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Uncertainty and crude oil returns☆

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ABSTRACT

We use a copula approach to investigate the effect of uncertainty on crude-oil returns. Using copulas to construct multivariate distributions of time-series data permit the calculation of the dependence structure between the series independently of the marginal distributions. Further, we implement the copula estimation using a rolling window method to allow for a time-varying effect of equity and economic policy uncertainty on oil returns. The results show that higher uncertainty, as measured by equity and economic policy uncertainty indices, significantly increase crude-oil returns only during certain periods of time. That is, we find a positive dependence prior to the financial crisis and Great Recession. Interestingly, estimation of the copula over the entire sample period leads to a negative dependence between the equity and economic policy indices and the crude-oil return.
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1. Introduction

The recent financial crisis and Great Recession, and its aftermath, sparked a debate among economists about the proximate cause of the distressed macroeconomy. That is, did inadequate demand or policy and regulatory uncertainty lead to the economic collapse and slow recovery?[1]

To pursue the hypothesis on one side of this debate that the Great Recession and its subsequent slow recovery reflect policy and regulatory uncertainty. Baker et al. (2013) develop new uncertainty measures — economic policy uncertainty (EPU) and equity market uncertainty (EMU) indexes. Their innovative approach relies in large part on an automated text-search process of 10 large US newspapers. For the EPU index, the search identifies articles that use words related to economic policy, regulation, and uncertainty. Since their approach may raise concerns from other researchers about reliability, the authors also compute the EMU index, using the same automated text-search process, but replace the words that relate to economic policy and regulation with words that relate to the market. They then compare the EMU index with another market uncertainty index, the Chicago Board Options Exchange Market Volatility Index (VIX), showing that the two series demonstrate high co-movement. Finally, these indexes come at a daily frequency, which matches the daily frequency of the oil price that we examine in this paper.

This paper applies a copula-based approach to shed new light on the dynamic relationship between these new innovative news-based measures of economic policy uncertainty or equity-market uncertainty, developed by Baker et al. (2013), and oil price movements. That is, to the extent that policy and equity-market uncertainty affect oil price movements and to the extent that oil price movements affect the business cycle, such uncertainty measures should receive the attention of policy makers.

Following the seminal work of Hamilton (1983), a large literature exists that connects oil price movements (shocks) with recessions and inflationary episodes in the US economy (e.g., see Kang and Ratti (2013a) and Antonakakis et al. (2014) for detailed reviews). A literature also exists that emphasizes the role of economic policy uncertainty on real activity (e.g., see Bloom (2009); Kang and Ratti (2013a); and Antonakakis et al. (2014) for detailed reviews), which, in turn, probably affects oil price movements (shocks).

Early studies by Bernanke (1983) and Pindyck (1991), and more recently, Degiannakis et al. (2014) argue that oil price movements (shocks) probably affect stock-market uncertainty through firm-level investment uncertainty. Equity-market uncertainty also probably feeds into oil price movements (shocks) because, as Bloom's (2009)

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[1] These two potential causes need not reflect mutually exclusive explanations, however That is, the collapse in aggregate demand could result from collapsing consumer and business confidence.

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firm-based theoretical framework notes, equity-market uncertainty affects hiring and investment and, hence, production decisions of firms. In a recent paper, Ajmi et al., (2015) indicate that equity-market uncertainty drives economic policy uncertainty in the US, which, in turn, implies an indirect channel through which the former can affect the oil market, given the above discussion of the relationship between economic policy uncertainty and oil prices.

We investigate the dependence between oil returns (i.e., the natural logarithmic difference in the oil price) and these news-based uncertainty indices, using an approach that goes beyond the simple analysis of correlation, and, at the same time, can capture nonlinearity and dynamic dependence. This method also allows us to measure not only the strength of dependence but also the dependence structure in a flexible way. We achieve these objectives with copula functions in the time-varying context. We conduct our analysis at a daily frequency because crude-oil prices, already volatile in the aftermath of the global financial crisis, became even more unstable as concerns that the recent unrest in North Africa and the Middle East could spread to major oil producing countries.

Choosing a lower frequency for the data analysis (e.g., monthly data, as generally used in the existing literature) could lead to a situation where extreme co-movement occurs less frequently within the sample period. Given that we use daily data, however, we cannot categorize our oil price movements into supply-side, aggregate-demand, and oil-specific demand shocks as suggested by the on-going research of Kilian and Park (2009). We believe, however, that the movements in the two uncertainty indexes can identify the types of shocks that drive the oil price, as they reflect the situation of the economy and the equity market, in general.

An increase (decrease) in the uncertainty indexes probably negatively (positively) affects the economy. This, in turn, reduces (increases) the demand for oil and its price. The price of oil, however, responds to a global market. Nonetheless, as recently noted by Colombo (2013) and Ajmi et al. (2014), the US EPU measure drives the EPU measure of the major European countries, as well as, Canada, India, and China, implying that a shock to the US EPU affects worldwide uncertainty and, hence, affects the global oil market. Increased uncertainty, however, can also lead to an increased oil price as oil suppliers can stock-up due to precautionary motive. So, the movement in the oil price can reflect either a demand shock or a supply shock. The ultimate effect depends on the strength of these two channels at a specific point in time. A time-varying approach, which we follow, proves most important, rather than a mean-estimate based full-sample approach, to provide an accurate picture of the conditional dependence between oil and uncertainty.

Using daily data for the West Texas Intermediate (WTI) crude oil index, the EMU index, and the EPU index, we generally find that the oil and uncertainty indices exhibit time-varying dependence, according to the three (3) copula models used. The two uncertainty indexes also exhibit time-varying dependence, according to the eight (8) copula models used.

We structure the rest of the paper as follows. Section 2 briefly reviews the relevant literature. Section 3 describes the empirical methodology and estimation strategy. Section 4 describes the data and discusses our empirical results. Section 5 provides some concluding remarks.

2. Literature review

While several papers (e.g., Kang and Ratti (2013a) and Antonakakis et al. (2013), (2014)) examine the relationship between the oil returns and the EPU index at a monthly frequency. Our paper is the first to the best of our knowledge that uses copula models to analyze the relationship between these variables as well as between the EMU index and the oil returns. Moreover, our analysis also occurs at a daily, rather than a monthly, frequency. The copula method, which started with Embrechts et al. (2001) and Cherubini et al. (2004), provides a promising solution for understanding and modeling dependent random variables. Copulas provide a flexible methodology in situations where multivariate dependence is of interest and the usual assumption of multivariate normality is in question. As documented, for example, by Jondeau and Rockinger (2006), Junker et al. (2006); Luciano and Marena (2003), and McNeil et al. (2005), the widely used measure of dependence, the Pearson correlation coefficient, may not appropriately describe the type of dependence between returns and, as a result, could underestimate the joint risk of extreme events. To overcome this problem, the copula methodology offers one possible way to characterize the multivariate distributions of asset returns. Other complications refer directly to stylized facts related to the distributional characteristics of financial market returns — the departure from Gaussian distribution, asymmetry, and dynamic dependence.

To better understand our contribution to the literature dealing with uncertainty and oil returns, we briefly review the analysis of Kang and Ratti (2013a) and Antonakakis et al. (2014).[2] Kang and Ratti (2013a), investigate the effect of oil price shocks on EPU, using a structural vector autoregressive (SVAR) model, estimated with monthly oil data and the EPU index. As in Kilian and Park (2009), they disentangle the oil price shocks according to their origin (i.e., supply-side, aggregate-demand, and oil-specific demand shocks). They find that positive aggregate-demand shocks exercise a significant negative effect on policy uncertainty, whereas oil-specific demand shocks exert the opposite effect. Furthermore, supply-side shocks do not produce any effect.[3]

Antonakakis et al. (2014) extend Kang and Ratti (2013a) by developing a dynamic spillover index based on a structural variance decomposition approach of the SVAR model used in Kang and Ratti (2013a). The results reveal that the EPU (oil-returns) responds negatively to aggregate-demand oil-return shocks (EPU shocks). Furthermore, during the Great Recession of 2007–2009, total spillovers increased considerably. Moreover, in net terms, EPU provides the dominant transmitter of shocks between 1997 and 2009, while in the post 2009 period, supply-side and oil-specific demand shocks prove net transmitters of spillover effects.

SVAR models allow for the estimation of structural shocks and impulse responses from the empirical data. We can achieve this by first estimating the VAR model by maximum likelihood and second decomposing the residuals to identify structural shocks. The decomposition of the SVAR residuals assumes normality of the unobserved structural shocks. In most cases, however, the normality assumption is unrealistic. Moreover, we also assume the independence of the identified shocks, hence the well-known orthogonality restriction. When one does not believe that only two groups of economic shocks exist, the orthogonality constraint becomes restrictive due to the low dimension of many SVAR models (Blanchard and Quah, 1989). We can generalize this method to analyze SVAR models with high dimension. For a large system dimension, however, the number of restrictions needed for the identification of shocks increases considerably (Garratt et al., 1998). All these concerns underscore the need to consider a different method to obtain more confident results of the relationship between measures of uncertainty and oil returns.

3. Empirical methodology

We use a simple time-varying copula approach to examine the dynamic relationship between crude oil returns and uncertainty indices.

[2] Besides these papers, Kang and Ratti (2013b) analyzed the importance of oil returns and EPU on stock market returns of the US, Canada, and Europe, given the interrelatedness between uncertainty and oil price returns. Also, in a recent contribution, Kang and Ratti (forthcoming) extend the same analysis to China. Antonakakis and Filis (2013) employ a dynamic conditional correlation (DCC) model to examine the time-varying correlation between oil price shocks and stock market returns. Broadstock and Filis (2014) use the Scalar-BEKK extension of the DCC model to reconsider the time-varying correlation between oil price shocks and stock market returns. El Montasser et al. (2014) use time-varying predictive regressions to analyze the effect of world oil price on EPU and EMU of the Indian economy.

[3] As a robustness check, shocks to precautionary demand for oil significantly influence EPU in Europe and the energy-exporting Canada

Originally developed by Sklar (1959), copula functions link multivariate distributions to their univariate marginal functions. Many papers apply copula functions to measure the dependence structure of financial markets and to analyze derivative pricing and portfolio management (e.g., Aloui et al. (2011); Chan-Lau et al. (2004); Choe and Jang (2011) and Ning (2010)).

Aloui et al. (2011), (2013a) argue that copula functions enable the flexible modeling of correlated multivariate data by generating probability distributions. One can infer the degree of interdependence by constructing a multivariate joint distribution after specifying marginal univariate distributions and then choosing a copula function to examine the variables correlation structure.

Copula functions also characterize the dependence in the tails of the distribution. The upper and lower tail-dependence coefficients emerge from the copula function. In the finance literature, these tail dependence parameters measure the tendency for coordinated crashes or booms in markets.

Following Aloui et al. (2013b), we apply a rolling window procedure to explain the dynamic character of the dependence between oil returns and uncertainty. To reduce the computational cost of this method, we choose a window length of 250 days, which corresponds to approximately one trading year.

Malevergne and Sornette (2003) suggest that the dependence structure of a copula differs for raw returns and filtered returns (residuals). Aloui et al. (2013a) reach the same conclusion and show that the value of the tail dependence coefficients for the raw returns is much higher than for the filtered returns. In this work, we think that the analysis with raw returns provides more accurate results and we choose to not filter the data using a GARCH type model.

Methodologically, we first construct the marginal distribution for each series, using the empirical cumulative distribution function (ECDF) and then estimate the unknown parameters of the selected copula models using the canonical maximum likelihood (CML) method. We repeat this semi-parametric approach for each of the 250-day window until the end of our estimation period.

4. Data and results

4.1. Data and stochastic properties

In this section, we empirically investigate the relationship between oil returns and uncertainty indices from January 4, 2000 to May 12, 2014. We use the EMU and the EPU indices, developed by Baker et al. (2013), as two measures of the degree of uncertainty in the US economy. Data on these two measures of uncertainty come from the website: www.policyuncertainty.com. The daily news-based EPU index uses newspaper archives from Access World New's NewsBank service. The primary measure for this index equals the number of articles that contain at least one term from each of the 3 sets of terms, namely, economic or economy, uncertain or uncertainty, and legislation or deficit or regulation or congress or Federal Reserve or White House.[4] Using the same news source, the EMU index searches for articles containing the terms uncertainty or uncertain, economic or economy, and one or more of the following terms: equity market, equity price, stock market, or stock price.[5]

We use the daily spot price on West Texas Intermediate (WTI) crude to represent the oil market. These data come from the FRED database at the Federal Reserve Bank of St. Louis.[6] We express oil prices as annualized returns (i.e., the natural logarithmic difference expressed in percentage) multiplied by 252. Note that, instead of using the VIX,[7] a popular measure of the implied volatility of S&P 500 index options, we use the news-based measure of EMU index to ensure that both our measures of uncertainty are derived in a similar method (i.e., news article-based and, hence, the results, in terms of their relationship with oil, are comparable).[8]

Fig. 1 shows the evolution of the uncertainty indices and the WTI crude-oil returns. According to the plot, we observe a number of spikes in uncertainty associated with abrupt changes in crude oil returns. Moreover, we see a substantially higher level of uncertainty during the financial crisis and Great Recession from 2008 to 2010. The EMU and EPU indexes both experienced higher volatility from 2001 to 2003 with the peak right at the 9/11 terrorist attack on the Twin Towers and the Pentagon. Moreover, the EPU index also shows markedly higher volatility beginning in early 2008 and continuing through the remainder of the sample. The EMU index also seems to show slightly higher volatility beginning in early 2008, but the increase is less pronounced than the increase of the EPU index.

Table 1 presents descriptive statistics of the uncertainty index and the crude-oil return series. On average or at the median, the EPU index exceeds the EMU index. Conversely, the EMU exhibits more volatility compared with the EPU index, using either the standard deviation of the coefficient of variation. If we use the coefficient of variation, then crude-oil returns prove the most volatile of the three series, followed in order by the EMU and EPU indexes. The Jarque–Bera test suggests that all series depart from normality. The ADF tests with a constant (ADFc) and with a constant and a trend (ADFct) reject the null hypothesis of a unit root at the 1% significance level. The ERS point optimal test of Elliot et al. (1996) confirms that all data series are stationary. Table 2 reports the unconditional correlation between markets. We see a negative correlation between two uncertainty indices and crude oil returns, which runs counter to intuition. Finally, we observe a positive correlation of 0.366 between the two uncertainty indexes.

4.2. Empirical results

We select a copula family among the Gaussian, Student-t, Clayton, Frank, Gumbel, Tawn, survival Clayton, and survival Gumbel copulas, which cover a wide range of dependence structures. For pairs with negative dependence such as WTI–EMU and WTI–EPU, the choice is limited to the Gaussian, Student-t, and Frank copulas.[9] We use the AIC and BIC information criteria corrected for the numbers of parameters used in the models to select the best copula model (Manner, 2007; Brechmann, 2010). Selection of the best copula fit uses also the goodness-fit test (GOF) proposed by Genest et al. (2009).[10]

For each pair, Table 3 reports the estimated parameters of the best copula model, the values of Kendall's tau, and the lower and upper tail dependence coefficients. We use the concordance measure of Kendall's tau that we transform from the copula parameter because each family of copula exhibits a different range of dependence parameters. Kendall's tau is bound on the interval $[-1,1]$ and it reflects the degree to which random variables cluster around a monotone function. As expected,

[4] Further details appear at: http://www.policyuncertainty.com/us_daily.html.

[5] Further details appear at: http://www.policyuncertainty.com/equity_uncert.html.

[6] FRED appears at http://research.stlouisfed.org/fred2/.

[7] Often referred to as the fear index or the fear gauge, it represents one measure of the market's expectation of stock-market volatility over the next 30 day period.

[8] As indicated at: http://www.policyuncertainty.com/equity_uncert.html, the EMU exhibits a contemporaneous daily correlation with the VIX of over 0.3

[9] While the existing literature on copula is vast and extensive, most of the research is still limited to the bivariate case. Extension to the multivariate case has highly restrictive assumptions about the number of model parameters and the choice of adequate copula families. Indeed, using a one-parameter or two parameter copula model may not adequately parameterize the dependence among a large number of variables. Furthermore, for higher dimensions the choice of adequate copula families is limited to elliptically symmetric copulas which lack the flexibility of adequately modeling the dependence structure of the marginal, especially in the tail.

[10] The goodness-of-fit (GOF) test of Genest et al. (2009) is based on a comparison of the Cramér–Von Mises distance between the estimated and the empirical copulas. To find the p-values associated with the test statistics, we use a multiplier approach as described in Kojadinovic and Yan (2011). The highest p-values indicate that the distance between the estimated and empirical copulas is the smallest and that the copula in use provides the best fit to the data.

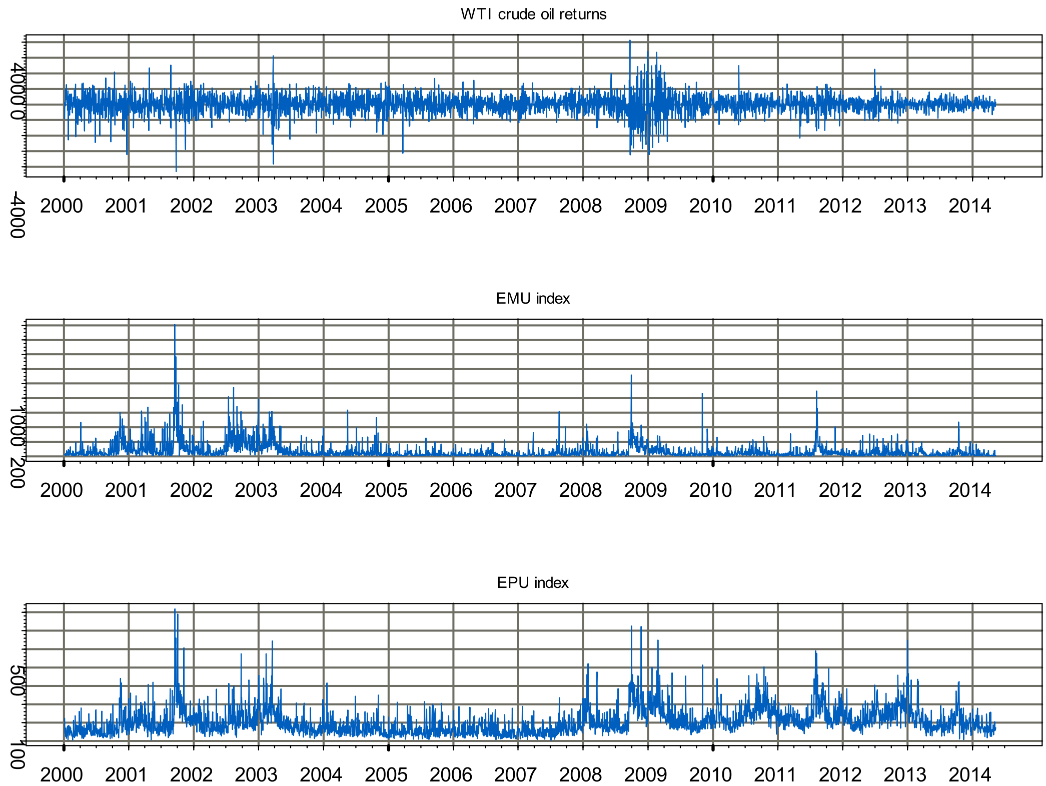

Fig. 1. Uncertainty indexes and WTI crude-oil returns.

the uncertainty indices exhibit a positive dependence and the asymmetric Gumbel copula provides the best model.[11] The tail dependence coefficients implied by the estimated parameters of the Gumbel copula show that the correlation between EPU and EMU strengthens during bullish periods (i.e., high uncertainty in equity markets associates with high uncertainty in economic policy).

The oil returns–EPU and oil returns–EMU pair show significant and negative dependence parameters in these two cases, indicating that the uncertainty indices and crude-oil returns respond negatively to each other. This counter-intuitive finding may suggest that spillover effects between oil returns and uncertainty indices exhibit a dynamic character. That is, the relationship may change over time. The symmetric Student-t copula[12] provides the best fit in these two cases. The Kendall's tau values that we transform from the Student-t copula parameters show a rather weak negative association between oil returns–EMU and oil returns–EPU. The lower and upper tail dependence coefficients are approximately zero, probably because structural breaks or regime shifts change the relationships between oil prices and the uncertainty indices in the high volatility regime.

To examine possible dynamic relationships between the oil returns and uncertainty indices, we adopt a time-varying copula approach for the analysis. Following Aloui et al. (2013b), we estimate the copula parameters based on a rolling window of 250 days.[13] Again, we apply the empirical cumulative distribution function (ECDF) for the marginal distributions and estimate the copula dependence parameters. We repeat this semi-parametric approach for each new window constructed from the remaining 3493 observations.

Fig. 2 shows the dynamic dependence between oil returns and uncertainty indices for the one-year rolling-window period. Since the best performing copula models for our sample belong to the elliptical and Archimedean families, we transform the estimated copula parameters into Kendall's tau using $\frac{2}{\pi}\arcsin(\theta)$ and $1-\frac{1}{\theta}$ for the Student-t and Gumbel copulas respectively. We compute Kendall's tau at day t using the previous 249 pairs of oil returns and uncertainty indices, and the pair at t itself.

The estimated dependence between oil returns–EMU, as measured by Kendall's tau, exhibits time variation, taking on values between −0.119 and 0.088. Recall from Table 2 that the unconditional constant correlation estimate is −0.076. The dependence reaches its peak in 2004, when crude oil prices rose to new highs in response to geopolitical crises, economic trends, and natural disasters.[14] Moreover, we also observe that the positive dependence continues, although at a lower level, during the financial crisis and Great Recession over 2007 to 2009, but turns into negative dependence in 2009.

For the oil returns–EPU pair, we see that the spillover fluctuates within a range of −0.132 and 0.084. This dependence also turns negative in 2009. These findings coincide with the range of fluctuation observed for the oil returns–EMU relationship. We notice an increase in the level of dependence that coincides with the period 2002–2003 (war in Afghanistan and second war in Iraq), the Great Recession of mid-2007 and 2008, as well as during the European Debt crisis in 2011.

For the EPU–EMU pair, the Kendall's tau takes values between 0.024 and 0.391. As we can see, the dependence between EPU and EMU rises substantially after major (world) events: 2001 terrorist attacks, 2002–2003 SARS outbreak, 2008/2009 global financial crisis, and the Arab spring.

[11] The Gumbel copula is an Archimedean and extreme value copula, exhibiting greater dependence in the upper tail than in the lower tail. The dependence parameter for this copula θ takes values higher or equal to 1. $\theta = 1$ implies independence and $\theta \to \infty$ implies perfect positive dependence.

[12] The Student-t copula is an elliptical copula allowing for the same lower and upper tail dependence coefficients, but not for asymmetries. The dependence parameter θ of this copula is restricted to the interval (-1,1). $\theta = 0$ leads to independence, while $\theta > 0$ and $\theta < 0$ lead to positive and negative dependence, respectively.

[13] Due to the computational cost of this procedure, we choose a window length of 250 days, which corresponds to approximately one year. Aloui et al. (2013a) show that copula results remain globally robust to the size of the rolling window.

[14] Oil price spikes after major world events such as Hurricanes Rita and Katrina in 2005, the conflict between Israel and Lebanon in 2006, and worries over Iranian nuclear plans.

Table 1
Descriptive statistics.

Panel A						
	Min	Mean	Max	Std dev	Skewness	Kurtosis
Oil returns	−4307.13	9.241	4136.25	599.230	−0.331	5.160
EMU	4.801	71.761	1811.327	106.411	4.728	39.510
EPU	3.382	105.973	719.072	72.496	1.989	7.413
Panel B						
	Median	Q(12)	J–B	ADFc	ADFct	ERS
Oil returns	33.386	36.617*	4209.163*	−19.190*	−19.190*	2.408*
EMU	36.375	6799.887*	256,799.362*	−8.843*	−9.429*	0.983*
EPU	88.161	10,637.869*	11,012.152*	−7.268*	−7.520*	1.257*

Notes: The table displays summary statistics for daily crude-oil returns and uncertainty indices. EMU and EPU denote the level in equity-market and economic policy uncertainty, respectively. The sample period runs from January 4, 2000 to May 12, 2014. Q(12) is the Ljung–Box statistics for serial correlation in returns for order 12. J–B is the empirical statistic of the Jarque–Bera test for normality. ADF denotes the augmented Dickey–Fuller test with constant (ADFc) and with constant and trend (ADFct). ERS is the Elliott–Rothenberg–Stock point optimal test.
* Indicates the rejection of the null hypotheses of no autocorrelation, normality, and unit root at the 1% level of significance.

We observe a higher level of dependence between uncertainty indices in early 2009. That is, increases in uncertainty occur in both equity markets and economic policy. At the same time, the dependence between the oil return and uncertainty indexes falls to low negative levels, but then increase. The rise in the dependence between the oil return and the policy uncertainty rises to a new peak by early 2010, whereas the rise in the dependence between the oil return and the equity market uncertainty rises more slowly, reaching a peak in late 2011. This suggests that a time delay exists in the effect of the uncertainty indexes on the oil return, where the time delay for the equity market index is longer.

At this stage, it is important to highlight the importance of our rolling estimation. While, as in Kang and Ratti (2013a) and Antonakakis et al. (2014), our full-sample estimation suggests a negative relationship between the uncertainty indexes and oil returns, our time-varying estimation at times reveals a completely different picture. The conditional dependence not only varies tremendously over our sample, but also, the dependence shows a positive dependence prior to the episodes of economic crises. In other words, relying on full-sample (mean) estimates, as produced by Kang and Ratti (2013a) and Antonakakis et al. (2014) can lead to misleading inferences about the true relationship between uncertainty indexes and oil returns, which, in fact, is time-varying.

Fig. 3 shows the evolution of the tail-dependence coefficients of the Student-t copula for the oil-return and uncertainty indices, which embodies equal upper and lower tail dependences, and the Gumbel copula for the uncertainty indices, which exhibits tail dependence only on the upper tail.

Fig. 3 illustrates how the probability for coordinated crashes or booms evolves over time. We compute the tail dependence coefficient at time t using the 249 trading days prior to day t and day t itself. As expected, the extreme dependence strength between the variables changes over time. We first note that time periods exist when the tail dependence coefficients are approximately zero, indicating that little or no relationship exists between the variable and other "stormy" time periods with a higher probability of joint extreme movements.

The oil returns–EPU and oil returns–EMU pairs exhibit mutual dependence during bear and bull markets. For the oil returns–EMU pair, the upper and lower tail-dependence coefficients fluctuate between 0 and 11.4%. The highest level of extreme dependence occurs in early 2004. The tail dependence increases also in 2005 and 2011. The oil returns–EPU pair shows a relatively small degree of tail dependence and fluctuates within a range of 0 and 6.5%. The highest level is reached in 2005. Two other peaks with approximately similar magnitude occur in 2008 and 2012. In sum, the oil-return and uncertainty indices exhibit similar dependence ranges, whereas the extreme dependence levels differ. Stated differently, during normal market conditions, the oil and uncertainty indices exhibit the same level of dependence. But during extreme market conditions, oil becomes more connected with EMU than with EPU.

Fig. 3 also shows the evolution of the upper tail-dependence coefficients of the Gumbel copula for the uncertainty indexes. As expected, extreme co-movement between the uncertainty indices becomes much stronger during 2008 and reaches 47% by early 2009. Similar rising tail dependence also occurs in 2001, 2011, and 2013. While our data sample do not allow us to know when the rise occurs, we do observe that this high level of dependence also exists at the beginning of our calculations in 2001, remaining at a high level off and on until dropping in early 2004.

Table 2
Unconditional correlations.

	WTI	EMU	EPU
WTI	1.000		
EMU	−0.076	1.000	
EPU	−0.030	0.366	1.000

Notes: This table gives the unconditional correlation between the uncertainty indices and the WTI crude oil returns series.

4.3. Robustness check

4.3.1. Sensitivity of results to other oil price series

We check the sensitivity of our results to the choice of alternative oil price series. Since the WTI is the dominant benchmark in the U.S, we choose the Brent which is the reference for about two-thirds of the oil traded around the world. To simplify the interpretation of the results, the estimated dependence parameters of the Student-t copula are transformed into Kendall's tau and plotted in Fig. 4.

For the Brent–EMU pair, the time varying Kendall's tau rank correlation coefficient fluctuates between −0.143 and 0.063 with an average value of −0.038. The minimum value is reached at the end of year 2008, when Lehman Brothers collapsed (September 2008) and the financial crisis started spreading. The time varying Kendall's tau coefficient between Brent and EPU ranges between −0.146 and 0.094 with an average value of 0.0005. The lowest level is also reached at the end of 2008. Except for the magnitude of the upward and downward movements in the series, the peaks and troughs mimic those of the WTI–EMU and WTI–EPU charts in Fig. 2.

To test the hypothesis that economic uncertainty tends to affect more future prices and not only spot prices, we repeat our estimation procedure using futures contract for WTI crude oil. We justify the use of future prices since they are less noisy in comparison to spot prices, which are more affected by short-run movements of demand and supply (Sadorsky, 2001; Boyer and Filion, 2007).

Table 3
Copula estimation results.

	Copula	Parameters (SE)		Kendall's τ	Tail dependence
Oil-EMU	Student-t	-0.032 (0.017)*	$v = 13.040$ (3.203)***	-0.020	$\lambda_u = \lambda_l = 1.692e$-02
Oil-EPU	Student-t	-0.027 (0.014)*	$v = 10.236$ (1.952)***	-0.017	$\lambda_u = \lambda_l = 5.319e$-02
EPU–EMU	Gumbel	-1.267 (0.017)***	–	0.209	$\lambda_l = 0$, $\lambda_u = 0.270$

Notes: This table presents the copula parameter's estimates, the tail dependence coefficients and the Kendall's tau values. Standard errors are given in parenthesis.
* Indicates significance at the 10% level.
*** Indicate significance at the 1% level.

The time varying Kendall's tau rank correlation coefficient between WTI futures and EMU ranges between -0.113 and 0.106 with an average value of -0.021. For the WTI futures–EPU pair, the rank correlation coefficient ranges in [-0.123, 0.089] with an average value of -0.005. Once again, the upward and downward movements as well as the peaks and troughs generally mimic the similar charts in Fig. 2 for the WTI–EMU and WTI–EPU pairs.

All in all, there are periods with positive rank correlation and other with negative rank correlation values. We can conclude that the relationship between the considered pairs is not constant over time and that the comovement is approximately symmetric (mean around zero).

4.3.2. Replacing oil with natural gas and gold

For the natural gas-EMU and natural gas-EPU pairs, the time varying Kendall's tau rank correlation coefficient ranges over [-0.09, 0.117] and [-0.057, 0.095] with an average values of 0.021 and 0.019, respectively (See Fig. 5.). The lowest levels of dependence are reached in 2008 and 2005. For the natural gas-EMU pair, the upward and downward movements generally reverse those of the WTI–EMU pair in Fig. 2 before 2006. But, after 2006, the movements of the natural gas-EMU generally correspond to those of the WTI–EMU in Fig. 2. For the natural gas-EPU pair, the upward and downward movements generally mimic those of the WTI–EPU pair in Fig. 2, although the dip in 2009 for the natural gas-EPU pair is not as deep as the drop in Fig. 2 for the WTI–EPU pair.

For the gold-EMU and gold-EPU pairs, the time varying Kendall's tau rank correlation coefficient ranges in [-0.06, 0.162] and [-0.154, 0.110] with an average values of 0.037 and -0.0006, respectively (See Fig. 5). The lowest levels of dependence are reached in 2007 and 2003. The obtained results do not differ from those of the other oil price series (symmetric comovement and dynamic dependence). It appears that the upward and downward movements in the gold-EMU and gold-EPU pairs correspond to those for the WTI–EMU and WTI–EPU pairs, except that the gold pairs generally move before the WTI pairs.

In sum, we expect gold and gas to exhibit less volatility than crude oil. Thus, uncertainty movements should affect gold and natural gas prices less. First, investors typically look at gold as a safe haven during crises. Second, the size of natural gas market relative to the crude oil market also implies lower volatility in natural gas prices. Our findings, where the upward and downward movements mirror each other for all series, do not sustain this idea. More specifically, we do not confirm the safe-haven role for gold.

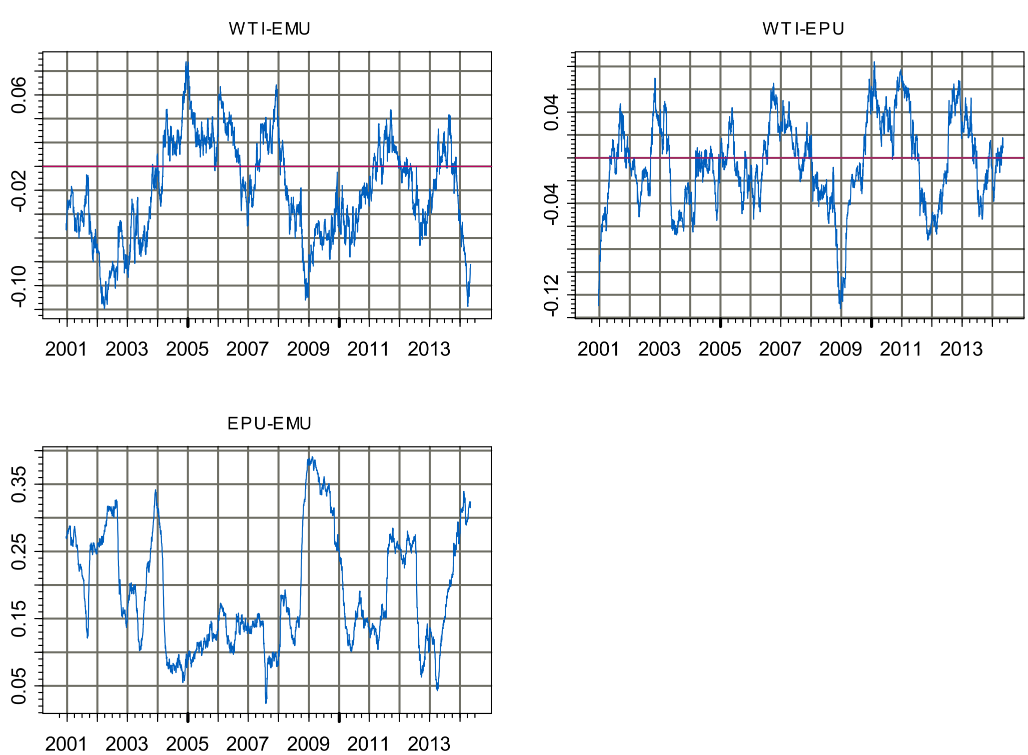

Fig. 2. Time-varying Kendall's tau for the relationship between WTI–EMU, WTI–EPU and EPU–EMU (250 observations).

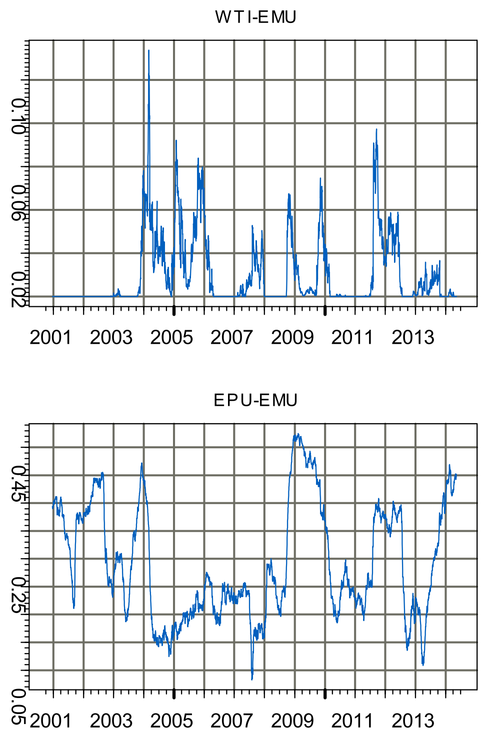

Fig. 3. Time-varying tail dependence coefficient for the relationship between crude oil and uncertainty indices (Student-t copula) and the relationship between EPU and EMU (Gumbel copula).

5. Conclusion

This paper investigates the effect of policy and market uncertainty on crude-oil returns. Using copulas, we construct multivariate distributions of time-series data to calculate the dependence structure between the series independently of the marginal distributions. Further, we implement the copula estimation using a rolling window method to allow for a time-varying effect of equity and economic policy uncertainty on oil returns.

We use new measures of uncertainty – economic policy uncertainty (EPU) and equity market uncertainty (EMU) indexes – developed by Baker et al. (2013). Their innovative approach employs an automated text-search process of 10 large US newspapers. For the EPU index, the search identifies articles that use words related to economic policy,

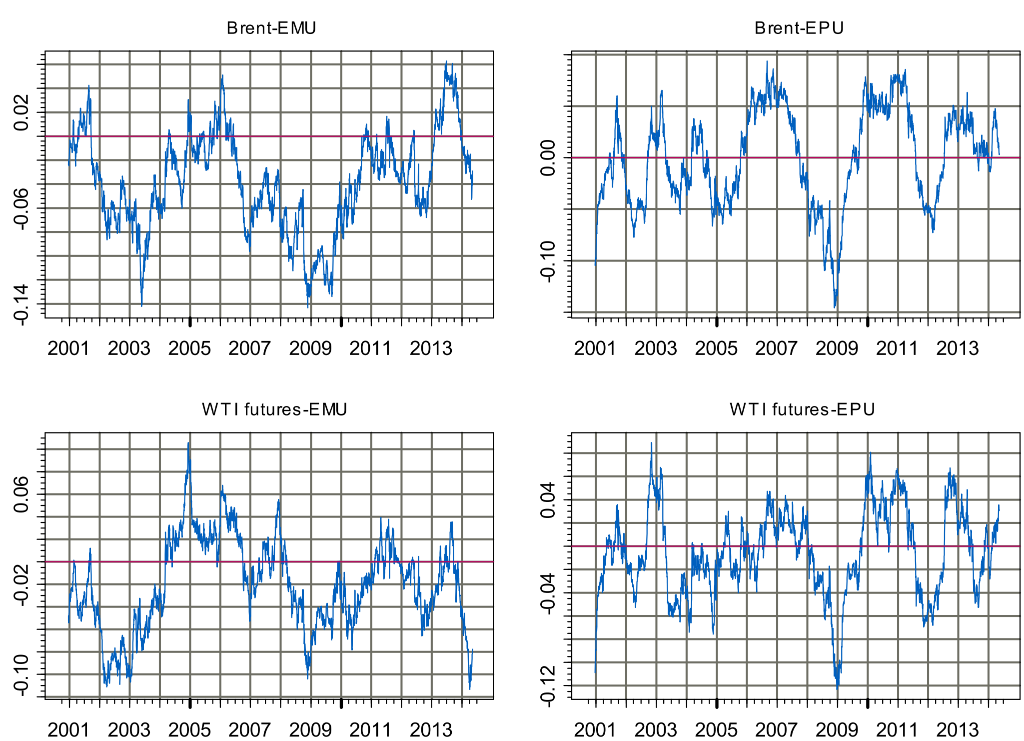

Fig. 4. Time-varying Kendall's tau for the relationship between uncertainty indices and crude oil returns.

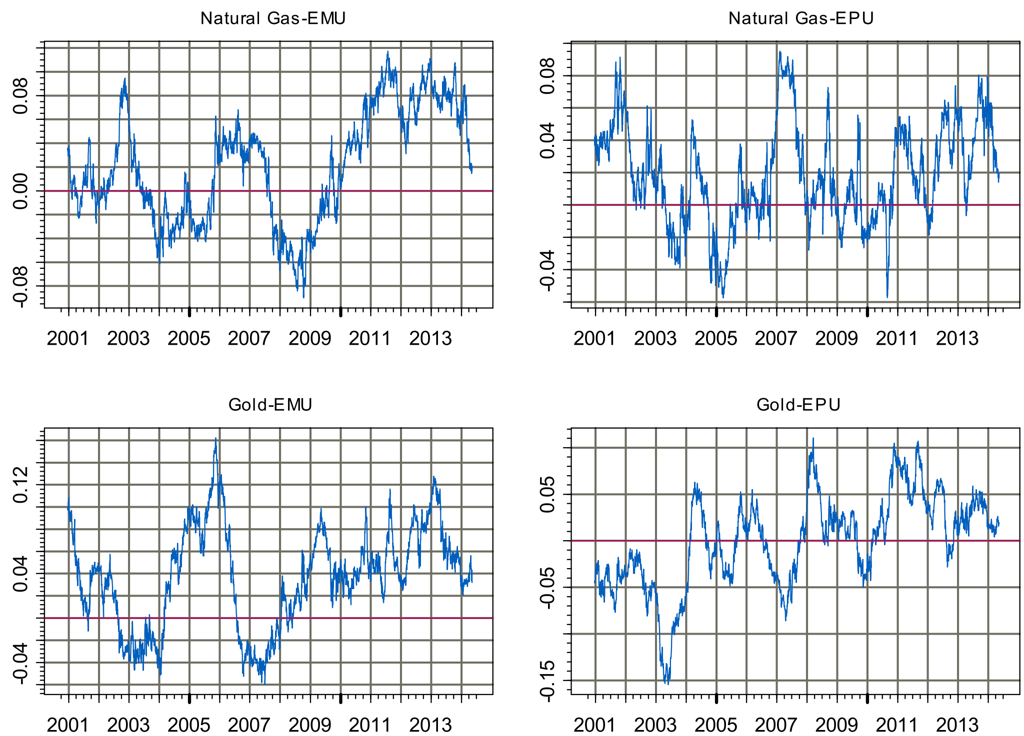

Fig. 5. Time-varying Kendall's tau for the relationship between uncertainty indices, gas and gold.

regulation, and uncertainty, while for the EMU index, they replace the words that relate to economic policy and regulation with words that relate to the market.

The results show that higher uncertainty, as measured by equity and economic policy uncertainty indices, significantly increases crude-oil returns only during certain periods of time. That is, we find a positive dependence prior to the financial crisis and Great Recession, Interestingly, estimation of the copula over the entire sample period leads to a negative dependence between the equity and economic policy indices and the crude-oil return.

We conjecture that the uncertainty measures affect oil returns through their effect on the beliefs of the participants in the oil market. That is, increases in uncertainty can generate positive or negative dependences as the participants respond to the increase in uncertainty given the existing situation in the overall economy. As a result, dependence can switch from positive to negative as market participants respond differently to increases in uncertainty.

Appendix A Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.01.012.

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