



Discussion Papers in Economics

**MEASURING FINANCIAL CONTAGION WITH
EXTREME COEXCEEDANCES**

By

Apostolos Thomadakis

(University of Surrey)

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Department of Economics
University of Surrey
Guildford
Surrey GU2 7XH, UK
Telephone +44 (0)1483 689380
Facsimile +44 (0)1483 689548
Web www.econ.surrey.ac.uk
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MEASURING FINANCIAL CONTAGION WITH EXTREME COEXCEEDANCES*

APOSTOLOS THOMADAKIS[†]

University of Surrey

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Abstract

This paper tests for contagion firstly, within the Euro Area (EA thereafter), and secondly from the US to the EA. Using “coexceedances” - the joint occurrences of extreme negative and positive returns in different countries in a given day - I define contagion within regions as the fraction of the coexceedances that cannot be explained by fundamentals (covariates). On the other hand, contagion across regions can be defined as the fraction of the coexceedance events in the EA that is left unexplained by its own covariates but that is explained by the exceedances from the US. Having applied a multinomial logistic regression model to daily returns on 14 European stock markets for the period 2004-2012, I can provide the following summary of the results. Firstly, I found evidence of contagion within the EA. Especially, the EA 10 year government bond yield and the EUR/USD exchange rate fail to adequately explain the probability of coexceedances in Europe. Therefore, these variables are important determinants of regional crashes. In addition, I have observed that negative movements in stock prices follow continuation patterns - coexceedances cluster across time. Secondly, there is no statistically significant evidence of contagion from the US to the EA, in the sense that US exceedances fail to explain high probabilities of coexceedances in the EA. This result holds under a large battery of robustness checks. I would rather interpret this as a normal interdependence between the two markets.

JEL classification: C25, E44, F36, G15

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[†]Correspondence to: School of Economics, Faculty of Business, Economics and Law, University of Surrey, Guildford, Surrey, GU2 7XH, United Kingdom. Email: A.Thomadakis@surrey.ac.uk

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1 Introduction

The aim of this paper is to shed light to whether contagion exists or not within the Europe region, but also to detect, if that is possible, contagion effects from the US to the Euro Area. In other words, I am interested in making a contribution to a better understanding of the degree to which European markets have become interconnected and to the level on which the sub-prime crisis which started in the US, spread across borders and increased or decreased the likelihood of a crisis in the EA.

The understanding of the relationship between financial markets signifies a key question, which has spawned a number of studies. Both investors and policymakers are particularly keen to understand the mechanisms that link markets - in order to be able firstly to assess the benefits of portfolio diversification and secondly to maintain financial stability. This motivation is even greater in times of financial crisis, where the vital question is whether and how the crisis propagates from one market or country to another. Therefore, we need to know whether or not we can classify this diffusion of shocks from one country to another as contagion.

In the existing literature, there is widespread disagreement on what is contagion. For some economists, contagion exists only when a crisis starts from one economy and spreads to another, when the two economies are located in separate geographic regions, with different structures and weak cross-market linkages. Others prefer to use the term shift-contagion (Forbes and Rigobon, 2002). According to this term, contagion is the significant increase in cross-market linkages after a shock to one country or to a group of countries. However, when the degree of comovement between two countries is high prior to the shock and continues being high even after the crisis, this does not constitute contagion. We would rather describe this as a normal interdependence between the countries under research.

In the present paper, I will use the term “pure contagion”, which means that a crisis might trigger additional crises elsewhere for reasons unexplained by fundamentals. In other words, a crisis in one market/country increases the likelihood of a crisis in another market/country over and above what would be implied by the interdependence that prevails between these markets/countries in non-crises times. This contrasts with many studies, which have involved simply comparing comovements before and during the crisis.

For the detection and identification of contagion in financial markets, many different approaches

have been proposed. On the one hand, we find studies that attempt to measure the effect of a shock in one country on another country: i) leading indicator approaches (Kaminsky *et al.*, 1998; Berg and Pattillo, 1999) and ii) probit/logit models (Eichengreen *et al.*, 1996; Forbes, 2001; Bae *et al.*, 2003; Christiansen and Ranaldo, 2009). In another strand of literature, we find studies that test discontinuities in the data-generating process: i) Markov-Switching models (Jeanne and Masson, 2000; Fratzscher, 2003) and ii) tests of structural breaks in the correlation coefficients (Corsetti *et al.*, 2001; Forbes and Rigobon, 2002; Rigobon, 2003).

There is a vast number of studies, by King and Wadhvani (1990), Boyer *et al.* (1999), Loretan and English (2000) and Forbes and Rigobon (2002) amongst others, which have been conducting tests on significant changes in correlations between asset returns during tranquil and turmoil periods. There are mainly two reasons why pure correlation-based tests are inappropriate and invalid for contagion testing. Firstly, correlation-based tests are a positive function of volatility. Given the fact that during crises financial returns exhibit high volatility, a correlation test is biased upwards resulting in spurious contagion. Secondly, correlation coefficient is a linear measure which gives equal weight to negative and positive return. This contradicts with the definition of contagion as a measure which captures non-linear changes in financial markets. For these reasons, this study will concentrate on the first strand of research and especially on multinomial logit models.

Along this line, there are studies which focus on extreme events in different financial markets and on the probability of observing large returns across different markets given than in one market or country there already exist extreme tail events. Bae *et al.* (2003) used a binomial logistic regression model for the extreme stock events in the US and the EA for the period 1995-2000. Their model, which is estimated separately for negative and positive tail events, shows evidence that interest rates, opposite to stock market volatility and exchange rate, might be a source of contagion within the EA. Additionally, they conclude that there is contagion phenomenon from the US to the EA, as extreme returns happening in the US have a significantly large positive impact to shocks occurring in EA. Chan-Lau *et al.* (2004) apply the extreme value theory (EVT) in order to quantify the joint behaviour of extremal realisations (coexceedances) of financial returns across emerging markets in Latin America and Asia. The same approach, EVT, was followed by Hartmann *et al.* (2004) who directly measured the expected number of stock and bond market crashes, for the G5 countries, conditional on the event that at least one market crashes.

The quantile regression model of Koenker and Bassett (1978) was applied by Baur and Schulze (2005) in order to analyse not only the occurrence of extreme events, but also the degree of the negative joint occurrences. The authors concentrate only on Hong Kong, Thailand and Malaysia, as the source countries of the Asian crisis, testing for contagion effects from the US, Latin America, Europe and other Asian countries. The results are mixed, as in some cases they found contagion, and in others interdependence. Investigating the link between extreme events on the stock and currency markets, Cumperayot *et al.* (2006) applied a bivariate probit model and concluded that only for some countries (Brazil, Canada, US and Switzerland) out of a total of 26, currency depreciation does decrease the probability of a stock market decline. Groop *et al.* (2006), within a multinomial logistic framework using the distance to default measure, were able to examine the occurrence of large changes in this measure as describing major shocks in banks' financial condition. The results show significant evidence that cross-border contagion has increased since the introduction of euro.

Fazio (2007), based on bivariate probit models, tried to identify contagion currency crises using exchange market pressure indices between country pairs for a sample of 14 emerging economies. By distinguishing between the transmission of shocks due to macroeconomic interdependence and contagion due to herding, he found evidence of contagion for few cases only and especially between countries belonging to the same region. In another paper, Christiansen and Rinaldo (2009), used the multinomial logit model in order to analyse the financial integration between the old European Union (EU) countries and the new EU member states and how this integration changed or not after the EU enlargement in 2004. Results show that for both old and new EU countries, the currency and interest rate play an important role in the transmission of shocks. Markwat *et al.* (2009) define three categories of crashes: local, regional, and global. Following an ordered logit model the authors conclude that: first, there is significant evidence that less severe crashes tend to be followed by more severe crashes; and second, the stock, bond and currency markets are important determinants of the probabilities of the different crash events.

In this paper, I propose to investigate the contagion effect - if any - within the EA as well as from the US to the EA, by examining how often extreme (negative and positive) returns on different markets occur simultaneously. Using a negative-positive coexceedance variable that counts the number of large negative-positive returns on a given day across countries, I provide an answer to the question: "How likely is it for a market or a country to have large returns on a particular day,

given that some other market or country have large returns on that day or the preceding day?”. Borrowing the definition of contagion from Bae *et al.* (2003), I define contagion within regions as the fraction of exceedance events that is not explained by the explanatory variables (such as bond yield, interest rate and exchange rate). On the other hand, contagion across regions can be defined as the fraction of the exceedance events in a particular region that is left unexplained by its own covariates but that is explained by the exceedances from another region.

In addition, within this particular framework, I am able to allow for both types of transmission mechanisms, contagion and interdependence. When two countries are closely linked to each other through economic fundamentals, trade links, political links or geographical position, among others, then the spillover of shock from the one to another will be the result of the normal dependence between the two markets. Consequently, we can say that interdependence refers to the dependence that exists both in tranquil or turbulent times. On the other hand, contagion constitutes a form of dependence that does not exist in tranquil times but only occurs in times when large or extreme shocks to financial markets occur. According to Dornbusch *et al.* (2000), contagion cannot be linked to observed changes in macroeconomics or other fundamentals and is solely the result of the behaviour of investors, financial agents or other irrational phenomena, such as financial panic, herd behaviour or loss of confidence. As described earlier, in this paper I define contagion as the dependence that still exists after correcting for interdependence (fundamentals).

Using a multivariate logistic regression model, I will examine which covariates-factors are associated with the coexceedances count variables. The main results of this paper can be summarised as follows. First, I found that the EA 10 year government bond yield and the EUR/USD are important determinants of regional crash. These covariates fail to explain extreme stock returns happening in the EA, and therefore there is evidence of contagion from these markets towards the stock market. What is more, there is evidence in favour of the continuation effect. This means that extreme negative returns do not occur abruptly, but rather evolve out of prior negative extreme returns. The probability of observing a crisis tomorrow in the EA, in the sense of joint occurrence of extreme negative returns in four or more countries simultaneously, increases when regional crash occurs today. Second, the results show that there is no evidence of contagion from the US to the EA. The probability of extreme returns in the EA is not statistically significant related to extreme returns happening in the US. According to the definition of contagion mentioned above, this con-

stitutes that there is no contagion phenomenon from the US towards the EA. This finding is also supported by the fact that the coefficients of the US stock market volatility are negatively statistically significant at 1% significance level. I will rather interpret this as normal interdependence between the two markets.

The paper is structured as follows. Section 2 describes the multinomial logit model, while Section 3 presents the data. In Section 4, I set-up the different models to be tested and present the empirical results, while Section 5 describes all the robustness checks that I performed. Finally, Section 6 presents the conclusions, as well as areas of future research.

2 Model

The paper follows the approach employed by Bae *et al.* (2003) and Christiansen and Rinaldo (2009), and models extreme returns as a discrete choice among a set of alternatives. The main goal is to model the number of extreme negative and positive returns within the EA occurring in more than one countries simultaneously, as a function of some covariates, and to express the results in terms of probabilities for choice of different events. McFadden (1974) proposed a modification of the logistic regression model and called it a discrete choice model or, as frequently referred, the multinomial, polychotomous logistic regression.

In this model, the dependent variable is an indicator of a discrete choice. At this point, I need to introduce the exceedance and coexceedance terms. An exceedance can be defined as the occurrence of an extreme negative (positive) return which lies below (above) a given threshold value of the return distribution in one country. Similarly, coexceedance refers to the occurrence of extreme negative and positive returns in different countries at the same day. In line with the majority of the studies examining extreme tail events, I choose the tail probability 5% for the definition of extremes. This decision can be defended given the large sample of daily observations, implying that the empirical distribution will contain a large number of observations in the tails. This will ensure that sufficient number of observations will be available to estimate the logit model and the conditional probabilities.¹ After all, I distinguish between the following events: no extreme return for a given day; only one country with an extreme return (exceedance); two countries with an

¹As a robustness check and in order to investigate the sensitivity of my results to the 5% quantile, in Section 5, I will estimate all the models using different exceedances definitions.

extreme return (coexceedance); three countries with an extreme return (coexceedance); and four or more countries with an extreme event (coexceedance).

The basic idea is to analyse each of the exceedance-coexceedance events in the general framework of probabilities model:

$$\Pr(\text{event } j \text{ occurs}) = \Pr(Y_i = j) = F(\text{covariates-explanatory variables}) \text{ for } j = 1, \dots, m, \quad (1)$$

where the function $F(\cdot)$ on the right-hand side will be devised using a logistic cumulative distribution. In addition, the set of covariates reflects the impact of changes in “relevant effects” (the independent variables) on the probability of observing a negative or a positive extreme return. In general form, by assuming that the probability associated with an event j of m possible events is given by $\Pr(Y_i = j)$, then the multinomial distribution can be defined as:

$$\Pr(Y_i = j) = \frac{\exp(x\beta_j)}{1 + \sum_{k=1}^m \exp(x\beta_k)} \text{ for } j = 0, 1, \dots, m, \quad (2)$$

where x is a vector of explanatory variables (including a constant) and β_j is a vector of coefficients for categories j to m . In order to remove the indeterminacy associated with the model, the event $Y = 0$ (zero exceedances) will be the base-benchmark model. Therefore, all coefficients are estimated in relation to this base:

$$\Pr(Y_0) = \frac{1}{1 + \sum_{k=1}^m \exp(x\beta_k)}. \quad (3)$$

The model is estimated using the log-likelihood function:

$$LL = \sum_{i=1}^N \sum_{j=1}^m I_{ij} \ln P_{ij}, \quad (4)$$

where N is the number of observations, I_{ij} is an indicator variable that equals one if the i^{th} observation falls in j^{th} event and zero otherwise. If the model contains no covariates, but only a constant term, then the restricted log-likelihood is given by:

$$LL_r = \sum_{j=1}^m n_j \ln \left(\frac{n_j}{n} \right) = \sum_{j=1}^m n_j \ln p_j, \quad (5)$$

where p_j is the sample proportion of observations that make choice j . In order to measure how well the model fits the data, as well as the percentage of the variation in the dependent variable that is explained by the estimated model, I am using the McFadden's pseudo- R^2 goodness-of-fit:

$$pseudo - R^2 = 1 - \left(\frac{LL_u}{LL_r} \right), \quad (6)$$

where LL_u is the value of the log-likelihood function at the estimated parameters (unrestricted model), and LL_r is its value when all the parameters - except constant - are set equal to zero (base model). Additionally, I use the χ^2 Wald test in order to test the hypothesis that coefficients of the explanatory variables are zero.

Finally, for the interpretation of the coefficient values, I compute the marginal effects of the explanatory variables on the probabilities. Following Greene (2008):

$$\frac{\partial P_{ij}}{\partial x_i} = P_{ij} \left[\beta_j - \sum_{k=0}^m P_{ik} \beta_k \right], \quad (7)$$

which measures the marginal changes in the response probabilities for any given unit change in the independent covariate. All the models are estimated using PCGive in OxMetrics.

3 Data

While the majority of studies calculate exceedances in terms of the sample period (unconditional) returns, in this paper I will use the standardised residuals of a GARCH model, and based on them I will construct the coexceedances variables. The reason for doing this lies in my aim to control the fact that more exceedances happen in periods of higher conditional volatility. Otherwise, my results may be influenced by the effects of time-varying volatility. As Bae *et al.* (2003) commented, with this method the probability of observation of an exceedance is always the same.

For the purposes of this study, I use daily (close-to-close)² data of industrial stock market return index for 14 European countries (part of the European Monetary Union) and the United States for the period from January 1, 2004 to July 11, 2012 - a total of 2224 observations.³ All the data cited

²I am aware of the potential bias that is introduced by using this type of returns since trading hours are not synchronous.

³The countries are: Austria (AUS), Belgium (BEL), Cyprus (CYP), Finland (FIN), France (FRA), Germany (GER), Greece (GRE), Ireland (IRE), Italy (ITA), Malta (MAL), Netherlands (NET), Portugal (POR), Slovenia

in this paper are obtained from Datastream and are expressed in euros - from the perspective of an unhedged European investor. I decided to use daily data instead of low-frequency data, because I treat contagion as a relatively short-lived phenomenon, whose extremes would not be captured by monthly or quarterly data. Return series are calculated by applying the formula, $r_t = \ln p_t - \ln p_{t-1}$, where p_t is the stock price in time t . Table 1 gives details on the exact sources employed on this paper and on their mnemonics, while Table 2 provides summary statistics for the industrial stock market index returns for all the countries under consideration. Figure 1 and 2 plot the industrial stock market return index and the return series, respectively, over the entire sample period.

Mean stock returns in annualised terms vary from -17.33% in the case of Slovenia to 14.51% for Finland, while volatilities - defined as the standard deviation of returns - vary between 17.18% for Malta to 37.28% for Ireland.⁴ What is more, all the series - except for Cyprus and Ireland - are characterised by negative skewness, implying that the distributions have a long left tail, and the mass of the distribution is concentrated on the right. This suggests that crashes occurs more often than booms. Opposite to that, the Cypriot and Irish markets have large positive skewness, indicating that large positive returns tend to occur more often than large negative returns in these countries. Furthermore, all the series display large positive kurtosis coefficients well above the Gaussian benchmark value of three for the normal distribution. Kurtosis is between 6.0327 (Italy) and 19.0235 (Portugal), a range that is inconsistent with the assumption of normality.⁵

The considerably large values of excess kurtosis are reflected in the high values of JB statistics, which lead us to the rejection of the null hypothesis of normal distribution at the 1% significance level. Finally, this table also shows the Ljung-Box (LB) Q statistic for fifth order serial correlation in levels and squares of returns, since there are five trading days in a week. The Q statistic points out that for five out of twelve countries (Cyprus, Ireland, Italy, Malta and Italy) there is no strong evidence for serial correlation in levels, while the squared returns are strongly correlated, which suggests temporal variation in second moments - evidence of time-varying volatility (heteroskedasticity).

Table 3 illustrates unconditional correlations among the countries for the full sample period. One can observe that all values (except those involving Malta) are positive, thereby reflecting

(SLO) and Spain (SPA).

⁴The annualised values are computed using 252 trading days per year.

⁵The fact that for Portugal and Ireland the kurtosis is two to three times larger than for any other country, indicates that in these two markets there are more events at the tails (extreme events).

regional and economic relationships among countries. Correlation is taking its largest value between France and Germany (0.86). Given the well-known time variability of correlations, these sample correlations may be biased and misleading. All the series were tested on whether they are stationary or not. Results from the Augmented Dickey Fuller (ADF) test are reported in Table 2.

In Table 4, I report the number of negative (RN_t) and positive (RP_t) exceedances and coexceedances for the 14 European markets. The total 2224 days in my sample are divided into five categories: those for which there are no exceedances in any country (1536 such days for negative extreme events); only one exceedance (413 for negative extreme returns); two; three; and four or more coexceedances. I also identify which countries participate in those events and how often. The columns labeled “5th quantile”, “95th quantile”, “Mean” and “Volatility” report the 5% and 95% quantile of the standardised residuals together with the mean value and the volatility. The lowest mean for negative extreme returns belongs to Austria, Malta and Spain indicating that in these countries the extreme returns introduce more risk. Furthermore, the high volatility for Malta, Greece and Portugal implies that negative returns vary more in these countries than in the other countries. Looking at the top-tail events, Cyprus, Ireland and Malta are experiencing the higher values of mean and volatility, a result which is expected if one takes closer look at the descriptive statistic of the series.

What is more, Table 5 documents some stylised facts on the dynamic properties of the different types of exceedances events. Following Markwar *et al.* (2009), I use the “exceedance-coexceedance transition matrix”, in order to understand how the exceedances evolve and to assess whether modelling extreme returns using coexceedances is appropriate or not. each ij th entry of this transition matrix represents the probability of observing the state in column j , given that on the previous day the state in row i occurred. Several interesting results emerge from this matrix. Panel A shows how the probabilities of observing a bottom-tail coexceedance (no matter how many countries are involved) on the next day increases from 0.22 when no exceedance occurs today via 0.25, 0.43 and 0.43 to 0.51 when four or more exceedances occur today. For both three and four or more coexceedances I find probabilities of occurrence, conditional on the occurrence of a coexceedance on the previous day. The probabilities of observing extreme negative returns in four or more countries, for example, increase from 0.04 when no exceedance occurred on the previous day, via 0.13 to 0.17 following the occurrence of a two- or three-countries coexceedances, respectively.

The same pattern is also true for extreme positive returns. Furthermore, I found increasing probabilities of occurrence for three and four or more exceedances, conditional on the occurrence of an exceedance on the previous day. To be more precise, the probabilities of observing a joint occurrence of exceedances increase from 0.04 when there are no extreme returns in any country on the previous day, to 0.06 when there is only one exceedance, to 0.13 following the occurrence of four or more countries in the bottom tail. These results indicate that extreme returns do not happen abruptly but rather evolve out of prior extreme returns, which suggests that modelling extreme returns as a exceedance/coexceedance effect makes sense.

Panel B of Table 5 shows the transition probabilities using the definition of exceedances based on standardised residuals. As I mentioned earlier, my aim is to examine whether the results of exceedances dynamics are driven by the volatility effect which is observed during times of extreme downturns, as Boyer *et al.* (1999), Loretan and English (2000) and Forbes and Rigobon (2002) argued. After controlling for volatility, I found lower probabilities for three and four or more exceedances when an exceedance occurred on the previous day. For instance, the probability of observing extreme negative return in three countries today and a joint occurrence (four or more countries) tomorrow decreases from 0.17 to 0.05. The probability that a joint occurrence continues is 0.09, compared to the 0.14 for sample returns. Therefore, I conclude that there are volatility dependences in the dynamic patterns of coexceedances - especially concerning the more severe events - that one should take into account when testing for contagion using extreme return measures.

Additionally, and in order to discriminate the impact of contagion from the effect of fundamentals, I use a large set of explanatory variables. In my choice of variables, I follow the existing literature, and select to a large extent the same variables as Bae *et al.* (2003), Markwat *et al.* (2009) and Christiansen and Rinaldo (2009). Importantly, the frequency of all the explanatory variables does correspond with the frequency of my observations. First, since I used industrial stock market return index to compute the exceedances, I decide to add in my model the financial stock market return index. By doing so I will be able to see how the two sectors are linked, as well as the dynamics that explain their behaviour. Additionally, to investigate whether shocks in the bond market lead to increased crash likelihood, I include daily yields on long maturity bonds - 10 year government bond yields. I expect a negative effect of bond yields on probabilities of coexceedances. A fall in their yields - or an increase in their prices - may point at an increase in

the probability of four or more countries coexceedances.

I also include the 3-month interbank interest rate, *EURIBOR*, which is the reference rate at which Euro interbank deposits are being offered within the European Monetary Union zone by one bank to another, reflects the average cost of funding of banks in the interbank market for a specific maturity. On average, stock market returns are negatively correlated with interest rates, since the latter imply higher costs of capital. So, I expect that higher interest rates will increase the contagion probability. For the currency market I use the exchange rate of the Euro against the US Dollar. If Euro depreciates against the US Dollar, extreme returns are more likely to happen. This is true if one considers that a depreciation will lead to a lower value of the stock index. Figure 3 illustrates the four explanatory variables.

Finally, I will also use two covariates related to the US. These are: i) the exceedance variable counting the number of days with extreme negative (below the 5%) and positive (above the 95%) percentile of the standardised residuals of the industrial stock market distribution; and ii) the volatility of the industrial stock market. Volatility is computed as the squared root of the conditional volatility of the AR(1)-GARCH(1,1), following a common practice in the existing literature. To be more precise, I estimate the model: $USI_t = c_0 + c_1USI_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim N(0, \sigma_t^2)$ and the variance follows a GARCH(1,1) process: $\sigma_t^2 = c_2 + c_3\sigma_{t-1}^2 + c_4\varepsilon_{t-1}^2$.

- RN_{t-1} and RP_{t-1} : lagged values of negative and positive co-exceedances variables.
- EAF : return on financial stock market index for the Europe (EMU only).
- $EA10Y$: return on 10 year government bond yield for the Europe (EMU only).
- $EURIBOR3M$: return on 3 month Euro Interbank Offered Rate.
- EUR/USD : return on currency exchange rate.
- $USRN$ and $USRP$: negative and positive exceedance variable for the US.
- $USRN_{t-1}$ and $USRP_{t-1}$: lagged values of negative and positive exceedance variable for the US.
- USI and USI_{t-1} : return on industrial stock market index for US and its lagged value.

- $USIvol$ and $USIvol_{t-1}$: volatility of return on industrial stock market index for the US and the lagged value.

4 Empirical framework and results

In this section, I perform four sets of estimations - the base model, the “continuation or reversal effect”, the “contagion within the EA” model, and the “contagion from the US to EA” model.

4.1 Base model

Model 1 of tables 6 and 7 reports estimates of probabilities of coexceedances for bottom- and top-tail events for the EA. Equation 1 can be written as a function of the explanatory variables. So, the probability of being in category i is given by:

$$\Pr(Y_i = j) = \text{function}(x\beta'_j) \text{ for } j = 1, \dots, m. \quad (8)$$

This is the base model against which I compare all the other models. What I found is that there is a probability of 69.06% that none of the 14 European countries of my sample has a negative extreme return, while for the top-tail events this probability reaches 64.52%. The probability that one country has an extreme negative return is 18.57% (21.71% for top-tail events), while joint occurrence of extreme returns in four-and-more countries is 5.44% (4.94% for top-tail events). These probabilities are associated with the coefficients β_{01} and β_{04} respectively; and can be easily computed from Equation 2. For example:

$$\Pr(Y = 1) = \frac{\exp(\beta_{01})}{1 + \sum_{j=1}^4 \exp(\beta_{0j})} = \frac{\exp(\beta_{01})}{1 + [\exp(\beta_{01}) + \exp(\beta_{02}) + \exp(\beta_{03}) + \exp(\beta_{04})]}. \quad (9)$$

Since Model 1 does not include explanatory variables, but only the constant term, these probabilities can also arise from Table 4, which presents analytically the number of negative and positive exceedances and coexceedances for each country.

4.2 Continuation or reversal effect

In this section, I am interested to explore if extreme returns - negative and positive exceedances - in stock prices are followed by subsequent movements in the opposite (reversal) or in the same direction (continuation). Existing literature has identified both patterns. DeBondt and Thaler (1985), influenced by experiments in psychology showing that dramatic and unexpected news make people overreact, tried to investigate whether such behaviour affects stock prices. They found a reversal pattern in long-term (3- to 5-year) returns, as well as that stocks with low past returns tend to have higher future returns. Most recent papers by Jegadeesh (1990) and Lehmann (1990) provide evidence of shorter-term (3- to 12-month) return reversals. These studies show that investors who select their stocks based on the previous week or month returns generate significant abnormal returns.

In contrast, Jegadeesh and Titman (1993) and Fama and French (1996) have found that short-term returns tend to continue (continuation pattern); stocks with higher returns in the previous twelve months tend to have higher future returns. This finding is also supported by Christiansen and Ranaldo (2009), who have argued that the number of extreme negative returns today is positively related to the number of extreme negative return yesterday.

Model 2 of tables 6 and 7 has one explanatory variable, the lagged value of the negative/positive coexceedances (RN_{t-1}/RP_{t-1}). Equation 1 now becomes:

$$\Pr(Y_i = j) = \text{function}(\beta_{0j} + \beta_{1j}RN_{t-1}) \text{ for } j = 1, \dots, m. \quad (10)$$

The first column of each model shows the parameter estimates and their significance level, while the second column presents the impact of each covariate on the probability of exceedances. The third column reports the joint significance level of each explanatory variable ($\beta_{j1} = \beta_{j2} = \beta_{j3} = \beta_{j4} = 0$). As one observes from those tables, only for the bottom-tail events all (except for one) the coefficients are significant and positive, indicating that the more extreme negative returns we have yesterday, the more likely it is to have extreme negative returns today. In other words, there is significant evidence for the presence of a continuation effect. Extreme negative returns follow a domino effect. This result is particularly noteworthy given the fact that I have taken into account volatility, since I computed coexceedances using the standardised residuals from a GARCH(1,1) model. We know

by definition that extreme negative returns are more likely to occur in times of high volatility.

Moreover, the $\Delta prob$, which expresses the marginal probability of exceedances with respect to the lagged value of this covariate, indicates that an increase in negative returns yesterday increases the probability of all exceedances, but the effect decreases as we move to higher number of joint occurrences. A similar interpretation can be applied to the positive coexceedances, even though the lagged variable is of no importance, as it is only significant at 10% level.

4.3 Contagion within Euro Area

Are the coexceedances related to different asset type returns? In Model 3, the explanatory variables on top of the past values of the coexceedances are: the EA financial stock market index returns; the aggregate 10-year government bond for the Euro Area; the short-term (3 month) *EURIBOR* interest rate; and the currency exchange rate between Euro and US Dollar. By adding these covariates, I am interested to see first, what is the relationship between the financial and industrial stock market; second, the effect of monetary policy decisions, as adopted by international authorities and policymakers; and third, the impact that credit crunch had on the credit and liquidity risk perception of the market. The model has the form:

$$\Pr(Y_i = j) = function(\beta_{0j} + \beta_{1j}RN_{t-1} + \beta_{2j}EAF + \beta_{3j}EA10Y + \beta_{4j}EURIBOR3M + \beta_{5j}EUR/USD) \text{ for } j = 1, \dots, m. \quad (11)$$

For both negative and positive coexceedances (Model 3 of tables 6 and 7), only the financial stock market has a strong significant effect, with the coefficients to have the expected sign. In particular, the likelihood of observing negative coexceedances is negatively related to stock returns. This relationship implies that the lower the stock return, the higher the probability that four or more countries will experience negative returns in a given day. Using a numerical example, looking in the marginal effect of this covariate, a 5% decrease in the returns of the financial sector increases the probability of four or more exceedances by 7.15%.

To continue, I detect no significant link between the 10-year government bond yield and the *EUR/USD* exchange rate with the occurrence of extreme returns. Regarding the 10-year bond yield, the result is consistent with Markwat *et al.* (2009), even though these authors include in

their study a bond portfolio which consists of bonds with long and short maturities. Moving now to the currency rate, my result is consistent with Christiansen and Ranaldo (2009), who also found that the relation between negative extreme return probabilities and exchange rate movements is absent. Noteworthy to say, that these authors perform their analysis separately for new and old EU countries, and conclude that for both cases currency returns fail to adequately explain either negative or positive extreme returns. What is more, Bae *et al.* (2009), who employed the Euro-US Dollar bilateral exchange rate and the short rate in Germany as a proxy, using a binomial logit model conclude that the coefficient on the exchange rate is positive and significant for bottom-tail events.

Finally, the likelihood of observing bottom-tail events in three and in four-or-more countries is statistically significant at 5% and 1% significance level, respectively, for the *EURIBOR* 3-month interest rate. The positive coefficients of the interest rate are in line with the expectations. Higher reference rate for overnight transactions in the Euro Area will significantly increase the probability of stock market extreme tail events. Additionally, the explanatory variable is significant at 1% level as indicates the Wald test for zero exclusion.

Overall, in this section I found that in neither case is 10 year government bond yield and the *EUR/USD* exchange rate of importance and therefore it does not provide any substantial information. In other words, they fail to explain coexceedances happen in the EA. According to the definition of contagion that I use this constitutes evidence of contagion. Adding the financial stock returns and the three interest rates to the model increases the pseudo- R^2 up to 17.02%.

Figures 4 and 5 illustrate the coexceedances response curves of the EA for the bottom- and top-tail events respectively. The curves show the probabilities of the different types of exceedances for different levels of explanatory variables. Varying the value of each variable from its minimum to its maximum, I compute the probabilities of observing a type of exceedance event for all observations. Those figures support the findings presented in tables 6 and 7.

4.4 Contagion from the US to the Euro Area

In this section, I am interested in investigating if there is a fraction of the coexceedances in the Euro Area left unexplained by its own covariates that can be explained by exceedances and/or other US explanatory variables, and especially stock market volatility. Of interest is whether the

United States had an extreme return that seems more helpful in predicting the number of negative or positive extreme returns in the EA. If so, I will interpret this as an evidence of contagion from the United States to the EA. I reestimate Model 3, but now I add two covariates related to exceedances ($USRN$) and stock market volatility ($USIvol$) from the US during the preceding trading session that day.⁶ The new model, Model 4, has the form:

$$\Pr(Y_i = j) = function(\beta_{0j} + \beta_{1j}RN_{t-1} + \beta_{2j}EAF + \beta_{3j}EA10Y + \beta_{4j}EURIBOR3M + \\ + \beta_{5j}EUR/USD + \beta_{6j}USRN_{t-1}/USRP_{t-1} + \beta_{7j}USIvol_{t-1}) \text{ for } j = 1, \dots, m. \quad (12)$$

The estimated results for the bottom and top tails are given in Table 8. The most important finding is that the regression coefficients on the number of exceedances in the US are insignificant. This means that US extreme returns do not seem to be helpful in predicting the number of negative extreme returns in the EA. Using the definition of contagion according to which: contagion from the US to the EA can be defined as the fraction of the exceedance events in the EA that is left unexplained by its own covariates but that is explained by the exceedances from the US - this does not constitute evidence of contagion. I will rather interpret this as normal interdependence between the two regions.

For the other explanatory variable, the US stock market volatility, I found that the coefficients related with extreme negative returns in three and in four or more countries are statistically significant at 1% level. This means that the higher the US volatility yesterday, the less likely it is to have extreme events on the Euro Area today; falling stock markets in the US do not propagate or diffuse shock to the EA. Furthermore, the Wald statistic indicates that we reject the null hypothesis that the volatility coefficients are equal to zero, or equally the explanatory variable $USIvol_{t-1}$ is overall significant at the 1% level of significance. Unfortunately, there is paucity of studies matching the range of covariates that I am using and the sample period of my observations. For example, Bae *et al.* (2003) conclude that firstly, Europe's probability of negative extreme returns is significantly affected by extreme returns in the US; and secondly that the effect of the conditional volatility from the US is strangely negative. However, for the estimation of this result the authors plagued daily data from 1996 to 2000 into a binomial logit model.

⁶In Section 5 I will perform the same exercise using three- and five-day lagged values.

Looking to other covariates, $EA10Y$, $EURIBOR$ and EUR/USD are all insignificant for both bottom- and top-tail events. Any relation between probabilities of extreme returns and movements in these covariates seems absent. The only exception is the coefficient of $EURIBOR3M$ related with top-tail events in four or more countries, which is significant at 5% significance level and has a negative sign. This implies that a lower interest rate will lower the cost for borrowing money and will therefore boost the stock market. Consequently the probability of extreme positive returns will be higher. Contrary to that, and as presented by my findings in the previous section, for top-tail events the rate was insignificant and did not add any explanatory power to the model. A possible explanation could be the interconnection between the rate at which European banks lent and borrow money from each other, with the US stock market.

5 Robustness checks

In this section I perform several checks in order to assess the robustness of the contagion effect that I found within the EA; and interdependence between the US and the EA.

A concern with these results is that the number of exceedances in the US might not reflect its real influence upon extreme returns in Europe, since as mentioned already earlier, the two markets are open and simultaneously operate for a small fraction of time. This turns out not to be the case. I reestimated Model 4, replacing the US negative exceedances and the US industrial volatility by their values at time t , $t - 3$ and $t - 5$.⁷ The coefficients (table 9, 10 and 11) of US exceedances are still insignificant for all exceedance outcomes for both positive and negative tails, and the partial derivatives too. Contrary, the stock market volatility of the US does seem to be very helpful in predicting exceedances in Europe, as both the coefficients and the derivatives are statistically significant at 1% level.

Furthermore, in order to measure the effect of bond, interest rate and currency changes on negative and positive extreme returns simultaneously, as well as to capture possible overreaction to bad and good news, not captured by the other variables, I include three dummy indexes associated with extreme events in bond, interest rate and currency markets. While for bond and interest rate the extreme observations are those below the 5% quantile, extreme currency depreciations

⁷The reason for going back five days is that during crises periods investors might need time to assess the potential effect of extreme events in the market on other markets.

are defined as those depreciations above the 95% quantile of the empirical distribution of currency returns. These dummy variables are included in the model with one- and five-day lag, such that the model will be predictive in nature. For bottom-tail events and only for the model with five-day lag there is some significant relation between coexceedance events in three countries and interest and exchange rate movements. The explanation power of the indicators continues to exist for positive extreme returns. Interestingly, even when I include (tables 12 and 13) or exclude (Model 6 of tables 6 and 7) these variables, the estimated coefficients for average bond, interest rate and currency changes remain insignificant. Given the fact that each extreme indicator simply subsumes all effects of the corresponding market rates (bond, interest and currency rate) on stock market returns, this implies that stock markets only react to substantial depreciations. Following Markwat *et al.* (2009), I interpret this finding as another form of contagion, from these markets to stock market.

Another concern with my results is whether or not the bear market period, starting on June 2007 and afterwards, may bias my findings. For that reason, I performed the same analysis splitting my sample period into two sub-periods, from January 2004 to May 2007 and from June 2007 to July 2012. Results, which are reported on tables 14, 15, 16 and 17, are similar to those reported before.

Another issue that I needed to tackle in order to render my results comparable with previous studies is the GARCH standardised residuals. I reestimated all the models, but this time I defined exceedances differently from the way I had defined them so far, as I use sample period returns (tables 18 and 19). Even though this approach does not seem to be appropriate, since I will always have an outcome where there are more exceedances in periods of higher conditional volatility, the results are somewhere in the middle. With this definition of exceedances, more coefficients are significant. For Model 3 and for bottom-tail events, I found that the probability of coexceedances is affected by the interest rate and by exchange rate shocks. If currency falls (*EUR/USD* rises), extreme returns are more likely. Additionally, few of the bond yield and *EURIBOR* rate coefficients are significant and of negative sign, which implies that negative exceedances will occur when bond yields and interest rates are low. If yield decreases by 10% the probability of three exceedances will increase by 1.7%. When I examine top-tail events, the interest rate coefficients are negative and significant. In other words, the likelihood of observing positive extreme returns in more than one

country increases when the interest rate in the region falls.

Looking at bottom-tail events of Table 19, the regression coefficients on the number of exceedances in the US are insignificant for all but three-country coexceedances. In computing the derivative of the exceedance probabilities at the unconditional mean of the covariates, I note that an increase in the number of exceedances in the US increases the probability of three-country exceedances in the EA. In addition, the conditional volatility of the US is helpful to predict exceedances in the Euro Area. The Wald statistic indicates that this variable is significant at the 1% level. This result holds for upper-tail events as well.

I use two more definitions of exceedances. Firstly, I define exceedances by the 2.5% quantile rather than the 5% quantile. Obviously, by proceeding this way there are fewer exceedances. Results (tables 20 and 21) from the multinomial logit model, are not sensitive to this alternative exceedance definition. Secondly, in order to allow for more general specification regarding the period of exceedances and their dynamics within a region, I reestimate (not reported) all the model regressions, but use exceedances computed over three days instead of over one day. In that way, I define coexceedance events as those in which more than one market experiences an extreme return within a three-day window. Once again, results, hardly differ from the original one in tables 6, 7 and 8.⁸

6 Conclusion

Using the concept of coexceedances of Bae *et al.* (2003), I have in this paper investigated if there is any evidence of contagion, first within the Euro Area region, and second, from the US to the EA. The fraction of EA coexceedances that cannot be explained by EA fundamentals-covariates constitutes evidence of contagion. Similarly, the fraction of the coexceedances in Europe that is left unexplained by its own covariates, but that is explained by the exceedances from the US, implies contagion from the US to the EA. The results show that: a) the probability of extreme returns today is conditional upon the probability of extreme returns yesterday, extreme movements of stock prices followed by movements in the same direction; b) regional covariates, like bond yields and exchange rate do not seem to explain much about the probability of bottom-tail and top-tail events within the EA - consequently, there is evidence of contagion from these markets to the stock market;

⁸Results are available upon request.

c) US exceedances fail to explain high probabilities of extreme negative returns in Europe - there is no statistically significant evidence of contagion effect from the US to the EA.

There is a long list of several extensions that would be accommodated in the framework and are likely to improve performance. First, it would be very interesting to implement this model in order to include other regions, like Asia and Latin America, and look for contagion in a global way. Second, one could consider alternative estimation approaches. It is well known, and mentioned by Bae *et al.* (2003), that multinomial models are unordered models, which means that they fail to account for the ordinal nature of the coexceedances. Other options could possibly include the use of extreme value theory, in the spirit of Longin and Solnik (2001) and Hartman *et al.* (2004), or the quantile regression analysis introduced by Koenker and Bassett (1978) and applied by Baur and Schulze (2005) and Cappiello *et al.* (2005) in financial contagion tests. Finally, another interesting issue would be to examine the out-of-sample exercise. What matters in a model is not its ability to produce an accurate in-sample fit, but rather its out-of-sample performance. In other words, a useful suggestion would be to test the forecasting properties of the model.

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Appendix A

Table 1. Data

Variable	Source	Mnemonic/Code
Industrial Stock Return $100 * [\ln(p_t) - \ln(p_{t-1})]$	Stock Market Industrial Index, Datastream	INDUS-OE(RI), -BG(RI), -CP(RI), -FN(RI), -FR(RI), -BD(RI), -GR(RI), -IR(RI), -IT(RI), -MA(RI), -NL(RI), -PT(RI), -SJ(RI), -ES(RI), -EM(RI), -US(RI)
Financial Stock Return $100 * [\ln(p_t) - \ln(p_{t-1})]$	Stock Market Financial Index, Datastream	FINANEM(RI), -US(RI)
Bond Yield $100 * [\ln(p_t) - \ln(p_{t-1})]$	10 Yea Benchmark Bond Index, Datastream	S08729(RY), S96475(RY)
Change in Short-term Interest Rate $p_t - p_{t-1}$	EURIBOR 3 Month, Datastream	Y03728
Exchange Rate $100 * [\ln(p_t) - \ln(p_{t-1})]$	US to EURO Datastream	Y12764

Table 2. Descriptive Statistics of Daily Returns on the Industrial Stock Market Index, January 2, 2004, to July 11, 2012

	AUS	BEL	CYP	FIN	FRA	GER
Mean	0.0410	0.0058	-0.0343	0.0576	0.0307	0.0176
Median	0.0823	0.0776	0.0113	0.0971	0.0626	0.0676
Maximum	7.2556	9.4607	15.919	10.0217	10.5267	11.3452
Minimum	-6.8762	-8.4949	-10.0463	-8.8469	-8.6128	-10.9461
Std. Dev.	1.3262	1.5372	1.4386	1.7180	1.4779	1.5881
Skewness	-0.6534	-0.3934	0.5918	-0.0465	-0.0663	-0.3396
Kurtosis	6.7534	7.0719	14.3736	6.2789	8.1378	9.4300
Jarque-Bera	1463.788***	1593.889***	12117.16***	997.0841***	2447.772***	3874.139***
LB(5)	40.926***	22.788***	9.7366*	14.120**	13.585**	12.354**
LB(5) squares	1090.9***	983.97***	1146.4***	1059.3***	1109.6***	993.43***
ADF	-29.3514***	-42.8544***	-47.2255***	-45.4187***	-46.6178***	-45.2227***
Observations	2224	2224	2224	2224	2224	2224

Notes: * denotes significance at 10%, ** significance at 5%, *** significance at 1%.

Table 2 Cont. Descriptive Statistics of Daily Returns on the Industrial Stock Market Index, January 2, 2004, to July 11, 2012

	GRE	IRE	ITA	MAL	NET	POR
Mean	-0.0066	0.0518	-0.0081	0.0568	0.0119	0.0121
Median	0.0097	0.0003	0.0412	0.0210	0.0467	0.0457
Maximum	10.5594	30.2040	6.9346	7.8288	10.3118	10.2696
Minimum	-17.3290	-14.8419	-8.1958	-6.3757	-9.4108	-17.5869
Std. Dev.	1.9028	2.3485	1.3777	1.0826	1.6227	1.3934
Skewness	-0.5401	0.9589	-0.4008	-0.0357	-0.2422	-0.9627
Kurtosis	9.4672	18.7405	6.0327	12.3314	6.9977	19.0235
Jarque-Bera	3983.926***	23300.47***	911.9051***	8069.469***	1502.746***	24135.96***
LB(5)	30.100***	8.9718	10.409*	11.031*	21.327***	24.762***
LB(5) squares	866.42***	1026.4***	1119.4***	941.49***	1043.0***	989.72***
ADF	-42.5293***	-48.0227***	-45.5102***	-45.2467***	-43.6853***	-43.1789***
Observations	2224	2224	2224	2224	2224	2224

Notes: * denotes significance at 10%, ** significance at 5%, *** significance at 1%.

Table 2 Cont. Descriptive Statistics of Daily Returns on the Industrial Stock Market Index, January 2, 2004, to July 11, 2012

	SLO	SPA	EA	US
Mean	-0.0688	0.0119	0.0183	0.0213
Median	-0.0009	0.0803	0.0867	0.0605
Maximum	12.1809	8.0541	9.7730	9.0832
Minimum	-9.0942	-7.5817	-8.1131	-9.2310
Std. Dev.	1.6484	1.4295	1.3953	1.4717
Skewness	-0.0022	-0.3159	-0.2474	-0.2991
Kurtosis	8.0063	6.5257	7.8961	7.8778
Jarque-Bera	2322.546***	1188.939***	2244.131***	2238.038***
LB(5)	17.815***	2.3430	14.493**	27.723***
LB(5) squares	1084.5***	1018.5***	1050.2***	1116.3***
ADF	-43.8801***	-46.3066***	-45.0905***	-52.5282***
Observations	2224	2224	2224	2224

Notes: * denotes significance at 10%, ** significance at 5%, *** significance at 1%.

Table 3. Unconditional Pairwise Correlations Between the Stock Returns for Industrial Index

	AUS	BEL	CYP	FIN	FRA	GER	GRE	IRE	ITA	MAL	NET	POR	SLO	SPA	EA	US
AUS	1															
BEL	0.6849	1														
CYP	0.1635	0.1666	1													
FIN	0.7133	0.7636	0.1327	1												
FRA	0.7091	0.7874	0.1384	0.8326	1											
GER	0.6653	0.7431	0.1417	0.7738	0.8683	1										
GRE	0.4061	0.4269	0.1654	0.4080	0.4501	0.4121	1									
IRE	0.4905	0.5079	0.0492	0.5303	0.5771	0.5170	0.3008	1								
ITA	0.6551	0.7195	0.1368	0.7565	0.8341	0.7691	0.4111	0.5042	1							
MAL	0.0099	-0.0026	-0.0374	-0.0064	-0.0012	0.0138	-0.0237	0.0044	-0.0086	1						
NET	0.6869	0.7545	0.1628	0.7760	0.8401	0.7999	0.4302	0.5270	0.7753	0.0014	1					
POR	0.5210	0.5535	0.1407	0.5546	0.5943	0.5524	0.3511	0.4028	0.5748	0.0008	0.5601	1				
SLO	0.2316	0.2396	0.1091	0.1880	0.2189	0.1840	0.1540	0.1142	0.1900	0.0257	0.2016	0.1469	1			
SPA	0.6679	0.7020	0.1533	0.7499	0.8201	0.7654	0.4210	0.5498	0.7693	-0.0036	0.7489	0.5942	0.2107	1		
EA	0.7468	0.8160	0.1579	0.8613	0.9689	0.9435	0.4702	0.5968	0.8693	0.0024	0.8887	0.6257	0.2185	0.8632	1	
US	0.3288	0.3885	0.0320	0.4103	0.4708	0.5361	0.1730	0.2936	0.4229	-0.0083	0.4689	0.2513	0.0692	0.4119	0.5095	1

Table 4. Number of Coexceedances Based on the 5% and 95% Percentile of the GARCH(1,1) standardised Residuals

	Number of negative coexceedances										Number of positive coexceedances									
	5 th quantile	Mean	Volatility	≥4	3	2	1	0	0	1	2	3	≥4	Volatility	Mean	95 th quantile				
AUS	-1.7605	-2.4609	0.6873	73	9	13	17	2112	2112	27	25	19	41	0.4562	1.9094	1.4349				
BEL	-1.7799	-2.3618	0.5887	71	10	15	17	2112	2112	31	13	18	50	0.5028	1.9736	1.5088				
CYP	-1.5453	-2.2095	0.8534	11	7	33	61	2112	2112	61	26	6	19	0.9306	2.3283	1.5439				
FIN	-1.7375	-2.3117	0.6621	80	12	6	14	2112	2112	19	12	16	65	0.4756	2.0366	1.5071				
FRA	-1.7396	-2.2664	0.5636	87	10	8	7	2112	2112	9	14	15	74	0.4042	1.9804	1.5458				
GER	-1.7107	-2.3636	0.6981	75	7	15	15	2112	2112	16	12	18	66	0.4935	1.9698	1.4754				
GRE	-1.6249	-2.3174	0.9780	45	9	18	40	2112	2112	39	24	18	31	0.6408	2.0540	1.5342				
IRE	-1.5236	-2.0900	0.7049	53	6	18	35	2112	2112	39	23	16	34	1.6359	2.2477	1.4917				
ITA	-1.7844	-2.4200	0.6025	77	13	15	7	2112	2112	16	19	19	58	0.4481	1.8768	1.4789				
MAL	-1.5312	-2.6907	1.1560	14	3	23	72	2112	2112	70	22	8	12	0.7896	2.6635	1.6011				
NET	-1.7220	-2.2798	0.5438	82	7	14	9	2112	2112	19	8	16	69	0.7772	2.0062	1.5200				
POR	-1.6904	-2.4009	0.9139	50	10	14	38	2112	2112	45	25	11	31	0.7335	2.1613	1.5211				
SLO	-1.6847	-2.2503	0.5847	16	6	24	66	2112	2112	69	18	11	14	0.6906	2.2187	1.5949				
SPA	-1.7765	-2.4722	0.8124	73	11	12	16	2112	2112	24	13	16	59	0.4314	1.9073	1.4795				
US	-1.7298	-2.3301	0.6105	112	112	112	112	2112	2112	112	112	112	112	0.3913	1.9729	1.5108				
<i>Total</i>				121	40	114	413	1536	1435	483	127	69	110							

Notes: A positive (negative) or “top-tail” (“bottom-tail”) exceedance for daily index returns correspond to the subset of ordered returns that comprise the highest (lowest) five percent of all returns. Coexceedances represent joint occurrences of exceedances across country indices by day. A coexceedance of i means that i countries have an exceedance on the same day. Coexceedances are reported for $i=1,2,3,4$ or more. For example, of 2224 trading days, there are 114 occurrences of negative or bottom-tail coexceedances with two countries only, and 15 of those occurrences include Germany (GER) as one of the two countries with bottom-tail coexceedances. For United States there are only exceedances. The columns labeled “Mean” and “Volatility” show the mean and standard deviation of the returns standardised residuals below the 5% quantile and above the 95% quantile.

Table 5. Exceedance-Coexceedance Transition Probabilities

	Negative coexceedances					Positive coexceedances				
	0	1	2	3	≥4	0	1	2	3	≥4
0	0.78 (1271)	0.14 (227)	0.03 (53)	0.01 (18)	0.04 (61)	0	0.70 (1065)	0.20 (305)	0.04 (61)	0.01 (23)
1	0.66 (226)	0.19 (65)	0.04 (14)	0.01 (5)	0.01 (33)	1	0.68 (297)	0.18 (80)	0.05 (22)	0.02 (10)
2	0.57 (46)	0.25 (20)	0.04 (3)	0.01 (1)	0.13 (11)	2	0.62 (66)	0.20 (22)	0.08 (9)	0.05 (5)
3	0.57 (20)	0.14 (5)	0.06 (2)	0.06 (2)	0.17 (6)	3	0.67 (29)	0.16 (8)	0.06 (3)	0.10 (4)
4	0.50 (66)	0.20 (26)	0.07 (10)	0.07 (9)	0.17 (23)	4	0.50 (56)	0.20 (23)	0.11 (12)	0.06 (7)
<i>B. Standardised Residuals</i>										
0	0.71 (1093)	0.18 (283)	0.04 (65)	0.01 (26)	0.04 (73)	0	0.67 (959)	0.21 (296)	0.05 (72)	0.03 (42)
1	0.69 (281)	0.17 (71)	0.05 (22)	0.02 (8)	0.06 (27)	1	0.62 (301)	0.23 (113)	0.06 (29)	0.03 (14)
2	0.62 (70)	0.20 (23)	0.09 (10)	0.02 (2)	0.07 (8)	2	0.54 (68)	0.28 (35)	0.08 (11)	0.05 (7)
3	0.67 (27)	0.22 (9)	0.02 (1)	0.02 (1)	0.05 (2)	3	0.58 (40)	0.26 (18)	0.04 (3)	0.04 (5)
4	0.54 (65)	0.23 (28)	0.12 (15)	0.02 (2)	0.09 (11)	4	0.61 (67)	0.22 (24)	0.08 (9)	0.04 (4)

Notes: The exceedance-coexceedance probabilities should be interpreted in the following way: the i th element is the probability of observing the state in column j , given that on the previous the state in row i occurred. Panels A and B are based on the exceedance - coexceedance events identified in the series of sample returns and standardised residuals, respectively, of the 14 European stock market industrial indices over the sample period January 2, 2004 - July 11, 2012 (2224 observations).

Table 6. Multinomial logit regression results for negative daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances								
	Model 1			Model 2			Model 3		
	Coeff.	Δ prob.		Coeff.	Δ prob.		Coeff.	Δ prob.	
β_{01} (constant)	-1.3134***	-0.1360***		-1.3767***	-0.1435***		-1.3492***	-0.1784***	
β_{02}	-2.6007***	-0.1035***	***	-2.8206***	-0.1091***	***	-3.0602***	-0.1056***	***
β_{03}	-3.6480***	-0.0551***		-3.7001***	-0.0558***		-4.4631***	-0.0349***	
β_{04}	-2.5411***	-0.1066***		-2.6770***	-0.1114***		-4.5414***	-0.0353**	
β_{11} (RN_{t-1})				0.1148**	0.0119		0.1157**	0.0160*	
β_{12}				0.3184***	0.0131***	***	0.2876***	0.0102***	***
β_{13}				0.0966	0.0008		0.0634	0.0002	
β_{14}				0.2196***	0.0090**		0.1799*	0.0012	
β_{21} (EAF)							-0.4089***	-0.0529***	
β_{22}							-0.9632***	-0.0332***	***
β_{23}							-1.3755***	-0.0107***	
β_{24}							-1.8006***	-0.0143***	
β_{31} ($EA10Y$)							-0.0089	-0.0026	
β_{32}							0.1405*	0.0055*	
β_{33}							0.0299	-0.0002	
β_{34}							-0.0291	-0.0002	
β_{41} ($EURIBOR3M$)							-0.0472	-0.0081	
β_{42}							-0.0645	-0.0023	***
β_{43}							0.2493**	0.0022**	
β_{44}							0.3205***	0.0028***	
β_{51} (EUR/USD)							-0.0504	-0.0070	
β_{52}							-0.1288	-0.0046	
β_{53}							0.0952	0.0009	
β_{54}							-0.1306	-0.0009	
Log-likelihood		-2115.5159			-2103.3774			-1755.3360	
Pseudo- R^2					0.57%			17.02%	
χ^2 stat					23.537***			719.62***	

Table 7. Multinomial logit regression results for positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Positive coexceedances								
	Model 1			Model 2			Model 3		
	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.0889***	-0.1070***	-1.1497***	-0.1150***	-1.1075***	-0.1439***			
β_{02}	-2.4247***	-0.1044***	***	***	-2.8237***	-0.1048***	***	***	
β_{03}	-3.0348***	-0.0756***	***	***	-3.7899***	-0.0570***	***	***	
β_{04}	-2.5684***	-0.0975***	***	***	-4.2694***	-0.0406***	***	***	
β_{11} (RP_{t-1})			0.0969**	0.0122	0.0898*	0.0127			
β_{12}			0.1711**	0.0073*	0.1933**	0.0070**		**	
β_{13}			0.1587	0.0036	0.2065*	0.0029			
β_{14}			0.1026	0.0030	0.2387**	0.0021**			
β_{21} (EAF)					0.4655***	0.0643***		***	
β_{22}					0.9417***	0.0337***		***	
β_{23}					1.2983***	0.0191***		***	
β_{24}					1.7927***	0.0021***		***	
β_{31} ($EA10Y$)					0.0261	0.0031			
β_{32}					0.1301*	0.0052*			
β_{33}					0.0392	0.0004			
β_{34}					0.0083	-4.9172 $\times 10^{-5}$			
β_{41} ($EURIBOR3M$)					0.0179	0.0031			
β_{42}					-0.0045	-0.0004			
β_{43}					-0.0281	-0.0005			
β_{44}					0.0930	0.0009			
β_{51} (EUR/USD)					-0.1131	-0.0225			
β_{52}					0.0670	0.0038			
β_{53}					0.1673	0.0032			
β_{54}					0.2186	0.0025			
Log-likelihood		-2300.2409		-2292.8969		-1971.2463			
Pseudo- R^2				0.32%		14.30%			
χ^2 stat				8.9548*		652.26***			

Table 8. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.4036***	-0.2013***	-0.4575***	-0.0529*	
β_{02}	-2.7984***	-0.0972***	*** -1.9603***	-0.0736***	***
β_{03}	-3.1251***	-0.0172***	-2.4923***	-0.0304***	
β_{04}	-2.5511***	-0.0068***	-1.9060***	-0.0070***	
β_{11} (RN_{t-1}/RP_{t-1})	0.0981*	0.0140	0.0804	0.0118	
β_{12}	0.2310***	0.0082**	* 0.1897**	0.0067**	**
β_{13}	0.0510	0.0001	0.1703	0.0018	
β_{14}	0.1011	0.0002	0.2534**	0.0009**	
β_{21} (<i>EAF</i>)	-0.3903***	-0.0525***	0.4778***	0.0688***	
β_{22}	-0.9331***	-0.0327***	*** 1.0086***	0.0350***	***
β_{23}	-1.6346***	-0.0095***	1.4969***	0.0176***	
β_{24}	-2.3888***	-0.0073***	2.4092***	0.0093***	
β_{31} (<i>EA10Y</i>)	-0.0107	-0.0031	0.0283	0.0036	
β_{32}	0.1422*	0.0056*	0.1419*	0.0055*	
β_{33}	0.0643	0.0003	0.0362	0.0003	
β_{34}	0.0639	0.0001	-0.0646	-0.0003	
β_{41} (<i>EURIBOR3M</i>)	-0.0303	-0.0046	-0.0769	-0.0115	
β_{42}	-0.0726	-0.0026	-0.1349	-0.0045	
β_{43}	0.1337	0.009	-0.2215*	-0.0026*	
β_{44}	0.1098	0.0003	-0.2455**	-0.0009*	
β_{51} (<i>EUR/USD</i>)	-0.0559	-0.0078	-0.1062	-0.0208	
β_{52}	-0.1533	-0.0055	-0.0793	0.0041	
β_{53}	0.0896	0.0006	0.1952	0.0028	
β_{54}	-0.2027	-0.0006	0.2857	0.0012	
β_{61} ($USRN_{t-1}/USRP_{t-1}$)	0.3608	0.0506	0.3818	0.0610	
β_{62}	0.9022**	0.0323**	* 0.2816	0.0067	**
β_{63}	0.3065	0.0012	1.2283***	0.0149***	
β_{64}	0.8999*	0.0025*	1.0852**	0.0040**	
β_{71} (<i>USIvol_{t-1}</i>)	0.0386	0.0114	-0.5368***	-0.0828***	
β_{72}	-0.2140	-0.0081	*** -0.7367***	-0.0234***	***
β_{73}	-1.2890***	-0.0081***	-1.2416***	-0.0142***	
β_{74}	-2.3016***	-0.0074***	-2.6126***	-0.0102***	
Log-likelihood	-1718.9232		-1922.3871		
Pseudo- R^2	18.74%		16.42%		
χ^2 stat	791.7***		749.1***		

Appendix B

Table 9. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.4278***	-0.2031***	-0.4443***	-0.0493*	
β_{02}	-2.9224***	-0.1045***	*** -1.9596***	-0.0729***	***
β_{03}	-3.1436***	-0.0174***	-2.6196***	-0.0353***	
β_{04}	-2.6767***	-0.0077***	-1.8789***	-0.0071***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1127**	0.0157*	0.0932*	0.0136	
β_{12}	0.2910***	0.0107***	*** 0.2017**	0.0070**	***
β_{13}	0.0971	0.0003	0.2245**	0.0028*	
β_{14}	0.2155*	0.0006	0.3028***	0.0011**	
β_{21} (EAF)	-0.3932***	-0.0528***	0.4848***	0.0699***	
β_{22}	-0.9140***	-0.0327***	*** 0.9930***	0.0340***	***
β_{23}	-1.6202***	-0.0096***	1.4198***	0.0182***	
β_{24}	-2.3082***	-0.0075***	2.3847***	0.0095***	
β_{31} ($EAI0Y$)	-0.0105	-0.0030	0.0304	0.0039	
β_{32}	0.1324*	0.0054*	0.1397*	0.0053*	
β_{33}	0.0604	0.0003	0.0494	0.0005	
β_{34}	0.0689	0.0002	-0.0571	-0.0003	
β_{41} ($EURIBOR3M$)	-0.0259	-0.0040	-0.0764	-0.0112	
β_{42}	-0.0528	-0.0019	-0.1485	-0.0050	
β_{43}	0.1313	0.0008	-0.2120*	-0.0027	
β_{44}	0.073	0.0003	-0.2493**	-0.0009*	
β_{51} (EUR/USD)	-0.0575	-0.0081	-0.1268	-0.0250	
β_{52}	-0.1415	-0.0052	0.1201	0.0059	
β_{53}	0.1005	0.0007	0.2213	0.0035	
β_{54}	-0.2502	-0.0008	0.2920	0.0013	
β_{61} ($USRN/USRP$)	0.1851	0.0263	-0.1944	-0.0437	
β_{62}	0.3659	0.0129	0.6105*	0.0261*	
β_{63}	0.1851	0.0008	0.6782	0.0101	
β_{64}	0.9485**	0.0030**	0.3295	0.0014	
β_{71} ($USIvol$)	0.0588	0.0138	-0.5345***	-0.0820***	
β_{72}	-0.1006	-0.0039	*** -0.7643***	-0.0244***	***
β_{73}	-1.2778***	-0.0082***	-1.0776***	-0.0132***	
β_{74}	-2.2035***	-0.0076***	-2.6029***	-0.0105***	
Log-likelihood	-1721.1083		-1925.9232		
Pseudo- R^2	18.64%		16.27%		
χ^2 stat	788.07***		742.9***		

Table 10. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances			
	Model 4					
	Coeff.	Δ prob.	Coeff.	Δ prob.		
β_{01} (constant)	-1.3803***	-0.1975***	-0.4912***	-0.0573**		
β_{02}	-2.7031***	-0.0935***	***	-2.0594***	-0.0783***	***
β_{03}	-3.0954***	-0.0169***		-2.4480***	-0.0305***	
β_{04}	-2.7067***	-0.0086***		-1.9718***	-0.0078***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1160**	0.0162*		0.0943*	0.0139	
β_{12}	0.2990***	0.0107***	***	0.1989**	0.0070**	**
β_{13}	0.0686	0.0001		0.2229**	0.0026*	
β_{14}	0.1697	0.0005		0.2839**	0.0011**	
β_{21} (EAF)	-0.3997***	-0.0535***		0.4803***	0.0688***	
β_{22}	-0.9624***	-0.0337***	***	0.9968***	0.0349***	***
β_{23}	-1.6396***	-0.0095***		1.5010***	0.0182***	
β_{24}	-2.3176***	-0.0082***		2.3659***	0.0099***	
β_{31} (EA10Y)	-0.0097	-0.0028		0.0262	0.0031	
β_{32}	0.1366*	0.0054*		0.1440*	0.0056*	
β_{33}	0.0545	0.0003		0.0476	0.0004	
β_{34}	0.0395	0.0001		-0.0539	-0.0003	
β_{41} (EURIBOR3M)	-0.0329	-0.0049		-0.0731	-0.0109	
β_{42}	-0.0850	-0.0031		-0.1218	-0.0041	
β_{43}	0.1204	0.0008		-0.2308*	-0.0028*	
β_{44}	0.1157	0.0004		-0.2271*	-0.0009*	
β_{51} (EUR/USD)	-0.0529	-0.0076		-0.1052	-0.0206	
β_{52}	-0.1156	-0.0041		0.0804	0.0042	
β_{53}	0.0956	0.0007		0.1890	0.0028	
β_{54}	-0.1911	-0.0006		0.2972	0.0014	
β_{61} (USRN/USRP _{t-3})	0.1135	0.0199		0.2171	0.0429	
β_{62}	-0.2337	-0.0103		-0.1065	-0.0061	
β_{63}	0.1359	0.0007		-0.4444	-0.0066	
β_{64}	0.6939	0.0025		-1.2448	-0.0058	
β_{71} (USIvol _{t-3})	0.0200	0.0090		-0.5126***	-0.0792***	
β_{72}	-0.2743	-0.0103	***	-0.6385***	-0.0199**	***
β_{73}	-1.3192***	-0.0082***		-1.2136***	-0.0144***	
β_{74}	-2.0874***	-0.0078***		-2.4252***	-0.0102***	
Log-likelihood	-1722.1841		-1926.6335			
Pseudo- R^2	18.59%		16.24%			
χ^2 stat	781.07***		736.68***			

Table 11. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances			
	Model 4					
	Coeff.	Δ prob.	Coeff.	Δ prob.		
β_{01} (constant)	-1.3822***	-0.1976***	-0.5021***	-0.0591**		
β_{02}	-2.7218***	-0.0942***	***	-2.0988***	-0.0806***	***
β_{03}	-3.0776***	-0.0164***		-2.3832***	-0.0289***	
β_{04}	-2.6181***	-0.0083***		-2.0194***	-0.0079***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1141**	0.0160*		0.0963*	0.0142	
β_{12}	0.2900***	0.0104***	***	0.2002**	0.0071**	***
β_{13}	0.0739	0.0002		0.2309**	0.0026*	
β_{14}	0.1497	0.0004		0.2999***	0.0011**	
β_{21} (EAF)	-0.4055***	-0.0543***		0.4810***	0.0692***	
β_{22}	-0.9663***	-0.0338***	***	0.9862***	0.0348***	***
β_{23}	-1.6549***	-0.0093***		1.5096***	0.0179***	
β_{24}	-2.3203***	-0.0082***		2.3604***	0.0097***	
β_{31} (EA10Y)	-0.0064	-0.0023		0.0265	0.0032	
β_{32}	0.1349*	0.0053*		0.1414*	0.0056*	
β_{33}	0.0627	0.0003		0.0435	0.0004	
β_{34}	0.0408	0.0001		-0.0551	-0.0003	
β_{41} (EURIBOR3M)	-0.0367	-0.0054		-0.0707	-0.0105	
β_{42}	-0.0940	-0.0034		-0.1167	-0.0039	
β_{43}	0.1274	0.0008		-0.2440**	-0.0029*	
β_{44}	0.1075	0.0004		-0.2236*	-0.0008	
β_{51} (EUR/USD)	-0.0563	-0.0082		-0.1046	-0.0207	
β_{52}	-0.1107	-0.0038		0.0864	0.0045	
β_{53}	0.0985	0.0007		0.1993	0.0029	
β_{54}	-0.1758	-0.0006		0.3309	0.0015	
β_{61} (USRN/USRP _{t-5})	0.6101**	0.0936**		-0.2450	-0.0404	
β_{62}	0.8193**	0.0271*	**	-0.0934	-0.0008	
β_{63}	-0.6496	-0.0050		-0.5401	-0.0063	
β_{64}	0.4913	0.0012		-0.9613	-0.0039	
β_{71} (USIvol _{t-5})	0.0009	0.0060		-0.4836***	-0.0743***	
β_{72}	-0.2992	-0.0111	***	-0.6006***	-0.0188**	***
β_{73}	-1.3220***	-0.0080***		-1.2779***	-0.0150***	
β_{74}	-2.1377***	-0.0080***		-2.4132***	-0.0100***	
Log-likelihood	-1715.5163		-1925.8793			
Pseudo- R^2	18.90%		16.27%			
χ^2 stat	790.3***		731.29***			

Table 12. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.3584***	-0.1855***	-1.0800***	-0.0480***	
β_{02}	-3.0674***	-0.1042***	*** -2.8074***	-0.1150***	***
β_{03}	-4.4621***	-0.0208***	-3.7542***	-0.0695***	
β_{04}	-4.5557***	-0.0314***	-4.2767***	-0.0432***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1151**	0.0156*	0.0736	0.0032	
β_{12}	0.3205***	0.0112***	*** 0.2236***	0.0092**	***
β_{13}	0.1429	0.0005	0.2253**	0.0041*	
β_{14}	0.2563**	0.0016**	0.2973***	0.0030***	
β_{21} (EAF)	-0.4022***	-0.0532***	0.4683***	0.0219***	
β_{22}	-0.9838***	-0.0335***	*** 0.9549***	0.0385***	***
β_{23}	-1.5123***	-0.0071***	1.3154***	0.0241***	
β_{24}	-1.8954***	-0.0134***	1.8862***	0.0192***	
β_{31} (EA10Y)	-0.0090	-0.0025	0.0165	0.0004	
β_{32}	0.1349*	0.0052*	0.1561**	0.0067**	
β_{33}	0.0394	0.0001	0.0470	0.0007	
β_{34}	-0.0267	-0.0002	0.0323	0.0002	
β_{41} (EURIBOR3M)	-0.0154	-0.0020	0.0519	0.0029	
β_{42}	-0.1167	-0.0044	* -0.0018	-0.0003	
β_{43}	0.0802	0.0004	0.0059	9.3656 $\times 10^{-6}$	
β_{44}	0.2273**	0.0017**	0.1948*	0.0020*	
β_{51} (EUR/USD)	-0.05425	-0.0075	-0.1191	-0.0076	
β_{51}	-0.1251	-0.0043	0.0751	0.0034	
β_{53}	0.1113	0.0006	0.1631	0.0032	
β_{54}	-0.1195	-0.0007	0.2020	0.0021	
β_{61} (EA10Y dummy $_{t-1}$)	0.0146	0.0129	0.3317	0.0242*	
β_{62}	-0.7717	-0.0289	* -0.8689*	-0.0378*	***
β_{63}	-1.8604*	-0.0094*	-0.4832	-0.0087	
β_{64}	-1.3760**	-0.0102**	-2.0711***	-0.0220***	
β_{71} (EURIBOR3M dummy $_{t-1}$)	0.2752	0.0624	-0.7007**	-0.0383**	
β_{72}	-0.6554	-0.0251	-0.2946	-0.0092	**
β_{73}	-9.0735	-0.0480	-0.6655	-0.0115	
β_{74}	-1.2856*	-0.0096*	-2.1223**	-0.0221**	
β_{81} (EUR/USD dummy $_{t-1}$)	-0.0477	-0.0100	-3423.64***	-201.87***	
β_{82}	0.5120	0.0204	-380.063***	-6.6219***	***
β_{83}	-0.8724	-0.0045	-112.237***	2.5258***	
β_{84}	-0.6748	-0.0051	-18.3762***	2.3894***	
Log-likelihood	-1742.2647		-1955.6297		
Pseudo- R^2	17.64%		14.98%		
χ^2 stat	745.76***		683.49***		

Table 13. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.3606***	-0.1897***	-1.0483***	-0.1269***	
β_{02}	-3.0548***	-0.1080***	*** -2.7765***	-0.1049***	***
β_{03}	-4.3952***	-0.0013***	-3.7422***	-0.0523***	
β_{04}	-4.5231***	-0.0324***	-4.2628***	-0.0376***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1158**	0.0162*	0.0876*	0.0116	
β_{21}	0.2895***	0.0104***	*** 0.1909**	0.0071**	**
β_{13}	0.0461	2.9966×10^{-6}	0.1955*	0.0025	
β_{14}	0.1531	0.0009	0.2264**	0.0019*	
β_{21} (EAF)	-0.4079***	-0.0556***	0.4681***	0.0607***	
β_{22}	-0.9643***	-0.0341***	*** 0.9430***	0.0343***	***
β_{23}	-1.4870***	-0.0004***	1.3480***	0.0185***	
β_{24}	-1.8754***	-0.0137***	1.8470***	0.0164***	
β_{31} (EA10Y)	-0.0061	-0.0021	0.0304	0.0034	
β_{32}	0.1420*	0.0057*	0.1374*	0.0055*	
β_{33}	0.0339	9.9538×10^{-6}	0.0681	0.0008	
β_{34}	-0.0261	-0.0002	0.0383	0.0002	
β_{41} (EURIBOR3M)	-0.0480	-0.0076	0.0277	0.0046	
β_{42}	-0.0786	-0.0027	** -0.0072	-0.0005	
β_{43}	0.1297	4.7516×10^{-5}	-0.0499	-0.0008	
β_{44}	0.2585***	0.0021***	0.0848	0.0007	
β_{51} (EUR/USD)	-0.0545	-0.0077	-0.1171	-0.0214	
β_{52}	-0.1198	-0.0042	0.0689	0.0038	
β_{53}	0.0967	3.8473×10^{-5}	0.1951	0.0033	
β_{54}	-0.1421	-0.0009	0.2622	0.0027	
β_{61} (EA10Y dummy $_{t-5}$)	0.2282	0.0374	-0.5158*	-0.0686	
β_{62}	0.2033	0.0064	-0.5654	-0.0168	**
β_{63}	-1.2492	-0.0004	-2.4900**	-0.0365**	
β_{64}	-0.9388	-0.0078	-1.7187***	-0.0150**	
β_{71} (EURIBOR3M dummy $_{t-5}$)	-0.1232	-0.0124	-0.7950***	-0.1258***	
β_{72}	-0.3261	-0.0108	-0.4005	-0.0090	*
β_{73}	-38.0166***	-0.0127***	-0.5062	-0.0048	
β_{74}	-1.4341**	-0.0108**	-0.5990	-0.0039	
β_{81} (EUR/USD dummy $_{t-5}$)	0.1045	0.0191	-327.308***	-53.618***	
β_{82}	-0.0172	-0.0012	-85.1460***	-0.5091***	***
β_{83}	-27.9417***	-0.0094***	-35.1611***	0.6147***	
β_{84}	0.1105	0.0007	-21.6649***	0.5146***	
Log-likelihood	-1742.3953		-1952.5896		
Pseudo- R^2	17.63%		15.11%		
χ^2 stat	739.91***		678.75***		

Table 14. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to May 31, 2007

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.1809***	-0.1652***	-0.7530***	-0.0785***	
β_{02}	-2.8356***	-0.0897***	*** -2.4523***	-0.1352***	***
β_{03}	-5.0786***	-0.0174***	-4.1278***	-0.0532***	
β_{04}	-7.0400***	-0.0032***	-5.1139***	-0.0324***	
β_{11} (RN_{t-1}/RP_{t-1})	-0.0048	-0.0017	0.0664	0.0060	
β_{12}	0.1456	0.0051	0.2347*	0.0129*	***
β_{13}	-0.1814	-0.0006	0.3813**	0.0049*	
β_{14}	0.2674	0.0001	0.6609***	0.0043***	
β_{21} (EAF)	-0.7087***	-0.0971***	0.7747***	0.1122***	
β_{22}	-1.9539***	-0.0626***	*** 1.5056***	0.0760***	***
β_{23}	-3.2043***	-0.0109***	2.7379***	0.0342***	
β_{24}	-4.8289***	-0.0022***	3.6575***	0.0228***	
β_{31} ($EA10Y$)	0.0487	0.0065	0.0297	0.0048	
β_{32}	0.2245	0.0075	*	0.1275	
β_{33}	-0.3971	-0.0015	-0.2946	-0.0045	
β_{43}	-0.8921**	-0.0004**	0.0384	0.0001	
β_{41} ($EURIBOR3M$)	-0.3410**	-0.0520**	-0.1939	-0.0382	
β_{42}	-0.4490*	-0.0132*	** -0.0155	0.0036	
β_{43}	0.5131*	0.0022**	-0.3447	-0.0040	
β_{44}	-0.1020	-9.0049×10^{-6}	-0.4192	-0.0024	
β_{51} (EUR/USD)	-0.1960	-0.0269	-0.2651*	-0.0575*	
β_{52}	-0.5073*	-0.0161	*	0.1003	
β_{53}	-1.1828**	-0.0041**	-0.0917	-0.0002	
β_{54}	-0.9634*	-0.0004	-0.1027	-0.0001	
Log-likelihood	-638.8298		-872.7635		
Pseudo- R^2	17.48%		11.25%		
χ^2 stat	270.12***		216.21***		

Table 15. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, January 2, 2004, to May 31, 2007

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.8336***	-0.2549***	-0.7003	-0.0911	
β_{02}	-5.0273***	-0.1545***	*** -2.1789***	-0.1235**	*
β_{03}	-8.8446***	-0.0280***	-2.2349	-0.0238	
β_{04}	-7.8307***	-0.0032***	-1.4398	-0.0055	
β_{11} (RN_{t-1}/RP_{t-1})	-0.0343	-0.0053	0.0682	0.0078	
β_{12}	0.0008	0.0003	0.2128*	0.0118	**
β_{13}	-0.3150	-0.0010	0.2849	0.0031	
β_{14}	0.2028	9.5818×10^{-5}	0.5849***	0.0029***	
β_{21} (EAF)	-0.7157***	-0.0996***	0.7736***	0.2251***	
β_{22}	-1.9450***	-0.0597***	*** 1.4935***	0.0762***	***
β_{23}	-3.1410***	-0.0098***	2.7658***	0.0307***	
β_{24}	-4.8914***	-0.0021***	3.8617***	0.0186***	
β_{31} ($EA10Y$)	0.0487	0.0068	0.0290	0.0048	
β_{32}	0.2148	0.0069	* 0.1214	0.0075	
β_{33}	-0.4779	-0.0016	-0.3272	-0.0044	
β_{34}	-0.9202**	-0.0004**	0.0353	0.0001	
β_{41} ($EURIBOR3M$)	-0.3064**	-0.0471*	-0.1951	-0.0387	
β_{42}	-0.4081*	-0.0115	* -0.0202	0.0033	
β_{43}	0.4930*	0.0019**	-0.3568	-0.0037	
β_{44}	-0.0566	8.3242×10^{-6}	-0.5283*	-0.0024	
β_{51} (EUR/USD)	-0.2128	-0.0296	-0.2560	-0.0563*	
β_{52}	-0.5709*	-0.0175*	* 0.1225	0.0135	
β_{53}	-1.0787**	-0.0034*	-0.0808	-0.0001	
β_{54}	-1.0383*	-0.0004*	-0.1738	-0.0005	
β_{61} ($USRN/USRPT_{t-1}$)	0.4359	0.0604	0.2181	0.0181	
β_{62}	1.3500*	0.0420*	0.8458	0.0477	**
β_{63}	0.9838	0.0028	1.9387***	0.0231***	
β_{64}	0.5993	0.0002	1.4691**	0.0070**	
β_{71} ($USIvol_{t-1}$)	0.6631	0.0892	-0.0583	0.0087	
β_{72}	2.1997**	0.0686**	** -0.2931	-0.0143	
β_{73}	3.7750**	0.0120**	-2.0730	-0.0258	
β_{74}	0.7444	0.0002	-4.0220**	-0.0211**	
Log-likelihood	-632.2362		-861.8604		
Pseudo- R^2	18.34%		12.36%		
χ^2 stat	282.64***		236.9***		

Table 16. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, June 1, 2007, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.3951***	-0.1869***	-1.3717***	-0.1838***	
β_{02}	-3.2479***	-0.1066***	-3.3944***	-0.0769***	***
β_{03}	-4.5730***	-0.0352***	-4.0450***	-0.0463***	
β_{04}	-4.4544***	-0.0395***	-4.7571***	-0.0235***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1683***	0.0242**	0.0916	0.0135	
β_{12}	0.3692***	0.0123***	0.1350	0.0029	***
β_{13}	0.1393	0.0007	-0.0948	0.0009	
β_{14}	0.1715	0.0011	-0.0068	-0.0001	
β_{21} (EAF)	-0.3553***	-0.0463***	0.3793***	0.0505***	
β_{22}	-0.8522***	-0.0279***	0.9120***	0.0205***	***
β_{23}	-1.2118***	-0.0093***	1.1209***	0.0128***	
β_{24}	-1.5780***	-0.0144***	1.7212***	0.0087***	
β_{31} ($EA10Y$)	-0.0375	-0.0065	0.0420	0.0049	
β_{32}	0.0728	-0.0030	0.2109**	0.0050**	
β_{33}	-0.0483	-0.0003	0.1804*	0.0021	
β_{34}	-0.0835	-0.0007	0.1098	0.0005	
β_{41} ($EURIBOR3M$)	-0.0147	-0.0029	0.0016	0.0009	
β_{42}	-0.0570	-0.0021	-0.1265	-0.0031	***
β_{43}	0.1901	0.0016*	-0.0731	-0.0008	
β_{44}	0.3034***	0.0030***	0.0887	0.0005	
β_{51} (EUR/USD)	0.0042	0.0008	0.0031	-0.0022	
β_{52}	-0.0463	-0.0018	0.1871	0.0044	*
β_{53}	0.3373	0.0029	0.4419*	0.0054*	
β_{54}	-0.1985	-0.0019	0.6267**	0.0033***	
Log-likelihood	-1067.1715		-1035.1653		
Pseudo- R^2	19.76%		19.72%		
χ^2 stat	525.61***		508.66***		

Table 17. Multinomial logit regression results for negative and positive daily return coexceedances of 11 European countries industrial market indices, June 1, 2007, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.5118***	-0.2206***	-0.9451***	-0.1248***	
β_{02}	-3.1455***	-0.1062***	*** -2.8943***	-0.0663***	***
β_{03}	-3.0419***	-0.0135***	-3.2173***	-0.0340***	
β_{04}	-2.6339***	-0.0072***	-2.8265***	-0.0057***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1514**	0.0224**	0.0772	0.0111	
β_{12}	0.3127***	0.0106***	** 0.1467	0.0032	
β_{13}	0.1223	0.0004	0.0927	0.0008	
β_{14}	0.0915	0.0001	0.0148	-1.1207×10^{-5}	
β_{21} (EAF)	-0.3413***	-0.0470***	0.3830***	0.0515***	
β_{22}	-0.8080***	-0.0273***	*** 0.9281***	0.0207***	***
β_{23}	-1.5104***	-0.0073***	1.1971***	0.0126***	
β_{24}	-2.1118***	-0.0066***	2.1616***	0.0046***	
β_{31} (EA10Y)	-0.0387	-0.0071	0.0406	0.0048	
β_{32}	0.0699	0.0029	0.2171**	0.0051**	
β_{33}	0.0180	0.0001	0.1698	0.0018	
β_{34}	0.0398	0.0001	0.0135	-4.2756×10^{-6}	
β_{41} (EURIBOR3M)	0.0043	0.0009	-0.0558	-0.0071	
β_{42}	-0.0480	-0.0018	-0.1925*	-0.0044*	
β_{43}	0.0474	0.0002	-0.1802	-0.0018	
β_{44}	0.1172	0.0003	-0.1593	-0.0003	
β_{51} (EUR/USD)	0.0004	0.0002	0.0166	0.0004	
β_{52}	-0.0553	-0.0021	0.1779	0.0041	*
β_{53}	0.4433	0.0023	0.4335	0.0048	
β_{54}	-0.2157	-0.0007	0.6938***	0.0015***	
β_{61} (USRN/USRP _{t-1})	0.3303	0.0475	0.5655*	0.0881*	
β_{62}	0.8320**	0.0288*	-0.2214	-0.0084	
β_{63}	0.0864	-0.0001	0.4896	0.0044	
β_{64}	0.6798	0.0019	0.3739	0.0005	
β_{71} (USIvol _{t-1})	0.0758	0.0161	-0.3201**	-0.0459**	
β_{72}	-0.0656	-0.0025	*** -0.3529	-0.0069	***
β_{73}	-1.3747***	-0.0072***	-0.6466**	-0.0065*	
β_{74}	-1.9685***	-0.0066***	-1.8995***	-0.0041***	
Log-likelihood	-1041.3059		-1015.9221		
Pseudo- R^2	21.70%		21.25%		
χ^2 stat	577.34***		547.14***		

Table 18. Multinomial logit regression results for negative and positive daily return coexceedances (computed on sample returns) of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-1.6440***	-0.2139***	-1.2375***	-0.1783***	
β_{02}	-3.5806***	-0.0852***	*** -2.3092***	-0.0944***	***
β_{03}	-5.4086***	-0.0256***	-4.9042***	-0.0326***	
β_{04}	-6.5019***	-0.0097***	-5.7943***	-0.0148***	
β_{11} (RN_{t-1}/RP_{t-1})	0.2400***	0.0324***	0.0771	0.0094	
β_{12}	0.3201***	0.0071***	*** 0.3816***	0.0114***	***
β_{13}	0.6441***	0.0030***	0.5213***	0.0035***	
β_{14}	0.5015***	0.0007***	0.4083***	0.0010***	
β_{21} (EAF)	-0.3124***	-0.0392***	0.3870***	0.0544***	
β_{22}	-0.8272***	-0.0199***	*** 1.1301***	0.0324***	***
β_{23}	-1.4293***	-0.0068***	1.6631***	0.0111***	
β_{24}	-2.6429***	-0.0040***	2.4257***	0.0063***	
β_{31} ($EA10Y$)	0.0226	0.0045	0.0617	0.0098	
β_{32}	-0.1900**	-0.0050**	** 0.0863	0.0022	
β_{33}	-0.3343***	-0.0017***	0.0392	0.0001	
β_{34}	-0.1164	-0.0001	0.2134**	0.0005**	
β_{41} ($EURIBOR3M$)	-0.1262***	-0.0172**	-0.1212***	-0.0192**	
β_{42}	-0.2111***	-0.0049***	*** -0.1123	-0.0025	***
β_{43}	-0.0134	7.3671×10^{-5}	-0.3776***	-0.0025***	
β_{44}	0.0717	0.0001	-0.4561***	-0.0011***	
β_{51} (EUR/USD)	-0.0915	-0.0099	-0.0352	-0.0095	
β_{52}	-0.7095***	-0.0182***	*** 0.3935**	0.0126**	*
β_{53}	0.0767	0.0005	0.3525	0.0025	
β_{54}	-0.1460	-0.0001	0.0584	0.0001	
Log-likelihood	-1457.0941		-1712.5521		
Pseudo- R^2	24.89%		20.24%		
χ^2 stat	965.27***		861.69***		

Table 19. Multinomial logit regression results for negative and positive daily return coexceedances (computed on sample returns) of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-2.2605***	-0.3000***	-1.3465***	-0.1902***	
β_{02}	-4.8669***	-0.1121***	*** -3.9546***	-0.1176***	***
β_{03}	-6.3538***	-0.0281***	-5.3245***	-0.0367***	
β_{04}	-8.2019***	-0.0116***	-6.9144***	-0.0178***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1963***	0.0272***	0.0716	0.0092	
β_{12}	0.1968*	0.0040	*** 0.3016***	0.0092***	***
β_{13}	0.4339***	0.0019***	0.4409***	0.0031***	
β_{14}	0.3786***	0.0005***	0.2639**	0.0006*	
β_{21} (<i>EAF</i>)	-0.3489***	-0.0449***	0.3936***	0.0558***	
β_{22}	-0.8802***	-0.0204***	*** 1.0880***	0.0321***	***
β_{23}	-1.4246***	-0.0064***	1.6286***	0.0113***	
β_{24}	-2.6140***	-0.0038***	2.3147***	0.0006***	
β_{31} (<i>EA10Y</i>)	0.0259	0.0049	0.0597	0.0095	
β_{32}	-0.1792**	-0.0046**	** 0.0852	0.0023	*
β_{33}	-0.3393***	-0.0016***	0.0276	7.9866×10^{-5}	
β_{34}	-0.1273	-0.0001	0.2463**	0.0006**	
β_{41} (<i>EURIBOR3M</i>)	-0.0332	-0.0049	-0.1078**	-0.0180**	
β_{42}	-0.0179	-0.0003	* -0.0037	0.0007	**
β_{43}	0.1174	0.0005	-0.2785**	-0.0019**	
β_{44}	0.2465***	0.0003***	-0.2276**	-0.0005*	
β_{51} (<i>EUR/USD</i>)	-0.1135	-0.0124	-0.0356	-0.0095	
β_{52}	-0.6602***	-0.0162***	*** 0.3632**	0.0121**	
β_{53}	-0.0428	-2.3820×10^{-5}	0.3404	0.0025	
β_{54}	-0.2165	-0.0002	0.0974	0.0002	
β_{61} ($USRN_{t-1}/USRP_{t-1}$)	0.0682	0.0071	-0.0035	-0.0020	
β_{62}	0.3721	0.0089	0.0854	0.0027	
β_{63}	1.2706**	0.0060**	0.3404	0.0025	
β_{64}	-0.1294	-0.0002	0.2460	0.0006	
β_{71} (<i>USIVol_{t-1}</i>)	0.5041***	0.0680***	0.0924	0.0105	
β_{72}	1.0054***	0.0230***	*** 0.5603***	0.0175***	***
β_{73}	0.7234**	0.0029*	0.3816	0.0025	
β_{74}	1.3293***	0.0018***	0.9277***	0.0024***	
Log-likelihood	-1426.7515		-1702.2431		
Pseudo- R^2	26.45%		20.72%		
χ^2 stat	1022.2***		881.54***		

Table 20. Multinomial logit regression results for negative and positive daily return coexceedances (computed as the 2.5% quantile) of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 3				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-2.1002***	-0.1975***	-1.7249***	-0.2052***	
β_{02}	-3.9807***	-0.0653***	*** -3.7553***	-0.0668***	***
β_{03}	-5.9298***	-0.0121***	-5.2632***	-0.0232***	
β_{04}	-5.6142***	-0.0172***	-5.2484***	-0.0186***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1600**	0.0151**	0.1775**	0.0224**	
β_{12}	0.3567***	0.0059***	** 0.1383	0.0021	**
β_{13}	-0.1313	-0.0003	0.4453**	0.0019**	
β_{14}	0.1549	0.0004	-0.2688	-0.0011	
β_{21} (EAF)	-0.3770***	-0.0351***	0.4780***	0.0578***	
β_{22}	-0.7481***	-0.0122***	*** 0.8532***	0.0149***	***
β_{23}	-1.4563***	-0.0030***	1.1286***	0.0048***	
β_{24}	-1.5633***	-0.0049***	1.2629***	0.0044***	
β_{31} (EA10Y)	-0.0143	-0.0012	0.0423	0.0052	
β_{32}	-0.1180	-0.0020	0.0551	0.0009	
β_{33}	0.2392	0.0005*	0.0062	-8.2801×10^{-6}	
β_{34}	0.0143	5.7152×10^{-5}	0.1099	0.0003	
β_{41} (EURIBOR3M)	-0.0509	-0.0058	-0.0048	-0.0005	
β_{42}	0.2401**	0.0042***	*** -0.0901	-0.0017	
β_{43}	0.3555***	0.0007***	0.1451	0.0006	
β_{44}	0.4246***	0.0013***	0.0910	0.0003	
β_{51} (EUR/USD)	-0.2198**	-0.0212**	-0.1455	-0.0195	
β_{52}	-0.3252	-0.0052	0.0491	0.0013	
β_{53}	-0.0653	-7.5771×10^{-5}	0.4552	0.0022	
β_{54}	0.0450	0.0002	0.3411	0.0013	
Log-likelihood	-1196.1397		-1391.6114		
Pseudo- R^2	16.24%		11.87%		
χ^2 stat	463.55***		374.49**		

Table 21. Multinomial logit regression results for negative and positive daily return coexceedances (computed as the 2.5% quantile) of 11 European countries industrial market indices, January 2, 2004, to July 11, 2012

	Negative coexceedances		Positive coexceedances		
	Model 4				
	Coeff.	Δ prob.	Coeff.	Δ prob.	
β_{01} (constant)	-2.1195***	-0.2075***	-1.0335***	-0.1222***	
β_{02}	-3.1339***	-0.0439***	*** -2.4210***	-0.0347***	***
β_{03}	-3.6033***	-0.0013***	-3.4285***	-0.0094***	
β_{04}	-3.1162***	-0.0014***	-3.2968***	-0.0063***	
β_{11} (RN_{t-1}/RP_{t-1})	0.1472*	0.0143*	0.1914**	0.0237**	
β_{12}	0.2725**	0.0038**	0.1371	0.0016	**
β_{13}	-0.0641	-3.5312×10^{-5}	0.4357**	0.0011**	
β_{14}	0.0861	3.4355×10^{-5}	-0.2903	-0.0006	
β_{21} (<i>EAF</i>)	-0.3517***	-0.0336***	0.5267***	0.0628***	
β_{22}	-0.8632***	-0.0124***	*** 1.0576***	0.0150***	***
β_{23}	-2.1661***	-0.0008***	1.4887***	0.0040***	
β_{24}	-2.5072***	-0.0012***	1.6682***	0.0032***	
β_{31} (<i>EA10Y</i>)	-0.0210	-0.0019	0.0476	0.0059	
β_{32}	-0.1074	-0.0016	** 0.0378	0.0004	
β_{33}	0.3757**	0.0001**	-0.0521	-0.0001	
β_{34}	0.1954*	0.0001*	0.0495	8.6015×10^{-5}	
β_{41} (<i>EURIBOR3M</i>)	-0.0320	-0.0035	-0.1097*	-0.0130*	
β_{42}	0.1880*	0.0029*	-0.3015***	-0.0043**	**
β_{43}	0.1037	4.3284×10^{-5}	-0.0915	-0.0002	
β_{44}	0.2136*	0.0001*	-0.2052	-0.0003	
β_{51} (<i>EUR/USD</i>)	-0.2166**	-0.0210*	-0.1580	-0.0204	
β_{52}	-0.4106*	-0.0058*	0.0545	0.0011	
β_{53}	-0.0845	-2.2206×10^{-5}	0.5669*	0.0017*	
β_{54}	0.0098	2.1536×10^{-5}	0.3916	0.0008	
β_{61} ($USRN_{t-1}/USRP_{t-1}$)	0.2880	0.0277	-0.0932	-0.0136	
β_{62}	1.1834**	0.0176	0.6486	0.0102	
β_{63}	-19.5946	-0.0081	-0.1757	-0.0005	
β_{64}	1.3544*	0.0006	1.4178**	0.0029**	
β_{71} (<i>USIVol_{t-1}</i>)	0.0181	0.0035	-0.5730***	-0.0680***	
β_{72}	-0.7757**	-0.0117**	*** -1.2352***	-0.0176***	***
β_{73}	-2.7092***	-0.0011***	-1.7912***	-0.0049***	
β_{74}	-3.3429***	-0.0017***	-2.0215***	-0.0039***	
Log-likelihood	-1156.7197		-1362.7701		
Pseudo- R^2	19%		13.7%		
χ^2 stat	542.01***		431.68***		

Appendix C

Figure 1. Industrial Stock Market Return Index

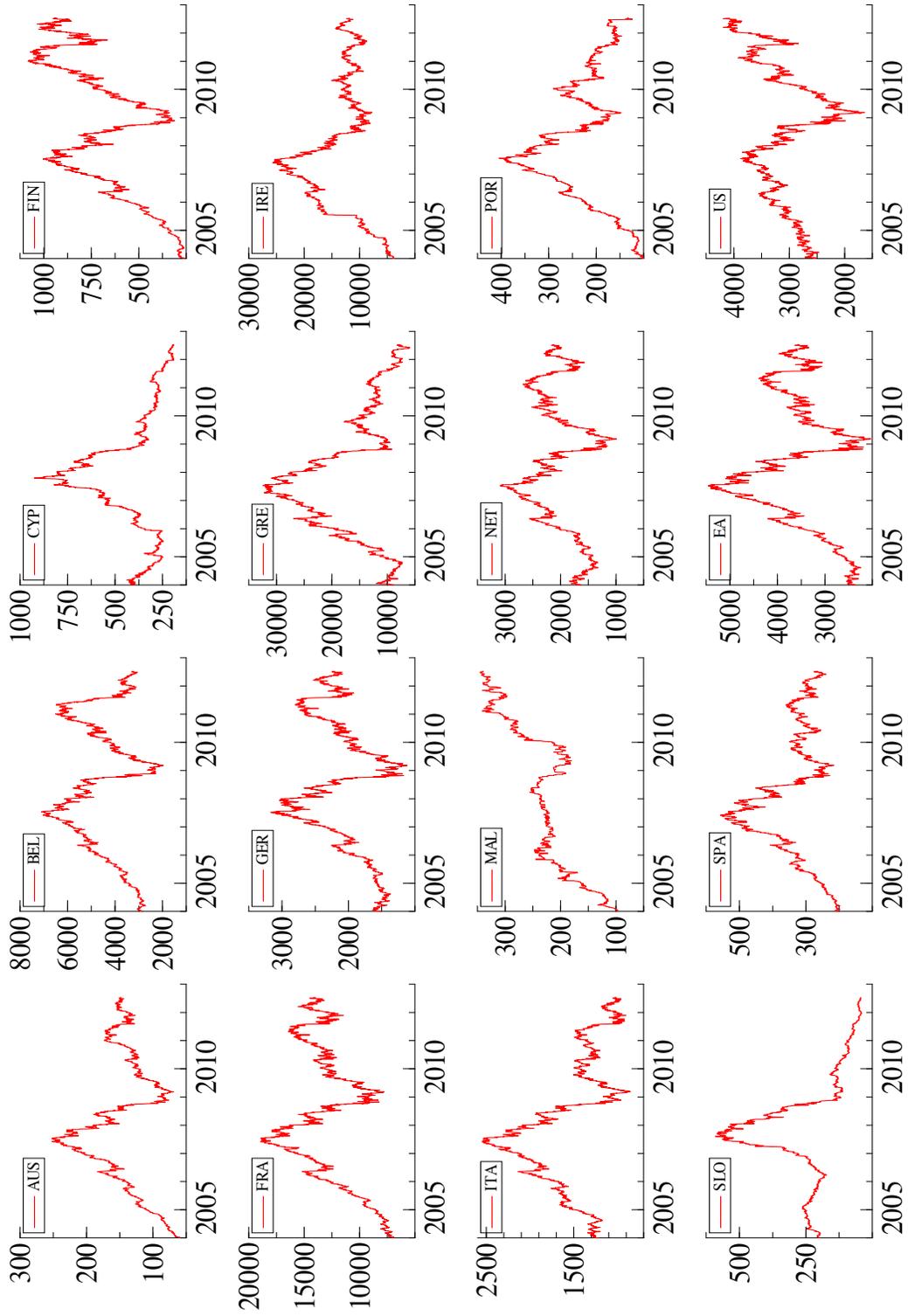


Figure 2. Industrial Stock Market Returns

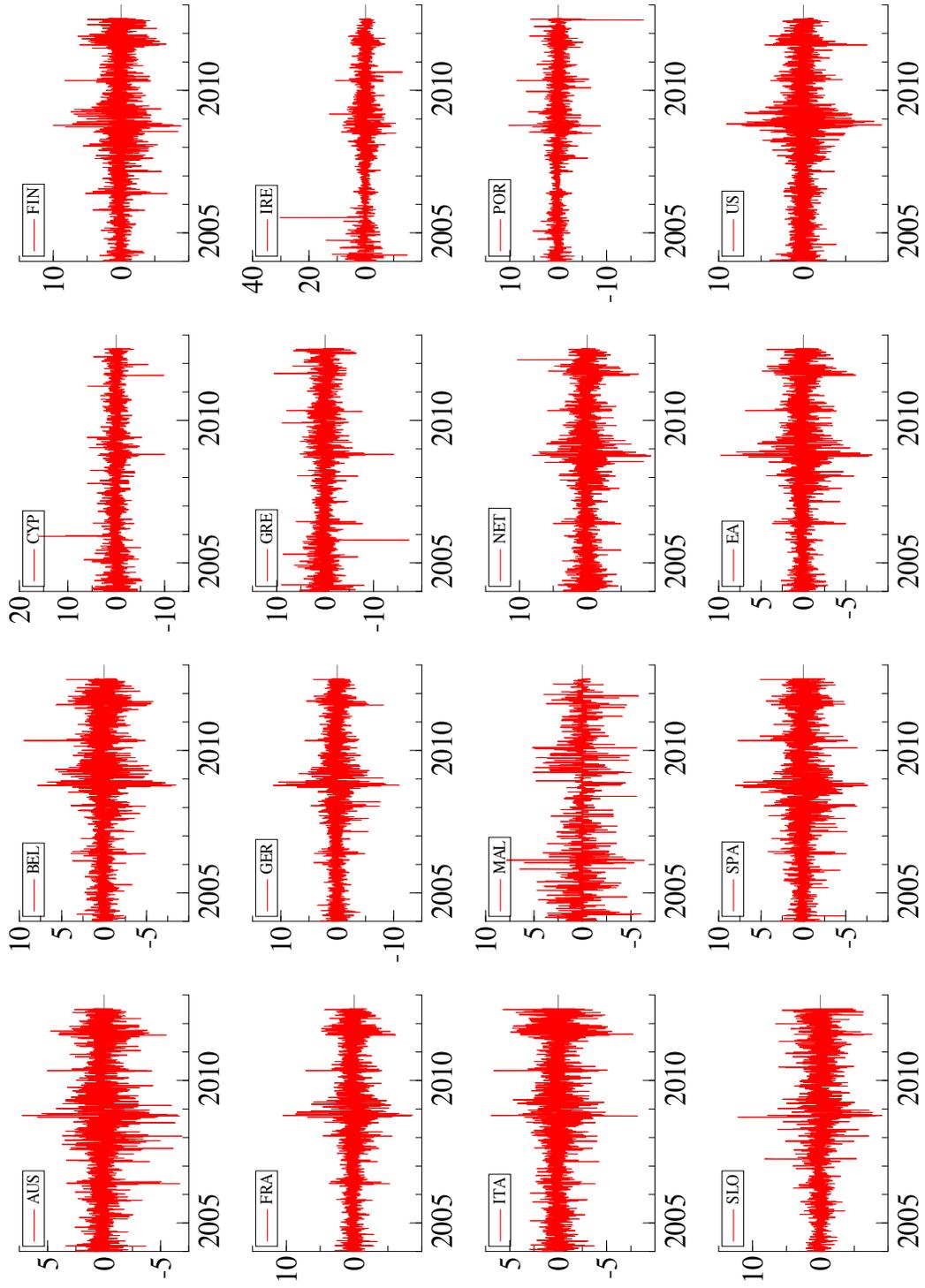


Figure 3. EA Financial Stock Market Return Index, EA 10 Year Government Bond Yield, EURIBOR 3 Month Interest Rate and EUR/USD Exchange Rate

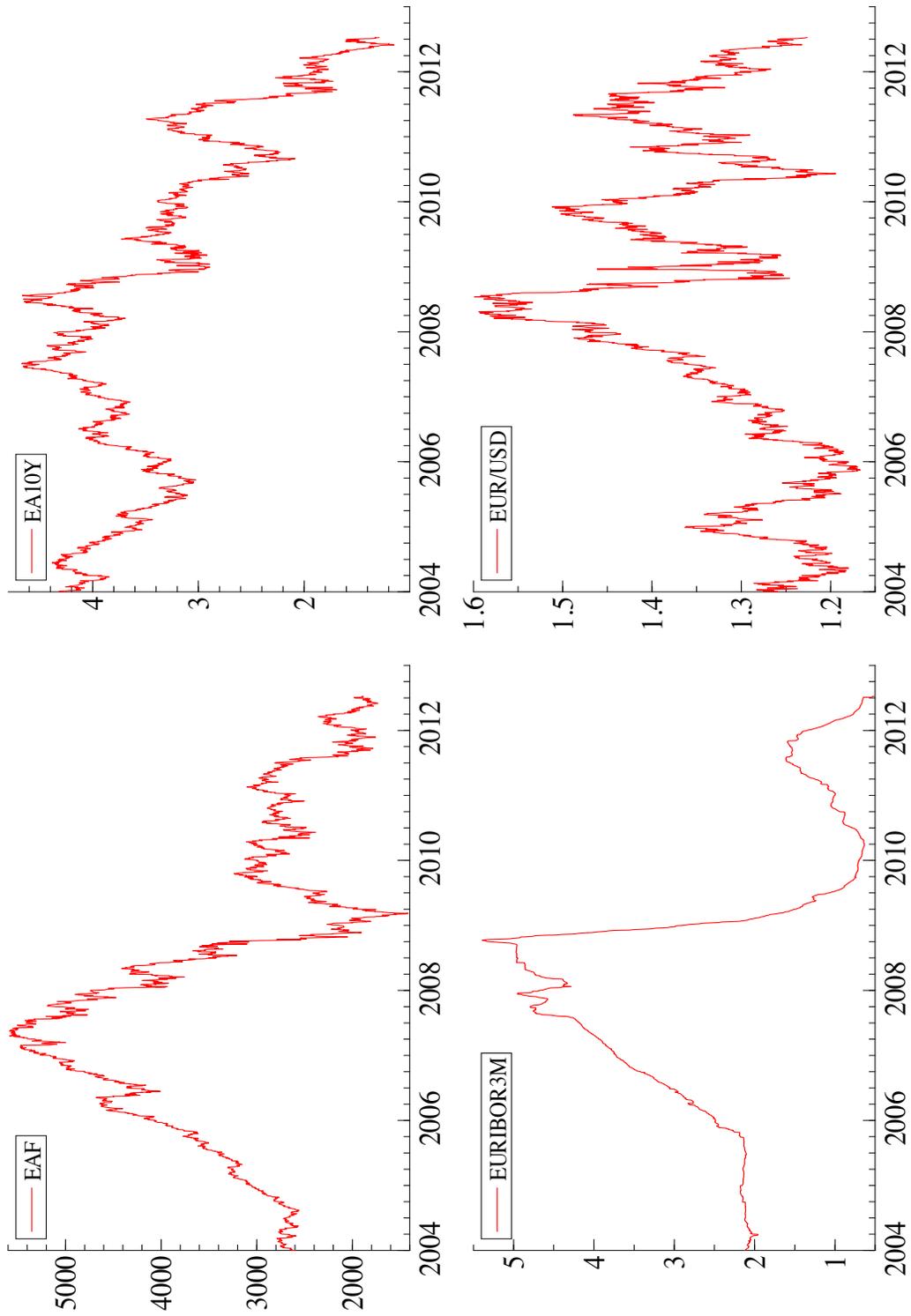


Figure 4. Coexistence Response Curves of Negative Extreme Returns in EA (Model 3)

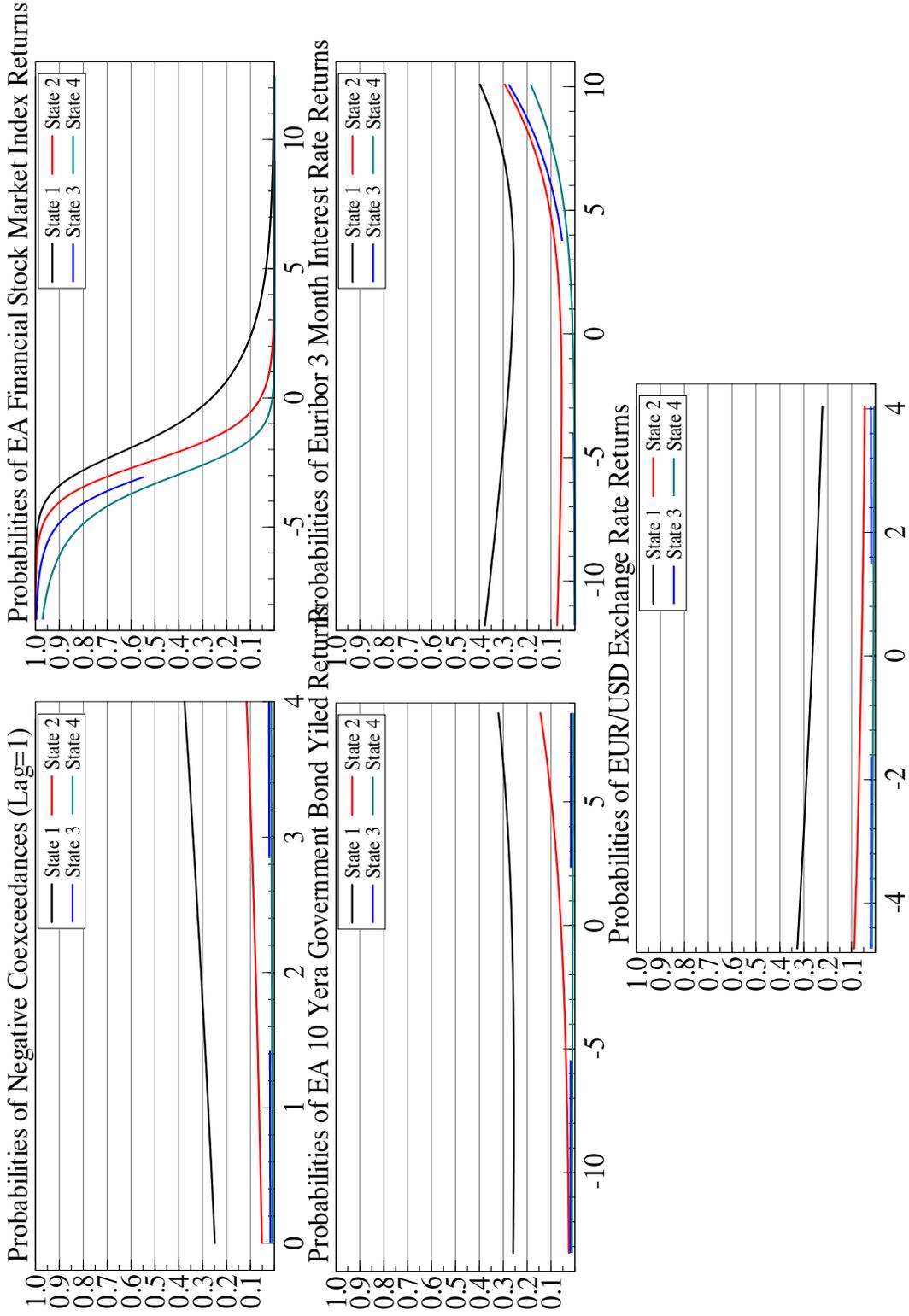


Figure 5. Coexceedance Response Curves of Positive Extreme Returns in EA (Model 3)

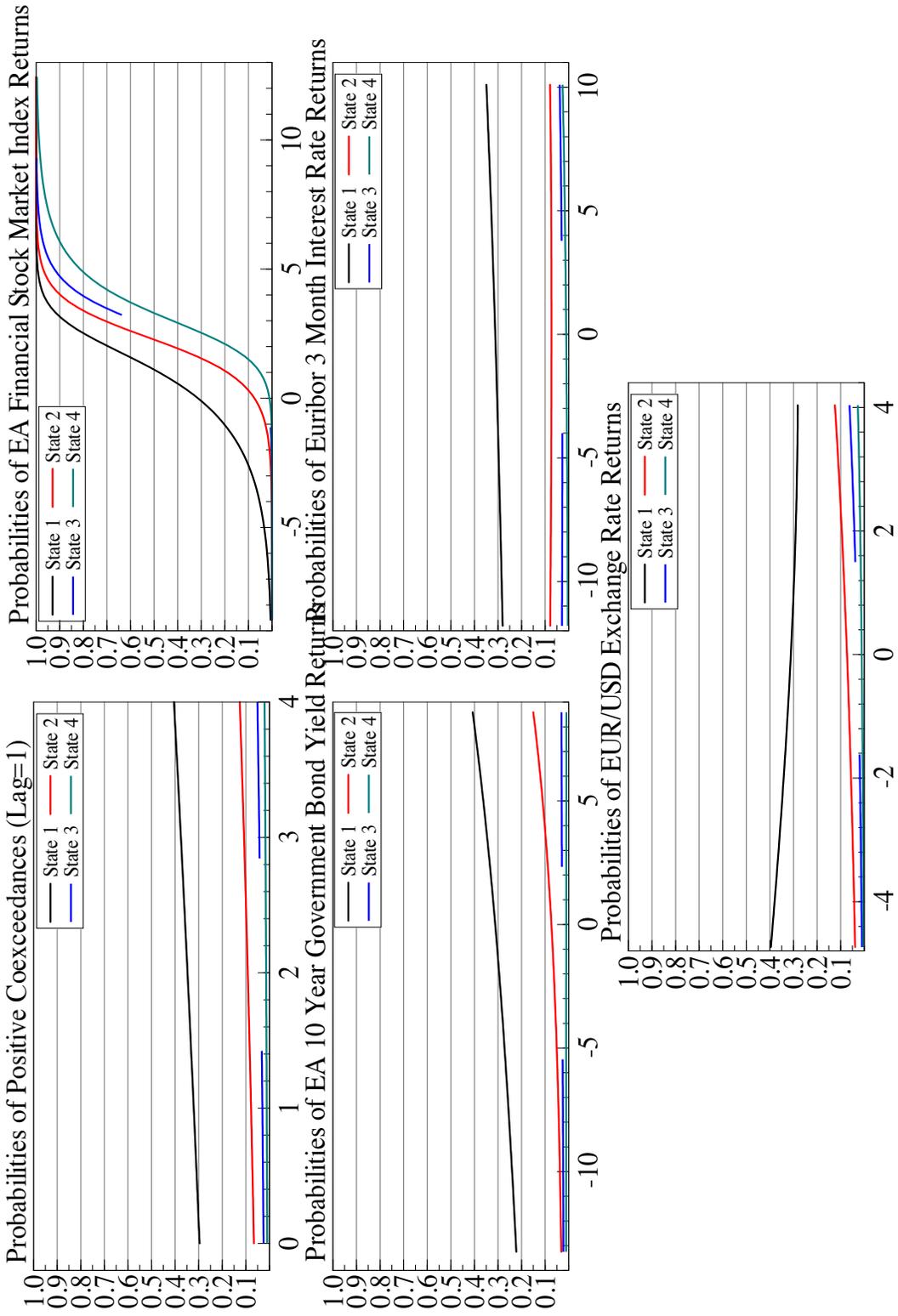


Figure 6. Coexceedance Response Curves of Negative Extreme Returns in EA (Model 4)

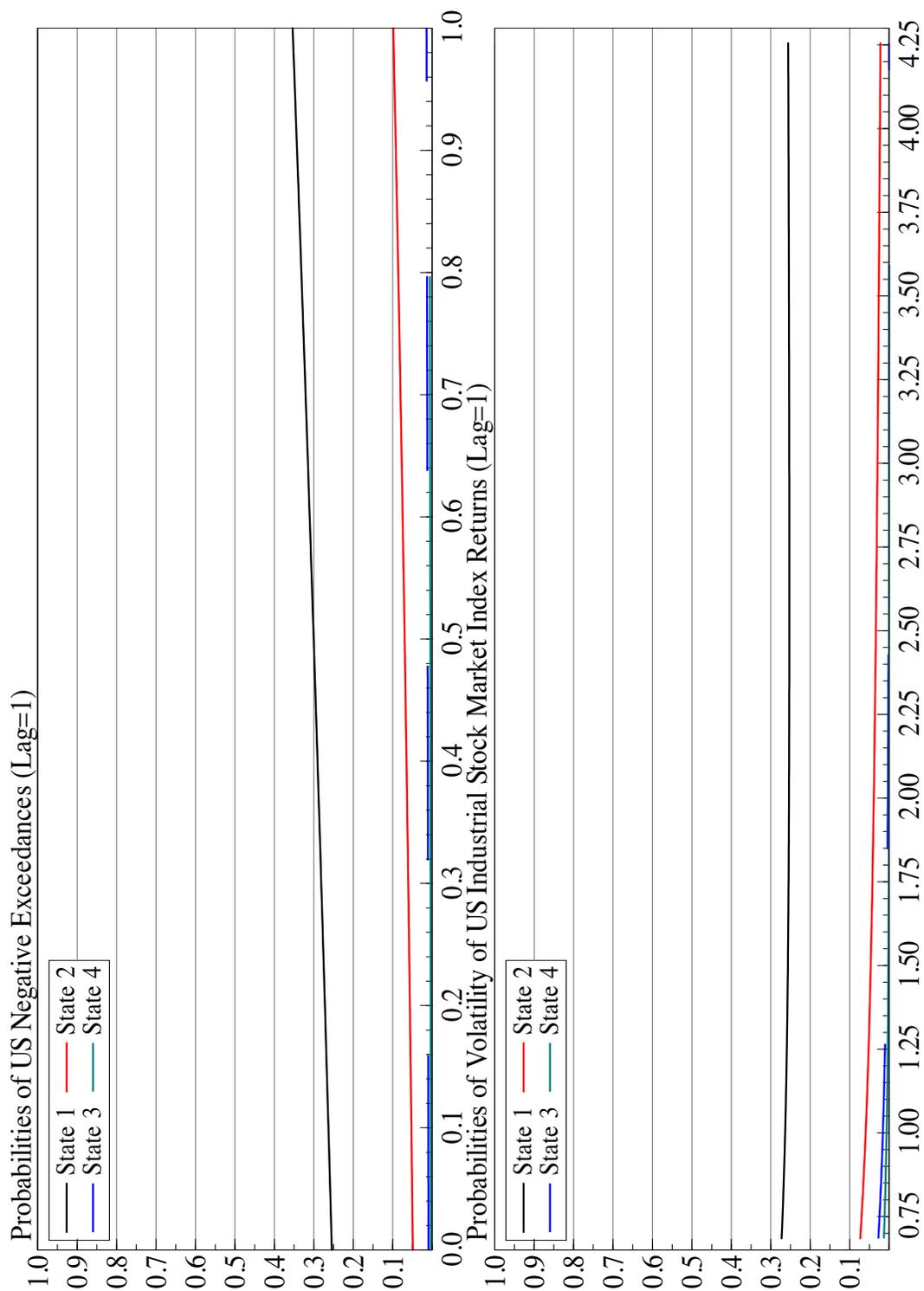


Figure 7. Coexceedance Response Curves of Positive Extreme Returns in EA (Model 4)

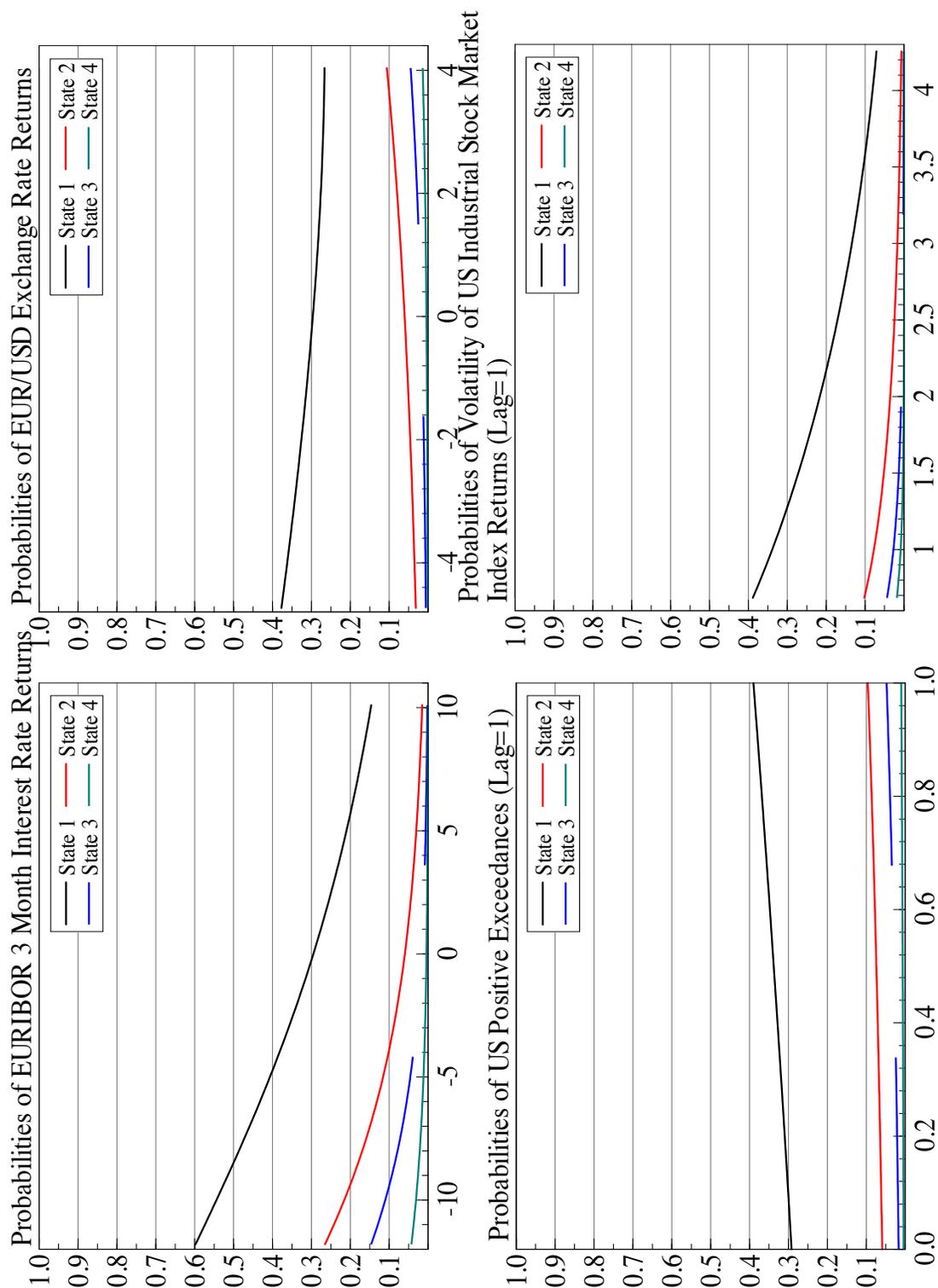


Figure 8. Probabilities of Negative Co-exceedances

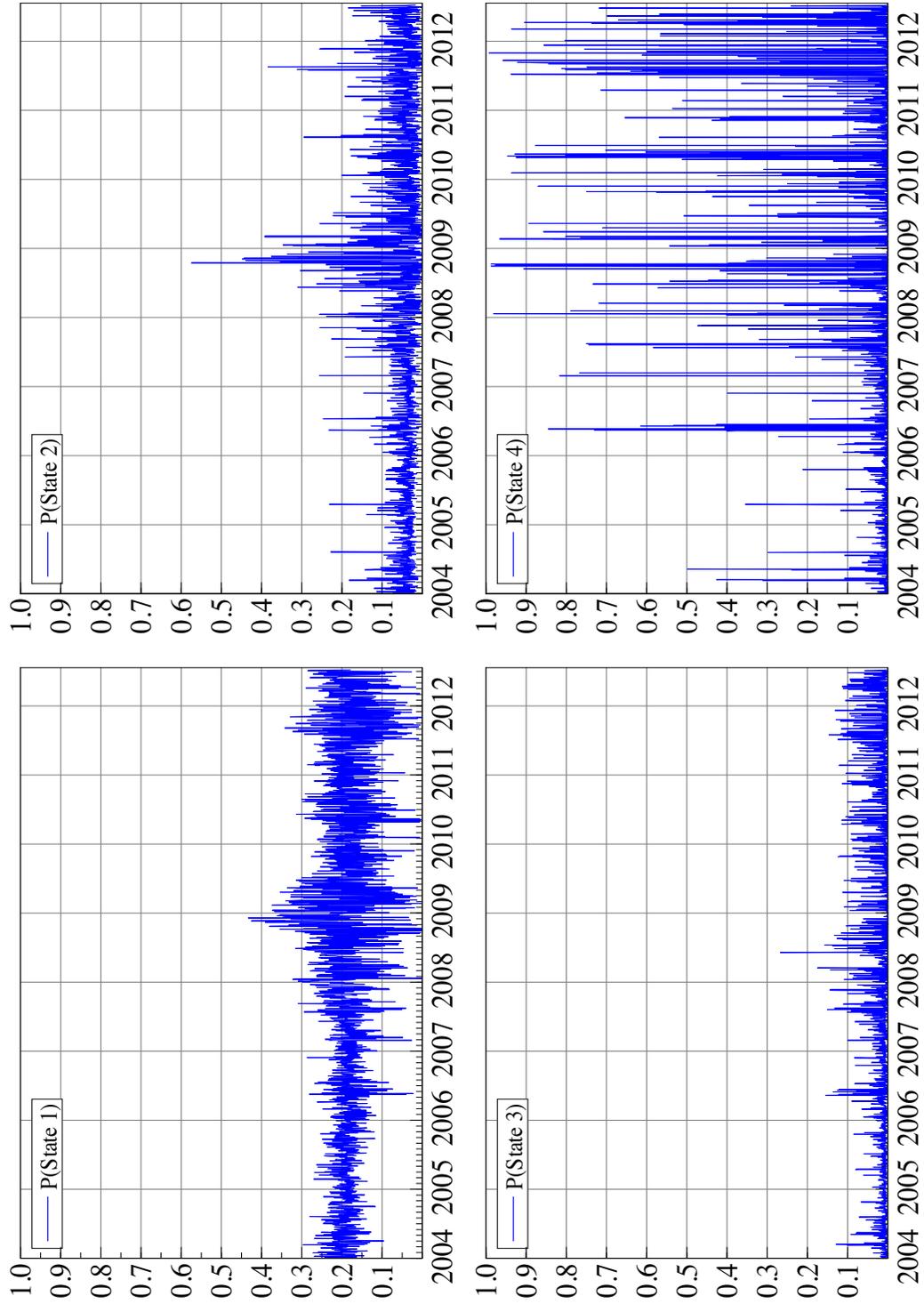


Figure 9. Probabilities of Positive Co-exceedances

