future oil supplies. Oil price within a given month is only determined by the supply and demand shocks from the oil market. The three assumptions above are consistent with a vertical short-run supply curve of crude oil and a downward sloping demand curve. Fourth, whereas stock price is allowed to respond to all three oil supply and demand shocks, shocks to stock market will not affect global oil supply, aggregate demand and oil price within a given month, but only with a delay of at least one month.

The orthogonal structural innovations ξ_τ are then used as the explanatory variables $X_\tau = \left(X_{GOP,\tau}, X_{KI,\tau}, X_{OIL,\tau}, X_{STK,\tau}\right)'$ in the copula-MIDAS-X model. $X_{GOP,\tau}$ represents shocks to global oil supply, $X_{KI,\tau}$ represents shocks to aggregate demand, $X_{OIL,\tau}$ is the shocks to U.S. precautionary oil demand (i.e. U.S. oil specific shocks), and $X_{STK,\tau}$ is U.S. stock specific shocks. Panel (c) of Figure 2 with four sub-figures (the last row) shows the orthogonal innovations X_τ. To some extent, the patterns observed in panel (c) are consistent with those in panel (a). For example, the innovations are much more volatile in the periods such as 2008-2009, and 2015-2017.

4. Empirical results

This section has three parts: the in-sample estimates of the marginal models for oil and stock returns, the in-sample estimates of the copula models for the relationship between oil and stock, and the out-of-sample performance evaluation of oil and stock portfolios.

4.1 In-sample estimates of marginal models

Table 2 shows the in-sample estimates of the marginal models for daily oil and stock returns from 1997 to 2016. The ARMA-TGARCH model with student's t error in equation (8) is used as the returns are non-normally distributed, serially correlated, and volatility clustered. For $i = OIL, STK$,

$$\begin{aligned} r_{i,t} &= \delta_{i,0} + \delta_{i,1} r_{i,t-1} + \sqrt{h_{i,t}}\varepsilon_{i,t} + \delta_{i,2}\sqrt{h_{i,t-1}}\varepsilon_{i,t-1},\ \varepsilon_{i,t}\left|\Omega_{t-1} \sim i.i.d.\,\mathrm{T}\left(v_i\right)\right., \\ h_{i,t} &= \phi_{i,0} + \phi_{i,1} h_{i,t-1}\varepsilon_{i,t-1}^2 + \phi_{i,2} h_{i,t-1}\varepsilon_{i,t-1}^2 \mathrm{I}\left(\varepsilon_{i,t-1} < 0\right) + \phi_{i,3} h_{i,t-1}. \end{aligned} \tag{8}$$

The last row of Table 2 indicates that both marginal models are correctly specified. We fail to reject the Kolmogorov-Smirnov tests with the null hypothesis that the model is correctly specified. This justifies estimating copula models using the marginal CDFs of the residuals $\left(\hat{\varepsilon}_{OIL,t}, \hat{\varepsilon}_{STK,t}\right)$. Oil and stock returns are heavily tailed (v_i is around 8 for both variables) and the stock returns are serially correlated ($\delta_{STK,1} > 0$). The conditional mean of $r_{OIL,t}$ only has an intercept because the ARMA coefficients are insignificant if added. Large (small) volatilities are likely to be followed by large (small) volatilities ($\phi_{i,3} > 0$) and bad news tends to have a greater impact on volatilities than good news ($\phi_{i,2} > 0$). The results of the marginal models are not only in line with the summary statistics in Table 1, but also with studies such as Filis et al. (2011), Aloui et al. (2013), Pan (2014), and Zhu et al. (2014).

4.2 In-sample estimates of copula models

This section investigates the asymmetric features of the oil and stock dependence in section 4.2.1 and the economic factors influencing the oil and stock dependence in section 4.2.2.

Table 3 provides the in-sample estimates of four copulas models. We first transform the standardized residuals $\left(\hat{\varepsilon}_{OIL,t}, \hat{\varepsilon}_{STK,t}\right)$ into marginal CDFs $\left(\hat{u}_{OIL,t}, \hat{u}_{STK,t}\right)$ by probability integral transformations of the student's t distribution and then plug the marginal CDFs into the copula models. Two types of copula-MIDAS-X models proposed in this paper are used. The Gaussian copula-MIDAS-X model in equations (1)-(3) focuses on the correlation between oil and stock without any tail dependence, while the SJC copula-MIDAS-X model in equations (1), (5), and (6) focuses on the tail dependence of oil and stock. The maximum lag is chosen to be 24.[③] Remember that in the Gaussian copula-MIDAS-X model, γ_s measures the impact that the lagged $X_{s,\tau}$ has on the oil and stock correlation and ω_s measures how long the impact lasts for $s = 1, \cdots, S$. Similarly, γ_s^j and ω_s^j in the SJC copula-MIDAS-X model measure the size and the length of the impacts from lagged $X_{s,\tau}$ on the lower or upper tail dependence between oil and stock returns for $s = 1, \cdots, S$, $j = L, U$.

To investigate the importance of the mixed frequency data sampling approach, two more copulas with just monthly or just daily data are included.

SJC copula-X (monthly data):

$$\begin{aligned} &\left(u_{OIL,\tau}, u_{STK,\tau}\right) \sim C^{SJC}\left(u_{OIL,\tau}, u_{STK,\tau}; \kappa_\tau^L, \kappa_\tau^U\right),\ \kappa_\tau^j = \Lambda\left(\lambda_\tau^j\right), \\ &\lambda_\tau^j = c^j + \sum_{s=1}^{S} \gamma_s^j X_{s,\tau-1},\ \ j = L, U,\ s = 1, \cdots, S. \end{aligned} \tag{9}$$

$\left(u_{OIL,\tau}, u_{STK,\tau}\right)$ are the marginal CDFs of monthly oil and stock returns, c^j is the intercept, and γ_s^j measures how much impact the 1-month lagged variable $X_{s,\tau-1}$ has on the latent tail dependence λ_τ^j. The number of monthly explanatory variables is $S = 4$, $\left(X_{1,\tau\text{-}1}, \cdots, X_{S,\tau\text{-}1}\right)' = \left(X_{GOP,\tau-1}, X_{KI,\tau-1}, X_{OIL,\tau-1}, X_{STK,\tau-1}\right)'$. This dynamic copula model with explanatory variables is also used in Patton (2004).

③ The maximum lag is chosen to be 24 as this is the minimum lag that reaches the highest value of the log likelihoods. The plots of log likelihoods can be provided upon request.

SJC copula (daily data):

$$
\begin{aligned}
&\left(u_{OIL,t}, u_{STK,t}\right) \sim C^{SJC}\left(u_{OIL,t}, u_{STK,t}; \kappa_t^L, \kappa_t^U\right),\ \kappa_t^j = \Lambda\left(\lambda_t^j\right), \\
&\lambda_t^j = c^j + \alpha^j \Phi^{-1}\left(u_{OIL,t-1}\right)\Phi^{-1}\left(u_{STK,t-1}\right) + \beta^j \lambda_{t-1}^j,\ \ j = L, U.
\end{aligned}
\tag{10}
$$

Here c^j is the intercept, and α^j and β^j are the same as in equation (5). Because all variables are daily, we do not include any monthly variables into the model. This dynamic copula model without explanatory variables is also used in Patton (2006).

4.2.1 The asymmetry of oil and stock dependence

Table 3 tells us that the dependence between oil and stock returns is asymmetric. They are more likely to decrease together than increase together.

Of the four copulas, the SJC copula-MIDAS-X model has the best in-sample goodness-of-fit performance with the highest log likelihoods and the lowest HQIC values (Hannan-Quinn Information Criterion). When we switch from the SJC copula-MIDAS-X model to the Gaussian copula-MIDAS-X model, the HQIC value rises (from -205.16 to -175.01), indicating that there is a nonlinear tail dependence between oil and stock returns captured by the SJC copula. Besides, the HQIC values are even higher for the SJC copula with just daily data and the SJC copula-X with just monthly data. This demonstrates the importance of using both monthly and daily information in explaining the oil and stock dependence. Reboredo and Rivera-Castro (2014), by means of wavelet cross-correlation, also find a strong dependence between oil and U.S. stock returns at both the daily and monthly levels.

Furthermore, the estimates of the SJC copula-MIDAS-X model show that oil and stock are more likely to decrease together than increase together. The intercept of the long-run component in the lower tail is generally higher than the intercept in the upper tail ($c^L > c^U$). After a logistic transformation, the lower tail dependence coefficient is 0.4027 on average, while the upper tail dependence coefficient is only 0.3087.

Figure 3 also reveals the asymmetric dependence pattern between oil and stock returns. Panel (a) plots the lower tail dependence ranging from 0.35 to 0.65 and panel (b) plots the upper tail dependence ranging from 0.15 to 0.45. The solid black line is the daily lower or upper tail dependence coefficient $\kappa_t^j = \Lambda\left(\lambda_t^j\right)$, while the red dotted line is the monthly long-run component of the lower or upper tail dependence $\kappa_\tau^j = \Lambda\left(\lambda_\tau^j\right),\ \ j = L, U$. The daily tail dependence always fluctuates around the long-run monthly component of the tail dependence. More importantly, the lower tail dependence is generally higher than the upper tail dependence, suggesting that oil and stock markets are more likely to crash together than boom together.

The implication of the positive and asymmetric tail dependence between oil and stock markets is that the two markets do not provide diversification benefits during extreme financial conditions such as the recent subprime crisis. This asymmetric dependence between oil and stock returns has been well documented in the literature;

see Aloui et al. (2013) for Central and Eastern European (CEE) transition economies, Pan (2014) for BRIC countries, Reboredo and Rivera-Castro (2014) for the U.S. and European markets, and Zhu et al. (2014) for Asia-Pacific countries. Wang et al. (2013) use the SVAR model of Kilian and Park (2009) but find no significant nonlinear Granger causality relationship between monthly oil and stock returns. The copula approach of this paper enables us to uncover the asymmetric tail dependence between daily oil and stock returns, helping to explain this contradiction. Besides, Sukcharoen et al. (2014) find that the oil and stock dependence in the U.S. is symmetric and quite low from 1982 to 2007. Our result of a much higher asymmetric tail dependence differs from theirs as we account for the sample after the subprime crisis.

4.2.2 The determinants of oil and stock dependence

In Table 3, the result of the SJC copula-MIDAS-X model indicates that the dependence between oil and stock returns is affected by aggregate demand and stock specific shocks, but not by global oil supply and precautionary oil demand shocks.

First, oil and stock tend to decrease dramatically when aggregate demand declines or when the stock market crashes. In the lower tail of the SJC copula-MIDAS-X model, both γ_{KI}^{L} and γ_{STK}^{L} are significantly negative, while neither γ_{GOP}^{L} nor γ_{OIL}^{L} is significant. A negative γ_{KI}^{L} means that if aggregate demand declines, both oil and stock markets experience bearish performance and extreme decreases in prices, leading to an increase in the lower tail dependence. This is exactly what happened during the subprime crisis of 2008-2009. A decline in aggregate demand leads to bullish oil and stock markets so that the lower tail dependence goes up, which is also observed during 2008 and 2009 in panel (a) of Figure 3. The importance of aggregate demand on the relationship between oil and stock markets has been discussed quite often; see Kilian and Park (2009), Filis et al. (2011), Wang et al. (2013), and Fang and You (2014). Meanwhile, a negative γ_{STK}^{L} means that if stock prices are driven down by bad news unrelated to global oil supply and aggregate demand, both oil and stock prices decrease dramatically, resulting in an increase in the lower tail dependence as well. These conclusions are supported by Aloui et al. (2013), Mollick and Assefa (2013), and Zhu et al. (2014), who point out that the dependence between oil and stock is closely related to the global financial crisis originating in the stock market. Furthermore, it should be noted that $\left|\gamma_{KI}^{L}\right|$ is more than twice as big as $\left|\gamma_{STK}^{L}\right|$, which implies that the impact of aggregate demand on the lower tail dependence of oil and stock returns is much larger than the impact of stock specific shocks.

Second, oil and stock returns are more likely to increase together when aggregate demand increases. In the upper tail part of the SJC copula-MIDAS-X model, only γ_{KI}^{U} is significantly positive, while the other three factors are insignificant. A positive γ_{KI}^{U} suggests that an increase in aggregate demand causes bullish performance in the oil and stock markets, leading to an increase in the upper tail dependence between them. This situation occurred in late 2009 due to the global recovery from the subprime crisis and in 2016-2017 due to the rising demand from emerging markets. In both cases, rising aggregate demand is followed by booms in the oil and stock markets. These findings are rarely discussed, as the literature focuses on the dependence between oil and stock in recessions rather than in booms.

Third, aggregate demand influences the dependence between oil and stock for two years, while the impact of stock specific negative shocks lasts for a quarter. Figure 4 visualizes the decaying impacts of lagged monthly economic variables on the current oil and stock dependence by plugging the estimates of ω_s into the weight function $\varphi_k(\cdot)$ in equation (4). Panels (a) and (b), based on Gaussian copula-MIDAS-X, plot the impact of aggregate demand and the impact of stock specific shocks on the oil and stock correlation, respectively. Panels (c) and (d), based on SJC copula-MIDAS-X, plot the impact of aggregate demand and the impact of stock specific shocks on the lower and upper tail dependence between oil and stock. The horizontal axis is the number of months the impact lasts and the vertical axis is the weight each lagged month takes on the current correlation or tail dependence. In the figure, panel (a) shows that aggregate demand influences the oil and stock correlation for two years, and panel (c) shows that aggregate demand influences the dependence between oil and stock in the lower and upper tails for two years, as the weights decay to zero at around 20 to 24 lags. On the contrary, panel (d) shows that the influence of U.S. stock specific shocks on the lower tail dependence lasts for 3 months, which is much shorter than the impact of aggregate demand. This indicates that global demand, as one of the most important factors of the oil and stock dependence, influences the linkage between oil and stock markets for about two years, while stock specific bad news has a negative effect on oil and stock markets that is quickly absorbed by the markets within a quarter. There are a large number of studies on how long stock prices are affected by oil prices, oil supply, and aggregate demand; see Sadorsky (1999), Papapetrou (2001), Ewing and Thompson (2007), Park and Ratti (2008), and Wang et al. (2013). However, few studies examine the impacts on the cross-market dependence between oil and stock.

Last, the effects of global oil supply and precautionary oil demand shocks on the oil and stock dependence are limited. Neither global oil production shocks nor oil specific shocks, regarded as precautionary oil demand shocks in Kilian (2009), have significant coefficients in the Gaussian or SJC copula-MIDAS-X models. The limited contributions of global oil supply contrast with Cunado and de Gracia (2014), who find that the response of European stock price changes to oil price changes are mostly driven by oil supply shocks rather than demand shocks between 1973 and 2001, much earlier than our sample. The limited contributions of oil specific shocks differ somewhat from several papers. Apergis and Miller (2009) find that U.S. oil market idiosyncratic demand shocks play an important role in explaining stock returns, but their sample is from 1981 to 2007 without the 2008 financial crisis periods. Fayyad and Daly (2011) provide evidence that increased oil prices have predictive power for U.S. stock returns, but they do not account for global oil supply and aggregate demand shocks.

Our findings on the economic factors behind the oil and stock dependence contribute to the literature on the contemporaneous dependence between oil and stock returns; see Filis et al. (2011), Aloui et al. (2013), Naifar and Al Dohaiman (2013), Sukcharoen et al. (2014), and Zhu et al. (2014). These copula-based studies usually investigate one economic determinant of the oil and stock dependence in a qualitative way. For instance, Aloui et al. (2013) qualitatively relate the contagion effect between the oil and stock markets to the 2008-2009 global financial crisis. Sukcharoen et al. (2014) qualitatively document that the relatively strong oil and stock dependence is possibly due to the introduction of the euro in 1999. This paper pushes their results further by examining four potential economic factors of the oil and stock dependence in a unified and quantitative framework. We examine how the oil and stock dependence is affected simultaneously by global oil supply, aggregate demand, precautionary oil demand, and stock specific shocks. Even though the four economic factors overlap with each other from an economic point of view, we decompose them into four uncorrelated shocks by means of the SVAR model of Kilian and Park (2009), avoiding the multi-collinearity problem. More importantly, the SJC copula-MIDAS-X model allows us to distinguish their different impacts when both markets crash together and when both markets boom together. But the separation of the economic factors in the lower and upper tail dependence is rarely reported in existing studies.

The investment implications of understanding the economic determinants of the oil and stocks dependence are twofold. First, regulators and investors should be concerned with changes in aggregate demand in the preceding two years. Aggregate demand is the most influential factor that predicts the oil and stock dependence and its impact lasts for about two years in both bear and bull markets. Second, investors should also pay attention to negative news from the stock market in the preceding three months, as it may result in crashes in both stock and oil prices. Stock specific bad news has explanatory power for the downside dependence between oil and stock returns, but the effects usually last no more than a quarter, which is possibly explained by the overreaction of market participants.

4.3 Out-of-sample evaluation of portfolio performance

To explore the economic value of investigating the factors affecting the oil and stock dependence, we consider the optimization problem of an investor allocating wealth between Brent oil and the S&P 500 index under short sales constraints. There are 281 daily observations and 14 monthly observations in the out-of-sample period (January 1, 2017 to February 28, 2018). A recursive window method is used. At the beginning of each day in the out-of-sample period $t+1$, investors use the historical information up to day t (starting from January 1, 1997) to forecast the joint distribution of oil and stock returns on day $t+1$ and then determine the optimal weights on oil and stock by minimizing the portfolio's risk. This can be done for investors who use the Gaussian copula-MIDAS-X, SJC copula-MIDAS-X, or SJC copula models. For investors using the SJC copula-X model, the procedure is similar except that they use monthly information up to month τ and rebalance their portfolios once a month.

We take the Conditional Value-at-Risk (CVaR) as the portfolio risk measure. CVaR, also known as Expected Shortfall, is used in our analysis as it is a coherent risk measure focusing on extreme loss, which is more likely to be captured by copula models. It is often used by investors and scholars in portfolio risk management, such as Agarwal and Naik (2004), Kakouris and Rustem (2014), Zhao et al. (2015). We solve the mean-CVaR optimization problem in equation (11), as suggested by Rockafellar and Uryasev (2000).

$$\min_{\eta_{t+L}} CVaR_{q,t+L} = VaR_{q,t+L} + \frac{1}{Mq}\sum_{m=1}^{M}\left[-\eta'_{t+L}\hat{r}^{m}_{t+L} - VaR_{q,t+L}\right]^{+},$$
$$\text{s.t.}\begin{cases} \eta_{OIL,t+L} + \eta_{STK,t+L} = 1 \\ \eta'_{t+L}\bar{\mu}_{t+L} \geq \mu_{0,t+L} \\ 0 \leq \eta_{i,t+L} \leq 1, \quad i = OIL, STK. \end{cases} \tag{11}$$

$\eta_{t+L} = \left(\eta_{OIL,t+L}, \eta_{STK,t+L}\right)'$ are the weights on oil and stock. $q = 5\%$ is the probability level and $VaR_{q,t+L}$ is the 5% Value-at-Risk on day $t+L$ based on the information up to day t. $[z]^{+} = \max(0, z)$. $\eta'_{t+L}\hat{r}^{m}_{t+L}$ is the predicted portfolio return on day $t+L$ based on the information up to day t in the m^{th} simulated scenario. We consider $M = 10000$ simulations. $\bar{\mu}_{t+L}$ is the vector of expected oil and stock returns based on the marginal models in equation (8). $\mu_{0,t+L}$ is the target portfolio return, which is the 3-month Treasury bill rate on day t.

Table 4 provides the portfolio performance measures based on the four copulas models. We consider three types of investors who rebalance their portfolios on a daily ($L=1$), weekly ($L=5$), and monthly ($L=22$) basis. In each case, the portfolios' annualized return (Mean), annualized standard deviation (SD), Sharpe ratio and 5% CVaR are reported. Also, the bottom of each panel reports the results of the DM test of Diebold and Mariano (1995) with the SJC copula-MIDAS-X model as the benchmark.④ The null hypothesis is that there is no difference in CVaR between the benchmark and alternative copula. It is worth mentioning that the performance of the SJC copula-X based strategy is the same for daily, weekly, and monthly rebalancing frequency as the investor only uses monthly information to adjust their portfolio weights. Three points

④ The loss function of DM test is $d_t = CVaR_{j,t} - CVaR_{benchmark,t}$, where $CVaR_{j,t}$ is the CVaR predicted by the alternative copula j (j= Gaussian copula-MIDAS-X, SJC copula-X, SJC copula), and $CVaR_{benchmark,t}$ is the CVaR predicted by the benchmark copula (SJC copula-MIDAS-X). A significant positive DM test statistic indicates that SJC copula-MIDAS-X has lower CVaR than the alternative copula.

can be summarized from Table 4.

First, the strategy using the SJC copula-MIDAS-X model outperforms the other three strategies in the out-of-sample period. Of the four copula-based strategies, the SJC copula-MIDAS-X strategy has the lowest CVaR for any rebalancing frequency. The rejections of pairwise DM tests also indicate that the CVaR values of the SJC copula-MIDAS-X based strategy are statistically lower than other strategies.

Second, using mixed frequency information is generally more important than describing the tail dependence. If an investor switches from the SJC copula-MIDAS-X model to the Gaussian copula-MIDAS-X model, meaning he ignores the nonlinear tail dependence between oil and stock, the CVaR only increases from 18.45% to 19.05% on a daily basis, from 17.92% to 19.41% on a weekly basis, and from 16.92% to 18.41% on a monthly basis. If the investor switches from the SJC copula-MIDAS-X model to the SJC copula-X or SJC copula models, meaning he uses only monthly or daily information, the CVaR increases even more in most cases. This implies that using mixed frequency data contributes more than capturing the oil and stock tail dependence to forecasting the joint distribution of oil and stock returns and to improving portfolio performance. The advantage of using mixed frequency information over using single frequency information is also illustrated in Gong et al. (2018), who find that mixed frequency information helps investors better predict the liquidity risk in the stock index futures market.

Third, investors with daily or weekly rebalancing frequencies should follow the mixed frequency copula-based strategies. The advantage of the copula-MIDAS-X models over the SJC copula-X and SJC copula models decreases as the investor switches from rebalancing his portfolio every day to every week to every month. For example, for daily investors, the Gaussian and SJC copula-MIDAS-X based strategies have lower CVaR than the other two strategies using just monthly or daily information. For weekly and monthly investors, the gaps between mixed frequency copulas and the other two copulas in terms of CVaR are narrowed gradually, in particular, the Gaussian copula-MIDAS-X model even has slightly higher CVaR than the SJC copula-X model. Therefore, mixed daily and monthly information is more useful for investors with relatively higher rebalancing frequencies (daily or weekly in our case), while it is less valuable for investors with a lower rebalancing frequency (monthly).

In summary, this section uses the copula-MIDAS-X model to investigate the economic factors affecting the dependence between oil and stock markets. It is found that aggregate demand and stock specific negative shocks are the key economic determinants of the oil and stock dependence, while global oil supply and precautionary oil demand have limited contributions. Declines in aggregate demand and bad news from the U.S. stock market tend to result in bearish performance in both oil and stock markets, while aggregate demand growth tends to lead to bullish performance in both oil and stock markets. The impact of aggregate demand lasts for two years, and the impact of stock specific negative shocks lasts for a quarter. Furthermore, the out-of-sample portfolio performance highlights the economic value of capturing the economic determinants of the oil and stock dependence. Investors who rebalance their portfolio daily or weekly should adopt the strategy using both monthly and daily information.

5. Robustness check

5.1 In-sample estimates before the financial crisis

To check whether the in-sample results are driven by the 2008 financial crisis, in Table 5 we exclude the 2008 financial crisis period and re-estimate the four copulas models in section 4.2.

Table 5 shows the in-sample results with the sample from January 1, 1997 to June 30, 2008. Most of the results are generally consistent with Table 3. The SJC copula-MIDAS-X model still has the best in-sample goodness-of-fit performance. The dependence between oil and stock is asymmetric. Aggregate demand and stock specific shocks are still the important factors closely related with the oil and stock correlation and their tail dependence. However, when the financial crisis period is excluded, the lower tail dependence between oil and stock is reduced. In Table 5, it can be calculated from SJC copula-MIDAS-X that the lower tail dependence on average is 0.3174. Remember in Table 3, the lower tail dependence is 0.4027. It implies that accounting for the financial crisis period drives up the lower tail dependence between oil and stock markets.

5.2 Out-of-sample evaluation of portfolio performance with transaction costs

To analyze the effects of transaction costs on portfolio performance, in Table 6 we perform the out-of-sample analysis with transaction costs. The procedure is similar to that in section 4.3, except that three levels of transaction costs are considered. Panel (a) is tc_{OIL}=0.02% and $tc_{STK}=0.02\%$, which means the transaction fees of both oil and stock are 2 basis points per dollar. Panel (b) is tc_{OIL}=0.02% and $tc_{STK}=0.04\%$ with 2 basis points higher in stock transaction fees. Panel (c) is tc_{OIL}=0.04% and $tc_{STK}=0.02\%$ with 2 basis points higher in oil transaction fees. We use the transaction fees of Brent oil futures traded in Intercontinental Exchange and S&P 500 ETF as the reference values of tc_{OIL} and tc_{STK}.

Most of the results in Table 6 are consistent with those in Table 4. The strategy using the SJC copula-MIDAS-X model outperforms the other three strategies in most cases with lower CVaR values.

However, two conclusions with transaction costs should be pointed out. First, daily rebalancing strategies become less attractive to investors due to the higher transaction costs associated with higher rebalancing frequency. In Table 4 without transaction costs, the CVaR values of the SJC copula-MIDAS-X model are consistently the lowest among the four models. However, in Table 6 with transaction costs, there are a few exceptions. An example can be found in panel (b) with daily rebalancing frequency, in which the SJC copula-MIDAS-X model has higher CVaR than the SJC copula-X model. Second, the portfolio performance is more sensitive to the transaction fees of stock than to the transaction fees of oil. Consider the scenario from panel (a) to (b), when the stock transaction costs double. All the portfolios are shown to perform much worse, associated with decreased Sharpe ratios and increased CVaR values. Then, consider another scenario from panel (a) to (c), when the oil transaction costs double. The performance of the portfolios in this case does not worse off as much as in the previous scenario. It tells us that the portfolio performance is more likely to be affected by stock transactions costs than oil transaction costs. It can be partly explained by the larger and more fluctuated weights on stock than on oil during the out-of-sample period.

6. Conclusion

The dependence between oil and stock markets is an important issue for global portfolio investors and risk managers, as they tend to add crude oil into a stock portfolio for diversification. In this paper, a copula-MIDAS model with explanatory variables (copula-MIDAS-X) is proposed to investigate the economic factors influencing the oil and stock dependence. The new model, which is built upon the models of Colacito et al. (2011) and Gong et al. (2018), extends the mixed frequency data sampling scheme from correlation to the more general dependence measure copula and incorporates low frequency economic explanatory variables into the copula model. This allows us to describe the oil and stock dependence regardless of their marginal distributions and to measure the impacts of economic factors on the oil and stock dependence.

An empirical analysis of Brent oil prices and the U.S. stock market demonstrates that the copula-MIDAS-X model has better in-sample goodness-of-fit and out-of-sample performance than other copulas. The dependence between oil and stock returns is asymmetric, which implies that the diversification benefit of adding oil into a stock portfolio is limited during financial crises. More importantly, the oil and stock dependence is influenced by aggregate demand and negative news from the stock market. The impact of aggregate demand lasts for two years, while the impact of bad news in the stock market lasts for one quarter. This suggests that market regulators and investors should pay more attention to changes in aggregate demand as they are influential and have long-lasting effects on the oil and stock markets. Also, investors who rebalance their portfolios daily or weekly should account for both daily returns and monthly economic information in their portfolio management.

Reference

[1] Agarwal, V., Naik, N.Y. Risks and portfolio decisions involving hedge funds [J]. The Review of Financial Studies. 2004, 17(1): 63-98.

[2] Aloui, C., Nguyen, D.K., Njeh, H. Assessing the impacts of oil price fluctuations on stock returns in emerging markets [J]. Economic Modelling. 2012, 29(6): 2686-2695.

[3] Aloui, R., Hammoudeh, S., Nguyen, D.K. A time-varying copula approach to oil and stock market dependence: The case of transition economies [J]. Energy Economics. 2013, 39: 208-221.

[4] Apergis, N., Miller, S.M. Do structural oil-market shocks affect stock prices? [J]. Energy Economics. 2009, 31(4): 569-575.

[5] Ciner, C. Oil and stock returns: Frequency domain evidence [J]. Journal of International Financial Markets, Institutions and Money. 2013, 23: 1-11.

[6] Clements, M.P., Galvão, A.B. Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States [J]. Journal of Business & Economic Statistics. 2008, 26(4): 546-554.

[7] Colacito, R., Engle, R.F., Ghysels, E. A component model for dynamic correlations [J]. Journal of Econometrics. 2011, 164(1): 45-59.

[8] Conrad, C., Loch, K., Rittler, D. On the macroeconomic determinants of long-term volatilities and correlations in US stock and crude oil markets [J]. Journal of Empirical Finance. 2014, 29: 26-40.

[9] Cunado, J., de Gracia, F.P. Oil price shocks and stock market returns: Evidence for some European countries [J]. Energy Economics. 2014, 42: 365-377.

[10] Diebold, F.X., Mariano, R.S. Comparing Predictive Accuracy [J]. Journal of Business & Economic Statistics. 1995, 13(3): 253-263.

[11] Engle, R. Dynamic conditional correlation [J]. Journal of Business & Economic Statistics. 2002, 20(3): 339-350.

[12] Engle, R.F., Ghysels, E., Sohn, B. Stock market volatility and macroeconomic fundamentals [J]. Review of Economics and Statistics. 2013, 95(3): 776-797.

[13] Ewing, B.T., Thompson, M.A. Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices [J]. Energy Policy. 2007, 35(11): 5535-5540.

[14] Fang, C.R., You, S.Y. The impact of oil price shocks on the large emerging countries' stock prices: Evidence from China, India and Russia [J]. International Review of Economics & Finance. 2014, 29: 330-338.

[15] Fayyad, A., Daly, K. The impact of oil price shocks on stock market returns: comparing GCC countries with the UK and USA [J]. Emerging Markets Review. 2011, 12(1): 61-78.

[16] Filis, G., Degiannakis, S., Floros, C. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries [J].

International Review of Financial Analysis. 2011, 20(3): 152-164.
[17] Ghysels, E., Santa-Clara, P., Valkanov, R. The MIDAS touch: Mixed data sampling regression models [R]. Working paper, University of California at Los Angeles, Anderson Graduate School of Management. 2004.
[18] Ghysels, E., Santa-Clara, P., Valkanov, R. There is a risk-return trade-off after all [J]. Journal of Financial Economics. 2005, 76(3): 509-548.
[19] Gong, Y., Chen, Q., Liang, J. A mixed data sampling copula model for the return-liquidity dependence in stock index futures markets [J]. Economic Modelling. 2018, 68: 586-598.
[20] Huang, R.D., Masulis, R.W., Stoll, H.R. Energy shocks and financial markets [J]. Journal of Futures Markets. 1996, 16(1): 1-27.
[21] Joe, H. Multivariate models and multivariate dependence concepts [M]. Chapman & Hall/CRC. 1997.
[22] Kakouris, I., Rustem, B. Robust portfolio optimization with copulas [J]. European Journal of Operational Research. 2014, 235(1): 28-37.
[23] Kilian, L. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market [J]. American Economic Review. 2009, 99(3): 1053-1069.
[24] Kilian, L., Park, C. The impact of oil price shocks on the US stock market [J]. International Economic Review. 2009, 50(4): 1267-1287.
[25] Mollick, A.V., Assefa, T.A. US stock returns and oil prices: The tale from daily data and the 2008-2009 financial crisis [J]. Energy Economics. 2013, 36: 1-18.
[26] Naifar, N., Al Dohaiman, M.S. Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables [J]. International Review of Economics & Finance. 2013, 27: 416-431.
[27] Pan, Z. Modelling tail dependence between energy market and stock markets in the BRIC countries [J]. Applied Economics Letters. 2014, 21(11): 789-794.
[28] Papapetrou, E. Oil price shocks, stock market, economic activity and employment in Greece [J]. Energy Economics. 2001, 23(5): 511-532.
[29] Park, J., Ratti, R.A. Oil price shocks and stock markets in the US and 13 European countries [J]. Energy Economics. 2008, 30(5): 2587-2608.
[30] Patton, A.J. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation [J]. Journal of Financial Econometrics. 2004, 2(1): 130-168.
[31] Patton, A.J. Modelling asymmetric exchange rate dependence [J]. International Economic Review. 2006, 47(2): 527-556.
[32] Reboredo, J.C., Rivera-Castro, M.A. Wavelet-based evidence of the impact of oil prices on stock returns [J]. International Review of Economics & Finance. 2014, 29: 145-176.
[33] Rockafellar, R.T., Uryasev, S. Optimization of conditional value-at-risk [J].

Journal of Risk. 2000, 2: 21-42.
[34] Sadorsky, P. Oil price shocks and stock market activity [J]. Energy Economics. 1999, 21(5): 449-469.
[35] Sukcharoen, K., Zohrabyan, T., Leatham, D., Wu, X. Interdependence of oil prices and stock market indices: A copula approach [J]. Energy Economics. 2014, 44: 331-339.
[36] Wang, Y., Wu, C., Yang, L. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries [J]. Journal of Comparative Economics. 2013, 41(4): 1220-1239.
[37] Zhao, S., Lu, Q., Han, L., Liu, Y., Hu, F. A mean-CVaR-skewness portfolio optimization model based on asymmetric Laplace distribution [J]. Annals of Operations Research. 2015, 226(1): 727-739.
[38] Zhu, H.M., Li, R., Li, S.F. Modelling dynamic dependence between crude oil prices and Asia-Pacific stock market returns [J]. International Review of Economics & Finance. 2014, 29: 208-223.

Tables

Table 1 Descriptive statistics of daily Brent oil and S&P 500 returns

	Full sample 1997/1/1-2018/2/28		In-sample 1997/1/1-2016/12/31		Out-of-sample 2017/1/1-2018/2/28	
	OIL	STOCK	OIL	STOCK	OIL	STOCK
Mean	0.0213	0.0248	0.0198	0.0224	0.0474	0.0671
Std. Dev.	2.3074	1.2156	2.3414	1.2412	1.6055	0.6154
Skewness	-0.0232	-0.2207	-0.0179	-0.1998	-0.2497	-2.1490
Ex.Kurtosis	4.8092	7.8654	4.7437	7.5116	0.5271	13.5702
J-B $\left(\times 10^3\right)$	4.98***	13.38***	4.59***	11.53***	0.0058*	2.32***
Ljung-Box	44.26***	141.15***	42.78***	133.12***	36.20**	84.64***
ARCH	110.59***	71.49***	106.91***	68.93***	24.95	71.12***
ADF	-70.44***	-76.90***	-68.48***	-74.86***	-16.57***	-16.64***

The table reports the summary statistics of daily Brent oil and S&P 500 returns. Std. Dev. is standard deviation. Ex. Kurtosis is excess kurtosis. J-B is the Jarque-Bera test statistic for normality. Ljung-Box and ARCH are the Ljung-Box tests for serial correlation and for GARCH effect with 12 lags. ADF is the augmented Dicky-Fuller unit root test. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 2 In-sample estimates of marginal models: Brent oil returns and S&P 500 returns

	OIL Estimates	Std. Err.		STOCK Estimates	Std. Err.
$\delta_{i,0}$	0.0198	(0.0189)	$\delta_{i,0}$	0.0096*	(0.0050)
			$\delta_{i,1}$	0.5709***	(0.1653)
			$\delta_{i,2}$	-0.6434***	(0.1617)
$\phi_{i,0}$	0.0072	(0.0059)	$\phi_{i,0}$	0.0182***	(0.0040)
$\phi_{i,1}$	0.0129***	(0.0041)	$\phi_{i,1}\left(\times 10^5\right)$	0.0131***	(0.0047)
$\phi_{i,2}$	0.0383***	(0.0085)	$\phi_{i,2}$	0.1591***	(0.0193)
$\phi_{i,3}$	0.9673***	(0.0057)	$\phi_{i,3}$	0.9063***	(0.0109)
ν_i	7.9192***	(0.8575)	ν_i	8.4157***	(1.0076)
logL	-4.2944		logL	-2.9498	
K-S	0.0036		K-S	0.0048	

The table reports the in-sample estimates of marginal models for daily Brent oil returns and S&P 500 returns from January 1st, 1997 to December 31st, 2016. ***, ** and * denote significance at the 1%, 5% and 10% levels. logL is the log likelihoods of each marginal model. K-S is the Kolmogorov-Smirnov test statistic with the null hypothesis that the model is correctly specified.

Table 3 In-sample estimates of U.S. oil-stock dependence by copula models

Gaussian copula-MIDAS-X			SJC copula-MIDAS-X			SJC copula-X			SJC copula		
	Estimates	Std. Err.		Estimates	Std. Err.		Estimates	Std. Err.		Estimates	Std. Err.
α	0.0154*	(0.0079)	α^L	0.1104***	(0.0245)	c^L	-3.9634***	(1.3291)	α^L	-4.1601***	(0.0011)
β	0.9898***	(0.0064)	β^L	0.9877***	(0.0041)	γ_{GOP}^L	-1.8479	(1.7780)	β^L	0.7894***	(0.0003)
c	0.0010	(0.0008)	c^L	-0.3941***	(0.1279)	γ_{KI}^L	-0.1246***	(0.0153)	c^L	-0.1824***	(0.0045)
γ_{GOP}	0.0023	(0.0026)	γ_{GOP}^L	0.0209	(0.0181)	γ_{OIL}^L	0.2494	(0.3090)	α^U	-2.7463***	(0.0023)
γ_{KI}	-0.0009**	(0.0004)	γ_{KI}^L	-0.0052***	(0.0016)	γ_{STK}^L	0.0209	(0.0707)	β^U	0.7498***	(0.0012)
γ_{OIL}	-0.0002	(0.0002)	γ_{OIL}^L	-0.0039	(0.0027)	c^U	-4.9114***	(1.2875)	c^U	-0.8816***	(0.0176)
γ_{STK}	-0.0007	(0.0009)	γ_{STK}^L	-0.0022*	(0.0011)	γ_{GOP}^U	-1.6662	(2.2945)			
ω_{GOP}	8.9286	(7.1104)	ω_{GOP}^L	143.1754	(137.7120)	γ_{KI}^U	0.0790	(0.0932)			
ω_{KI}	3.5742	(3.9236)	ω_{KI}^L	2.5623***	(0.7160)	γ_{OIL}^U	-0.2251	(0.2276)			
ω_{OIL}	229.0317	(430.7674)	ω_{OIL}^L	142.5450**	(56.3763)	γ_{STK}^U	-0.1338	(0.1391)			
ω_{STK}	2.0013	(3.1969)	ω_{STK}^L	88.7827**	(35.4266)						
			α^U	0.1324	(0.1567)						
			β^U	0.9885***	(0.0088)						
			c^U	-0.8064*	(0.4353)						

			γ_{GOP}^{U}	-0.0506	(0.0973)						
			γ_{KI}^{U}	0.0059***	(0.0019)						
			γ_{OIL}^{U}	0.0047	(0.0053)						
			γ_{STK}^{U}	0.0110	(0.0072)						
			ω_{GOP}^{U}	264.1391	(482.6373)						
			ω_{KI}^{U}	5.5951**	(2.6876)						
			ω_{OIL}^{U}	249.6003	(590.9999)						
			ω_{STK}^{U}	2.0030	(2.2869)						
logL	99.2923		logL	126.1545		logL	8.9739		logL	28.4704	
HQIC	-175.0100		HQIC	-205.1600		HQIC	3.4837		HQIC	-44.0820	

The table reports the in-sample estimates of four copulas models for oil and U.S. stock dependence: Gaussian copula-MIDAS-X, SJC copula-MIDAS-X, SJC copula-X and SJC copula. The in-sample period is from January 1st, 1997 to December 31st, 2016. logL is the log likelihoods of both copula density and marginal models. HQIC is the Hannan-Quinn information criteria. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 4 Out-of-sample oil and stock portfolio performance

Daily ($L=1$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	15.9081	18.0557	13.3798	13.2185
SD	7.3163	7.1811	8.9841	8.9660
SR	2.1743	2.5143	1.4893	1.4743
CVaR(5%)	19.0481	18.4508	20.3525	20.3863
DM test	2.4622**		12.6975***	14.4550***
Weekly ($L=5$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	15.8893	16.8909	13.3798	14.1212
SD	8.8968	9.3792	8.9841	10.6177
SR	1.7860	1.8009	1.4893	1.3300
CVaR(5%)	19.4137	17.9212	19.3525	19.5510
DM test	7.5688***		6.1269***	8.3586***
Monthly ($L=22$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	13.3893	14.7974	13.3798	14.2868
SD	8.4148	8.5264	8.9841	9.9337
SR	1.5912	1.7355	1.4893	1.4382
CVaR(5%)	18.4137	16.9212	18.3525	19.4258
DM test	6.1269***		5.6911***	26.8943***

The table reports the out-of-sample performance of oil and stock portfolios from January 1st, 2017 to February 28th, 2018 based on the four copulas models: Gaussian copula-MIDAS-X, SJC copula-MIDAS-X, SJC copula-X and SJC copula. We consider three types of investors with mean-CVaR optimization who rebalance their portfolios on a daily ($L=1$), weekly ($L=5$) and monthly ($L=22$) basis. The table reports the portfolios' annualized return (Mean), annualized standard deviation (SD), Sharpe ratio (SR), 5% CVaR, and the pairwise Diebold and Mariano (1995) test statistic (DM test) with SJC copula-MIDAS-X as the benchmark model. The target portfolio return for CVaR minimization is the 3-month Treasury bill rate. The null hypothesis of DM test is that there is no difference in CVaR between the benchmark and alternative copula, and the rejection of the null indicates lower CVaR for the benchmark model. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 5 In-sample estimates of U.S. oil-stock dependence by copula models: excluding the 2008 financial crisis

Gaussian copula-MIDAS-X			SJC copula-MIDAS-X			SJC copula-X			SJC copula		
	Estimates	Std. Err.		Estimates	Std. Err.		Estimates	Std. Err.		Estimates	Std. Err.
α	0.1030**	(0.0460)	α^L	0.1913*	(0.1003)	c^L	-4.7966**	(1.9495)	α^L	-4.9989***	(0.0610)
β	0.8134***	(0.0471)	β^L	0.9860***	(0.1195)	γ^L_{GOP}	2.4725	(2.1496)	β^L	0.8259***	(0.0015)
c	0.0026*	(0.0014)	c^L	-0.5091*	(0.2861)	γ^L_{KI}	-0.6301***	(0.0332)	c^L	-0.7072***	(0.0808)
γ_{GOP}	0.0068	(0.0094)	γ^L_{GOP}	0.1071	(0.1175)	γ^L_{OIL}	0.1365	(0.1833)	α^U	-1.9336***	(0.0177)
γ_{KI}	-0.0039**	(0.0020)	γ^L_{KI}	-0.0064**	(0.0030)	γ^L_{STK}	-0.1949	(0.7428)	β^U	0.3172***	(0.0021)
γ_{OIL}	-0.0006	(0.0022)	γ^L_{OIL}	-0.0456	(0.0585)	c^U	-4.9390***	(0.5502)	c^U	-0.8408***	(0.0930)
γ_{STK}	-0.0019	(0.0077)	γ^L_{STK}	-0.0018*	(0.0009)	γ^U_{GOP}	-0.4344	(2.0638)			
ω_{GOP}	21.4925	(18.5263)	ω^L_{GOP}	143.1764	(319.4299)	γ^U_{KI}	0.2924	(0.6238)			
ω_{KI}	2.2679*	(1.3615)	ω^L_{KI}	4.3980**	(2.1853)	γ^U_{OIL}	-0.3829	(1.2170)			
ω_{OIL}	228.8089	(268.3012)	ω^L_{OIL}	142.546	(94.1792)	γ^U_{STK}	0.3461	(0.7111)			
ω_{STK}	10.5220	(22.4488)	ω^L_{STK}	88.7926**	(36.2233)						
			α^U	0.1180	(0.1588)						
			β^U	0.9898***	(0.0021)						
			c^U	-0.8159**	(0.3479)						
			γ^U_{GOP}	-0.0502	(0.0481)						
			γ^U_{KI}	0.0024***	(0.0008)						

			γ^{U}_{OIL}	0.0038	(0.0076)						
			γ^{U}_{STK}	0.0152	(0.0532)						
			ω^{U}_{GOP}	264.1034	(496.0135)						
			ω^{U}_{KI}	6.0550**	(2.4498)						
			ω^{U}_{OIL}	249.5776	(372.7494)						
			ω^{U}_{STK}	2.7339	(1.9856)						
logL	54.4056		logL	68.6231		logL	6.3353		logL	14.8671	
HQIC	-96.4181		HQIC	-124.8530		HQIC	-0.2775		HQIC	-17.3409	

The table reports the in-sample estimates of four copulas models for oil and U.S. stock dependence: Gaussian copula-MIDAS-X, SJC copula-MIDAS-X, SJC copula-X and SJC copula. The in-sample period is from January 1st, 1997 to June 30th, 2008. logL is the log likelihoods of both copula density and marginal models. HQIC is the Hannan-Quinn information criteria. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 6 Out-of-sample oil and stock portfolio performance with transaction costs

(a) tc_{OIL} =0.02%, tc_{STK} = 0.02%

Daily ($L=1$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	10.9081	13.0557	13.1398	8.2185
SD	7.3163	7.1811	8.9841	8.966
SR	1.4909	1.8181	1.4626	0.9166
CVaR(5%)	19.4318	17.0193	20.4690	25.3549
DM test	2.4811***		12.7064***	14.5896***
Weekly ($L=5$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	14.8493	15.8509	13.1398	13.0812
SD	8.8968	9.3792	8.9841	10.6177
SR	1.6691	1.6900	1.4626	1.2320
CVaR(5%)	18.5884	18.5323	20.4690	23.7295
DM test	2.5860***		6.1469***	8.3629***
Monthly ($L=22$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	13.1493	14.5574	13.1398	14.0468
SD	8.4148	8.5264	8.9841	9.9337
SR	1.5626	1.7073	1.4626	1.4141
CVaR(5%)	19.3437	18.1543	20.4690	21.4233
DM test	4.1337***		5.6990***	26.9930***

(b) tc_{OIL} =0.02%, tc_{STK} = 0.04%

Daily ($L=1$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	6.7351	8.7761	12.9182	3.8878
SD	7.3181	7.1847	8.9842	8.9685
SR	0.9203	1.2215	1.4379	0.4335
CVaR(5%)	23.6085	21.3060	20.6908	29.6906
DM test	2.4630***		-2.7892	14.4993***
Weekly ($L=5$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	13.9855	14.9642	12.9182	12.1815
SD	8.8986	9.3814	8.9842	10.6196
SR	1.5717	1.5951	1.4379	1.1471
CVaR(5%)	19.4557	19.4233	20.6908	24.6328
DM test	2.6189***		6.1472***	8.3647***
Monthly	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**

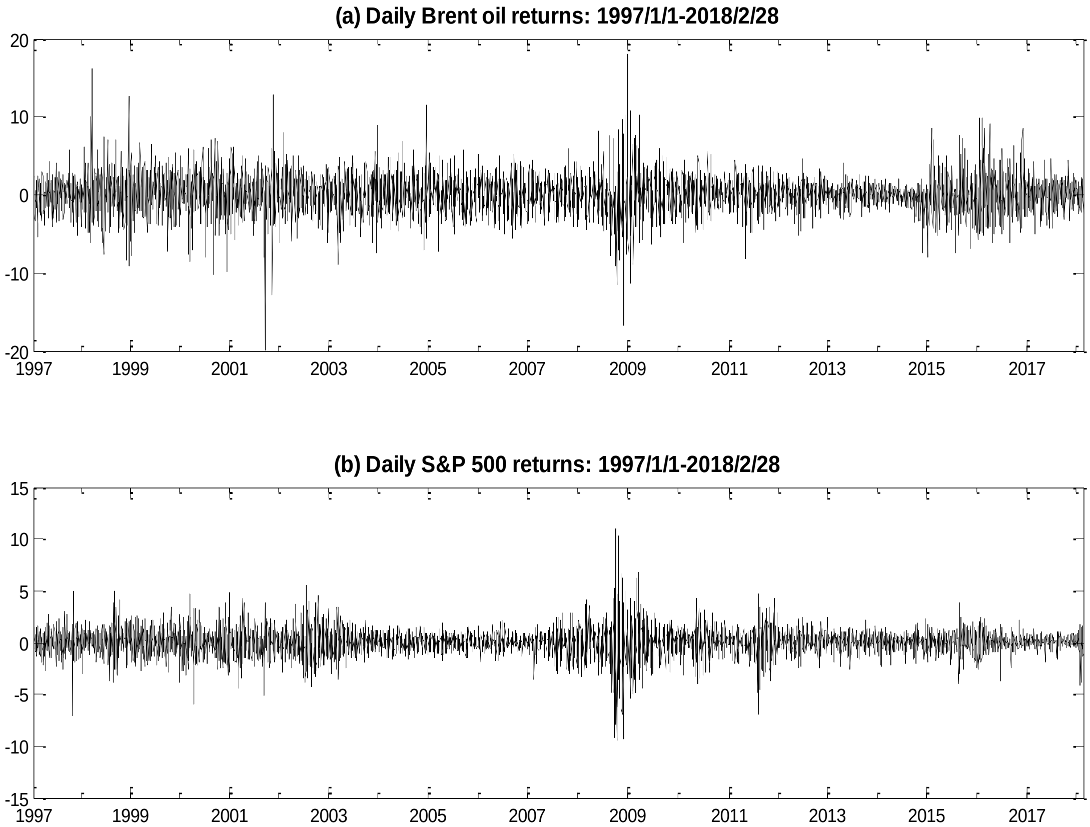
($L=22$)				
Mean	12.9465	14.3508	12.9182	13.8391
SD	8.4134	8.5249	8.9842	9.9327
SR	1.5388	1.6834	1.4379	1.3933
CVaR(5%)	19.5438	18.3581	20.6908	21.6290
DM test	4.1345***		5.6933***	27.1280***

(c) tc_{OIL} =0.04%, $tc_{STK} = 0.02\%$

Daily ($L=1$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	10.0811	12.3353	13.1214	7.5492
SD	7.3147	7.1777	8.9840	8.9636
SR	1.3782	1.7186	1.4605	0.8422
CVaR(5%)	20.2556	17.7329	20.4872	26.0195
DM test	2.4822***		3.7373***	14.4616***
Weekly ($L=5$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	14.6731	15.6976	13.1214	12.9409
SD	8.8951	9.3770	8.9840	10.6159
SR	1.6496	1.6740	1.4605	1.2190
CVaR(5%)	18.7613	18.6814	20.4872	23.8662
DM test	2.5994***		6.1410***	8.4174***
Monthly ($L=22$)	**Gaussian copula -MIDAS-X**	**SJC copula -MIDAS-X**	**SJC copula-X**	**SJC copula**
Mean	13.1121	14.524	13.1214	14.0145
SD	8.4162	8.5279	8.9840	9.9347
SR	1.5580	1.7031	1.4605	1.4107
CVaR(5%)	19.3837	18.1907	20.4872	21.4575
DM test	4.1384***		5.7045***	27.1298***

The table reports the out-of-sample performance of oil and stock portfolios from January 1st, 2017 to February 28th, 2018 based on the four copulas models: Gaussian copula-MIDAS-X, SJC copula-MIDAS-X, SJC copula-X and SJC copula. We consider three types of investors with mean-CVaR optimization who rebalance their portfolios on a daily ($L=1$), weekly ($L=5$) and monthly ($L=22$) basis, and panels (a), (b) and (c) represent different transaction costs. The table reports the portfolios' annualized return (Mean), annualized standard deviation (SD), Sharpe ratio (SR), 5% CVaR, and the pairwise Diebold and Mariano (1995) test statistic (DM test) with SJC copula-MIDAS-X as the benchmark model. The target portfolio return for CVaR minimization is the 3-month Treasury bill rate. The null hypothesis of DM test is that there is no difference in CVaR between the benchmark and alternative copula, and the rejection of the null indicates lower CVaR for the benchmark model. ***, ** and * denote significance at the 1%, 5% and 10% levels.

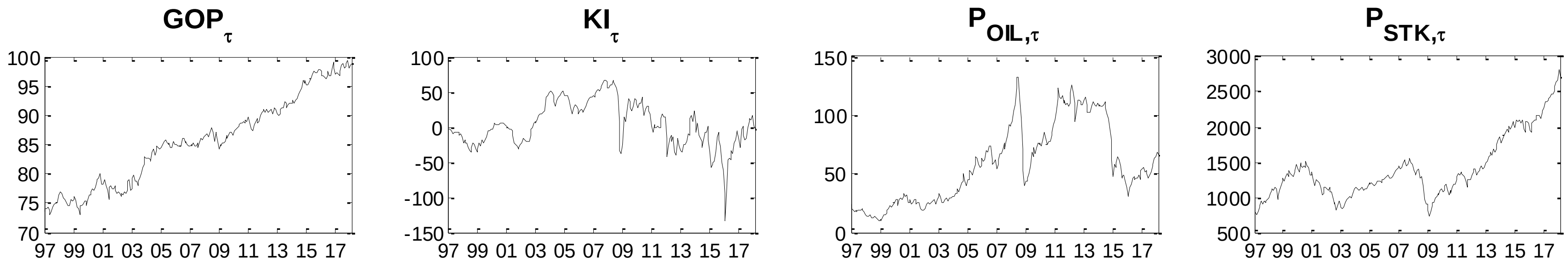
Figures



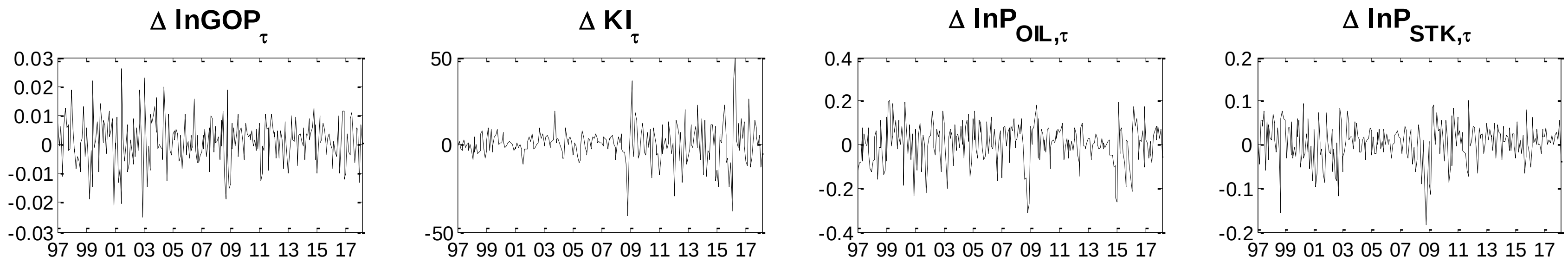
Notes: The figure plots daily Brent oil and S&P 500 index returns from January 1st, 1997 to February 28th, 2018. The returns are calculated as the log difference of daily price multiplied by 100.

Figure 1. Daily returns of Brent oil and S&P 500 index

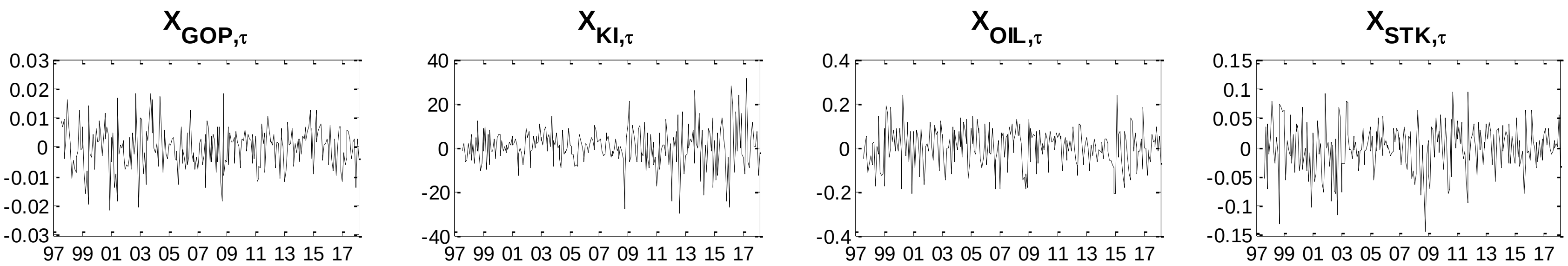
Panel (a): Levels



Panel (b): Changes

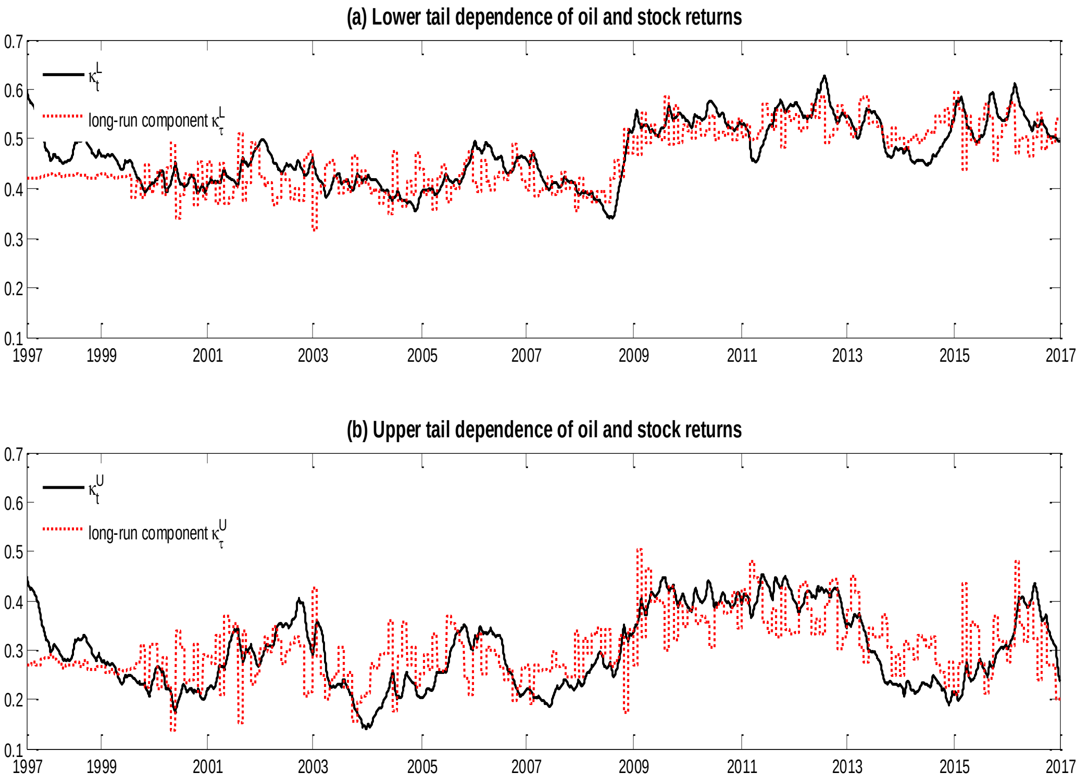


Panel (c): Innovations



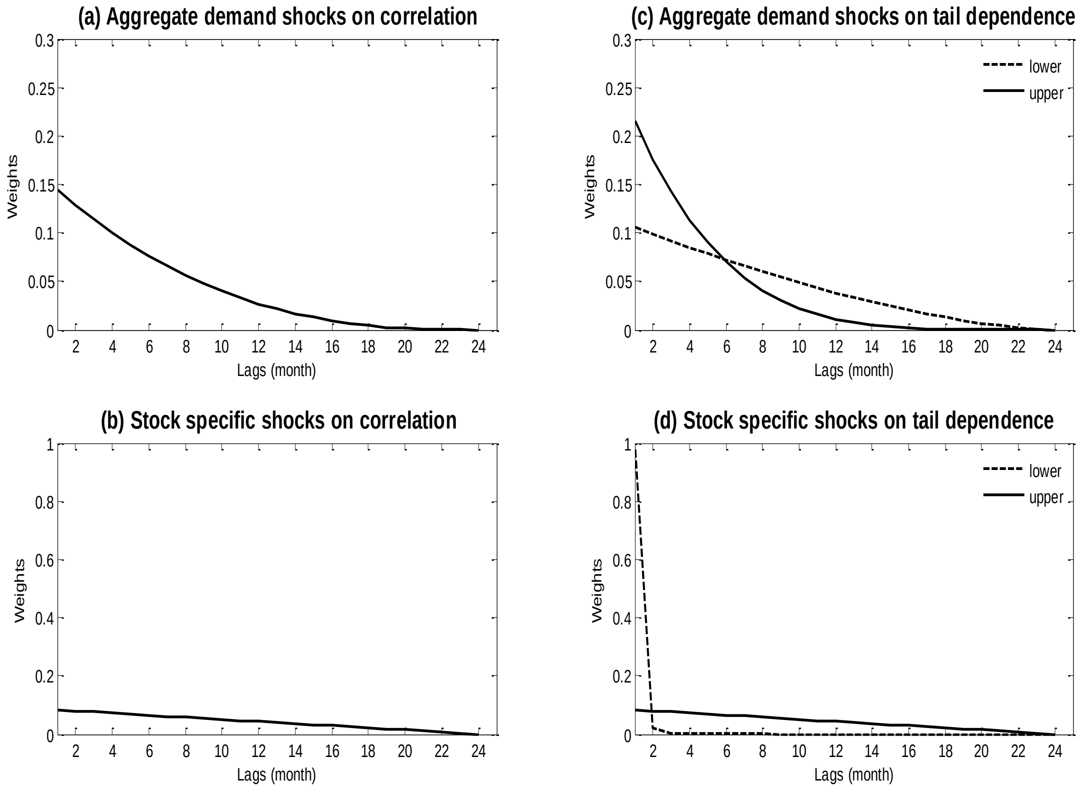
Notes: Panel (a) shows the monthly global oil production in thousands barrel per day (GOP_τ), Kilian index (KI_τ), monthly Brent oil price ($P_{OIL,\tau}$) and monthly S&P 500 index ($P_{STK,\tau}$). Panel (b) shows the changes of the four variables $\left(\Delta \ln GOP_\tau, \Delta KI_\tau, \Delta \ln P_{OIL,\tau}, \Delta \ln P_{STK,\tau}\right)$. Panel (c) shows the orthogonal innovations $\left(X_{GOP,\tau}, X_{KI,\tau}, X_{OIL,\tau}, X_{STK,\tau}\right)$. The sample is from January 1997 to February 2018.

Figure 2. Monthly oil production, Kilian index, Brent oil price and S&P 500 index



Notes: The figure plots the lower tail dependence of oil and stock returns in panel (a) and the upper tail dependence of oil and stock returns in panel (b). The solid black line is the logistic transformation of daily tail dependence $\kappa_t^j = \Lambda\left(\lambda_t^j\right)$, and the red dotted line is the logistic transformation of monthly long-run dependence $\kappa_\tau^j = \Lambda\left(\lambda_\tau^j\right)$, $j = L, U$. The sample is from January 1st, 1997 to December 31st, 2016.

Figure 3. Tail dependence of oil and stock returns



Notes: Panels (a) and (b) plot the impact of aggregate demand and the impact of stock specific shocks on the oil and stock correlation based on Gaussian copula-MIDAS-X, respectively. Panels (c) and (d) plot the impact of aggregate demand and the impact of stock specific shocks on the tail dependence between oil and stock based on SJC copula-MIDAS-X, respectively. The horizon axis is the number of months the impact lasts, and the vertical axis is the weight proportion each lagged month takes on the current correlation or tail dependence. The sample is from January 1st, 1997 to December 31st, 2016.

Figure 4. Impacts of lagged monthly economic factors on current oil and stock dependence