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Mutual excitation between OECD Stock and Oil Markets: A Conditional Intensity Extreme Value Approach

ABSTRACT

We analyze the degree of mutual excitation that exists between extreme events across the stock markets of OECD member nations and the Brent and WTI crude oil markets. For this analysis, marked point process models are proposed which are able to capture the dynamics of the intensity of occurrence and comovement during periods of crisis. The results show a significant, negative interdependence between most OECD markets, especially those of the USA, Japan and France. These major oil importing countries display links between equity market losses and positive returns in both oil markets. However, positive interdependence is not observed between any of the OECD countries except for South Korea. The great advantage of this methodology is that, apart from using the size distribution of extreme events, it also uses the occurrence times of extreme events as a source of information. With this information, these models are better able to capture the stylized facts of extreme events in financial markets such as clustering behavior and cross-excitation.

Keywords: Extreme Value Theory, Financial Markets, Oil Markets, Value at Risk; Interdependence.

1 Introduction

Financial globalization has strongly impacted the rapid development and integration of different financial markets. Thus, a great deal of research attention has focused on understanding comovements between oil prices and stock market returns during periods of financial stress (Marimoutou et al., 2009; Cologni and Manera, 2009; Wen et al., 2012; and Mollick and Assefa, 2013).

Existing financial literature suggests mostly a negative association between stock and oil markets prices, i.e., most countries exhibit interdependence or comovements between negative returns in equity markets and positive returns in oil markets (Jones and Kaul, 1996; Sadorsky, 1999; Ciner, 2001; Papapetrou, 2001; and Nandha and Faff, 2008), denoted here as *negative interdependence*. However, more recent studies have also provided some evidence of *positive interdependence*, i.e., comovements between negative returns for both markets (Park and Ratti,2008; Narayan and Narayan, 2010; Ono, 2011; and Aloui et al., 2013).

In this paper, we provide evidence on the oil–equity relationship during periods of financial turmoil by analyzing the degree of self-excitation (from one country to itself) and cross-excitation (from one market to another) that exists between extreme events across the stock markets of OECD member nations and the Brent and West Texas Intermediate (WTI) crude oil markets using a point process theory. Models of this type have been used recently in finance, including credit risk modeling (Errais et al. 2010; Giesecke and Zhu, 2013), high frequency (Bacry et al. 2012; Bacry et al. 2013), financial contagion (Aït-Sahalia et al. 2014; Aït-Sahalia et al. 2015) and extreme financial risk (Chavez-Demoulin and McGill, 2012; Herrera and Schipp, 2014; Grothe et al. 2014).

We show how these events, such as stock market crashes and oil price shocks, are of particular relevance for financial risk management. The reason for such attention on the relationship between OECD stock markets and crude oil markets is due to these countries are important net importers of crude and consumers of refined products. Therefore, extreme oil prices movements could have significant impacts on the state of the economy in these countries.

The main advantage of this type of methodology is that instead of using the whole time series, only the most extreme movements in each of these indices are examined, the most important events when considering financial market stress. In addition, the feedback between the intensity of these extreme events across markets, and between the intensity and the magnitude of the extreme events in the same market, is a key element of the specification. The model proposed is an autoregressive conditional intensity peaks over threshold (ACI-POT), a model of autoregressive conditional intensity for extreme events that occur over a predefined threshold.

In this study we try to answer the following research questions: how are the extreme events of the oil market and the financial markets related? Can we use this relationship in the context of financial risk, for example, to provide superior forecasts of extreme risk? Is there a relationship between the intensity of occurrence of extreme events and the size of them?

According to our empirical results, by focusing specifically on the extreme events overwhelming evidence negative interdependence is revealed. In particular, we observe negative interdependence between Brent and U.S., Japan, Germany, France, U.K. and Spain. For the WTI index we found negative interdependence with U.S., Japan South Korea and France. In contrast, very little evidence of positive interdependence is discovered. Furthermore, the ACI-POT approach offers gains in extreme risk forecast accuracy, when this interdependence is considered.

The negative interdependence may be due to the effect of oil supply shocks, which Ready (2016) finds to be the most important driver of variation in oil prices, which are in turn related to equity returns. If a supply shock reflects tightening (increase) of supply this would lead to higher (lower) oil prices and lower (higher) equity prices as higher oil prices dampen economic activity. The importance of such an oil supply shock channel would in part explain the negative interdependence between oil and equity markets. If positive interdependence were observed, this may be attributable to aggregate demand shocks underlying oil prices as these would be positive (or negative) news for both oil and equity prices. However Ready (2016) finds demand shocks to be much less important than supply shocks in explaining equity returns.

The paper proceeds as follows: Section 2 presents review of related literature. Section 3 introduces the ACI-POT methodology. Section 4 presents the empirical analysis of interdependence between markets and finally Section 4 presents the main conclusions and possible future lines of research.

2 Review of the literature and Motivation for the study

In this section we summarize the debate on the relationship between stock market returns and oil price shocks. Early works examining the connection between oil and stock markets provide theoretical motivations based on asset pricing theory. This theory suggests that the reaction of stock price returns to oil shocks is mainly determined by current and future expected cash-flows. As a result, oil price shocks tend to have a negative impact on stock market returns. Jones and Kaul (1996) were among the first to investigate the effect of oil price shocks on stock market returns using this motivation. They suggest that, for the U.S and Canadian stock markets, the reaction of stock price returns to oil shocks is mainly determined by current and future expected cash-flows. However, in the case of UK and Japan, the hypothesis cannot be justified. Park and Ratti (2008) consider the U.S and 13 countries in Europe (mostly OECD countries) and finds negative interdependence between oil prices and stock markets. Miller and Ratti (2009) analyze the interaction of oil prices with stock markets in some OECD countries such as Canada, France, Germany, Italy, England and the U.S. showing that stock indices respond negatively to increases in oil prices in the long-run in a cointegration framework. Cologni and Manera (2009) show that crises in the oil market partially explain the recessions that occurred in the G7 countries (Germany, Canada, U.S, France, Italy, Japan and England).

Filis et al. (2011) analyze importing countries (U.S, Germany and the Netherlands) and oil exporters (Canada, Mexico and Brazil) showing that fuel prices have a negative effect on stock markets, with the exception of the financial crisis of 2008, where the effect is positive between markets.

Some recent studies however, have also reported evidence of positive interdependence between these markets, mainly for oil-exporting countries. A plausible explanation for the tendency of stocks and oil prices to move together for some period of time is that an increase in the price of oil should be accompanied by a positive impact on stock prices of this country as a consequence of higher revenues in the oil export industry. For instance, Hammoudeh et al. (2004) through cointegration analysis investigate the intra- and interlinks among U.S. oil prices and oil industry equity indices. Their results indicate that these indices have one positive long-run relationship. El-Sharif et al. (2005) examine the link between crude oil prices and the U.K equity market, finding evidence of positive interdependence, which is quite reasonable as the U.K. is the largest oil producer in the European Union. Zhu et al. (2014) consider the markets of Asia-Pacific, relevant to the current study since it considers Australia, Japan and South Korea, finding positive dependence before the global financial crisis and weak linkages overall.

Figure 1 provides preliminary evidence of comovements between stock markets and WTI crude oil market from 1994 to 2014. In the top panel we illustrate the relationship between the S&P 500 stock market index and the WTI crude oil index, representing one of the most important oil-importing countries. On the other hand, the bottom panel exhibits the interdependence between the WTI crude oil index and the SPTSX stock market from Canada, which has been a net exporter since 1982 and one of the world's largest net exporter. The extent to which the markets move together is measured by simple correlation, which is displayed at the bottom of each figure as a barcode plot. To capture long-term variations, we use a rolling window of six months, approximately 125 business days. The intensity of the gray color, from black to white, indicates the degree of correlation between both markets.

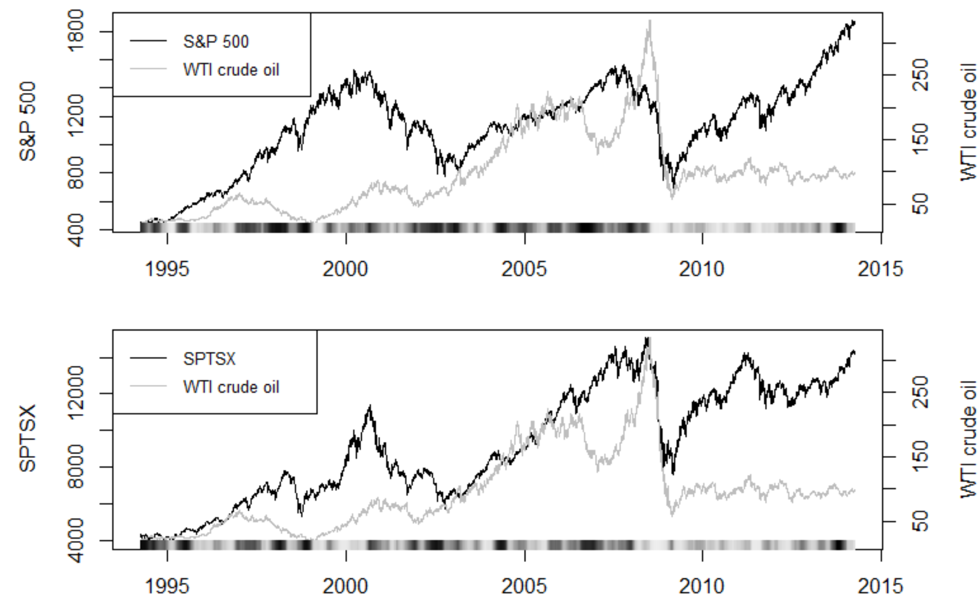

Figure 1: Time series data on the relationship between the WTI crude oil price and the S&P500 (top panel) and SPTSX (bottom panel) stock market indexes from 1994 to 2014. Raw correlation between markets is displayed at the bottom of each figure as a barcode plot. The intensity of the gray color in the barcode plot, from black to white, indicates the degree of correlation negative or positive between both markets.

A dark grey color indicates that they move in the opposite direction, negative interdependence according to our previous definition, while a light gray color indicates that both markets move in the same direction or exhibit positive interdependence.

From the top plot, we can see that from 1997 to late 2007 the WTI index and the S&P 500 index were most of the time negatively correlated, just before the beginning of subprime crisis, justifying the future expected cash-flow theory proposed by Jones and Kaul (1996). However, when the global financial crisis finally started, we observe that both markets exhibit a very high and positive correlation, until the global economy begins to strengthen again.

In the case of the Canada, an oil-exporting country, the WTI crude oil index and the SPTSX stock market show a similar trend but with alternating periods in the sign of the correlation. For instance, during the Dot-com bubble occurred roughly from 1999 to 2001, both markets showed positive price correlation, as well as, during the subprime crisis. The same direction of the price movements is justifiable as a consequence of higher revenues in the oil export industry in this country.

This first empirical exercise shows evidence of asymmetric effects on the response of the stock market returns of oil-importing or exporting countries to oil price shocks, during bull and bear markets, when this is measured by correlation. However, correlation is not a measure of dependence at extreme levels, nor during periods of financial crisis.

For this reason, this paper contributes to the related literature by taking into account the dynamic behavior of extreme events in the oil and stock market returns to determine the relationship between both markets during periods of turmoil. By doing so, it is possible to examine both the degree and dynamic of dependence in these markets at extreme levels, while avoiding the modeling of well-known empirical stylized facts of market price returns such as autocorrelation, volatility and fat tail behavior. The econometric framework is based on point process theory and allows us to capture the dynamics of the intensity of occurrence of oil shock prices and stock market crashes and relate it to the magnitude of these events.

3 Methodology

The ACI-POT methodology combines the autoregressive conditional intensity (ACI) model of Russell (1999) and the peaks over threshold (POT) approach from extreme value theory, developed by Davison and Smith (1990). This section introduces an ACI-POT model in a slightly different form to the one proposed in Haustch and Herrera (2015), by including interdependence between the magnitude of extreme events and their intensity.

3.1 Multivariate ACI-POT Model

Suppose that we have observed the random variables $\{Z_t\}_{t\geq 1}$ which may correspond, for example, to the returns of a currency, commodity or stock market index. A marked point process is a stochastic process counting random events occurring over time, with each time-location having an associated mark which in turn has its own stochastic structure.

Consider an observation Z_t whose magnitude has exceeded a previously defined threshold $u > 0$. Then, t_j denotes the times of occurrence of this event and $Y_j = Z_{t_j} - u$ denotes the size of the extreme event that exceeds this threshold. This procedure is the so called POT approach and defines a stochastic process of exceedances through pairs (t_j, Y_j) in the set of events $\Omega = (0,1] \times (u, \infty)$, where for convenience time has been re-scaled between 0 and 1. We define a marked point process (MPP) $N(t)$ as a counting process of arrivals of extreme events up to the current time t, and in which some additional features are measured at each time event. In our case the mark is the magnitude Y of the extreme events. Extending this idea to the multivariate case, a m −MPP is described componentwise as $N^m(t) := N^m\ ((0,t] \times \mathrm{y}) = \sum_{j\geq 1} \mathbb{I}\{t_j^m \leq t\ ,\ Y_j^m = y\}$ for $m = 1, \dots, \mathrm{M}$ with $\mathbb{I}\{\cdot\}$ being an indicator function. While the dynamic of this stochastic process can be described by its conditional intensity

$$\lambda^{\mathrm{m}}(\mathrm{t}, \mathrm{y}|\mathcal{F}_{\mathrm{t}}) = \lim_{\Delta \mathrm{t} \to 0} \frac{1}{\Delta \mathrm{t}} \mathrm{P}\{\mathrm{N}^{\mathrm{m}}\ (\mathrm{t} + \Delta \mathrm{t}) > 0|\mathcal{F}_{\mathrm{t}}\},$$

where $\mathcal{F}_{\mathrm{t}} = \left\{\left(\mathrm{t}_{\mathrm{j}}^{\mathrm{m}}, \mathrm{Y}_{\mathrm{j}}^{\mathrm{m}}\right)\ \forall \mathrm{j}, m :\ \mathrm{t}_{\mathrm{j}}^{\mathrm{m}} < t\ , m = 1, \dots, M\right\}$ denotes the entire history of the multivariate process. Consequently, the intensity $\lambda^{\mathrm{m}}(\mathrm{t}, \mathrm{y}|\mathcal{F}_{\mathrm{t}})$ can be decomposed into two parts: one characterizing the ground intensity, ${\lambda^{\mathrm{m}}}_{\mathrm{g}}(\mathrm{t}|\mathcal{F}_{\mathrm{t}})$, which describes the temporal dynamics of the extreme events occurring over the threshold $u^m > 0$, and the process of the marks describing the conditional probability density function of the size of the extreme events $\mathrm{g}^{\mathrm{m}}(\mathrm{y}|\mathcal{F}_{\mathrm{t}}, \mathrm{t})$:

$$\lambda^{m}(t, y|\mathcal{F}_t) = \lambda^{m}{}_{g}(t|\mathcal{F}_t)\, g^{m}(y|\mathcal{F}_t, t).$$

Figure 2 illustrates the dynamic behavior of a bivariate ACI-POT. The first and third panels describe the path of the bivariate point processes $N^1(t)$ and $N^2(t)$, which are stochastic processes of exceedances through pairs (t_j^1, Y_j^1) and (t_j^2, Y_j^2), respectively.

The second and fourth panels exhibit the corresponding conditional intensity functions $\lambda^1(t, y|\mathcal{F}_t)$ and $\lambda^2(t, y|\mathcal{F}_t)$ generated by these events. Notice that the intensity of these processes increase with the arrival of extreme events in the same market (self-excitation) as well as in the other market (cross-excitation), producing patterns in both the time and magnitude of extreme events during periods of turmoil.

In this study, the ground intensity $\lambda^{m}{}_{g}(t|\mathcal{F}_t)$ is specified through the ACI model proposed by Russell (1999)[1]

$$\lambda_g^m(t|\mathcal{F}_t) = \exp\left(\Phi_{N(t)}^m\right) \lambda_0^m(t), \tag{1}$$

where $\lambda_0^m(t)$ is the baseline component which corresponds to a survival function that changes continuously and depends only on the lapsed time since the last extreme event (i.e., $t - t_j^m$). This function allows the conditional intensity to be non-monotonically decreasing or increasing. On the other hand, the stochastic process $\Phi_{N(t)}^m$ describes the dynamics and persistence of the conditional intensity and is updated whenever a new extreme event is observed.

This process is responsible for capturing the comovements between different marginals and commonly corresponds to a vector autoregressive moving average process VARMA (1,1):

$$\Phi_{N(t)}^m = \left(A\varepsilon_{N(t)-1}^m + B\Phi_{N(t)-1}^m\right) i_{N(t)-1}^m\,, \tag{2}$$

[1] Some applications of this model in the business context are Kehrle and Peter (2013), Kwok and Li (2008) and Hall and Hautsch (2006).

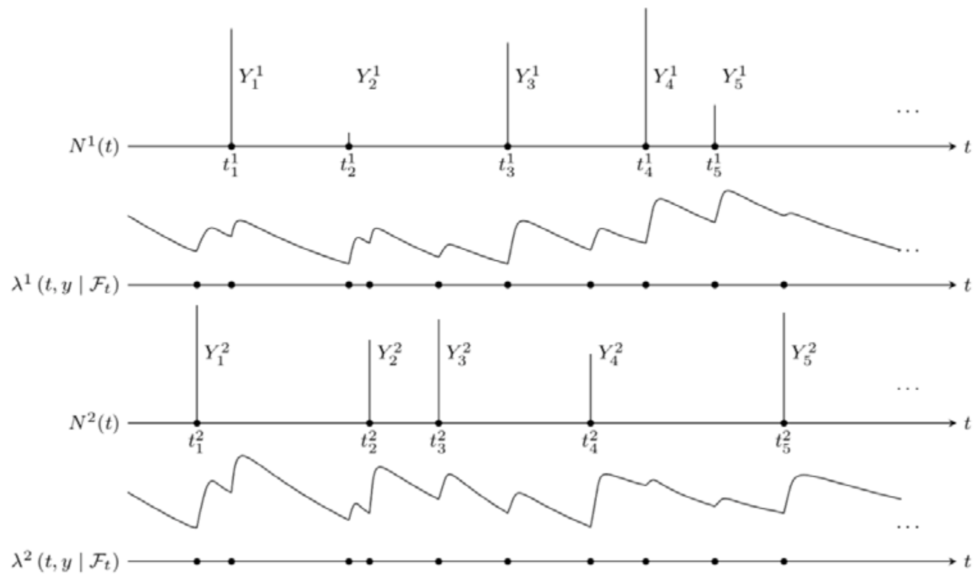

Figure 2: Description of the dynamic behavior of a bivariate MPP. The first and third panel describe the path of the point processes $\mathrm{N}^1(\mathrm{t})$ and $\mathrm{N}^2(\mathrm{t})$, while the second and fourth panel exhibit the corresponding conditional intensity functions $\lambda^1(\mathrm{t},\mathrm{y}|\mathcal{F}_\mathrm{t})$ and $\lambda^2(\mathrm{t},\mathrm{y}|\mathcal{F}_\mathrm{t})$. $\mathrm{t}_\mathrm{j}^\mathrm{m}$ denotes the times of occurrence of the event j in the market m and $\mathrm{Y_j}^\mathrm{m}$ denotes the size of this extreme event.

where A is a vector of $\mathrm{M} \times 1$ coefficients $\{\alpha_m\}$ and B is a matrix of $\mathrm{M} \times \mathrm{M}$ autoregressive coefficients $\{\beta_{mn}\}$, with $m, n = 1, \dots, \mathrm{M}$ capturing the persistence in the time series.

The autoregressive component within each dimension, or self-excitation, is captured in the parameters that run along the diagonal of this matrix (β_{11} and β_{22}), while possible influences of the other markets, cross-excitement, are captured by the remaining coefficients (β_{12} and β_{21}). In addition, $i_{N(t)-1}^m$ is an indicator function taking a value of 1 if the last extreme event corresponds to the marginal m and zero otherwise, while $\varepsilon_{N(t)-1}^m$ is the generalized residual of the point process $N^m(\mathrm{t})$ that is given by

$$\varepsilon_{j-1}^m = 1 - \int_{t_{j-1}^m}^{t_j^m} \lambda_\mathrm{g}^\mathrm{m}(\mathrm{s}|\mathcal{F}_\mathrm{s})\, ds.$$

If the model is well-specified, then the random variables ε_j^m have a translated exponential distribution with a mean equal to zero and standard deviation equal to one.[2] In order to test the goodness of fit of this approach, the test for excess dispersion of Engle and Russell (1998) is used. This test is asymptotically normally distributed as $\sqrt{n_\varepsilon/8}(\hat{\sigma}_\varepsilon^2 - 1)$, where n_ε is the number of innovations ε_j^m and $\hat{\sigma}_\varepsilon^2$ denotes the empirical variance of the innovations.

As is common in VARMA models, stationarity of the process is assured when the spectral radius (Spr) of the matrix B, or equivalently, if the maximum of the eigenvalues of the matrix is less than one. On the other hand, the choice of the survival function is closely related to the flexibility in the form of the conditional intensity. Here, we propose two alternatives in order to capture the dynamic of extreme events, the generalized gamma and the Birnbaum-Saunders distributions. The hazard function of the generalized gamma is defined as:

$$\lambda_0(t|\,\mu,\sigma,Q) = \frac{|Q|(Q^{-2})^{Q^{-2}}}{\sigma\, t\,\Gamma(Q^{-2})} exp\left(Q^{-2}\big(Qw - exp(Qw)\big)\right),$$

with $\mu > 0$, $\sigma > 0$ and $Q \in \mathbb{R}$, where $\eta \sim \Gamma(Q^{-2}, 1)$, $w = ln(Q^2\,\eta)$ and $t = exp(\mu + \sigma w)$. Special cases of this hazard function are standard gamma, Chi-squared, log-normal, exponential and Weibull (see Prentice, 1974; and Stacy, 1962 for more details). In the case of the Birnbaum-Saunders distribution, its hazard function is defined as:

$$\lambda_0(t|\,\mu,\sigma) = \frac{\phi(\zeta(t/\sigma)/\,\mu)t^{-3/2}(t+\sigma)}{\Phi(-\zeta(t/\sigma)/\,\mu)2\mu\sqrt{\sigma}},$$

with $\mu > 0$, $\sigma > 0$, where $\zeta(t) = \sqrt{t} - 1/\sqrt{t}$, $\phi(\cdot)$ and $\Phi(\cdot)$ are the N(0,1) probability density and probability distribution functions, respectively (Birnbaum & Saunders, 1969)

On the other hand, we also need to characterize the conditional probability density function of the sizes of extreme events. The Pickand-Balkema-De Haan theorem (Balkema and De Haan,

[2] This is a well-known result in the point processes literature and corresponds to the random change transformation, see Theorem 7.4.I in Daley and Vere-Jones (2003).

1974; Pickands, 1975) shows that, under certain conditions the generalized Pareto distribution is the limit distribution for exceedances over the threshold

$$g^m(y|\mathcal{F}_t,t)=\begin{cases}\dfrac{1}{\delta^m(t|\mathcal{F}_t)}\left(1+\xi^m\dfrac{y_m-u^m}{\delta^m(t|\mathcal{F}_t)}\right)_+^{-\frac{1}{\xi^m}-1}, & \xi\neq 0,\\ \dfrac{1}{\delta^m(t|\mathcal{F}_t)}exp\left(-\dfrac{y_m-u^m}{\delta^m(t|\mathcal{F}_t)}\right), & \xi=0,\end{cases} \tag{3}$$

where $\xi \in \mathrm{R}$ is the shape parameter and $\delta^m(t|\mathcal{F}_t)$ is the scale parameter that also incorporates the internal history of the process through the base intensity of the process

$$\delta^m(t|\mathcal{F}_t)=\delta_0^m+\delta_1^m\lambda^m{}_g(t|\mathcal{F}_t). \tag{4}$$

This specification allows the size of extreme events to be directly related to the intensity with which the extreme events occur. The idea of linking the size of extreme events with their intensity is not new and has been used by different authors in different contexts (Chavez-Demoulin and McGill, 2012; Santos et al., 2013; Hammoudeh et al., 2013; Herrera, 2013andis very intuitive. During periods of financial turmoil, the arrival intensity of new extreme events increases, as well as proportionally the size of these events.

Combining the specifications of the base process in (1) and the density for the marks in (3), the log-likelihood function of the multivariate ACI-POT model, given an m −dimensional process observed over a period of time (0, T] is given by:

$$\ln L=\sum_{m=1}^{M}\sum_{j=1}^{N^m(T)}\ln g^m(y|\mathcal{F}_t,t)+\sum_{m=1}^{M}\sum_{j=1}^{N^m(T)}\left\{i_j^m\ln\lambda_g^m(t|\mathcal{F}_t)-\int_{t_{j-1}^m}^{t_j^m}\lambda_g^m(s|\mathcal{F}_s)ds\right\}.$$

Note that if the scale parameter defined in (4) is not dependent upon the dynamics of the base intensity of the process, then the maximum likelihood can be estimated separately and independently.

In the empirical analysis of comovements between stock markets and oil markets, it is also important to consider risk measures that can help investors protect their investment portfolio. The risk measure that is most commonly used is Value-at-Risk (VaR) due to its simplicity and its ability to quantify risk in a single number, which for self-excited models, such as the ACI-POT, takes the following form for the period $t^* > t$

$$VaR_{\alpha}^{t^*} = \mathrm{u}^{\mathrm{m}} + \frac{\delta^{\mathrm{m}}(t^*|\mathcal{F}_{\mathrm{t}})}{\xi^{\mathrm{m}}}\left[\left(\frac{1-\alpha}{\lambda_g^m(t^*|\mathcal{F}_t)}\right)^{-\xi^{\mathrm{m}}} - 1\right]$$

where α is the confidence level. Note that the estimator is only defined for $\lambda_g^m(t^*|\mathcal{F}_t) > 1-\alpha$ (see Herrera, 2013, for details of the derivation).

4 Empirical Analysis

Among the 34 OECD members, 10 countries are chosen for this study, based on oil consumption (US, Japan, Germany, Canada, South Korea and Mexico), or the highest gross domestic product (GDP) for those that do not belong to the former category (France, England, Australia and Spain). It should be noted that these countries are mostly within the top 15 in both rankings and also belong to the category of developed countries according to the Human Development Index, which considers variables such as a standard of living, large industrial and commercial development, wealth, education and health, not economic growth alone.

4.1 Data Description and threshold selection

Daily data covering the period from January 2, 1994 until August 15, 2014 are obtained from Bloomberg. The observations from January 2, 1994 to December 31, 2012 are considered for estimation of the models, while the period from January 2, 2013 to August 15, 2014 is used for backtesting. For oil markets, data relates to WTI and Brent crude oil in US dollars, while for stock markets indices we consider the S&P 500 in the U.S., Nikkei 225 in Japan, DAX 30 in

Germany, SPTSX in Canada, KOSPI in South Korea, MEXBOL in Mexico, CAC 40 in France, UKX in the UK, ASX 200 in Australia and IBEX 35 in Spain.

The summary statistic of each of the negative log-returns series are reported in Table A.1. We observe that the mean is close to zero for all of them. Oil markets returns exhibit higher standard deviations than financial markets. In addition, all of the markets analyzed exhibit negative skewness, while for most of the markets, the Ljung-Box autocorrelation test and the Jarque-Bera test reject at the 1% confidence level the null hypothesis of independence and normality, respectively. In all cases, null hypothesis of nonstationarity is rejected at 1% confidence level by the Augmented Dickey-Fuller test.

An important first step here is to select the threshold that defines which observations are defined as extreme events. This choice involves a balance between bias and variance, and is a difficult problem as no single objective approach has been proposed in the literature. Smith (1987) proposes a graphical technique in order to obtain the best model fit. Chavez Demoulin (1999) proposes to start with a threshold that considers 10% of the sample as exceedances and then perform a sensitivity analysis on the model fit using between 5% and 10% of the sample. Chavez-Demoulin and Embrechts (2004) show that small variations in the threshold typically have very little impact on model estimation. Herrera (2013) proposes a sensitivity analysis which is based upon mean square to evaluate the stability of the VaR at different thresholds. Here, this approach is followed, with VaR evaluated given thresholds from the 0.88 to 0.94 quantiles of the dataset. The result of this sensitivity analysis shows that a threshold at the 90% quantile provides the best in-sample VaR estimates across all combinations and hence is the threshold used in all subsequent analysis.

4.2 Analysis of Extreme Comovements

During the subsequent analysis, subscript 1 represents the stock markets, while subscript 2 represents the oil markets. In order to determine the baseline associated to each ACI-POT model for each pair of markets, we consider the specification that minimizes the Akaike Information Criterion (AIC).

The values of the maximized log- likelihoods and AIC for the ACI-POT models for the cases of both negative and positive interdependence are presented in Tables A.2. The estimated coefficients of the selected models for each pair are reported in Tables A.3 and A.4 for the case of negative interdependence, and Tables A.5 and A.6 for positive interdependence. In these Tables one can also observe diagnostic tests (log-likelihood, AIC, spectral Radio: Spr) and analysis of generalized residuals ε_j^m (mean values, standard deviation, and test against over-dispersion).

4.2.1 Negative Interdependence

According to the results in Table A.2, the ACI-POT model that best fits each of the markets includes a baseline of the generalized gamma type, as this type of hazard function allows for flexible non-monotonic behavior. Tables A.3 and A.4 report the estimated coefficients of the selected models, where most are found to be statistically significant for both the Brent and WTI markets. Regarding the coefficients that are associated with the innovations of the model (i. e., α_1 and α_2), one can see that most of them tend to have a positive value for the stock markets while it is negative for oil markets, indicating a negative influence of innovations to the intensity of extreme events in oil, while reinforcing the trend of extreme events to occur in the stock markets. As a consequence, this result indicates that an unanticipated positive shock in the global demand for oil has a negative effect on the stock market return.

The estimates of the persistence matrix B, capturing self- and cross excitation, reveal a high degree of persistence within most of the financial markets, a commonly observed pattern when considering extreme events, or volatility more generally. Estimates of the self-exciting coefficient in the stock market, β_1^1, are all larger than 0.71, with the exception of Mexico (in the case of Brent), which is under 0.30. While self-excitation is also observed in the oil markets, β_2^2

is not as strong as that of the stock markets for each case, with the results for Canada being the lowest value for both markets (i.e., 0.43 and 0.26 for Brent and WTI, respectively). These results together indicate that stock markets tend to exhibit greater persistence and clustering behavior in extreme events than oil markets do. This result is not surprising since investors decrease their demand for stocks during financial crisis period, as they rebalance their trading strategies against the stock market by investing more in the oil markets.

Comovements between the markets are captured by the cross-excitation coefficients β_2^1 and β_1^2, where the results are mixed. For example, the influence of the oil market on the occurrence extreme events in the stock markets has a mean equal to 0.28. Greater comovement in extreme events with the USA, Japan, Germany, France, UK and Spain is observed for Brent, while greater comovement is observed with the USA, Japan, South Korea and France for WTI. Note that the USA, Japan, Germany and France, are four of the world's largest net oil importers (1st, 3rd, 4th and 7th, respectively) and appear to be more susceptible. In contrast, the impact of extreme events in the stock markets on extreme events in the oil markets, captured by the coefficient β_1^2, the mean does not exceed 0.13, with Mexico as the only exception. This result reveals there is an asymmetric effect in terms of the strength of the relationship between the markets where extreme shocks in the oil markets have a much larger effect on the stock markets than vice-versa.

In relation to Eq. (4) that relates the size of extreme events to the intensity when these extreme events occur, estimates of δ_1^m are significant and positive for all of the markets, revealing that the intensity and size of extreme events are strongly related. These results are consistent with those obtained by other authors in different financial contexts (Chavez-Demoulin and McGill, 2012; Santos et al., 2013; Hammoudeh et al., 2013; Herrera, 2013).

Another interesting result is that the value obtained for the spectral radius, apart from revealing whether an ACI-POT model is stationary, is a measure of the proportion of extreme events that are endogenously generated, and thus are the product of interdependence between markets. It is observed that, for most pairs analyzed, more than 91% of extreme events within these markets are the result of cross and self-excitement. The only exceptions, although smaller, are MEXBOL when compared to SPTSX for Brent and WTI, with values close to 88%. Regarding the goodness of fit of the ACI-POT models, Tables A.3 and A.4 report the means and standard deviations of the generalized residuals, which are close their theoretical values. This is corroborated by the test for excess dispersion, which indicates that the residuals are exponentially distributed at a 95% confidence level.[3]

4.2.2 Positive Interdependence

The second analysis considers whether returns in both markets move in the same direction at extreme levels. In this case, we focus on the negative returns in both markets, again taking the position of an investor trying to minimize losses. The first step corresponds to the selection of the functional form of the baseline for each ACI-POT model. These results are shown in Table A.2. In this case, the most common choice is the generalized gamma hazard function with the Birnbaum-Saunders hazard functions preferred in the remaining cases.

Tables A.5 and A.6 display parameter estimates of the selected models. Regarding the autoregressive parameters in the persistence matrix *B*, and the innovations matrix *A*, few clear trend emerge relative to the case of negative interdependence. Many of the coefficients are insignificant and often change sign across the different markets. Some evidence of links between South Korea and France with the Brent index, and South Korea with the WTI index is revealed. However, in most cases, the oil and stock markets generally tend to exhibit a high degree of own-persistence, β_1^1 and β_2^2, often more than in the negative interdependence analysis, simply reflecting underlying volatility clustering. Overall, these results indicate that extreme negative events in both markets occur independently.

[3] That is, the value obtained from the test can be found in the interval $[-1.96, 1.96]$.

Consistent with the results obtained in the case of negative interdependence, the relationship between the size of the events and the intensity of the events is again statistically significant and positive for all of the markets. The value obtained for the spectral radius (in this case, for most of the ACI-POT models) is close to 0.81, which is much lower than that which was observed in the first analysis. The only exceptions over 0.9 are the Nikkei and Kospi in conjunction with Brent, and the Nikkei and SPTSX for WTI. Finally, with regard to the goodness of the fit of the selected ACI-POT models, in Tables A.5 and A.6 the mean and standard deviation of the generalized residuals and their respective tests for excess dispersion are reported. Again, in all cases, the residuals are found to be exponentially distributed.

In summary, according to the results of both analyses of interdependence, only clear evidence in favor of negative interdependence is revealed, in contrast to many of the earlier studies which report evidence of both forms of dependence. Note that both sets of analyses are not mutually exclusive since different regions of the tails of the joint bivariate distribution are considered.

4.3 Analysis of the VaR Accuracy

This section considers the predictive power of the ACI-POT models in terms of forecasting VaR at three different confidence levels, 0.95, 0.99 and 0.999. To evaluate predictive accuracy, a set of well-known statistical tests are used.

The first of these is the unconditional coverage likelihood ratio test (LR_{uc}), which assesses whether the fraction of VaR violations (i.e., returns above the estimated value of VaR) is significantly different from the expected number. The second is the independence likelihood ratio test (LR_{ind}), which assesses the independence of VaR violations. The third statistical test, the conditional coverage ratio test (LR_{cc}), is a combination of both tests and therefore it evaluates the correct coverage as well as the independence of VaR violations. These three tests were introduced by Christoffersen (1998).

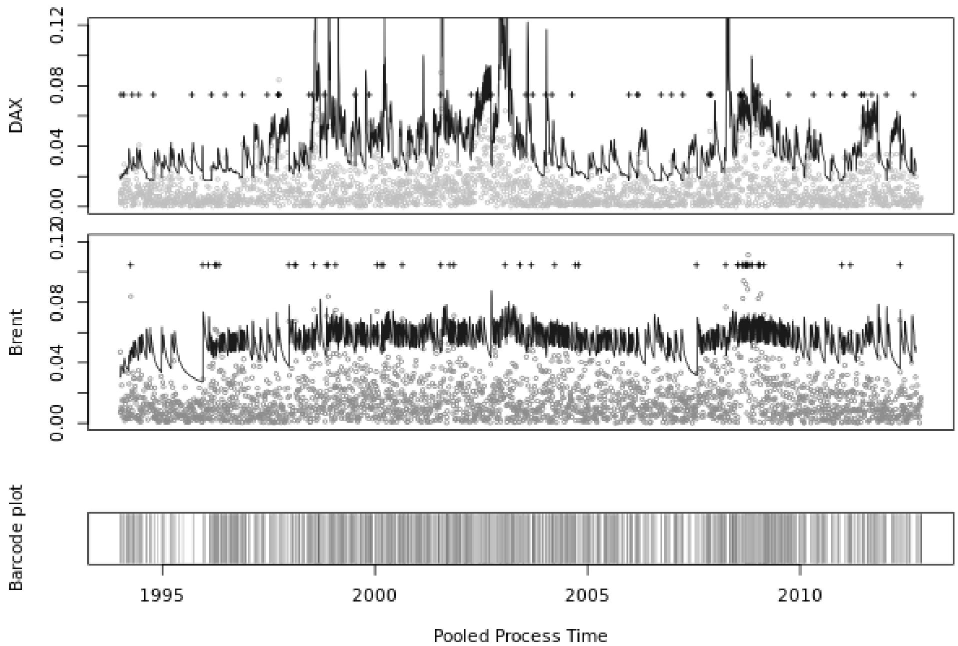

Figure 3: Estimates of the VaR in-sample with a confidence level of 0.99 for the DAX (top panel) together with the Brent index (central panel), respectively. The model corresponds to the ACI-POT model with generalized gamma hazard function for the baseline. The color bar (lower panel) indicates the time of occurrence of extreme events, while the intensity of the color indicates the number of extreme events occurring simultaneously (comovements). Light gray color indicates that extreme events tend to occur independently, while dark gray indicates comovements and therefore interdependence. Symbols "+" indicate violations of VaR estimates.

The last statistical test is the dynamic quantile test (DQ_{hit}), introduced by Engle and Manganelli (2004) and is an alternative test of independence of the VaR violations. These statistical tests are described in detail in Herrera (2013).

During the analysis, a level of significance of 0.05 is used to determine whether the individual tests are rejected. Finally, although the analysis of interdependence seems to make much more sense in the case of negative interdependence, we decided to analyze both cases. Table A.7 and Table A.8 show the results for negative interdependence. For all of the countries considered, the results are satisfactory both in-sample and out-of-sample. In-sample, the best results are for the DAX and Nikkei indices together with Brent, with 92% and 87.5% result in non-rejection, respectively, while the average is 82%.

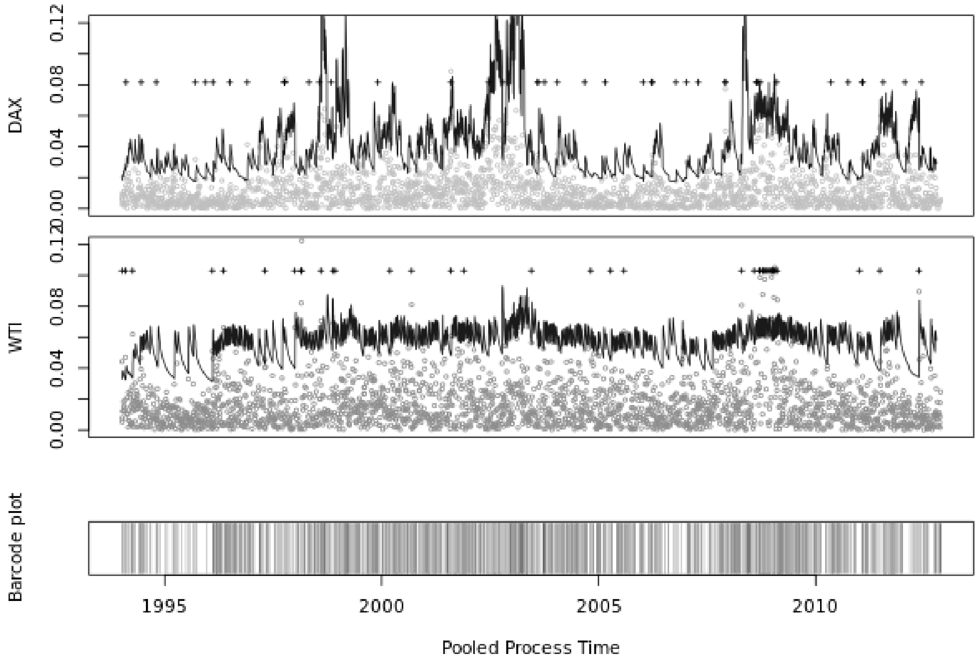

Figure 4: Estimates of the VaR in-sample with a confidence level of 0.99 for the DAX (top panel) together with the WTI index (central panel), respectively. The model corresponds to the ACI-POT model with generalized gamma hazard function for the baseline. The color bar (lower panel) indicates the time of occurrence of extreme events, while the intensity of the color indicates the number of extreme events occurring simultaneously (comovements). Light gray color indicates that extreme events tend to occur independently, while dark gray indicates comovements and therefore interdependence. Symbols "+" indicate violations of VaR estimates.

In the case of the WTI index, the best results are the DAX and Kospi indices, with 92% and 87.5% of tests not-rejected, respectively, while the average is only 75%. Figures 3 and 4 present estimates of the VaR in-sample at a confidence level of 0.99 for the DAX (top panel) together with Brent and WTI indices (central panel), respectively. The model corresponds to the ACI-POT model with the generalized gamma hazard function for the baseline.

The color bar (lower panel) indicates the time of occurrence of extreme events, while the intensity of the color indicates the number of extreme events occurring simultaneously. A light gray color indicates that extreme events that occur independently, while dark gray indicates comovements and therefore interdependence. The "+" symbol indicates violations of VaR estimates.

The advantage of the ACI-POT models is that the occurrence times and the inter-exceedance times of extreme events seem to adequately capture the dynamics of the arrival intensity of new events, thus avoiding clustering of VaR violations. This is a desirable feature for portfolio diversification during a period of stress.

In the back-testing period, the results are better; on average, in 86% of cases across both Brent and WTI, the accuracy tests are not rejected. The best results are obtained for the SPTSX and MEXBOL together with Brent, while for the WTI, the best results are obtained for pairs that include the SP500, SPTSX and IBEX indices, all with 92% of the accuracy tests passed. For all of the models considered, both in-sample and back-testing, the greatest difficulty for the model was the VaR confidence level of 95% in the stock markets. This may be because, at this level, the degree of clustering is higher, so a higher-order VARMA process in the specification of Eq. 2 may be necessary.

Regarding accuracy tests of the VaR for the analysis of positive interdependence between markets, the results are presented in Table A.9 and Table A.10. For the in-sample analysis, only 70% of the approved tests were obtained for the analysis of the comovement of stock markets with both Brent and WTI, although these results improve to 79% and 77%, respectively, during backtesting.

5 Conclusions

While there is a wide range of research and literature that analyzes the interdependence or comovements between oil markets and financial markets, there are currently no other studies that analyze the comovements among OECD equity markets and oil markets using only extreme events. For this reason, this study presents a methodology which allows one to jointly analyze the behavior of these markets, capturing common stylized facts in such returns including phenomena such as the tendency to cluster around extreme events, cross and self-excitation and the relationship between intensity and size of these. This also allows one to examine and determine the proportion of extreme events that are due to an endogenous mechanism which is caused by multiple comovements between markets.

Our work has significant implications. First, according to the results, there is a strong negative interdependence between these markets. In particular, for the analyzed Brent markets, greater comovement of extreme events between the US, Japan, Germany, France, UK and Spain is observed, while for WTI markets, greater comovement is reached with the US, Japan, South Korea and France. Second, regarding the results of positive interdependence, they are only significant in the markets of South Korea and France for the Brent index, and South Korea for the WTI index. Third, according to the VaR estimates, both for the in-sample and out-of-sample pairs that are analyzed, the ACI-POT models show a satisfactory result for most confidence levels, with the exception in some cases with a confidence level at 0.95.

Finally, the great advantage that we observe in this methodology over others that are based on EVT is that, apart from using the size distribution of extreme events, this methodology also uses the timing of extreme events as an information source. For future work it is proposed to extend the methodology to other markets, offering a different perspective on the existence of interdependence among financial markets during periods of stress. In addition, the models could include other relevant covariates in the study, as for example, macroeconomic indicators or covariates reflecting economic activity. However, the inclusion of covariates observed at different frequencies requires a significantly methodological approach.

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A. Appendix

A. Tables and Figures

	Mean	Sd.	Min	Max	Skewness	Kurtosis	Ljung-Box	Jarque-Bera	ADF.test
SP	0.000	0.011	-0.095	0.110	-0.240	11.733	88.193 ***	19775 ***	-18.459 ***
Nikkei	0.000	0.015	-0.121	0.132	-0.129	8.283	33.423 ***	7060 ***	-17.280 ***
DAX	0.000	0.014	-0.089	0.108	-0.116	7.646	9.572 *	5614 ***	-18.440 ***
SPTSX	0.000	0.010	-0.098	0.094	-0.737	13.972	36.411 ***	31623 ***	-18.059 ***
Kospi	0.000	0.017	-0.128	0.113	-0.202	7.350	14.890 **	5174 ***	-16.787 ***
MEXBOL	0.001	0.016	-0.143	0.122	-0.018	9.802	46.609 ***	9899 ***	-16.513 ***
CAC	0.000	0.014	-0.095	0.106	-0.027	7.569	40.262 ***	5425 ***	-18.509 ***
UKX	0.000	0.011	-0.093	0.094	-0.124	9.186	50.269 ***	9935 ***	-19.339 ***
AS30	0.000	0.009	-0.086	0.061	-0.509	9.218	23.716 ***	10308 ***	-18.078 ***
Ibex	0.000	0.014	-0.096	0.135	-0.038	8.193	31.387 ***	6975 ***	-16.986 ***
Brent	0.001	0.021	-0.144	0.129	-0.203	6.065	19.295 ***	1927 ***	-14.883 ***
WTI	0.000	0.022	-0.165	0.133	-0.248	6.071	21.461 ***	1922 ***	-15.150 ***

Table A.1: Descriptive statistics of daily log-returns. The Ljung-Box statistics are significant for a lag of 5 trading days. *, **, and *** represent significance at 10%, 5% and 1% levels, respectively. The sample period is from January 2, 1994 until August 15, 2014.

Stock Markets	Oil Indices	Negative Interdependence				Positive Interdependence			
		Log-likelihood		AIC		Log-likelihood		AIC	
		BS	G.gamma	BS	G-gamma	BS	G.gamma	BS	G-gamma
SP	Brent	-432.877	-453.445	-833.754	**-870.891**	-416.152	-419.489	-800.303	**-802.979**
Nikkei	Brent	-300.385	-316.392	-568.770	**-596.784**	-237.179	-253.756	-442.359	**-471.511**
DAX	Brent	-344.310	-373.661	-656.621	**-711.322**	-300.359	-288.870	**-568.717**	-541.739
SPTSX	Brent	-419.706	-473.943	-807.413	**-911.886**	-412.184	-414.823	-792.367	**-793.647**
Kospi	Brent	-209.966	-224.004	-387.932	**-412.008**	-170.971	-181.523	-309.941	**-327.045**
MEXBOL	Brent	-326.495	-330.353	-620.990	**-624.706**	-294.531	-292.047	**-557.061**	-548.093
CAC	Brent	-355.367	-387.717	-678.735	**-739.433**	-337.567	-337.416	**-643.134**	-638.833
UKX	Brent	-469.554	-491.876	-907.108	**-947.751**	-441.704	-437.080	**-851.407**	-838.159
AS30	Brent	-554.801	-582.167	-1077.601	**-1128.333**	-520.711	-528.767	-100.942	**-102.153**
IBEX	Brent	-354.615	-373.648	-677.231	**-711.296**	-327.232	-324.990	**-622.465**	-613.981
SP	WTI	-397.294	-424.216	-762.587	**-812.433**	-406.653	-419.115	-781.306	**-802.231**
Nikkei	WTI	-264.232	-294.536	-496.463	**-553.072**	-203.389	-238.048	-374.779	**-440.096**
DAX	WTI	-301.295	-328.301	-570.590	**-620.602**	-279.130	-275.719	**-526.260**	-515.438
SPTSX	WTI	-386.315	-444.524	-740.629	**-853.049**	-392.265	-405.672	-752.530	**-775.344**
kopi	WTI	-155.819	-168.881	-279.637	**-301.763**	-129.603	-147.068	-227.206	**-258.136**
MEXBOL	WTI	-291.325	-298.078	-550.649	**-560.156**	-275.898	-271.438	**-519.796**	-506.877
CAC	WTI	-301.945	-329.847	-571.891	**-623.693**	-298.665	-306.276	-565.329	**-576.552**
UKX	WTI	-411.265	-422.698	-790.531	**-809.395**	-406.895	-409.608	-781.789	**-783.215**
AS30	WTI	-495.657	-531.090	-959.314	**-102.618**	-491.794	-504.400	-951.589	**-972.799**
IBEX	WTI	-298.261	-314.790	-564.522	**-593.580**	-291.199	-295.796	-550.397	**-555.593**

Table A.2: Results for the log-likelihood estimations of the ACI-POT models. The estimations are for the negative and positive interdependence between stock and oil market indices. BS and G.gamma correspond to the ACI-POT models with Birnbaum-Saunders and generalized gamma hazard functions for the baseline. respectively. The model that show the best AIC is shown in bold.

Set	SP-Brent		Nikkei-Brent		DAX-Brent		SPTSX-Brent		Kospi-Brent	
Distribution	G. gamma		G. gamma		G. gamma		G. gamma		G. gamma	
	SP	Brent	Nikkei	Brent	DAX	Brent	SPTSX	Brent	Kospi	Brent
$\boldsymbol{\alpha^m}$	0.811 ***	-0.331 ***	0.998 ***	-0.182 *	0.998 ***	-0.296 **	0.998 ***	-0.613 ***	0.836 ***	0.037
$\boldsymbol{\beta_1^m}$	0.748 ***	0.165 ***	0.713 ***	0.100 ***	0.744 ***	0.109 ***	0.821 ***	0.177 ***	0.788 ***	0.006 *
$\boldsymbol{\beta_2^m}$	0.418 ***	0.580 ***	0.318 ***	0.778 ***	0.392 ***	0.734 ***	0.259 ***	0.427 ***	0.168	0.947 ***
$\boldsymbol{\delta_0^m}$	0.032 ***	0.024 *	0.016 *	0.036 **	0.042 ***	0.021	0.030 ***	0.025 *	0.034 ***	0.033 **
$\boldsymbol{\delta_1^m}$	0.003 ***	0.008 ***	0.006 ***	0.007 ***	0.004 ***	0.008 ***	0.003 ***	0.008 ***	0.007 ***	0.008 ***
$\boldsymbol{\zeta^m}$	0.062	0.079	0.149 **	0.091 *	-0.003	0.109 *	0.044	0.077	0.075	0.075
$\boldsymbol{\mu^m}$	2.042 ***	0.919 ***	1.949 ***	1.001 ***	2.168 ***	0.885 ***	2.497 ***	0.849 ***	1.898 ***	0.908 ***
$\boldsymbol{\sigma^m}$	1.822 ***	0.365 ***	1.666 ***	0.437 ***	2.005 ***	0.348 ***	2.243 ***	0.326 ***	1.785 ***	0.399 ***
$\boldsymbol{Q^m}$	-2.728 **	-0.512 **	-2.463 **	-0.530 **	-3.064 ***	-0.615 **	-2.905 ***	-0.550 ***	-3.160 ***	-0.671 ***
Diagnostics										
LL	-453.45		-316.39		-373.66		-473.94		-224.00	
AIC	-870.89		-596.78		-711.32		-911.89		-412.01	
Spr	0.940		0.927		0.946		0.914		0.954	
Residuals										
Mean (ε_j^m)	0.008	-0.118	0.019	-0.058	0.013	-0.080	0.006	-0.099	0.024	-0.037
Desv. Est.	0.980	0.983	0.950	0.959	0.948	0.959	0.919	0.985	0.928	0.902
Excess.dis	-0.306	-0.254	-0.745	-0.603	-0.788	-0.618	-1.192	-0.229	-1.058	-1.410

Set	MEXBOL-Brent		CAC-Brent		UKX-Brent		AS30-Brent		Ibex-Brent	
Distribution	G. gamma		G. gamma		G. gamma		G. gamma		G. gamma	
	MEXBOL	Brent	CAC	Brent	UKX	Brent	AS30	Brent	Ibex	Brent
$\boldsymbol{\alpha^m}$	-0.344 **	0.998 ***	0.978 ***	-0.285 ***	0.931 ***	-0.258 ***	0.998 ***	-0.547 ***	0.998 ***	-0.124 ***
$\boldsymbol{\beta_1^m}$	0.291	0.514 **	0.767 ***	0.088 ***	0.706 ***	0.121 ***	0.773 ***	0.197 ***	0.722 ***	0.082 ***
$\boldsymbol{\beta_2^m}$	0.206 ***	0.705 ***	0.330 **	0.812 ***	0.518 ***	0.699 ***	0.237 ***	0.565 ***	0.437 ***	0.742 ***
$\boldsymbol{\delta_0^m}$	0.030 ***	0.008	0.035 ***	0.027 *	0.032 ***	0.029 **	0.016 ***	0.025 *	0.029 ***	0.024 *
$\boldsymbol{\delta_1^m}$	0.005 ***	0.010 ***	0.005 ***	0.008 ***	0.004 ***	0.008 ***	0.003 ***	0.008 ***	0.006 ***	0.008 ***
$\boldsymbol{\zeta^m}$	0.127 **	0.091 *	-0.050 ***	0.089 *	-0.021	0.088 *	0.115 **	0.070	-0.027	0.121 **
$\boldsymbol{\mu^m}$	0.359 **	1.981 ***	2.140 ***	0.911 ***	2.074 ***	0.947 ***	2.011 ***	0.933 ***	1.987 ***	0.855 ***
$\boldsymbol{\sigma^m}$	0.353 ***	1.352 ***	2.100 ***	0.351 ***	1.989 ***	0.386 ***	2.174 ***	0.392 ***	2.024 ***	0.366 ***
$\boldsymbol{Q^m}$	-1.495 ***	-1.254 *	-3.873 ***	-0.512 **	-3.440 ***	-0.562 ***	-5.150 ***	-0.616 ***	-4.198 ***	-0.715 ***
Diagnostics										
LL	-330.35		-387.72		-491.88		-582.17		-373.65	
AIC	-624.71		-739.43		-947.75		-1128.33		-711.30	
Spr	0.884		0.961		0.953		0.909		0.921	
Residuals										
Mean (ε_j^m)	-0.046	0.011	0.012	-0.095	0.008	-0.076	0.019	-0.058	-0.019	-0.121
Desv. Est.	0.919	0.953	0.953	0.969	0.954	0.965	0.984	0.947	0.991	0.968
Excess.dis	-1.186	-0.699	-0.712	-0.466	-0.699	-0.540	-0.246	-0.797	-0.139	-0.486

Table A.3: Results of the bivariate ACI POT model analyzing negative interdependence of stock markets with the oil market Brent. The table includes the ten financial indices. the hazard function that best represents the indices (Birnbaum-Saunders or generalized gamma). the parameters for each model and its significance (* Significant at 10%. ** 5% and *** 1%). the log-likelihood (LL). Akaike information criterion (AIC). Spectral radius of the persistence (Spr). and parameter of the residuals or innovations. mean. standard deviation and test of exceedance in the dispersions.

Set	SP-WTI		Nikkei-WTI		DAX-WTI		SPTSX-WTI		Kospi-WTI	
Distribution	G. gamma		G. gamma		G. gamma		G. gamma		G. gamma	
	SP	WTI	Nikkei	WTI	DAX	WTI	SPTSX	WTI	Kospi	WTI
α^m	0.796 ***	-0.370 ***	0.998 ***	-0.316 ***	0.939 ***	-0.385 ***	0.998 ***	-0.726 ***	0.920 ***	-0.217 *
β_1^m	0.776 ***	0.173 ***	0.755 ***	0.119 ***	0.796 ***	0.124 ***	0.836 ***	0.230 ***	0.718 ***	0.134 **
β_2^m	0.330 ***	0.568 ***	0.280 ***	0.744 ***	0.199 ***	0.734 ***	0.141 ***	0.258 *	0.280 *	0.707 ***
δ_0^m	0.030 ***	0.024 *	0.013 *	0.032 **	0.044 ***	0.022 *	0.030 ***	0.016	0.043 ***	0.041 ***
δ_1^m	0.003 ***	0.010 ***	0.007 ***	0.008 ***	0.003 ***	0.010 ***	0.003 ***	0.011 ***	0.007 ***	0.008 ***
ζ^m	0.096 *	0.033	0.159 ***	0.075 *	0.013	0.051	0.026	0.058	0.072	0.040
μ^m	2.060 ***	0.935 ***	2.087 ***	0.990 ***	2.180 ***	0.870 ***	2.462 ***	0.939 ***	1.827 ***	0.945 ***
σ^m	1.864 ***	0.360 ***	1.686 ***	0.398 ***	1.913 ***	0.371 ***	2.407 ***	0.337 ***	1.551 ***	0.404 ***
Q^m	-2.871 **	-0.441 **	-2.107 **	-0.355 *	-2.535 **	-0.592 ***	-4.021 ***	-0.375 *	-2.266 ***	-0.502 **
Diagnostics										
LL	-424.216		-294.536		-328.301		-444.524		-168.881	
AIC	-812.433		-553.072		-620.602		-853.049		-301.763	
Spr	0.932		0.932		0.925		0.888		0.906	
Residuals										
Mean (ε_j^m)	0.005	-0.131	0.019	-0.090	0.016	-0.106	0.007	-0.098	0.026	-0.082
Desv. Est.	0.964	0.982	0.953	0.968	0.969	0.957	0.917	0.984	0.988	0.941
Excess.dis	-0.539	-0.268	-0.691	-0.477	-0.460	-0.646	-1.219	-0.245	-0.181	-0.862

Set	MEXBOL-WTI		CAC-WTI		UKX-WTI		AS30-WTI		Ibex-WTI	
Distribution	G. gamma		G. gamma		G. gamma		G. gamma		G. gamma	
	MEXBOL	WTI	CAC	WTI	UKX	WTI	AS30	WTI	Ibex	WTI
α^m	0.998 ***	-0.154 *	0.909 ***	-0.437 ***	0.582 ***	-0.114	0.998 ***	-0.603 ***	0.933 ***	-0.088
β_1^m	0.753 ***	0.055 ***	0.759 ***	0.144 ***	0.819 ***	0.054 *	0.802 ***	0.171 ***	0.772 ***	0.033
β_2^m	0.175 **	0.906 ***	0.339 ***	0.716 ***	0.194 **	0.899 ***	0.161 ***	0.663 ***	0.223 ***	0.935 ***
δ_0^m	0.028 ***	0.012	0.043 ***	0.018	0.035 ***	0.023 *	0.018 ***	0.026 *	0.030 ***	0.014
δ_1^m	0.005 ***	0.011 ***	0.005 ***	0.011 ***	0.003 ***	0.010 ***	0.003 ***	0.010 ***	0.006 ***	0.011 ***
ζ^m	0.150 **	0.044	-0.125 ***	0.049	-0.034	0.041	0.114 **	0.043	-0.021	0.079 *
μ^m	1.878 ***	0.880 ***	2.074 ***	0.900 ***	1.791 ***	0.954 ***	2.127 ***	0.951 ***	2.132 ***	0.903 ***
σ^m	1.832 ***	0.385 ***	1.884 ***	0.329 ***	1.646 ***	0.344 ***	2.255 ***	0.368 ***	1.664 ***	0.383 **
Q^m	-3.348 ***	-0.640 ***	-2.869 ***	-0.440 **	-2.803 **	-0.369 *	-4.985 **	-0.423 *	-1.612 ***	-0.623 **
Diagnostics										
LL	-298.078		-329.847		-422.698		-531.090		-314.790	
AIC	-560.156		-623.693		-809.395		-102.618		-593.580	
Spr	0.954		0.960		0.969		0.912		0.971	
Residuals										
Mean (ε_j^m)	0.019	-0.058	0.016	-0.117	0.018	-0.077	0.015	-0.063	-0.010	-0.093
Desv. Est.	0.969	0.950	0.945	1.008	0.921	0.977	0.973	0.952	0.993	0.957
Excess.dis	-0.459	-0.738	-0.823	0.130	-1.164	-0.344	-0.407	-0.717	-0.108	-0.643

Table A.4: Results of the bivariate ACI POT model analyzing negative interdependence of stock markets with the oil market WTI. The table includes the ten financial indices. the hazard function that best represents the indices (Birnbaum-Saunders or generalized gamma). the parameters for each model and its significance (* Significant at 10%. ** 5% and *** 1%). the log-likelihood (LL). Akaike information criterion (AIC). Spectral radius of the persistence (Spr). and parameter of the residuals or innovations. mean. standard deviation and test of exceedance in the dispersions.

Set	SP-Brent				Nikkei-Brent				DAX-Brent				SPTSX-Brent				Kospi-Brent			
Distribution	G. gamma				G. gamma				Bisa				G. gamma				G. gamma			
	SP		Brent		Nikkei		Brent		DAX		Brent		SPTSX		Brent		Kospi		Brent	
$\boldsymbol{\alpha^m}$	0.483	***	0.741	***	0.998	***	-0.280	***	0.292	***	0.367	***	0.246	***	0.962	***	0.998	***	-0.049	
$\boldsymbol{\beta_1^m}$	0.998	***	0.578	*	0.700	***	0.128	***	0.393		0.965	***	0.946	***	0.545	**	0.385	**	0.193	***
$\boldsymbol{\beta_2^m}$	-0.187	***	0.146		0.305	***	0.777	***	0.519		-0.449		-0.048	***	0.360	***	0.890	***	0.575	***
$\boldsymbol{\delta_0^m}$	0.037	***	0.050	***	0.019	***	0.040	***	0.048	***	0.052	***	0.041	***	0.034	***	0.046	***	0.059	***
$\boldsymbol{\delta_1^m}$	0.003	***	0.008	***	0.006	***	0.009	***	0.004	***	0.007	***	0.003	***	0.009	***	0.006	***	0.007	***
$\boldsymbol{\zeta^m}$	-0.006		-0.018		0.080	*	0.064		-0.029		-0.010		0.002		0.001		0.028		0.024	
$\boldsymbol{\mu^m}$	1.209	***	1.389	***	1.967	***	1.038	***	2.845	***	2.578	***	0.979	***	1.538	***	1.749	***	1.134	***
$\boldsymbol{\sigma^m}$	0.844	***	0.720	***	1.463	***	0.531	***	0.642	***	0.496	***	0.712	***	0.779	***	1.420	***	0.620	***
$\boldsymbol{Q^m}$	-1.337	***	-0.458	*	-1.574	**	-0.493	*					-1.256	***	-0.441		-1.972	***	-0.544	*
Diagnostics																				
LL	-419.49				-253.76				-300.36				-414.82				-181.52			
AIC	-802.98				-471.51				-568.72				-793.65				-327.05			
Spr	0.843				0.940				0.852				0.898				0.905			
Residuals																				
Mean ($\boldsymbol{\varepsilon_j^m}$)	-0.022		0.012		0.016		-0.106		-0.067		-0.082		-0.061		0.016		0.018		-0.060	
Desv. Est.	0.979		0.899		0.933		0.958		0.985		0.952		0.956		0.930		0.923		0.927	
Excess.dis	-0.322		-1.481		-0.980		-0.617		-0.229		-0.719		-0.665		-1.036		-1.125		-1.067	
Set	MEXBOL-Brent				CAC-Brent				UKX-Brent				AS30-Brent				Ibex-Brent			
Distribution	Bisa				Bisa				Bisa				G. gamma				Bisa			
	MEXBOL		Brent		CAC		Brent		UKX		Brent		AS30		Brent		Ibex		Brent	
$\boldsymbol{\alpha^m}$	0.552	***	0.306	***	0.425	***	0.262	***	0.310	***	0.288	***	0.183	**	0.998	***	0.350	***	0.382	***
$\boldsymbol{\beta_1^m}$	0.284		0.250		-0.071		-0.140		0.499		0.998	*	0.869	***	0.998	***	0.998	***	0.819	*
$\boldsymbol{\beta_2^m}$	0.412		0.477		0.998	*	0.987	***	0.444		-0.558		0.016		0.318	*	-0.246		-0.273	
$\boldsymbol{\delta_0^m}$	0.040	***	0.050	***	0.044	***	0.047	***	0.038	***	0.052	***	0.022	***	0.035	***	0.038	***	0.044	***
$\boldsymbol{\delta_1^m}$	0.004	***	0.007	***	0.004	***	0.008	***	0.003	***	0.007	***	0.003	***	0.009	***	0.005	***	0.008	***
$\boldsymbol{\zeta^m}$	0.091	*	0.012		-0.095	*	-0.007		-0.093	*	-0.005		0.072		0.014		-0.041		0.005	
$\boldsymbol{\mu^m}$	2.817	***	2.583	***	3.010	***	2.692	***	3.100	***	2.603	***	0.829	***	1.868	***	2.968	***	2.643	***
$\boldsymbol{\sigma^m}$	0.677	***	0.501	***	0.667	***	0.537	***	0.732	***	0.505	***	0.742	***	1.182	***	0.692	***	0.522	***
$\boldsymbol{Q^m}$													-1.956	***	-0.864	*				
Diagnostics																				
LL	-294.53				-337.57				-441.70				-528.77				-327.23			
AIC	-557.06				-643.13				-851.41				-102.15				-622.46			
Spr	0.716				0.832				0.879				0.896				0.812			
Residuals																				
Mean ($\boldsymbol{\varepsilon_j^m}$)	-0.017		-0.087		-0.044		-0.091		-0.041		-0.088		-0.035		0.003		-0.048		-0.085	
Desv. Est.	0.994		0.947		0.997		0.943		1.006		0.948		0.932		0.942		0.965		0.967	
Excess.dis	-0.094		-0.791		-0.042		-0.861		0.088		-0.788		-1.010		-0.873		-0.536		-0.503	

Table A.5: Results of the bivariate ACI POT model analyzing positive interdependence of stock markets with the oil market Brent. The table includes the ten financial indices. the hazard function that best represents the indices (Birnbaum-Saunders or generalized gamma). the parameters for each model and its significance (* Significant at 10%. ** 5% and *** 1%). the log-likelihood (LL). Akaike information criterion (AIC). Spectral radius of the persistence (Spr). and parameter of the residuals or innovations. mean. standard deviation and test of exceedance in the dispersions.

Set	SP-WTI				Nikkei-WTI				DAX-WTI				SPTSX-WTI				Kospi-WTI			
Distribution	G. gamma				G. gamma				Bisa				G. gamma				G. gamma			
	SP		WTI		Nikkei		WTI		DAX		WTI		SPTSX		WTI		Kospi		WTI	
α^m	0.428	***	0.968	***	-0.152	*	0.998	***	0.294	***	0.363	***	0.185	***	0.998	***	0.998	***	-0.056	
β_1^m	0.998	***	0.791	**	0.593	***	0.886	***	0.998	***	0.515		0.910	***	0.664	**	0.545	***	0.162	*
β_2^m	-0.140	***	0.071		0.146	***	0.553	***	-0.225	**	0.083		-0.006		0.350	***	0.526	*	0.654	***
δ_0^m	0.036	***	0.047	***	0.030	***	0.034	***	0.049	***	0.052	***	0.039	***	0.035	***	0.042	***	0.055	***
δ_1^m	0.003	***	0.008	***	0.005	***	0.009	***	0.003	***	0.007	***	0.003	***	0.009	***	0.007	***	0.008	***
ζ^m	0.036		-0.026		0.129	**	0.085	*	0.007		0.013		0.003		0.026		0.039		0.048	
μ^m	1.164	***	1.561	***	0.917	***	1.998	***	2.828	***	2.559	***	0.952	***	1.641	***	1.793	***	1.207	***
σ^m	0.850	***	0.746	***	0.488	***	1.019	***	0.631	***	0.483	***	0.727	***	0.740	***	1.410	***	0.565	***
Q^m	-1.476	***	-0.296		-0.865	***	-0.334						-1.388	***	-0.227		-1.821	***	-0.253	
Diagnostics																				
LL	-419.115				-238.048				-279.130				-405.672				-147.068			
AIC	-802.231				-440.096				-526.260				-775.344				-258.136			
Spr	0.858				0.933				0.846				0.902				0.896			
Residuals																				
Mean (ε_j^m)	-0.023		0.016		-0.060		0.014		-0.068		-0.083		-0.052		0.020		0.023		-0.069	
Desv. Est.	0.974		0.919		0.956		0.959		0.984		0.945		0.952		0.938		0.918		0.942	
Excess.dis	-0.392		-1.201		-0.652		-0.608		-0.249		-0.821		-0.716		-0.922		-1.180		-0.854	

Set	MEXBOL-WTI				CAC-WTI				UKX-WTI				AS30-WTI				Ibex-WTI			
Distribution	Bisa				G. gamma				G. gamma				G. gamma				G. gamma			
	MEXBOL		WTI		CAC		WTI		UKX		WTI		AS30		WTI		Ibex		WTI	
α^m	0.452	***	0.438	***	0.310	***	0.870	***	0.256	***	0.619	***	0.521	***	0.998	***	0.394	***	0.870	***
β_1^m	0.671	***	0.998	***	0.909	***	0.998	**	0.998	***	0.663		0.998	***	0.998	**	0.998	***	0.846	**
β_2^m	0.046	***	-0.580	***	-0.039		-0.044		-0.089	***	0.357		-0.154	***	-0.043		-0.133	***	0.086	
δ_0^m	0.039	***	0.051	***	0.047	***	0.046	***	0.039	***	0.050	***	0.021	***	0.047	***	0.040	***	0.046	***
δ_1^m	0.004	***	0.007	***	0.005	***	0.009	***	0.003	***	0.008	***	0.003	***	0.008	***	0.005	***	0.008	***
ζ^m	0.116	**	0.032		-0.111	**	-0.011		-0.069		-0.019		0.091	*	-0.009		-0.066		-0.012	
μ^m	2.843	***	2.532	***	1.117	***	1.518	***	0.883	***	1.455	***	1.147	***	1.670	***	1.081	***	1.521	***
σ^m	0.683	***	0.469	***	0.812	***	0.778	***	0.636	***	0.666	***	1.013	***	0.905	***	0.857	***	0.775	***
Q^m					-1.384	***	-0.425		-1.329	***	-0.254		-2.142	***	-0.497		-1.560	***	-0.423	
Diagnostics																				
LL	-275.898				-306.276				-409.608				-504.400				-295.796			
AIC	-519.796				-576.552				-783.215				-972.799				-555.593			
Spr	0.707				0.866				0.886				0.820				0.851			
Residuals																				
Mean (ε_j^m)	-0.021		-0.083		-0.020		0.020		-0.044		0.009		-0.008		0.005		0.005		0.016	
Desv. Est.	0.993		0.923		0.951		0.944		0.969		0.961		0.938		0.923		0.909		0.962	
Excess.dis	-0.101		-1.127		-0.728		-0.840		-0.465		-0.583		-0.921		-1.137		-1.319		-0.571	

Table A.6: Results of the bivariate ACI POT model analyzing positive interdependence of stock markets with the oil market WTI. The table includes the ten financial indices. the hazard function that best represents the indices (Birnbaum-Saunders or generalized gamma). the parameters for each model and its significance (* Significant at 10%. ** 5% and *** 1%). the log-likelihood (LL). Akaike information criterion (AIC). Spectral radius of the persistence (Spr). and parameter of the residuals or innovations. mean. standard deviation and test of exceedance in the dispersions.

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	183	0.00	0.04	0.00	0.04	0.11	13	0.09	0.43	0.18	0.44	0.61
SP	0.99	53	0.39	0.00	0.01	0.00	0.00	9	0.03	0.52	0.08	0.52	0.27
	0.999	7	0.32	0.89	0.61	0.89	0.56	3	0.01	0.83	0.03	0.83	0.00
	0.95	206	0.05	0.51	0.12	0.52	0.02	3	0.00	0.83	0.00	0.84	1.00
Brent	0.99	44	0.66	0.36	0.60	0.36	0.36	3	0.61	0.83	0.86	0.83	0.22
	0.999	6	0.56	0.90	0.84	0.90	0.60	0	0.37	1.00	0.67	-	-
	0.95	206	0.14	0.04	0.04	0.04	0.00	30	0.02	0.30	0.04	0.31	0.05
Nikkei	0.99	46	0.94	0.09	0.24	0.09	0.05	10	0.01	0.47	0.03	0.47	0.11
	0.999	9	0.07	0.85	0.18	0.85	0.93	2	0.07	0.89	0.19	0.89	0.83
	0.95	216	0.43	0.39	0.51	0.40	0.26	3	0.00	0.83	0.00	0.83	1.00
Brent	0.99	43	0.71	0.36	0.62	0.37	0.28	0	0.01	1.00	0.20	-	-
	0.999	5	0.83	0.92	0.97	0.92	0.80	0	0.38	1.00	0.68	-	-
	0.95	207	0.04	0.11	0.04	0.12	0.02	17	0.47	0.19	0.33	0.20	0.26
DAX	0.99	51	0.60	0.13	0.27	0.13	0.0	14	0.00	0.50	0.00	0.50	0.01
	0.999	8	0.17	0.87	0.39	0.87	0.34	3	0.01	0.83	0.03	0.83	0.46
	0.95	220	0.26	0.80	0.52	0.81	0.04	2	0.00	0.89	0.00	0.89	1.00
Brent	0.99	44	0.62	0.36	0.59	0.37	0.5	2	0.26	0.89	0.53	0.89	1.00
	0.999	5	0.90	0.92	0.99	0.92	0.36	0	0.37	1.00	0.67	-	-
	0.95	183	0.00	0.08	0.00	0.09	0.16	13	0.09	0.43	0.18	0.44	0.14
SPTSX	0.99	48	0.88	0.01	0.05	0.01	0.00	6	0.34	0.07	0.12	0.07	0.01
	0.999	7	0.32	0.89	0.61	0.89	0.14	2	0.07	0.89	0.19	0.89	0.06
	0.95	213	0.14	0.45	0.25	0.46	0.00	3	0.00	0.83	0.00	0.84	1.00
Brent	0.99	45	0.77	0.35	0.62	0.35	0.21	3	0.61	0.83	0.86	0.83	0.24
	0.999	6	0.56	0.90	0.84	0.90	0.63	0	0.37	1.00	0.67	-	-
	0.95	182	0.00	0.02	0.00	0.02	0.00	1	0.00	0.94	0.00	0.94	-
Kospi	0.99	50	0.52	0.12	0.25	0.13	0.01	1	0.11	0.94	0.28	0.94	1.00
	0.999	4	0.79	0.93	0.96	0.93	0.97	0	0.4	1.0	0.7	-	-
	0.95	208	0.16	0.86	0.37	0.86	0.03	2	0.00	0.88	0.00	0.88	-
Brent	0.99	44	0.80	0.35	0.63	0.36	0.52	2	0.37	0.88	0.66	0.88	1.00
	0.999	6	0.52	0.90	0.81	0.90	0.49	0	0.4	1.0	0.7	-	-

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	200	0.03	0.00	0.00	0.00	0.00	12	0.12	0.36	0.20	0.38	0.07
MEXBOL	0.99	56	0.16	0.00	0.00	0.00	0.00	2	0.35	0.88	0.64	0.88	0.97
	0.999	4	0.77	0.93	0.95	0.93	0.92	0	0.39	1.00	0.70	-	-
	0.95	219	0.41	0.25	0.37	0.27	0.01	2	0.00	0.88	0.00	0.88	0.96
Brent	0.99	44	0.74	0.36	0.63	0.36	0.04	2	0.35	0.88	0.64	0.88	1.00
	0.999	5	0.86	0.92	0.98	0.92	0.24	0	0.39	1.00	0.70	-	-
	0.95	210	0.07	0.00	0.00	0.00	0.00	15	0.24	0.28	0.27	0.29	1.00
CAC	0.99	61	0.06	0.00	0.00	0.00	0.00	12	0.00	0.39	0.00	0.39	0.02
	0.999	7	0.33	0.89	0.62	0.89	0.73	2	0.07	0.89	0.19	0.89	0.30
	0.95	223	0.35	0.87	0.64	0.87	0.16	2	0.00	0.89	0.00	0.89	0.95
Brent	0.99	46	0.84	0.34	0.62	0.34	0.24	2	0.27	0.89	0.54	0.89	1.00
	0.999	5	0.91	0.92	0.99	0.92	0.15	0	0.37	1.00	0.67	-	-
	0.95	193	0.00	0.00	0.00	0.00	0.00	15	0.42	0.64	0.65	0.65	1.00
UKX	0.99	61	0.06	0.24	0.09	0.24	0.13	10	0.01	0.26	0.01	0.27	0.28
	0.999	9	0.08	0.85	0.22	0.85	0.58	1	0.39	0.94	0.69	0.94	0.85
	0.95	227	0.46	0.96	0.76	0.96	0.05	3	0.00	0.82	0.00	0.83	0.95
Brent	0.99	46	0.81	0.34	0.62	0.35	0.14	3	0.72	0.82	0.92	0.82	1.00
	0.999	5	0.91	0.92	0.99	0.92	0.21	0	0.39	1.00	0.69	-	-
	0.95	201	0.01	0.00	0.00	0.00	0.00	20	0.95	0.99	1.00	0.99	0.06
AS30	0.99	54	0.34	0.16	0.23	0.16	0.00	8	0.08	0.14	0.07	0.14	0.00
	0.999	8	0.17	0.01	0.01	0.01	0.01	1	0.43	0.94	0.73	0.94	1.00
	0.95	222	0.32	0.89	0.60	0.90	0.02	3	0.00	0.83	0.00	0.84	1.00
Brent	0.99	48	0.93	0.32	0.61	0.32	0.41	2	0.26	0.89	0.52	0.89	0.13
	0.999	6	0.58	0.90	0.85	0.90	0.76	0	0.37	1.00	0.67	-	-
	0.95	202	0.02	0.01	0.00	0.01	0.01	23	0.53	0.17	0.32	0.18	0.00
Ibex	0.99	49	0.81	0.11	0.27	0.11	0.01	7	0.18	0.62	0.36	0.62	0.00
	0.999	6	0.58	0.90	0.85	0.90	0.92	1	0.43	0.94	0.73	0.94	0.23
	0.95	223	0.35	0.87	0.64	0.88	0.03	2	0.00	0.89	0.00	0.89	0.86
Brent	0.99	46	0.84	0.34	0.62	0.34	0.10	2	0.26	0.89	0.52	0.89	1.00
	0.999	5	0.90	0.92	0.99	0.92	0.10	0	0.37	1.00	0.67	-	-

Table A.7: VaR Accuracy test for the ACI POT model analyzing negative interdependence of stock markets with the oil market Brent. The in-sample period is from January 2. 1994 until December 31. 2012. The out-sample or backtest period corresponds from January 2. 2013 to August 15. 2014. Three confidence levels (5%. 1%. 0.1%) for the VaR estimation are used for each set of data. Entries in the rows are the significance levels (p-values) of the respective tests. The cells with values (-) means that the test cannot be estimated

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	186	0.00	0.00	0.00	0.00	0.01	13	0.09	0.43	0.18	0.44	0.65
SP	0.99	50	0.73	0.11	0.27	0.12	0.01	8	0.07	0.57	0.17	0.57	0.04
	0.999	6	0.58	0.90	0.85	0.90	0.16	2	0.07	0.89	0.19	0.89	0.00
	0.95	207	0.04	0.05	0.02	0.06	0.04	3	0.00	0.83	0.00	0.84	0.97
WTI	0.99	39	0.20	0.43	0.32	0.42	0.18	1	0.07	0.94	0.20	0.94	1.00
	0.999	6	0.58	0.90	0.85	0.90	0.55	0	0.37	1.00	0.67	-	-
	0.95	193	0.03	0.01	0.00	0.01	0.00	25	0.17	0.78	0.38	0.78	0.00
Nikkei	0.99	44	0.90	0.01	0.03	0.01	0.00	10	0.01	0.25	0.02	0.26	0.00
	0.999	10	0.03	0.83	0.08	0.83	0.59	2	0.06	0.88	0.18	0.88	0.13
	0.95	203	0.14	0.06	0.06	0.07	0.08	2	0.00	0.88	0.00	0.89	1.00
WTI	0.99	33	0.06	0.48	0.14	0.49	0.17	1	0.09	0.94	0.23	0.94	1.00
	0.999	6	0.50	0.90	0.79	0.90	0.0	0	0.38	1.00	0.68	-	-
	0.95	206	0.07	0.34	0.12	0.35	0.06	14	0.18	0.09	0.09	0.10	0.00
DAX	0.99	44	0.70	0.07	0.18	0.07	0.02	9	0.03	0.51	0.07	0.52	0.00
	0.999	6	0.55	0.90	0.83	0.90	0.06	2	0.07	0.89	0.19	0.89	0.09
	0.95	210	0.12	0.08	0.06	0.09	0.00	3	0.00	0.83	0.00	0.83	1.00
WTI	0.99	41	0.40	0.40	0.49	0.40	0.08	1	0.08	0.94	0.21	0.94	1.00
	0.999	6	0.55	0.90	0.83	0.90	0.66	0	0.38	1.00	0.68	-	-
	0.95	186	0.00	0.00	0.00	0.00	0.00	13	0.11	0.44	0.20	0.45	0.06
SPTSX	0.99	49	0.70	0.00	0.01	0.00	0.0	6	0.32	0.07	0.12	0.07	0.01
	0.999	6	0.55	0.90	0.83	0.90	0.89	2	0.07	0.89	0.19	0.89	0.08
	0.95	218	0.34	0.08	0.14	0.09	0.01	2	0.00	0.89	0.00	0.89	1.00
WTI	0.99	42	0.51	0.38	0.55	0.38	0.5	1	0.08	0.94	0.21	0.94	0.59
	0.999	7	0.31	0.88	0.59	0.88	0.73	0	0.38	1.00	0.68	-	-
	0.95	195	0.03	0.12	0.03	0.13	0.08	1	0.00	0.93	0.00	0.93	-
Kospi	0.99	46	0.92	0.09	0.24	0.09	0.09	1	0.30	0.93	0.59	0.93	1.00
	0.999	7	0.28	0.88	0.56	0.88	0.99	0	0.49	1.00	0.79	-	-
	0.95	210	0.26	0.29	0.30	0.31	0.36	3	0.00	0.78	0.01	0.79	1.00
WTI	0.99	42	0.62	0.38	0.60	0.38	0.09	1	0.30	0.93	0.59	0.93	1.00
	0.999	9	0.06	0.85	0.18	0.85	0.04	0	0.49	1.00	0.79	-	-

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	195	0.02	0.00	0.00	0.00	0.00	10	0.24	0.39	0.35	0.40	0.01
MEXBOL	0.99	47	0.83	0.00	0.00	0.00	0.00	3	0.91	0.80	0.96	0.80	0.20
	0.999	6	0.52	0.90	0.80	0.90	0.03	0	0.45	1.00	0.75	-	-
	0.95	208	0.18	0.08	0.09	0.09	0.04	3	0.00	0.80	0.00	0.80	0.81
WTI	0.99	41	0.49	0.39	0.55	0.39	0.33	1	0.21	0.93	0.46	0.93	1.00
	0.999	7	0.29	0.88	0.56	0.88	0.75	0	0.45	1.00	0.75	-	-
	0.95	201	0.03	0.01	0.00	0.01	0.00	16	0.41	0.24	0.36	0.25	1.00
CAC	0.99	60	0.06	0.00	0.00	0.00	0.00	12	0.00	0.38	0.00	0.38	0.01
	0.999	8	0.16	0.87	0.37	0.87	0.68	2	0.07	0.89	0.19	0.89	0.17
	0.95	200	0.02	0.24	0.04	0.26	0.01	3	0.00	0.83	0.00	0.83	-
WTI	0.99	40	0.32	0.41	0.44	0.41	0.17	1	0.08	0.94	0.21	0.94	1.00
	0.999	7	0.31	0.88	0.59	0.88	0.81	0	0.38	1.00	0.68	-	-
	0.95	192	0.00	0.00	0.00	0.00	0.00	14	0.90	0.70	0.92	0.71	0.56
UKX	0.99	53	0.35	0.64	0.58	0.64	0.22	7	0.04	0.15	0.04	0.15	0.01
	0.999	10	0.03	0.84	0.1	0.84	0.66	1	0.30	0.93	0.59	0.93	0.92
	0.95	207	0.08	0.36	0.14	0.37	0.64	2	0.00	0.87	0.00	0.87	1.00
WTI	0.99	39	0.25	0.42	0.38	0.42	0.48	0	0.02	1.00	0.05	-	-
	0.999	7	0.31	0.88	0.59	0.88	0.78	0	0.45	1.00	0.75	-	-
	0.95	197	0.02	0.00	0.00	0.00	0.00	18	0.68	0.84	0.90	0.84	0.15
AS30	0.99	58	0.10	0.04	0.03	0.04	0.00	8	0.07	0.56	0.17	0.57	0.00
	0.999	5	0.87	0.92	0.98	0.92	0.92	1	0.42	0.94	0.72	0.94	1.00
	0.95	208	0.10	0.04	0.03	0.04	0.00	2	0.00	0.89	0.00	0.89	1.00
WTI	0.99	43	0.61	0.37	0.59	0.37	0.24	1	0.07	0.94	0.20	0.94	1.00
	0.999	6	0.55	0.90	0.83	0.90	0.85	0	0.37	1.00	0.67	-	-
	0.95	206	0.07	0.00	0.00	0.00	0.00	18	0.69	0.24	0.47	0.25	0.01
Ibex	0.99	57	0.14	0.01	0.01	0.01	0.00	5	0.61	0.72	0.82	0.72	0.01
	0.999	4	0.75	0.93	0.95	0.93	1.00	1	0.42	0.94	0.72	0.94	0.23
	0.95	213	0.17	0.45	0.30	0.47	0.51	3	0.00	0.83	0.00	0.83	1.00
WTI	0.99	42	0.49	0.39	0.54	0.38	0.10	1	0.08	0.94	0.21	0.94	1.00
	0.999	6	0.55	0.90	0.83	0.90	0.14	0	0.37	1.00	0.67	-	-

Table A.8: VaR Accuracy test for the ACI POT model analyzing negative interdependence of stock markets with the oil market WTI. The in-sample period is from January 2. 1994 until December 31. 2012. The out-sample or backtest period corresponds from January 2. 2013 to August 15. 2014. Three confidence levels (5%. 1%. 0.1%) for the VaR estimation are used for each set of data. Entries in the rows are the significance levels (p-values) of the respective tests. The cells with values (-) means that the test cannot be estimated

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	199	0.01	0.07	0.01	0.07	0.20	10	0.01	0.48	0.03	0.49	0.46
SP	0.99	43	0.55	0.37	0.56	0.38	0.18	7	0.19	0.62	0.37	0.62	0.37
	0.999	7	0.32	0.89	0.61	0.89	0.62	2	0.07	0.89	0.20	0.89	0.08
	0.95	237	0.89	0.05	0.14	0.05	0.02	5	0.00	0.75	0.00	0.76	1.00
Brent	0.99	46	0.89	0.08	0.22	0.09	0.00	3	0.58	0.86	0.84	0.86	0.30
	0.999	7	0.32	0.01	0.01	0.01	0.02	0	0.37	1.00	0.67	-	-
	0.95	211	0.26	0.01	0.01	0.01	0.00	29	0.04	0.35	0.08	0.37	0.01
Nikkei	0.99	48	0.71	0.11	0.25	0.11	0.00	9	0.03	0.52	0.07	0.52	0.03
	0.999	6	0.52	0.90	0.80	0.90	0.02	3	0.01	0.83	0.03	0.83	0.49
	0.95	191	0.01	0.02	0.00	0.02	0.02	7	0.00	0.61	0.00	0.62	1.00
Brent	0.99	42	0.60	0.06	0.15	0.06	0.05	3	0.62	0.83	0.87	0.83	0.54
	0.999	6	0.52	0.90	0.80	0.90	0.48	0	0.38	1.00	0.67	-	-
	0.95	202	0.02	0.08	0.01	0.09	0.22	15	0.20	0.11	0.12	0.12	0.01
DAX	0.99	37	0.12	0.45	0.22	0.45	0.37	4	0.96	0.78	0.96	0.78	0.12
	0.999	5	0.90	0.92	0.99	0.92	0.97	0	0.37	1.00	0.66	-	-
	0.95	210	0.07	0.13	0.06	0.14	0.03	5	0.00	0.75	0.00	0.76	1.00
Brent	0.99	38	0.16	0.04	0.04	0.04	0.10	1	0.07	0.94	0.18	0.94	0.64
	0.999	5	0.90	0.92	0.99	0.92	0.46	0	0.37	1.00	0.66	-	-
	0.95	195	0.01	0.02	0.00	0.03	0.08	10	0.01	0.48	0.03	0.49	0.79
SPTSX	0.99	44	0.66	0.07	0.18	0.07	0.04	6	0.37	0.67	0.61	0.67	0.72
	0.999	8	0.17	0.87	0.38	0.87	0.51	1	0.43	0.94	0.73	0.94	0.13
	0.95	229	0.70	0.01	0.04	0.01	0.00	5	0.00	0.75	0.00	0.76	1.00
Brent	0.99	42	0.46	0.06	0.13	0.06	0.00	2	0.25	0.92	0.52	0.92	0.19
	0.999	8	0.17	0.01	0.01	0.01	0.03	0	0.37	1.00	0.67	-	-
	0.95	190	0.01	0.02	0.00	0.02	0.02	1	0.00	0.94	0.00	0.94	-
Kospi	0.99	48	0.73	0.11	0.26	0.11	0.00	1	0.07	0.94	0.20	0.94	1.00
	0.999	7	0.29	0.88	0.57	0.88	0.82	0	0.37	1.00	0.67	-	-
	0.95	214	0.33	0.03	0.07	0.04	0.12	5	0.00	0.75	0.00	0.76	1.00
Brent	0.99	44	0.80	0.00	0.00	0.00	0.00	5	0.62	0.75	0.84	0.75	0.14
	0.999	7	0.29	0.88	0.57	0.88	0.60	0	0.37	1.00	0.67	-	-

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	206	0.08	0.00	0.00	0.00	0.00	11	0.02	0.43	0.05	0.45	0.11
MEXBOL	0.99	44	0.74	0.00	0.00	0.00	0.00	1	0.07	0.94	0.19	0.94	0.75
	0.999	4	0.77	0.93	0.95	0.93	0.80	0	0.37	1.00	0.67	-	-
	0.95	196	0.01	0.35	0.03	0.36	0.03	6	0.00	0.70	0.00	0.71	1.00
Brent	0.99	42	0.52	0.01	0.02	0.01	0.00	1	0.07	0.94	0.19	0.94	0.86
	0.999	5	0.86	0.92	0.98	0.92	0.99	0	0.37	1.00	0.67	-	-
	0.95	205	0.03	0.09	0.02	0.10	0.27	12	0.04	0.40	0.08	0.41	0.57
CAC	0.99	52	0.51	0.02	0.06	0.02	0.05	6	0.38	0.67	0.63	0.68	0.41
	0.999	3	0.39	0.95	0.69	0.95	0.99	0	0.36	1.00	0.66	-	-
	0.95	206	0.04	0.49	0.09	0.50	0.22	5	0.00	0.75	0.00	0.76	1.00
Brent	0.99	42	0.42	0.06	0.12	0.06	0.00	1	0.06	0.94	0.18	0.94	0.99
	0.999	6	0.58	0.90	0.85	0.90	0.99	0	0.36	1.00	0.66	-	-
	0.95	203	0.02	0.00	0.00	0.00	0.01	11	0.02	0.29	0.04	0.30	0.4
UKX	0.99	45	0.70	0.08	0.19	0.08	0.21	4	0.96	0.02	0.08	0.03	0.04
	0.999	5	0.91	0.92	0.99	0.92	0.79	0	0.37	1.00	0.66	-	-
	0.95	204	0.02	0.66	0.06	0.67	0.31	5	0.00	0.75	0.00	0.76	1.0
Brent	0.99	42	0.40	0.06	0.12	0.06	0.03	1	0.07	0.94	0.18	0.94	0.95
	0.999	6	0.59	0.90	0.86	0.90	0.97	0	0.37	1.00	0.66	-	-
	0.95	213	0.11	0.00	0.00	0.00	0.00	22	0.73	0.85	0.93	0.86	0.48
AS30	0.99	47	0.96	0.09	0.24	0.09	0.01	10	0.01	0.23	0.02	0.23	0.0
	0.999	10	0.04	0.01	0.01	0.01	0.02	1	0.44	0.94	0.74	0.94	1.00
	0.95	229	0.60	0.01	0.03	0.01	0.00	5	0.00	0.72	0.00	0.73	1.00
Brent	0.99	41	0.34	0.05	0.10	0.05	0.00	4	0.96	0.78	0.96	0.78	0.3
	0.999	9	0.08	0.01	0.01	0.01	0.03	0	0.37	1.00	0.66	-	-
	0.95	201	0.01	0.07	0.01	0.08	0.21	16	0.28	0.14	0.19	0.15	0.2
Ibex	0.99	37	0.12	0.30	0.17	0.30	0.16	4	0.95	0.78	0.96	0.78	0.33
	0.999	6	0.58	0.90	0.85	0.90	0.60	1	0.44	0.94	0.74	0.94	1.0
	0.95	209	0.06	0.22	0.08	0.23	0.05	5	0.00	0.75	0.00	0.76	1.0
Brent	0.99	41	0.34	0.05	0.10	0.05	0.03	0	0.00	1.00	0.02	-	-
	0.999	6	0.58	0.90	0.85	0.90	0.96	0	0.36	1.00	0.66	-	-

Table A.9: VaR Accuracy test for the ACI POT model analyzing positive interdependence of stock markets with the oil market Brent. The in-sample period is from January 2. 1994 until December 31. 2012. The out-sample or backtest period corresponds from January 2. 2013 to August 15. 2014. Three confidence levels (5%. 1%. 0.1%) for the VaR estimation are used for each set of data. Entries in the rows are the significance levels (p-values) of the respective tests. The cells with values (-) means that the test cannot be estimated

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	198	0.01	0.20	0.01	0.22	0.45	9	0.01	0.52	0.02	0.53	0.54
SP	0.99	40	0.27	0.41	0.39	0.41	0.03	6	0.34	0.67	0.58	0.67	0.11
	0.999	8	0.17	0.87	0.39	0.87	0.41	2	0.07	0.89	0.19	0.89	0.04
	0.95	239	0.88	0.09	0.24	0.10	0.00	4	0.00	0.78	0.00	0.78	1.00
WTI	0.99	48	0.92	0.10	0.25	0.10	0.02	0	0.00	1.00	0.02	-	-
	0.999	6	0.58	0.00	0.01	0.00	0.02	0	0.37	1.00	0.67	-	-
	0.95	194	0.03	0.12	0.03	0.13	0.27	29	0.03	0.87	0.09	0.87	0.3
Nikkei	0.99	40	0.46	0.05	0.12	0.05	0.11	10	0.01	0.25	0.02	0.26	0.08
	0.999	10	0.03	0.83	0.08	0.83	0.97	1	0.40	0.94	0.70	0.94	0.02
	0.95	213	0.44	0.36	0.49	0.37	0.00	5	0.00	0.71	0.00	0.72	1.0
WTI	0.99	35	0.12	0.03	0.03	0.03	0.00	1	0.09	0.94	0.23	0.94	0.35
	0.999	6	0.50	0.90	0.79	0.90	0.09	1	0.40	0.94	0.70	0.94	0.35
	0.95	201	0.03	0.02	0.01	0.02	0.06	14	0.18	0.09	0.09	0.10	0.01
DAX	0.99	33	0.03	0.24	0.05	0.24	0.47	4	0.96	0.77	0.96	0.77	0.10
	0.999	3	0.41	0.95	0.71	0.95	0.52	1	0.42	0.94	0.72	0.94	0.46
	0.95	217	0.28	0.13	0.18	0.14	0.02	3	0.00	0.83	0.00	0.83	1.00
WTI	0.99	40	0.32	0.05	0.09	0.05	0.03	1	0.08	0.94	0.21	0.94	0.03
	0.999	6	0.55	0.90	0.83	0.90	0.56	0	0.38	1.00	0.68	-	-
	0.95	191	0.00	0.00	0.00	0.00	0.01	9	0.01	0.51	0.02	0.53	0.78
SPTSX	0.99	44	0.72	0.00	0.00	0.00	0.00	5	0.60	0.72	0.81	0.72	0.31
	0.999	7	0.31	0.88	0.59	0.88	0.72	1	0.42	0.94	0.72	0.94	1.00
	0.95	230	0.89	0.00	0.00	0.00	0.00	4	0.00	0.77	0.00	0.78	0.62
WTI	0.99	45	0.83	0.46	0.74	0.46	0.00	1	0.08	0.94	0.21	0.94	1.00
	0.999	7	0.31	0.01	0.01	0.01	0.02	0	0.38	1.00	0.68	-	-
	0.95	185	0.00	0.06	0.00	0.07	0.10	1	0.00	0.93	0.00	0.93	-
Kospi	0.99	43	0.75	0.43	0.70	0.43	0.09	1	0.30	0.93	0.59	0.93	1.00
	0.999	5	0.82	0.92	0.97	0.92	0.79	0	0.49	1.00	0.79	-	-
	0.95	215	0.48	0.08	0.17	0.09	0.23	4	0.01	0.71	0.02 1	0.72	0.85
WTI	0.99	43	0.75	0.01	0.03	0.01	0.00	3	0.71	0.78	0.90	0.78	0.17
	0.999	6	0.50	0.90	0.79	0.90	0.26	0	0.49	1.00	0.79	-	-

		VaR in-sample						VaR out-sample					
Index	α	Fail.	LRuc	LRind	LRcc	QTh	QTv	Fail.	LRuc	LRind	LRcc	QTh	QTv
	0.95	199	0.05	0.00	0.00	0.00	0.00	11	0.39	0.34	0.44	0.36	0.01
MEXBOL	0.99	43	0.70	0.00	0.00	0.00	0.00	2	0.61	0.87	0.86	0.87	0.72
	0.999	5	0.84	0.92	0.97	0.92	0.49	0	0.45	1.00	0.75	-	-
	0.95	214	0.35	0.01	0.02	0.01	0.00	3	0.00	0.80	0.00	0.80	1.00
WTI	0.99	41	0.49	0.06	0.13	0.06	0.00	0	0.02	1.00	0.06	-	-
	0.999	4	0.79	0.93	0.96	0.93	1.00	0	0.45	1.00	0.75	-	-
	0.95	209	0.10	0.07	0.05	0.08	0.19	13	0.11	0.34	0.18	0.36	0.34
CAC	0.99	58	0.11	0.01	0.01	0.01	0.01	7	0.15	0.61	0.32	0.61	0.09
	0.999	8	0.16	0.87	0.37	0.87	0.99	1	0.41	0.94	0.71	0.94	0.49
	0.95	230	0.84	0.05	0.15	0.06	0.00	4	0.00	0.77	0.00	0.78	1.00
WTI	0.99	42	0.49	0.40	0.55	0.40	0.04	1	0.08	0.94	0.21	0.94	0.09
	0.999	5	0.88	0.92	0.98	0.92	0.84	0	0.38	1.00	0.68	-	-
	0.95	192	0.00	0.00	0.00	0.00	0.00	12	0.50	0.51	0.64	0.52	0.64
UKX	0.99	48	0.83	0.10	0.26	0.10	0.09	4	0.54	0.04	0.09	0.04	0.02
	0.999	10	0.03	0.84	0.10	0.84	0.39	0	0.45	1.00	0.75	-	-
	0.95	226	0.65	0.02	0.06	0.02	0.00	4	0.00	0.74	0.00	0.74	1.00
WTI	0.99	41	0.41	0.38	0.48	0.38	0.22	1	0.20	0.93	0.43	0.93	1.00
	0.999	5	0.87	0.92	0.98	0.92	0.98	0	0.45	1.00	0.75	-	-
	0.95	210	0.13	0.00	0.00	0.00	0.00	19	0.86	0.93	0.98	0.93	0.03
AS30	0.99	53	0.34	0.02	0.05	0.03	0.00	9	0.03	0.19	0.04	0.19	0.00
	0.999	8	0.16	0.01	0.01	0.01	0.03	1	0.42	0.94	0.72	0.94	1.00
	0.95	235	0.85	0.02	0.07	0.03	0.00	5	0.00	0.72	0.00	0.73	0.74
WTI	0.99	37	0.15	0.30	0.21	0.31	0.00	1	0.07	0.94	0.20	0.94	0.34
	0.999	7	0.31	0.01	0.01	0.01	0.02	0	0.37	1.00	0.67	-	-
	0.95	203	0.04	0.05	0.02	0.05	0.14	18	0.69	0.05	0.13	0.05	0.03
Ibex	0.99	48	0.84	0.00	0.01	0.00	0.00	5	0.61	0.72	0.82	0.72	0.02
	0.999	9	0.07	0.85	0.20	0.85	0.97	2	0.07	0.89	0.19	0.89	0.04
	0.95	233	0.99	0.01	0.03	0.01	0.00	3	0.00	0.83	0.00	0.83	1.00
WTI	0.99	41	0.40	0.38	0.48	0.38	0.09	1	0.08	0.94	0.21	0.94	0.24
	0.999	5	0.88	0.92	0.98	0.92	0.52	0	0.37	1.00	0.67	-	-

Table A.10: VaR Accuracy test for the ACI POT model analyzing positive interdependence of stock markets with the oil market WTI. The in-sample period is from January 2. 1994 until December 31. 2012. The out-sample or backtest period corresponds from January 2. 2013 to August 15. 2014. Three confidence levels (5%. 1%. 0.1%) for the VaR estimation are used for each set of data. Entries in the rows are the significance levels (p-values) of the respective tests. The cells with values (-) means that the test cannot be estimated.