Master Thesis
Quantitative Finance

Analyzing tail dependencies using simple regression models

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Abstract

The Global Financial Crisis shows us the importance of managing the downside risk in the financial market. In this paper we investigate the bivariate and multivariate tail dependence structure across seven international stock markets from North America, Europe and Asia. Van Oordt and Zhou (2012) introduce the linear indicator regression model to investigate the tail dependence structure. However, the amount of parameters to be estimated is very large. Therefore, we introduce two variables selection methods and the logit indicator regression. We apply the variable selection to the data set and then perform the linear and logit regression. We see that the differences between the estimations of the regressions are insignificant. Furthermore, we observe distinction between the stock markets in the multivariate analysis that does not appear from the bivariate analysis. Therefore, we recommend using the logit indicator regression in a multivariate setting. Finally, we find the dependence structure within European markets is stronger than across other markets.

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1 Introduction

The financial crisis in 2007, also known as the Global Financial Crisis (GFC), showed us the inherent risk of investment in the financial market. The bursting of the housing bubble in the US developed into a liquidity crisis in the money-market. These liquidity problems affected the solvency of the banking system which led to the solvency crisis. The fall of Lehman Brothers at 15 September 2008 triggered a banking system crisis. Loss of reputation in money market funds resulted in massive withdrawals. Stock prices drop sharply due to lack of confidence, reinforced by an expected dilution of the equity value as a result of future government participation. Like a domino effect the world economy entered a worldwide financial crisis.[1] One of the reasons that it was global is because the financial markets all around the world are linked. Therefore we should uncover the dependence structure of the worldwide financial markets, particularly in the downturn. In this study, we examine the global tail dependence structure by investigating how and to what extend seven stock market indices in developed countries are linked.

The GFC emphasizes the importance of managing the downside risk for the regulators and financial market participants. In order to minimize and control the probability of extreme events that cause losses, we should probe the tail. We investigate the bivariate and multivariate tail dependence structure across international financial markets. The bivariate models uncover one by one linkage relations, whereas multivariate models uncover the relation across multiple markets. For example, we have three markets X, Y and Z. X does not cause a problem for Z and Y also does not cause a problem for Z. However when X and Y are combined together they can cause a problem for Z. From a bilateral linkage view we will not observe such a structure. We often have a bilateral idea and use a bivariate method to investigate linkages. However, in the GFC we see that it can go beyond bilateral, hence we will consider a multivariate approach.

One work that investigates the extreme linkages in financial markets is carried out by Van Oordt and Zhou (2012). They introduce the linear indicator regression and provide an empirical example on multidimensional tail dependence among international stock markets. The indicator regression measures the tail dependence τ, which is an estimator of the tail dependence structure and can be read as a probability. The estimator using the linear model exactly coincides with the non-parametric estimator under the EVT framework (see e.g. Embrechts et al, 2000). The advantage of this regression method is its simplicity to estimate bivariate and multivariate tail dependencies. This is important since the bivariate tail dependence structure is only an incomplete view of the complex multivariate tail dependence structure. You can straightforward extend the regression for analyzing high-dimensional tail dependencies by adding more explanatory variables into the regression.

The indicator regression given by Van Oordt and Zhou (2012) works if you include all the explanatory variables, but it suffers from a large number of parameters to be estimated. Secondly, the linear indicator regression may have large estimation variance, because the response variable is defined as a binary variable. According to Van Oordt and Zhou (2012), it is possible to reduce the number of parameters by recognizing the cases tail dependence and tail independence. But when using a

[1] For a detailed description of the origin and the dynamic of the global financial crisis we refer to e.g. In het spoor van de crisis (2010), chapter 2. For a discussion of the last crisis we refer to Buiter (2007), Chari et al. (2008), Lane and Milesi-Ferretti (2010), Claessens et al. (2010), Reinhart and Reinhart (2010) and Mishkin (2011) among others.

reduced number of explanatory variables, the theory does not hold and may lead to estimated probabilities outside the range [0, 1]. Therefore, we suggest the logit indicator regression in which we extend the original indicator regression by using a logit model instead of a linear model. Both linear and logit models belong to the general linearized models (GLM). The GLM allows the mean to depend on the linear predictor through a link function and allows the response probability distribution to be any member of the exponential family. The logit model is often used when the explanatory variables are binary and retains the advantage of the linear model. Furthermore, when using variables selection, the tail dependence estimators will still stay within the range [0, 1].

As mentioned before, the indicator regression models have many parameters to be estimated. In case of a large number of variables multicollinearity is likely to occur, due to the definition of the variables. In order to get reliable estimates of the parameters we will use two methods to select the variables. The first method is based on conditional probabilities (CP) and the second method is based on principal components analysis (PCA). The first method groups the dependence structures into four types: full tail dependent, full independent, almost dependent and almost independent (see e.g. Poon et al., 2004) and only select variables that meet certain conditions. This method may have an economical interpretation. The second method is often used to reduce the number of variables, it is more technical and explanatory in statistical sense, but may not have an economic interpretation.

It is not easy to manage the downturns, because we have little observations of the extreme events. However, the development of quantitative methods allows assessing the tail and describing extreme events. Extreme Value Theory (EVT) helps in the modelling of extreme events. The EVT provides a solid theoretical foundation in which we can build statistical models describing tail events. The advantage of EVT is that it treats the upper and lower tails separately, such that it allows skewness in the distribution. However, the EVT only provides information about tail events and does not describe the middle part of the distribution. See Embrechts et al. (1997) for a detailed treatment of EVT, and Embrechts (2000) for a discussion of the potential and limitations of EVT in risk management.

Morgenstern (1959) is the first who studies cross-country financial spillover effects. He explicitly refers to ‘statistical extremes’ of the 23 stock markets and their effects on foreign stock markets. More recent studies continue with the examination of the tail behavior of different financial markets using EVT, see e.g. Streatmans (2000) and Longin and Solnik (2001) for an application on stock market returns; Starica (1999) and Hartmann et al. (2003) for an application on currencies; Hartmann et al. (2004) for an application across two asset classes, namely bonds and stocks. We examine the linkage of international developed stock markets using indicator regression. The sample consists of seven stock markets, comprising the United States of America, the United Kingdom, France, Germany, Italy, Japan and Hong Kong and spans over the period 4 September 1995 to 29 March 2013.

In summary, we find the following results. Firstly, the logit indicator regression works, since it provides close estimated compared to the linear indicator regression. Furthermore, the estimates lie between the probability interval [0, 1]. Secondly, in the multivariate analysis we observe distinction between the stock markets that does not appear from the bivariate analysis. Thirdly, we see that variables selection methods reduce the amount of parameters to be estimated in the model significantly. Finally, we find the dependence structure within European markets is stronger than across the Asian or the American markets.

The remaining part of this paper is organized as follows. Chapter 2 explains the methodology we use in this paper. In this section, the generalized linear models, indicator regression, the method to reduce the number of variables and the method to define the tail will be explained. Chapter 3 describes the data set in detail. In chapter 4 we present the results of the empirical analysis. Finally, chapter 5 outlines our conclusions and discusses the analysis results.

2 Methods

In this chapter, we discuss the definitions and concepts considered in this research. As the aim of this paper is to investigate the bivariate and multivariate tail dependence structure, we will use the indicator regression introduced by Van Oordt and Zhou (2012). The regression model is a regression of the response variable on the explanatory variables and the interaction terms. Due to the definition of the explanatory variables, the correlations are very high and the amount of parameters to be estimated is also very large. Therefore, we propose two methods to select variables, namely selection based on conditional probabilities (CP) and principal components analysis (PCA). Although the number of parameters can be reduced, it imposes another problem. The estimates of the probability could be outside the range [0, 1], because the theory of Van Oordt and Zhou (2012) does not hold anymore. Nevertheless, we can solve this range problem by using the logit model. This model keeps the advantages of the linear model and keeps the estimated probabilities within the probability range [0, 1]. Before performing the regression analysis, we have to define extreme events for estimating the tail dependence and explain how to make up the choice of threshold value k in the quantile function. We introduce a model using z-statistics and a comparison by eyeballing.

We organize the remainder of this chapter as follows. Both the linear and logit model belongs to generalized linear models (GLM), for that reason we start with expounding the GLM theory in general in section 2.1. Afterwards, we explain the application of the linear and logit regression in section 2.2. We also describe how to find the correct standard errors using a bootstrap procedure. Next, in section 2.3, we describe the CP and PCA methods to reduce the explanatory variables. In section 2.4, we continue with the definitions of the tail in this study.

2.1 Generalized linear models

In this section we explain the general idea of GLM. Then, we explain the parameter estimation method. Afterwards, we describe the linear regression model with a normal distribution and the logit model with a binomial distribution.

2.1.1 GLM theory

GLM was first introduced by Nelder and Wedderburn in 1972. The purpose of the GLM approach is to: formulate linear models for a transformation of the mean value by utilizing the link function $g(\cdot)$ and keep the observations untransformed, thereby, preserving the distributional properties of the observations. Thus, the link function gives the relationship between the linear predictor and the mean of the distribution function. The GLM allows the response variable Y to have another distribution other than a normal distribution. However, it assumes each outcome of the response variable to be generated from a particular distribution in the exponential family.

We use η to express the linear combination $X\beta$, where X is the design matrix and β the parameters. It gives the relationship to the expected value of the data through the link function, that is $\eta = g(\mu)$. The canonical link function is the function that expresses the canonical parameters in terms of the mean, that is $\theta = g(\mu)$, where μ is the expected value of Y. Then substitute the parameter θ by the linear combination η. Using the inverse link function we have the following relation:

$$E(Y) = g^{-1}(\eta) = \mu,$$

where $\eta = X\beta$ is the linear predictor and $g(\cdot)$ is the link function.

Summarized, each GLM consist three elements, namely:

- A response variable Y with a distribution belongs to the exponential family with canonical parameter θ.
- A linear predictor $\eta = X\beta$, where β is a set of parameters and X are explanatory variables.
- An invertible link function $g(\cdot)$ which transforms the expectation of the response variable, $E(Y) = \mu$, to the linear predictor $\eta = X\beta$. The inverse of the link function gives the relation $g^{-1}(\eta) = \mu$.

For a detailed theory explanation of GLM, see McCullagh and Nelder (1989). For a more recent text version on GLM, see e.g. Dobson (2001), Madsen and Thyregod (2011).

2.1.2 ML – estimating parameters

One of the most commonly used approaches for the statistical parameters estimation is the method of maximum likelihood (ML). This method is also used for generalized linear models. Consider the observations $Y = y_1, \dots, y_n$ with a joint probability density function $f(y_1, \dots, y_N;\ \theta_1, \dots, \theta_n)$. In general the joint density function will be

$$f(y_1, \dots, y_n|\theta_1, .., \theta_n) = f_1(y_1|\theta_1) * f_2(y_2|\theta_2) \dots f_n(y_n|\theta_n).$$

The density function is denoted by $f(y;\theta)$. The likelihood function

$$L(\theta; y) = L(\theta_1, \dots, \theta_n|y_1, \dots, y_n) = f(y_1, \dots, y_n|\theta_1, \dots, \theta_n) = \prod_{i=1}^{n} f(y_i|\theta_i)$$

means observing the values $y_1, \dots, y_n$ to be fixed and θ will be the variable allowed to vary freely which maximizes the likelihood function. The estimator is often estimated by differentiating the log-likelihood function with respect to each element θ_j of $\theta$and solving the simultaneous equations

$$\frac{\delta l(\theta;y)}{\delta \theta_j} = 0 \text{ for } j = 1, \dots, p.$$

Equivalently it is possible to maximize the log-likelihood function. That is

$$l(\theta; y) = \log L(\theta; y) = f(y_1, y_2, \dots, y_n|\theta_1, \dots, \theta_n) = \sum_{i=1}^{n} f(y_i|\theta_i).$$

It is often easier to work with log-likelihood function than with the likelihood function itself, especially in exponential families, since finding the maximum includes taking the derivative of the function and solving for θ. More specifically, the derivative of a sum is easier to work with than a product.

2.1.3 Normal distribution – linear regression model

Consider a variable Y with normal distribution, mean μ and known variance σ^2 , that is $Y \sim N(\mu, \sigma^2)$. The probability function for Y is given as:

$$f_y = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}(y-\mu)^2)$$

and belongs to exponential family. The link function for a normal distribution is $g(\mu) = \mu$ where $\mu = \eta$, the link name is identity. In this case the link function and mean function gives the same linear regression model. Due to this property the OLS and ML estimation methods give identical results.

2.1.4 Binomial distribution – logit regression model

A binomial model is used to predict the number of successes and failures that we should expect out of a number of independent experiments, the trials. Consider a variable Y with binomial distribution, that is $Y \sim B(np, p(1-p))$. The probability function is given as:

$$f_y = \binom{n}{y} p^y (1-p)^{n-y} ,$$

where p is the probability that an observation equals one (success) and n is the number of trials. When $n = 1$, it gives the Bernouilli distribution. The function belongs to the exponential family. The canonical parameter for the binomial distribution is given as:

$$\theta = g(p) = \log(\frac{p}{1-p}).$$

By replacing the canonical parameter θ by the linear predictor $\eta = X\beta$, we obtain the logit regression model. The inverse link function is the logit function, and hence we may recover the original probability p by

$$p = g^{-1}(\frac{\exp(\eta)}{1+\exp(\eta)}).$$

The Tables 3 and 4 summarize the information of the two distributions above.

Table 1: **Summary of the density, support, mean value and variance for the normal and binomial distribution.**

Normal and binomial distribution				
Distribution	**Support**	**Density**	**E(Y)**	**V(Y)**
Normal $\mathbf{N(\mu, \sigma^2)}$	$\mathbb{R}$ $\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}_+$	$\frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(y-\mu)^2}{2\sigma^2})$	μ	σ^2
Binomial $\mathbf{Bin(n, p)}$	$0, 1, \ldots, n$ $n \in N, p \in [0, 1]$	$\binom{n}{y} p^y (1-p)^{n-y}$	np	$np(1-p)$

Table 2: **Summary of the normal and binomial distribution as an exponential model.**

Exponential model					
Distribution	**Parameter**	**Link function**	**Inverse Link function**	**Unit variance fraction $\mathbf{V_p(\mu)}$**	**Index parameter $\boldsymbol{\lambda}$**
Normal	μ	μ	μ	1	$1/_{\sigma^2}$
Binomial	p	$\log(\frac{p}{1-p})$	$\frac{\exp(\theta)}{1+\exp(\theta)}$	$\mu(1-\mu)$	n

2.2 Indicator regression

In the previous section, we explained the GLM theory, now we provide a detailed description of the application in our study and other methods we used. First, we show some notations of the indicator function. Second, we explain the indicator regression using a linear and logit model with the bootstrap procedure for finding the correct standard error. Subsequently, we explain the method for choice of the threshold k.

2.2.1 Notations and definitions

Let us introduce an indicator function $I_{x,t}$ which converts the sample x with n observations in to a vector consisting of zeros and ones. The t-th ($t = 1, \ldots n$) observation of vector $I_{x,t}$ is one if it is extreme and zero if not extreme. Here is extreme defined as a value smaller than the k-th lowest observations in sample x. The value v is the value of the k-th lowest observation in sample x and can be found by the quantile function $Q\left(\frac{k}{n}\right)$. The probability p that the random variable is less than v is at most $\frac{k}{n}$ and the probability that the random variable will be larger than v is at most $1 - \frac{k}{n}$. In a formula form:

$$I_{x,t} = \begin{cases} 1 & x_t < Q_x\left(\frac{k}{n}\right), \\ 0 & else \end{cases} \quad \textbf{(1)}$$

where $I_{x,t}$ is a binary variable and x_t is the value of observation at time t. With the similar notation for $I_{x,t}$, we have $I_{x\ and\ y,t} = I_{x,t}\, I_{y,t}$:

$$I_{x,t} I_{y,t} = \begin{cases} 1 & x_t < Q_x\left(\frac{k}{n}\right)\ and\ y_t < Q_y\left(\frac{k}{n}\right) \\ 0 & else \end{cases} \quad \textbf{(2)}$$

where $I_{x,t}$ and $I_{y,t}$ are binary variables and x_t and y_t are the values of observation at time t.

Notice that the vector $I_{x,t}$ is idempotent: the sum of the indicator function squared equals to the sum of indicator function itself, since it is a binary variable. In formula:

$$\sum_{t=1}^{n} I_{x,t} I_{x,t} = \sum_{t=1}^{n} I_{x,t}. \quad \textbf{(3)}$$

Furthermore, the notation $y|x_1$ stands for y as the response variable and x_1 as the explanatory variable. The notation overline on the subscript ($\overline{\cdot}$) denotes a scenario with a particular variable not being extreme. For example, $y|x_1\overline{x_2}$ denotes y being the response variable given the explanatory variable x_1 is extreme while x_2 is not extreme.

Moreover, we use S to denote a variable set with s variables, y to denote one variable of S as the response variable and X to denote the explanatory variable set with $m = 2^{s-1} - 1$ variables, that is $s - 1$ variables of S and the interaction terms. In section 3.2.2 we will explain in more detail.

2.2.2 Linear indicator regression

Van Oordt and Zhou (2012) provide an ordinary least squares (OLS) regression approach to estimate the tail dependence measure τ. This measure τ is commonly used to indicate the probability of the strength of the interdependence between the tail events of variables, where the tail event occurs with a low probability. Their research shows that their tail dependency measure τ exactly coincides with the non-parametric estimator (e.g. Embrechts et al., 2000). In case of a pairwise situation, the τ compares the probability of a joint event to that of a tail event of one variable. In elementary probability theory, the formula for dependency between two random variables y and a is:

$$\tau_{y|a} = \lim_{p \to 0} \frac{P\left(y < Q_y\left(\frac{k}{n}\right) and\ a < Q_a\left(\frac{k}{n}\right)\right)}{\frac{k}{n}}$$

$$= \lim_{p \to 0} \frac{P\left(y < Q_y\left(\frac{k}{n}\right),\ a < Q_a\left(\frac{k}{n}\right)\right)}{a\ < Q_a\left(\frac{k}{n}\right)} \quad (4)$$

$$= \lim_{p \to 0} P\left(y < Q_y\left(\frac{k}{n}\right) |a < Q_a\left(\frac{k}{n}\right)\right),$$

where $Q_y\left(\frac{k}{n}\right)$ is the k-th quantile of the distribution y. Since τ is a probability, $0 \leq \tau_{y|a} \leq 1$ must hold. $\tau_{y|a} = 1$ means complete tail dependence and $\tau_{y|a} = 0$ means tail independence. Van Oordt and Zhou (2012) calculate the measure $\tau_{y|a}$ as the ratio between the number of observations in which both y and a are extreme and those in which variable a is extreme and is given by:

$$\tau_{y|a} = \frac{\sum_{t=1}^{n} I_{y\ and\ a,t}}{\sum_{t=1}^{n} I_{a,t}}. \quad (5)$$

The estimator of τ is equivalent to the slope coefficient β of the OLS estimate from the regression. That is, the indicator for extreme values of y is regressed on the indicator for extreme values of a without intercept. The indicator regression model is as follows:

$$I_{y,t} = \beta_a I_{a,t} + \varepsilon_t, \quad (6)$$

where $\beta_a = \tau_{y|a}$ is the non-parametric parameter.

This model can be simply extended to reproduce higher dimensional tail dependence structure. In the paper they provide the example of three-dimensional dependence structure between the response variable y and the explanatory variables a and b, as the regression:

$$I_{y,t} = \beta_a I_{a,t} + \beta_b I_{b,t} + \beta_{a,b} I_a I_b + \varepsilon_t. \quad (7)$$

On the contrary to the studies which focus to the pairwise tail dependence, this regression includes all the interaction among the variables and gives a complete figure on the tail dependence in the multidimensional case. For example, a situation with response variable y and the explanatory variables a and b, where a is extreme and b is not extreme. In a pairwise situation, we can only say something about the estimators $\hat{\tau}_{y|a}$, $\hat{\tau}_{y|\bar{b}}$ and $\hat{\tau}_{a|\bar{b}}$. Using the indicator regression, $\hat{\tau}_{y|a,\bar{b}}$ can be derived as $\hat{\beta}_a \cdot 1 + \hat{\beta}_b \cdot 0 + \hat{\beta}_{a,b} \cdot 1 \cdot 0 = \hat{\beta}_a$. In the case of a and b both being extreme, then $\hat{\tau}_{y|a,b}$ is given by $\hat{\beta}_a \cdot 1 + \hat{\beta}_b \cdot 1 + \hat{\beta}_{a,b} \cdot 1 \cdot 1 = \hat{\beta}_a + \hat{\beta}_b + \hat{\beta}_{a,b}$.

Using the same logic, we are able to extend the indicator regression. Let us give the four-dimensional case as one more example: analyzing the tail dependence between the random variable y and the random variables a, b and c. The number of parameters β is the sum of number of the variables and the number of possible interaction terms. The interaction terms are ab, ac, bc and abc, which leads to 7 variables in total. The indicator regression is as follows:

$$I_{y,t} = \beta_a I_{a,t} + \beta_b I_{b,t} + \beta_c I_{c,t} + \beta_{a,b} I_{a,b,t} + \beta_{a,c} I_{a,c,t} + \beta_{b,c} I_{b,c,t} + \beta_{a,b,c} I_{a,b,c,t} + \varepsilon_t, \quad (8)$$

and leads to the non-parametric estimators:

$\hat{\tau}_{y|a\overline{bc}} = \hat{\beta}_a$, $\hat{\tau}_{y|\bar{a}b\bar{c}} = \hat{\beta}_b$, $\hat{\tau}_{y|\overline{ab}c} = \hat{\beta}_c$,

$\hat{\tau}_{y|ab\bar{c}} = \hat{\beta}_a + \hat{\beta}_b + \hat{\beta}_{ab}$, $\hat{\tau}_{y|a\bar{b}c} = \hat{\beta}_a + \hat{\beta}_c + \hat{\beta}_{ac}$, $\hat{\tau}_{y|\bar{a}bc} = \hat{\beta}_b + \hat{\beta}_c + \hat{\beta}_{bc}$,

$\hat{\tau}_{y|abc} = \hat{\beta}_a + \hat{\beta}_b + \hat{\beta}_c + \hat{\beta}_{ab} + \hat{\beta}_{ac} + \hat{\beta}_{bc} + \hat{\beta}_{abc}$

In general, it is possible to apply the indicator regression for every variables set S, where one variable is the response variable y, and $s-1$ variables plus the interaction terms as the explanatory variables. This leads to $m = 2^{s-1} - 1$ parameters, which is similar to the sum of all possible combinations without repetitions:

$$2^{s-1} - 1 = \binom{s-1}{1} + \binom{s-1}{2} + \cdots + \binom{s-1}{s-1}, \quad (9)$$

where $\binom{i}{j} = \left(\frac{i!}{j!(i-j)!}\right)$ denotes combinations of i variables taken j at a time without repetitions. The complete set of the explanatory variables is denoted by $X = [x_1, \dots, x_m]$, where x_i is a nx1 column.

2.2.3 The bootstrap procedure

To find the correct standard errors for the estimated probability $\hat{\tau}$, we use non-overlapping block bootstrap introduced by Hall (1985). The block bootstrap resamples the data using blocks instead of individual observations. The advantage of this method is keeping the dependency in the data instead of breaking it up. For the optimal block length we follow Hall (1995) and set it equal to $n^{1/3}$, where n is the length of data.

Define the nxm matrix X as the observations of explanatory variables, y as the nx1 vector of response variables and β as the mx1 regression coefficients, where n is the length of the data and m is the number of parameters. The blocks of new data are created by placing consecutive data in blocks with fixed length l. Given the l and n, then the number of possible blocks is $b = \frac{n}{l}$ where n, b and l are all integers. The number of blocks to be drawn is also b. The block bootstrapping method consists in choosing blocks of the response variable $y_1^*, y_2^*, \dots, y_b^*$ and the matching block of regressors $X_1^*, X_2^*, \dots, X_b^*$ by resampling them randomly and replacing them from available blocks $y_1, y_2, \dots, y_b$ and $X_1, X_2, \dots, X_b$. These lead to the new vector y^* and matrix X^*, then we fit the model and obtain the bootstrap regression coefficient estimates $\hat{\beta}^*$. Following, we derive the bootstrap probability estimator $\hat{\tau}^*$ using $\hat{\beta}^*$. Afterwards, we repeat these steps for r times, such that $\hat{\tau}^*$ is a mxr matrix. The correct standard errors of $\hat{\beta}_i$ (for $i = 1, \dots m$) can be calculated as

$$SE(\hat{\tau}^*) = \sqrt{\frac{\sum_{i=1}^{r} \left(\hat{\tau}_i^* - \bar{\tau}^*\right)^2}{r-1}}, \quad (10)$$

where $\bar{\tau}^* = \frac{\sum_{j=1}^{r} \hat{\tau}_j^*}{r}$, for $j = 1, \dots,$.

According to Efron and Tibshirani (1993) bootstrap with 1000 replications are in general accurate and using bootstrap replications of 2000 times should be very precise to calculate the standard errors. We choose to estimate the standard error by using 2000 times replications of the data set.

2.2.4 Logit indicator regression

In the last section we described the indicator regression model using OLS, Van Oordt and Zhou (2012) argue the indicator regression is a projection of the non-parametric measure τ. Since the response variable y is a binary variable, a logit model is more common. The variable y has a Bernoulli distribution which is a special case of the binominal distribution with $y \sim B(1, p)$. The expectation of y is p and the variance is $p(1-p)$. Because the variance depends on the expectation, the variable y may have heteroscedasticity. In addition, the estimated probabilities of the full linear model are within the range [0, 1] according to the theory, but suffer from a dimensional curse and may have multicollinearity. When we reduce the number of variables, it should still represent the tail dependencies well, but do not guaranty that the estimators are within the range [0, 1]. Since the logit model is possibly a solution to these problems, we suggest this regression model.

For a bivariate case, we start with a linear model η, using the inverse link function we obtain the probability p which equals to the measure $\tau_{y|a}$. In formula:

$$\eta = c + \beta_a I_{a,t} \tag{11}$$

and

$$p = g^{-1}\left(\frac{\exp(\eta)}{1 + \exp(\eta)}\right). \tag{12}$$

Similarly to the linear model, the logit model can be extended by using more parameters. To find the correct standard errors of the estimators, we use the same bootstrap procedure as the linear indicator regression model. That is we bootstrap the response and explanatory variables, then we derive the corresponding estimators. Afterwards we calculate the standard errors.

2.2.5 Comparing two tail dependencies

A sub-question of this study is the difference between the estimated probabilities by the linear and logit model. To find out the answer, we use bootstrap technique to do a simulation and the t-test to compare. First, we use bootstrap (described in section 3.2.3) to generate new data. Then, we estimate both probabilities using the same sample. This avoids dependency problems. Next, we estimate the difference between the probabilities. Afterwards, we repeat these steps for r replications to estimate the mean and standard deviation. As for the null hypothesis we assume that the probabilities of the two models do not differ. In formula:

$$H_0: \delta = 0$$

$$H_a: \delta \neq 0 \tag{13}$$

$$t = \frac{\bar{\delta}}{s(\hat{\delta})},$$

where $\delta = \tau_{lo} - \tau_{li}$ equals the difference between the probability derived by the logit (τ_{lo}) and linear model (τ_{li}). $\bar{\delta}$ and $s(\hat{\delta})$ is the average and the standard deviation of the difference between the estimators for r replications respectively. Note that the t-statistic follows an asymptotic normal distribution if the number of observation is large.

2.3 Reducing the number of variables

In the last sections, we described the indicator function, the regression models and defined the matrix of explanatory variables X. In this section, we discuss the reduction of the number of explanatory variables.

The indicator regression may have a problem. In high dimensional cases it may suffer from the large numbers of parameters to be estimated. For $s-1$ explanatory variables we have $2^{s-1}-1$ parameters to be estimated. Some variables possibly highly correlated with each other, due to the definition of the explanatory variables. A high correlation between the explanatory variable raises the variance in estimations of the regression parameters. This problem is known as multicollinearity, when two or more explanatory variables in the model are approximately determined by a linear combination. As a result, the information of at least one variable is almost comprised by the other variables. The degree of the problem varies and has different effects on the model. If there is a perfect multicollinearity, then it is impossible to obtain a unique estimate of regression coefficients with the entire explanatory variables in the model.

The choice of explanatory variables can be made up by performing different tests and argumentation. In this study, we will introduce two methodologies. We call the first method the conditional probability method (CP), in which we check the cases (almost) dependent and independent by calculating the conditional probability of each explanatory variable in bivariate case and decide whether a variable should be included. The second method makes use of a Principal Components Analysis (PCA) to reduce the variables. Hence we end up with four estimates, namely the linear and logit models with variables selected by CP and the models with variables selected by PCA.

2.3.1 Conditional Probability

In this method, we compute the conditional probability of each bivariate case. Consider the explanatory variables x_1 and x_2 with the indicators I_{x_1} and I_{x_2}, where x_1 is a cross product of x_2 and another variable. For example $x_1 = abcd$ and $x_2 = abc$. The variables I_{x_1} and I_{x_2} each follow a binomial distribution $B(k, p)$, where it is one if it is extreme and zero if it is not extreme, k is the sum of the number of extremes, n is the number of observations and $p = \frac{k}{n}$ is the tail. The conditional probability $\Pr(I_{x_1} | I_{x_2})$ can be computed as $\frac{\Pr(I_{x_1})}{\Pr(I_{x_2})}$, where $\Pr(I_x) = p$.

There are few cases possible to reduce the number of parameters, namely when the two variables x_1 and x_2 are full tail dependent, full independent, almost dependent and almost independent.[2] In the first case, we can leave out the interaction term of the variables, since

$$\Pr(I_{x_1} | I_{x_2}) = 1, \quad \textbf{(14)}$$

with

[2] In literature the dependence structures are often divided in four groups: independent, perfect dependent, asymptotic independent and asymptotic dependent, e.g. Poon et al. (2004).

$$\Pr\left(I_{x_1}\right) = \Pr(I_{x_2}).$$

Thus all variables containing the cross product x_1 can be deleted, because x_2 already contains all the information. In the second case, the interaction between the variables is zero, since it is independent. Thus all the interaction terms that include cross product x_1 can be omitted from the indicator regression. Notice that if the variables x_1 and x_2 are completely independent, there is still a probability to have joint crash present. The expected number of joint crash according to the binomial distribution is

$$E\left(\sum\nolimits_{t=1}^{n} I_{x_1}\right) = kp, \quad \textbf{(15)}$$

with a variance of

$$V\left(\sum\nolimits_{t=1}^{n} I_{x_1}\right) = kp(1-p).$$

In case of almost dependent case, we assume $p = 0.1$, and then we take the 95% quantile of the binomial distribution $B(k, p = 0.1)$ of variable x_2, where we denote this value as q. Afterwards, we exclude the variable I_{x_1} if the probability of joint crash is less than the tail probability under assumption. In formula:

$$\begin{cases} exclude\ variable\ I_{x_1} & if\ \Pr(x_1) \leq \Pr\left(\frac{q}{k}\right) \\ include\ variable\ I_{x_1} & if\ \Pr(x_1) > \Pr\left(\frac{q}{k}\right) \end{cases}. \quad \textbf{(16)}$$

For the case almost independent, we can make the same derivation with assumption $p = 0.9$ and find the 5% quantile of the $B(k, p = 0.9)$. We exclude the variable the probability of joint crash is more than the tail probability under assumption. In formula:

$$\begin{cases} exclude\ variable\ I_{x_1} & if\ \Pr(I_{x_1}) \geq \Pr\left(\frac{q}{k}\right) \\ include\ variable\ I_{x_1} & if\ \Pr\left(I_{x_1}\right) < \Pr\left(\frac{q}{k}\right) \end{cases}. \quad \textbf{(17)}$$

We apply this derivation for all cross products of the explanatory and will results in a new matrix X.

2.3.2 Principal Components Analysis

On contrary to the previous selection method the principal component analysis is a commonly used technical analysis to reduce the number of variables, which make use of spectral decomposition. It transforms an original set of variables into a smaller set of uncorrelated variables and tries to capture as much information in the original data set by using a few uncorrelated linear combinations of the original variables. The idea is invented by Pearson (1901) and independently developed by Hotelling (1933). For a detailed description of the PCA technique and selection of variables see for example Dunteman (1989).

PCA is based on a spectral decomposition of a covariance matrix or a correlation matrix. In this study we use the covariance matrix, which is computed by:

$$V = n^{-1}X'X, \quad \textbf{(18)}$$

where X is the explanatory variables to be analyzed. The decomposition is:

$$V = W\boldsymbol{\Lambda}W', \qquad \textbf{(19)}$$

where W is the eigenvectors matrix and Λ is the eigenvalues. Note that each eigenvector can be expressed as a linear combination of the originals variables. If the combination assigns a relatively high absolute weight to an original variable, we say that the original variables 'loads' on the eigenvector.

The total variance in X is the sum of the eigenvalues Λ, while the proportion explained by the k-th principal component is

$$\frac{\lambda_k}{\lambda_1+\lambda_2+\cdots+\lambda_m}. \qquad \textbf{(20)}$$

We order the eigenvalues Λ and their corresponding eigenvectors W from the largest to smallest, thus $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$ such that the first eigenvalues explains the largest variance of X, etc. Therefore, we are interested in the lowest eigenvalues. When an eigenvalue of the covariance matrix is very small (smaller than 0.002, say), it means that an eigenvector has nearly zero variance, and thus indicates the existence of a very strong linear dependence among the variables loading on this vector. This dependence may be remedied by removing any one of the loading variables, the one which loads highest.

2.4 The definition of tail

In the sections 3.1 to 3.3 we explained the linear and logit regressions models and the reduction of the regressors. In this section we describe the method to find the optimal k for the indicator regression. The k-lowest observations in the sample define the left tail, we make use of it in the quantile function to determinate which observation is extreme. There is a trade-off between bias and variance. On the one hand a low k leads to an unbiased (or low bias) estimator, but often have a high variance; on the other hand a higher k will results in lower variance but a higher bias. We need to find a stable number k, such that these are minimized.

2.4.1 Using z-statistics

Consider the pairwise situation (bivariate), given a response variable y and an explanatory variable a. We derive the estimator $\hat{\beta}_a$ in $I_{y,t} = \beta_a I_{a,t} + \varepsilon_t$ for all possible k in $Q\left(\frac{k}{n}\right)$, $k = 1, \dots, n$. We expect the beta will be unstable for the relative small k, then being stable for some k and will increase again as k increase. In the Figure 1 we give an example of $\hat{\beta}_a$. We see that the $\hat{\beta}_a$ varies a lot before a certain k, after that it becomes stable.

To determine for which k $\hat{\beta}_a$ is stable, we will apply a linear regression with rolling window and apply z-test for testing the coefficient of k is zero. That is, we regress $\hat{\beta}_a$ on k with $k = 1, \dots, w$, where w is the window length, and then we calculate the z-statistics. Afterwards we move on to the next window $k = 2, \dots, w+1$, derive z-statistics and repeat the steps until $k = n - w + 1, \dots, n$.

If the absolute value of z-statistics is small, then the null-hypothesis is rejected. There is significance evidence that the estimator $\hat{\beta}_a$ is not zero. In other words, the explanatory variable k has some relationship with the response variable $\hat{\beta}_a$. The choice of the window depends on the data length and the expectation of the tail. The higher the window length and the z-statistics are not significant, the stable $\hat{\beta}_a$ is. In formula:

$$\hat{\beta}_a = \alpha_0 + \alpha_1 k + \varepsilon$$

$$H_0: \alpha_1 = 0$$

$$Ha: \alpha_1 \neq 0 \qquad \textbf{(21)}$$

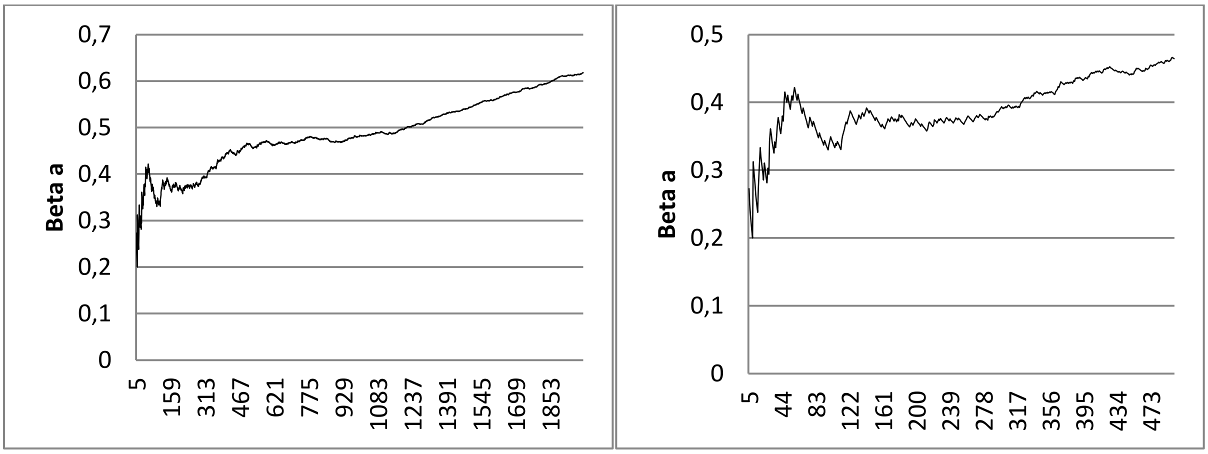
$$z = \frac{\hat{\alpha}_1}{SE(\hat{\alpha}_1)},$$

where

$$SE(\hat{\alpha}_1) = \sqrt{\frac{\frac{1}{n-2}\sum_{t=1}^{n} e_i^2}{\sum_{t=1}^{n}(k_i - \bar{k})^2}}.$$

In our case we will use a window with length 100, 200 and 300, such that we can compare the difference in the choice of k.

Figure 1: **Left - example plot of the $\hat{\beta}_a$ against k. Right – zoomed in version of the same plot.**



2.4.2 Extension of data variables

In previous pairwise situation, there are only two variables: one response variable and one explanatory variable. In case we have a data set S, we may want to explore the effect of each variable on the other. We have s possible response variable and each has $s - 1$ explanatory variable. Thus there are s x $(s - 1)$ situations. To compare the results, we choose for a common k such that $\hat{\beta}_a$ is stable for each pair. To find an optimal k for data set S, we do the regression (formula 6) for each possible y and derive the corresponding z-statistics as described in formula 21. Then take the absolute of the z-statistics, sum up these over each row for every y and sum over these rows again. This results in a n x 1 vector, let say the vector ss. The first local optimum is the best trade-off between the bias and variance – desired threshold k.

2.4.3 Comparison by eyeballing

In order to check the founded optimal solution k, we will plot the tail dependency estimates $\hat{\beta}_a$ as a function of k and select k in a stable region. This method follows the same reasoning of Hartmann et al. (2010) that is used in their proposed plotting method. Hartmann et al. (2010) argue that it should be possible to graphically detect the optimal solution because the expectational linkage estimator will consistently display the same bias-variance trade off. This reasoning builds on the theorizing of Goldie and Smith (1987) who, in the development of the asymptotic mean squared error (AMSE), state that it should be possible to identify the optimal threshold by plotting the estimators as a function of the higher order statistics, because one would find a stable area in which the optimal threshold will be located.[3]

[3] Danielsson et al. (2001) proposed the double bootstrap techniques to choose the optimal number of extreme order statistics. However, Hartmann et al. suggest that this method is only advisable for really large sample data set.

3 Data

Our data consists of the daily closing stock index levels of the S&P 500 from the United States, FTSE 100 from the United Kingdom, CAC 40 from France, DAX 30 from Germany, FTSE MIB from Italy, Nikkei 225 from Japan and HSI from Hong Kong.[4] The data was obtained from Bloomberg and spans over the period 4 September 1995 to 29 March 2013 (4,586 daily observations). The index of Italy was created by grafting two return series from the same country, that is returns are presented by MIBTEL before 31 December 1997, and the FTSE MIB returns after that date. The daily returns are calculated as log differences of the stock index.

The countries comprising United States of America, United Kingdom, France, Germany, Italy, Japan are also known as the Group of Six (G6). The G6 began in 1975 as a forum for the governments of the world's wealthiest countries (as net wealth and GDP). In addition we add Hong Kong to investigate the relation between the Asian market and the markets in major developed countries.

In the Table 1, we present the descriptive statistics. The average mean of the stock market returns over the seven countries is 0.013% and the median is 0.018%. The average stock market return of Japan is negative in this period. The absolute value of the minimum and maximum stock market return is highest for Hong Kong, on 28 and 29 October 1997 respectively during the Asian crisis. The skewness of the stock market returns is negative except for Hong Kong. A negative skewness points out a longer left tail, with the mass concentration at the right from the median. The table shows that all returns have considerable excess kurtosis which point to a peak in the center of the return distribution and heavy tails. The skewness and kurtosis together point out a non-normal distribution of the returns.

Table 2 reports the correlations between the seven stock market returns, each pair of stock markets have a positive correlation. The correlations within the European stock market are higher than the correlations between any European stock market and the US's stock market. For example, the correlations within the block UK, France, Germany and Italy are around 0.8, but the correlations between the US and the European block are only at a level around 0.5. The correlations between Asian block, which is Japan and Hong Kong, and the other five markets are the weakest. For example, the correlation between the US's and French stock market is 0.532, while the correlation between US's and Japanese stock market is only 0.112.

[4] In this research, we will use the following notation for the stock markets of the corresponding countries: United States of America – US; United Kingdom – UK; France – FR; Germany – GE; Italy – IT; Japan – JP; Hong Kong – HK.

Table 3: **Descriptive table of the seven stock market returns, defined as log differences of the stock index. The stock market indices are S&P500, FTSE100, CAC40, DAX30, FTSE MIB, Nikkei225 and HSI. The sample period spans over the period 4 September 1995 to 29 March 2013 (4,586 daily observations). The returns are notated in percentage.**

Summary statistics of stock returns							
	US	**UK**	**FR**	**GE**	**IT**	**JP**	**HK**
Mean	0.022	0.013	0.015	0.027	0.001	-0.008	0.019
Median	0.028	0.008	0.007	0.065	0.019	0.000	0.000
Std	1.255	1.207	1.481	1.541	1.519	1.492	1.689
Min	-9.470	-9.266	-9.472	-8.875	-8.599	-12.111	-14.735
Max	10.957	9.384	10.595	10.797	10.874	13.235	17.247
Skewness	-0.226	-0.154	-0.014	-0.118	-0.078	-0.295	0.092
Kurtosis	10.826	8.897	7.564	7.297	7.371	9.309	13.324

Table 4: **The correlation matrix of the seven stock market returns, defined as log differences of the stock index. The stock market indices are S&P500, FTSE100, CAC40, DAX30, FTSE MIB, Nikkei225 and HSI. The sample period spans over the period 4 September 1995 to 29 March 2013 (4,586 daily observations).**

Correlation of stock returns							
	US	**UK**	**FR**	**GE**	**IT**	**JP**	**HK**
US	1.000	0.508	0.532	0.557	0.490	0.112	0.176
UK	0.508	1.000	0.859	0.784	0.773	0.288	0.367
FR	0.532	0.859	1.000	0.855	0.856	0.283	0.345
GE	0.557	0.784	0.855	1.000	0.779	0.259	0.353
IT	0.490	0.773	0.856	0.779	1.000	0.247	0.310
JP	0.112	0.288	0.283	0.259	0.247	1.000	0.514
HK	0.176	0.367	0.345	0.353	0.310	0.514	1.000

4 Results

In this chapter, we present the results of the methods described in chapter 2. Section 4.1 presents the tail order statistics k. Section 4.2 describes the results of the bivariate tail dependencies. Section 4.3 and 4.4 describe the results of the multivariate tail dependencies using variables selected by conditional probability and principal component analysis respectively. For brevity, we will use the country name to refer to the corresponding stock market for the remaining part of this paper.

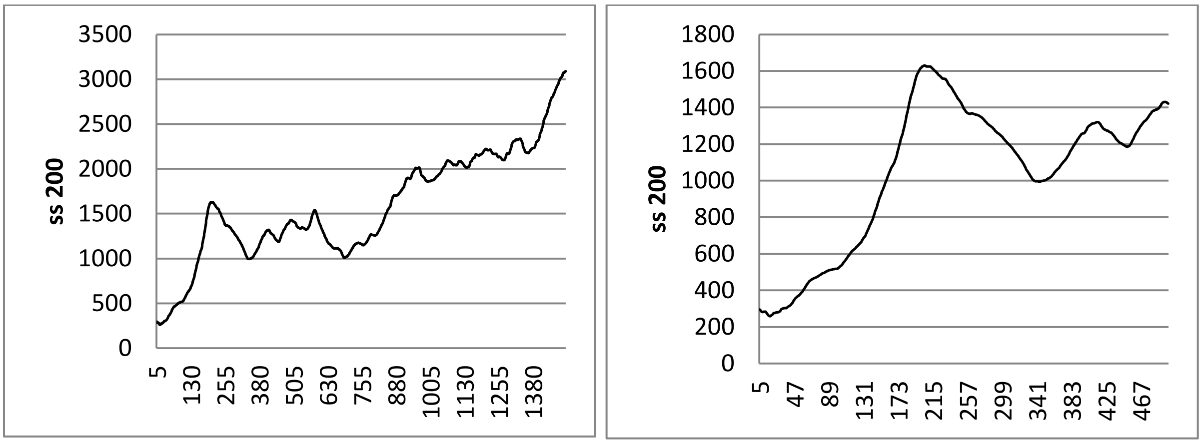
4.1 The definition of tail

Figure 2 presents the pairwise combinations of $\hat{\beta}_{US}$ against k, that are the combinations US with UK, France, Germany, Italy, Japan and Hong Kong. We see that the $\hat{\beta}_{US}$ fluctuates when k is low. In the Appendix A Figures 5 - 10, we presents the plots of the other six stock markets as the response variable.

For the choice of k we use the method of z-statistics presented at section 2.4. The window lengths we used are 100, 200 and 300, that is 2.2%, 4.4% and 6.5% of the total data respectively. The plots of the vector ss against k with window length 200 are presented in Figure 3 and Appendix A Figures 11 and 12 present the plots with window length 100 and 300 respectively. The first local maximum value for $w = 200$ is $k = 205$ (4.5%). For $w = 100$ it gives $k = 256$ (5.6%) and for $w = 300$ it gives $k = 197$ (4.3%). The optimal value k for window with length 200 and 300 are close, in terms of percentage it is almost the same, and therefore, we decide to use $k = 205$ to define the tail.

Figure 2: **Plot of the $\hat{\beta}_{US}$ against k for all pairwise combination with the US (see section 2.2.2).**

Figure 3: **Plot of the ss against k with window length $w = 200$ (see section 2.4.2). The optimal threshold value $k = 205$.**



4.2 Bivariate tail dependence

Tables 5 and 6 present the estimates of the pairwise tail dependence using the linear and logit model for the seven international stock markets as described in section 2.2. Table 7 reports the correlations between the stock markets. The interpretation of the number is the estimated conditional probability $\hat{\tau}$ with the standard error in the parenthesis. The standard error is based on a bootstrap with 2000 replications. For example $\hat{\tau}_{FR|GE} = 0.663$, this can be interpreted as the estimated probability of France is extreme given Germany is extreme is 66.3% with a standard error of 3.8% in a bivariate situation.

The results on pairwise tail dependence suggest that the group of seven stock markets can be divided in three blocks. The first block represents the US's stock market; the second block consists of the European stock markets: UK, France, Germany and Italy; the third block represents the Asian stock markets: Japan and Hong Kong. The link within each block is strongest and the link between blocks differs. For example, the results on pairwise tail dependence suggest that the European stock market suffers the least co-crashes with the two Asian stock markets, while the tail dependence with the US's stock market is higher, but strongest within the group.

The difference in pairwise tail dependence estimates between the linear model and the logit model are not significant. In most cases the standard errors of logit model are slightly smaller, but these differences are also not significant. The correlations of the stock markets and the tail dependence estimates have the same order in magnitude, but the correlations are smaller in all cases. For example, the tail dependence estimate between French and German stock markets is 0.663, while the correlation is 0.648.[5]

[5] Researchers point out that U.S. is a leading market and also has the latest closing market on a day, hence influence of the U.S. on other markets are likely on the following day (e.g. Martens and Poon, 2001). We compared the correlation and the bivariate results between the U.S. and the other countries with and without a lag, but our results differ in finding no significant effects. This is in line with the findings of for example Poon et al. (2004) and Savva et al. (2009). Therefore, we continue this study without returns synchronization.

Table 5: **Bivariate tail dependence results of the linear indicator regression (see section 2.2). The standard errors are presented in parenthesis.**

	Bivariate tail dependence – Linear model						
	US	**UK**	**FR**	**GE**	**IT**	**JP**	**HK**
US	-	0.376	0.361	0.366	0.346	0.122	0.137
		(0.035)	*(0.036)*	*(0.036)*	*(0.033)*	*(0.024)*	*(0.028)*
UK	0.376	-	0.644	0.590	0.561	0.215	0.268
	(0.038)		*(0.035)*	*(0.039)*	*(0.041)*	*(0.032)*	*(0.035)*
FR	0.361	0.644	-	0.663	0.639	0.210	0.263
	(0.038)	*(0.035)*		*(0.038)*	*(0.039)*	*(0.034)*	*(0.040)*
GE	0.366	0.590	0.663	-	0.556	0.195	0.244
	(0.036)	*(0.038)*	*(0.035)*		*(0.040)*	*(0.030)*	*(0.034)*
IT	0.346	0.561	0.639	0.556	-	0.171	0.254
	(0.034)	*(0.038)*	*(0.039)*	*(0.041)*		*(0.036)*	*(0.041)*
JP	0.122	0.215	0.210	0.195	0.171	-	0.356
	(0.204)	*(0.032)*	*(0.035)*	*(0.032)*	*(0035)*		*(0.043)*
HK	0.137	0.268	0.263	0.244	0.254	0.356	-
	(0.029)	*(0.037)*	*(0.042)*	*(0.043)*	*(0.044)*	*(0.043)*	

Table 6: **Bivariate tail dependence results of the logit indicator regression (see section 2.2). The standard errors are presented in parenthesis.**

	Bivariate tail dependence – Logit model						
	US	**UK**	**FR**	**GE**	**IT**	**JP**	**HK**
US	-	0.376	0.361	0.366	0.346	0.122	0.137
		(0.035)	*(0.037)*	*(0.037)*	*(0.033)*	*(0.024)*	*(0.028)*
UK	0.376	-	0.644	0.590	0.561	0.215	0.268
	(0.038)		*(0.035)*	*(0.039)*	*(0.041)*	*(0.033)*	*(0.035)*
FR	0.361	0.644	-	0.663	0.639	0.210	0.263
	(0.038)	*(0.035)*		*(0.038)*	*(0.039)*	*(0.035)*	*(0.041)*
GE	0.366	0.590	0.663	-	0.556	0.195	0.244
	(0.036)	*(0.038)*	*(0.035)*		*(0.040)*	*(0.030)*	*(0.034)*
IT	0.346	0.561	0.639	0.556	-	0.171	0.254
	(0.034)	*(0.038)*	*(0.039)*	*(0.041)*		*(0.036)*	*(0.042)*
JP	0.122	0.215	0.210	0.195	0.171	-	0.356
	(0.204)	*(0.032)*	*(0.035)*	*(0.033)*	*(0035)*		*(0.044)*
HK	0.137	0.268	0.263	0.244	0.254	0.356	-
	(0.029)	*(0.038)*	*(0.042)*	*(0.043)*	*(0.044)*	*(0.043)*	

Table 7: **Correlations of the indicator variables .**

	Correlation of the indicator variables						
	US	**UK**	**FR**	**GE**	**IT**	**JP**	HK
US	1.000	0.346	0.331	0.336	0.316	0.081	0.096
UK	0.346	1.000	0.627	0.571	0.540	0.178	0.234
FR	0.331	0.627	1.000	0.648	0.622	0.173	0.229
GE	0.336	0.571	0.648	1.000	0.535	0.157	0.209
IT	0.316	0.540	0.622	0.535	1.000	0.132	0.219
JP	0.081	0.178	0.173	0.157	0.132	1.000	0.326
HK	0.096	0.234	0.229	0.209	0.219	0.326	1.000

4.3 Multivariate tail dependence with selected variables by CP

In this section, we present the results of the indicator regression (section 2.2). The set of explanatory variables is reduced by the conditional probabilities method (2.3.1), the standard errors are based on a block bootstrap with 2000 replications. The corresponding results are presented in the Table 8 and Tables 10-15 (Appendix B).

After applying the variables selection method there is on average 34 variables left, where the US is an outlier with 43 explanatory variables for the regression. The variables 'US, JP' and 'US, HK' are excluded in all cases due to near tail independency, which means that in each regression 25 variables are omitted. The variable 'FR, GE, IT' for instance is excluded due to near tail dependency with 'GE, IT'. Reduction of such variables are as expected since it is an interaction term of European markets and the correlation within Europe is strong.

Most of the estimated linear probabilities are within the range [0, 1], however sometimes it violates the boundaries. This problem is caused by reduction of the original variables, such that the linear indicator regression theory does not hold. For example, the linear probability estimation of US (Table 10) consists five times negative probabilities. The estimated probability $\hat{\tau}_{US|UK,\overline{FR},\overline{GE},IT,JP,HK} = -0.190$ is negative due to a relative large negative coefficient $\hat{\beta}_{UK,IT,JP,HK} = -0.614$ compared to the other coefficients.

The t-statistics indicate that the difference between linear and logit model are only significant for a few cases with UK or Germany as the response variables. The t-statistics are insignificant for all situations with other five markets as response variable. For example, the t-statistic for Germany as the response variable given Italy is extreme and the others not is -2.747, that means the linear estimates are larger than the logit estimates at 5% significant level. Hence, the estimates using the logit model are close to the estimates using the linear model. Moreover, the logit model has the advantage that the estimates are always within the range [0, 1].[6]

We discuss the UK (Table 8) as an example in more details. The influence of UK on US using the linear model (0.293, Table 10) is larger than the reverse case US on UK (0.116), given other markets are not extreme. In both cases the bivariate estimates gives 0.376. Thus, from a bivariate view the influence across two markets are equal, but may differ in a multivariate situation.

In case of linear model the estimated probability of UK being extreme given a single market is extreme is the highest for France (0.249), followed by Germany (0.184) and US (0.116). In contrast, the estimated probability that UK is extreme given Japan or Hong Kong is extreme is less than 5%. Remarkable is the scenario where UK suffers from France, Japan and Hong Kong is extreme is only 4%, far below the 25% of France only.

The scenario where UK suffers from France, Italy and Hong Kong is 0.937, while the scenario where UK suffers from France, Germany and Japan is 0.547. We see that the link of UK with Italy is much

[6] For the fit of the logit model, we used the algorithm Iterative Reweighted Least Squares (IRLS). The logit model does not converge after 200 iteration steps except for Japan and Hong Kong as response variable. We do not expect the model will converge after increasing of the iteration steps, since this may be caused by other problems. A possible explanation is that multicollinearity still exists among the set of explanatory variables after applying the CP method. However, the multicollinearity should be less compared to the original set of variables.

stronger than the link of UK with Germany. Conversely, the link of UK with Italy (0.561) has the same magnitude compared to the link of UK with Germany (0.590) in the bivariate analysis. Hence, from the multivariate analysis we observe a distinction between Italy and Germany that does not appear from the bivariate analysis.

The difference between the estimated probabilities of the two models is in general insignificant. However, the difference for UK is extreme given only US, France or Italy is extreme is significant at the 5% level. These t-statistics are negative, thus the estimates of the linear model are larger than the estimates of logit model.

Table 8: Results of the multivariate indicator regression using linear and logit model with response variable UK. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%.

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,906	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,007	*0,001*	
$\widehat{\beta}_{US}$	0,116	2,499	$\hat{\tau}_{UK\mid US,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,116	*0,029*	0,083	*0,027*	-2,886**
$\widehat{\beta}_{FR}$	0,249	3,403	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,249	*0,070*	0,182	*0,068*	-2,269**
$\widehat{\beta}_{GE}$	0,184	3,313	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,184	*0,069*	0,169	*0,069*	-0,774
$\widehat{\beta}_{IT}$	0,086	1,924	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,086	*0,040*	0,048	*0,031*	-2,129**
$\widehat{\beta}_{JP}$	0,038	1,433	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,038	*0,018*	0,030	*0,014*	-1,413
$\widehat{\beta}_{HK}$	0,049	1,677	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,049	*0,023*	0,038	*0,018*	-1,539
$\widehat{\beta}_{US,FR}$	0,103	-0,332	$\hat{\tau}_{UK\mid US,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,467	*0,203*	0,660	*0,242*	1,392
$\widehat{\beta}_{US,GE}$	-0,109	-2,768	$\hat{\tau}_{UK\mid US,\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,191	*0,120*	0,135	*0,122*	-0,488
$\widehat{\beta}_{US,IT}$	-0,377	-3,956	$\hat{\tau}_{UK\mid US,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	-0,176	*0,162*	0,012	*0,038*	1,430
$\widehat{\beta}_{FR,GE}$	0,023	-1,870	$\hat{\tau}_{UK\mid\overline{US},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,455	*0,104*	0,485	*0,114*	0,614
$\widehat{\beta}_{FR,IT}$	0,160	-0,033	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,495	*0,106*	0,596	*0,129*	1,791*
$\widehat{\beta}_{FR,JP}$	0,152	-0,137	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,439	*0,354*	0,448	*0,325*	0,650
$\widehat{\beta}_{FR,HK}$	-0,021	-1,967	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,277	*0,453*	0,143	*0,399*	0,517
$\widehat{\beta}_{GE,IT}$	0,044	-0,934	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,314	*0,101*	0,354	*0,119*	0,112
$\widehat{\beta}_{GE,JP}$	-0,086	-1,598	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	0,135	*0,168*	0,147	*0,158*	0,275
$\widehat{\beta}_{GE,HK}$	-0,170	-2,573	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,063	*0,228*	0,077	*0,169*	0,126
$\widehat{\beta}_{IT,JP}$	0,069	-0,251	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,192	*0,255*	0,142	*0,262*	0,281
$\widehat{\beta}_{IT,HK}$	0,192	0,499	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,327	*0,191*	0,309	*0,211*	0,176
$\widehat{\beta}_{JP,HK}$	0,033	-0,396	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,119	*0,055*	0,101	*0,054*	-1,068
$\widehat{\beta}_{US,FR,GE}$	-0,185	0,430	$\hat{\tau}_{UK\mid US,FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,381	*0,155*	0,443	*0,159*	0,641
$\widehat{\beta}_{US,GE,IT}$	0,646	5,979	$\hat{\tau}_{UK\mid US,\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,590	*0,185*	0,760	*0,186*	1,533
$\widehat{\beta}_{FR,GE,JP}$	-0,011	0,479	$\hat{\tau}_{UK\mid\overline{US},FR,GE,\overline{IT},JP,\overline{HK}}$	0,547	*0,307*	0,529	*0,287*	-0,198
$\widehat{\beta}_{FR,GE,HK}$	0,265	3,228	$\hat{\tau}_{UK\mid\overline{US},FR,GE,\overline{IT},\overline{JP},HK}$	0,578	*0,337*	0,576	*0,320*	0,136
$\widehat{\beta}_{FR,IT,JP}$	0,184	1,681	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},IT,JP,\overline{HK}}$	0,937	*0,364*	0,957	*0,232*	-0,226
$\widehat{\beta}_{FR,IT,HK}$	-0,107	-0,067	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},IT,\overline{JP},HK}$	0,608	*0,274*	0,629	*0,277*	-0,210
$\widehat{\beta}_{FR,JP,HK}$	-0,458	-2,210	$\hat{\tau}_{UK\mid\overline{US},FR,\overline{GE},\overline{IT},JP,HK}$	0,041	*0,221*	0,043	*0,149*	-0,075
$\widehat{\beta}_{GE,IT,JP}$	-0,187	14,395	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,IT,JP,\overline{HK}}$	0,146	*0,531*	1,000	*0,470*	0,368
$\widehat{\beta}_{GE,IT,HK}$	-0,113	0,176	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,IT,\overline{JP},HK}$	0,272	*0,382*	0,305	*0,342*	0,387
$\widehat{\beta}_{GE,JP,HK}$	0,496	3,171	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,\overline{IT},JP,HK}$	0,543	*0,318*	0,531	*0,316*	0,361
$\widehat{\beta}_{IT,JP,HK}$	-0,068	-0,258	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},\overline{GE},IT,JP,HK}$	0,398	*0,345*	0,431	*0,355*	0,103
$\widehat{\beta}_{GE,IT,JP,HK}$	-0.281	-17.32	$\hat{\tau}_{UK\mid\overline{US},\overline{FR},GE,IT,JP,HK}$	0,285	*0,585*	0,161	*0,335*	-0,517

4.4 Multivariate tail dependence with selected variables by PCA

This section shows the results of indicator regression (section 2.2) with the explanatory variables selected by the PCA method (section 2.3.2), the standard errors are based on a block bootstrap with 2000 replications. The corresponding results are presented in the Table 9 and Tables 16 -21 (Appendix C).

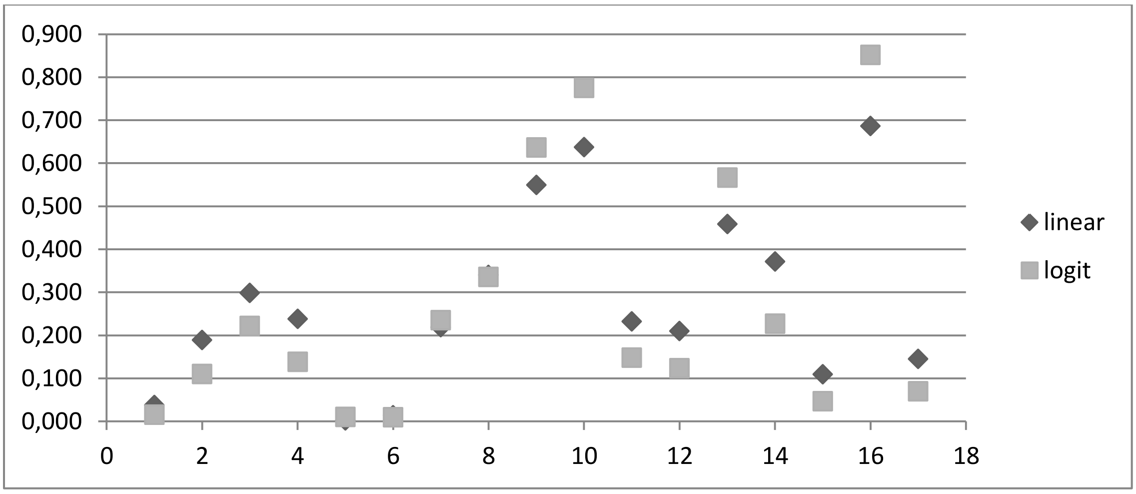
In contrast to the logit model with variables selection by CP, this model does converge in all seven cases. It implies that there is no noticeable problem with multicollinearity, since the number of explanatory variables decreased from 34 to 19 explanatory variables on average. In addition, the linear models have estimated probabilities between $0 \leq \hat{\tau} \leq 1$ in all cases, except for $\hat{\tau}_{US|\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},HK}$ and $\hat{\tau}_{HK|US,UK,\overline{FR},GE,\overline{IT},\overline{JP}}$. These two estimations are slightly negative, namely -0.106 and -0.047 respectively. In the first case for example, the estimator $\hat{\beta}_{IT,HK} = -0.209$ is relative large compared to the positive regression estimators $\hat{\beta}_{IT} = 0.050$ and $\hat{\beta}_{HK} = 0.053$. The sum of these three is causing negative probability estimation. Furthermore, the differences between the estimates of the linear and logit model by PCA selection are frequently significant compared to the estimates with variables selection by CP. Estimates of the linear model in situations where a European market is extreme given only one market is extreme are often significant larger.

We consider France (Table 9) as an example in details. Due to the number of explanatory variables has fallen by more than half, the problem of multicollinearity is solved and therefore the logit model does converge. In Figure 4, we plot the tail dependencies of France. The logit model often gives a significant lower estimation if the probability of the linear estimates is below 0.50 given only one particular market crashes. If given two or more markets crash, the estimates of the logit model is lower, but not significant. Significant higher estimation for linear probabilities are found if the estimation is higher than 0.5. The estimated probability of France will crash given US and UK crash is only 0.219 by the linear model. The estimated probability France will crash given US and Germany, UK and Germany will crash are 0.340 and 0.33 respectively. Whereas the estimated probabilities of France will crash given a combination of UK, Germany and Italy will crash are all higher. This implicates that US has less influence on France compared to the European markets. Similar results have also been found for the other European markets as the response variable.

Table 9: Results of the multivariate indicator regression using linear and logit model with response variable France. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-5,136				0,006	*0,001*	
$\widehat{\beta}_{US}$	0,038	0,991	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,038	*0,020*	0,016	*0,009*	-1,724*
$\widehat{\beta}_{UK}$	0,189	3,043	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,189	*0,056*	0,110	*0,048*	-4,117**
$\widehat{\beta}_{GE}$	0,298	3,883	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,298	*0,055*	0,222	*0,060*	-2,904**
$\widehat{\beta}_{IT}$	0,238	3,309	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,238	*0,047*	0,139	*0,041*	-3,787**
$\widehat{\beta}_{JP}$	0,002	0,548	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,002	*0,014*	0,010	*0,007*	0,958
$\widehat{\beta}_{HK}$	0,014	0,471	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},HK}$	0,014	*0,022*	0,009	*0,007*	-0,238
$\widehat{\beta}_{US,UK}$	-0,008	-0,076	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,219	*0,084*	0,235	*0,094*	0,545
$\widehat{\beta}_{US,GE}$	0,003	-0,421	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,340	*0,093*	0,335	*0,120*	0,156
$\widehat{\beta}_{UK,GE}$	0,062	-1,229	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,549	*0,080*	0,636	*0,100*	2,012**
$\widehat{\beta}_{UK,IT}$	0,210	0,018	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,637	*0,088*	0,775	*0,097*	3,274**
$\widehat{\beta}_{UK,JP}$	0,042	-0,207	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,232	*0,134*	0,148	*0,155*	-0,650
$\widehat{\beta}_{UK,HK}$	0,007	-0,335	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},HK}$	0,210	*0,080*	0,124	*0,088*	-1,599
$\widehat{\beta}_{GE,IT}$	-0,078	-1,790	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},\overline{HK}}$	0,459	*0,092*	0,566	*0,112*	2,260**
$\widehat{\beta}_{GE,JP}$	0,072	-0,520	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,\overline{HK}}$	0,371	*0,139*	0,227	*0,150*	-1,824*
$\widehat{\beta}_{JP,HK}$	0,094	1,105	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,HK}$	0,110	*0,050*	0,047	*0,035*	-2,372**
$\widehat{\beta}_{UK,GE,JP}$	0,022	1,367	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,\overline{HK}}$	0,687	*0,122*	0,852	*0,145*	2,008**
$\widehat{\beta}_{UK,JP,HK}$	-0,203	-2,076	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,HK}$	0,145	*0,101*	0,070	*0,067*	-1,080

Figure 4: Plot of the probability estimators with France as response variable using linear and logit model with explanatory variables selected by the PCA method. The numbers on the x-axis correspond to the probability estimates.



x-axis nr		x-axis nr	
1	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	10	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},\overline{HK}}$
2	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	11	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,\overline{HK}}$
3	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	12	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},HK}$
4	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	13	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},\overline{HK}}$
5	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,\overline{HK}}$	14	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,\overline{HK}}$
6	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},HK}$	15	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,HK}$
7	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	16	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,\overline{HK}}$
8	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	17	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,HK}$
9	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},\overline{HK}}$		

5 Conclusion

In this paper, we investigate the pairwise and multivariate tail dependence structure using the linear indicator regression model, proposed by van Oordt and Zhou (2012), and the new introduced logit indicator regression model. One of the advantages of this approach is its simplicity to extend the bivariate tail dependence analysis to multivariate tail dependence analysis. Our data consist of seven international stock markets, namely US, UK, France, Germany, Italy, Japan and Hong Kong.

The multivariate model is a regression of one variable on other variables and the interaction terms. The number of parameters to be estimated is very large when we use the linear indicator regression in an original setup. In addition, due to the definition of the explanatory variables in the regression, the correlation between the variables is very high. Therefore, we propose two methods to select variables to avoid multicollinearity, namely selection based on conditional probabilities (CP) and principal components analysis (PCA).

When we use a reduced number of explanatory variables, the theory of the linear indicator regression may not hold. That is, the probability estimation may be outside the range [0, 1]. Hence, we suggest using the logit indicator regression. This provides more theoretically correct tail dependence. Moreover, the results show an insignificant difference between the linear and logit model in the most cases. Furthermore, we observe distinction between the stock markets in the multivariate analysis that does not appear from the bivariate analysis. Therefore, we recommend using the multivariate analysis. The bivariate analysis is only an incomplete view of the multivariate analysis.

The variables selection methods CP and PCA reduce the number of variables. The number of variables using the first selection method has dropped by 46% on average with respect to the number of variables using a full model, whereas the number of variables using the second selection method has dropped by 70% on average. Both methods reduce a considerable number of variables, but the estimated regression coefficients of the logit model with variables selected by CP does not converge, except for Japanese and Hong Kong's stock markets as response variable. Therefore, multicollinearity may still exist in the first case, but less than the original indicator regression without any variables selection.

We find that the dependence structure within European markets is stronger than across other markets. That is, the tail dependence within Europe (UK, France, Germany, France and Italy) is the strongest, whereas the relation between US and Asia (Japan and Hong Kong) is the weakest. A possible explanation for the strong dependence structure within Europe is that the European countries are all members of the European Union, which has developed a single market. Moreover, according to the Transatlantic Economic Council[7], there is some specific cooperation between the US and EU and that might explain the influence on the financial markets.

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[7] According to the website of the European Commission, the Transatlantic Economic Council is defined as follows: 'A political body to oversee and accelerate government-to-government cooperation with the aim of advancing economic integration between the European Union and the United States of America'.

Last but not least, the US is the leading market according to different researchers. But due to time zone differences, its influence on other markets is likely on the next trading day. Since there is no significant change in correlation and bivariate analysis between with and without time zone differences, we did not use return synchronization. However, the estimated probability in multivariate case that a market will crash given US and other markets is extreme is lower than expected. That may indicate time zone differences may have an influence on multivariate tail dependency estimation. This is left for further research.

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7 Appendix

In the Appendix A – D, we present the plots and tables corresponding to the results of section 4.

A Definition of tail

Figure 5: **Plot of the $\widehat{\beta}_{UK}$ against k for all pairwise combination of the UK.**

Figure 6: **Plot of the $\widehat{\beta}_{FR}$ against k for all pairwise combination of the FR.**

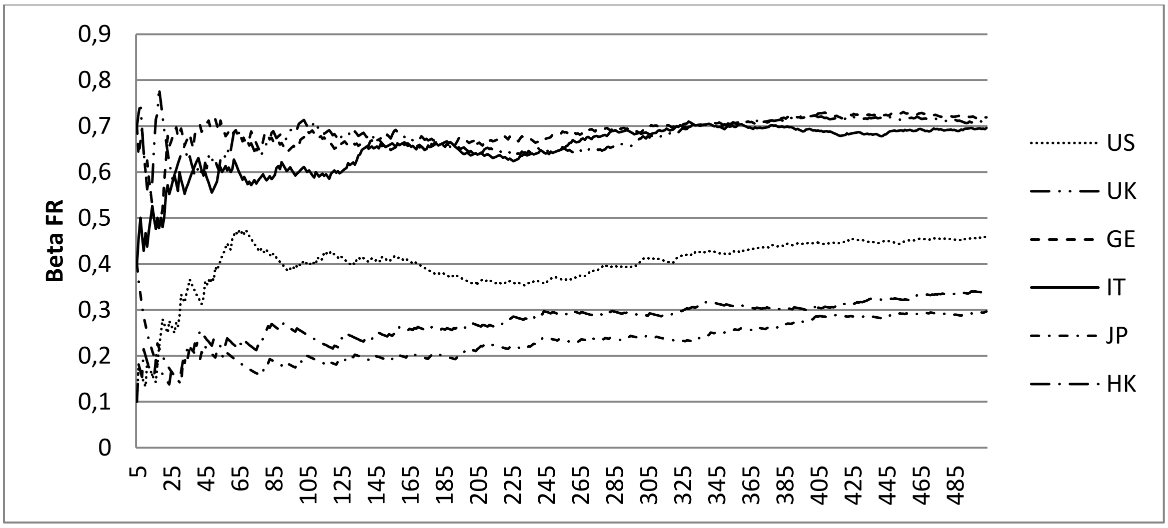


Figure 7: **Plot of the $\widehat{\beta}_{GE}$ against k for all pairwise combination of the GE.**

Figure 8: **Plot of the β_{IT} against k for all pairwise combination of the IT.**

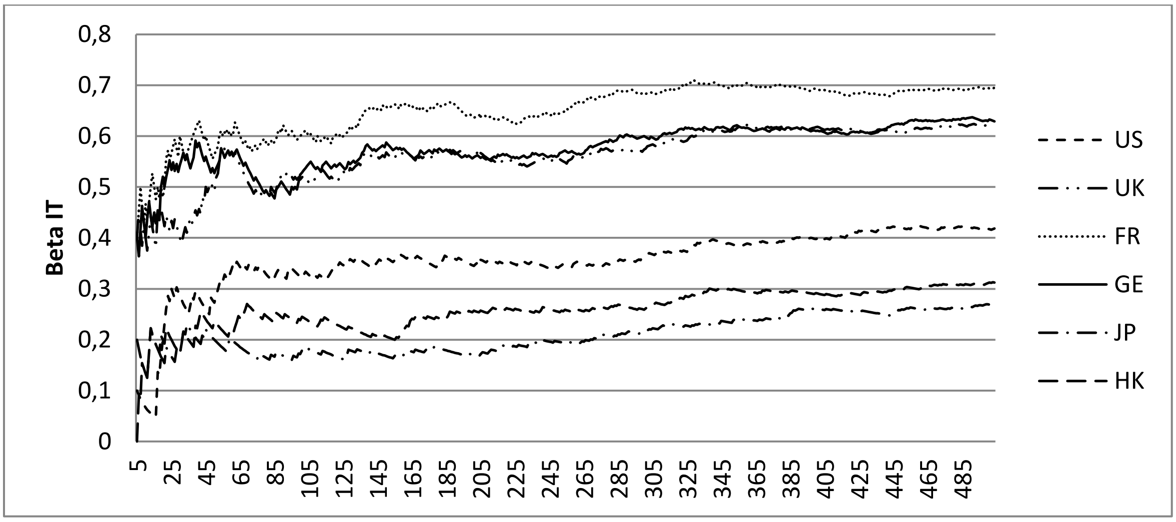


Figure 9: **Plot of the β_{JP} against k for all pairwise combination of the JP.**

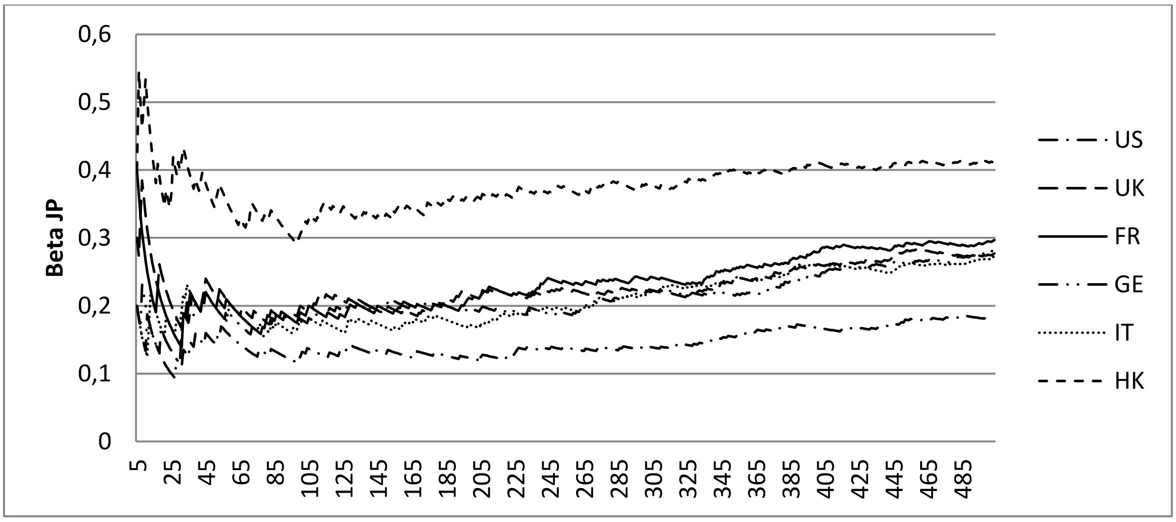


Figure 10: Plot of the β_{HK} against k for all pairwise combination of the HK.

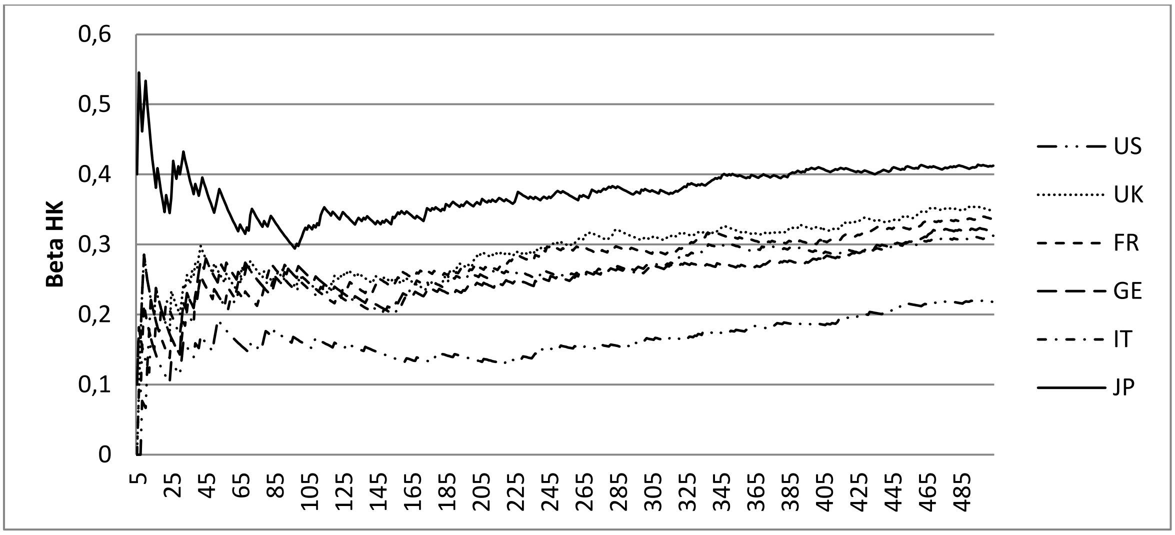
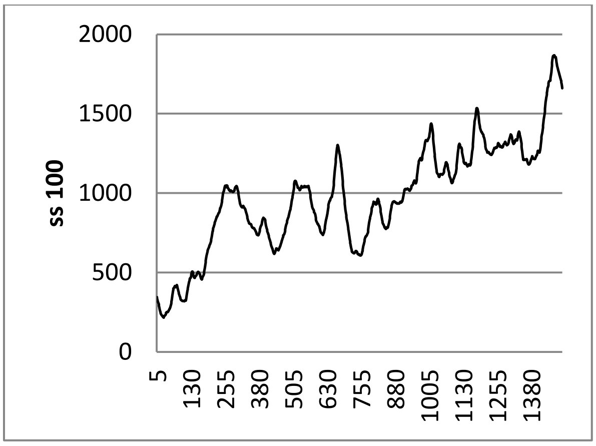


Figure 11: Plot of the ss against k with window length $w = 100$. The optimal threshold value $k = 256$.



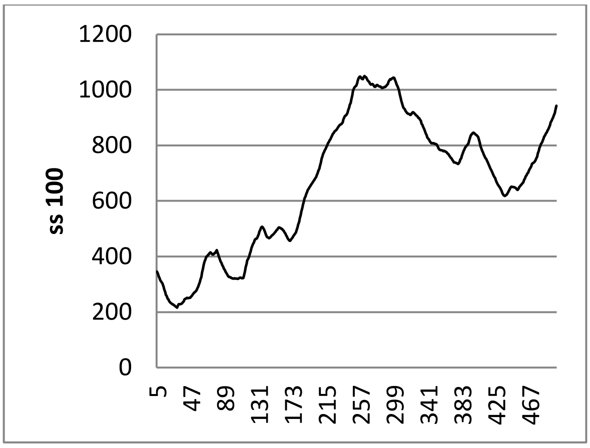
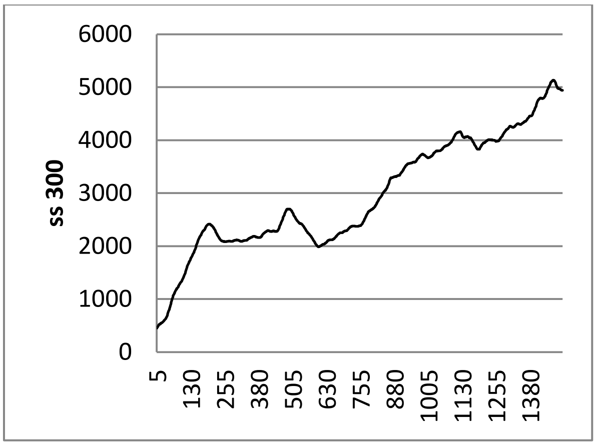
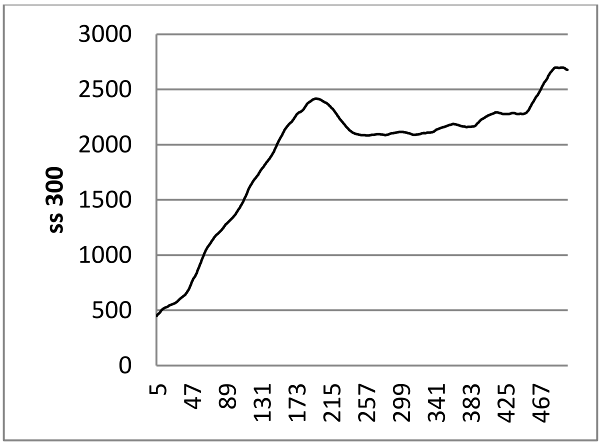


Figure 12: Plot of the ss against k with window length $w = 300$. The optimal threshold value $k = 197$.





B Multivariate tail dependence – CP

Table 10: Results of indicator regression using linear and logit model with response variable US. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,802	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,022	*0,003*	
$\widehat{\beta}_{UK}$	0,293	2,852	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,293	*0,067*	0,279	*0,069*	-0,696
$\widehat{\beta}_{FR}$	0,069	0,962	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,069	*0,059*	0,055	*0,037*	-0,339
$\widehat{\beta}_{GE}$	0,214	2,388	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,214	*0,070*	0,196	*0,074*	-0,752
$\widehat{\beta}_{IT}$	0,093	1,484	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,093	*0,053*	0,090	*0,050*	-0,384
$\widehat{\beta}_{JP}$	0,047	0,837	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,047	*0,021*	0,049	*0,021*	0,323
$\widehat{\beta}_{HK}$	0,055	0,758	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,055	*0,026*	0,045	*0,026*	-0,910
$\widehat{\beta}_{UK,FR}$	-0,031	-0,540	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,330	*0,123*	0,371	*0,148*	0,656
$\widehat{\beta}_{UK,GE}$	-0,322	-2,770	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,184	*0,111*	0,209	*0,115*	0,671
$\widehat{\beta}_{UK,IT}$	-0,358	-2,835	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,028	*0,143*	0,091	*0,100*	0,733
$\widehat{\beta}_{UK,JP}$	-0,159	-0,985	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,181	*0,248*	0,250	*0,252*	0,327
$\widehat{\beta}_{UK,HK}$	-0,073	-0,213	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,275	*0,255*	0,400	*0,247*	0,651
$\widehat{\beta}_{FR,GE}$	0,012	-0,280	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,295	*0,102*	0,325	*0,115*	0,512
$\widehat{\beta}_{FR,IT}$	0,128	0,443	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,289	*0,108*	0,286	*0,125*	0,152
$\widehat{\beta}_{FR,JP}$	0,046	-13,383	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,163	*0,415*	0,000	*0,373*	0,113
$\widehat{\beta}_{FR,HK}$	0,232	15,979	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,356	*0,572*	1,000	*0,464*	1,100
$\widehat{\beta}_{GE,IT}$	-0,235	-2,197	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,072	*0,093*	0,106	*0,069*	0,482
$\widehat{\beta}_{GE,JP}$	-0,276	-16,519	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	-0,015	*0,090*	0,000	*0,050*	0,142
$\widehat{\beta}_{GE,HK}$	0,071	0,656	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,339	*0,282*	0,500	*0,255*	0,601
$\widehat{\beta}_{IT,JP}$	0,272	0,789	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,413	*0,336*	0,333	*0,326*	-0,192
$\widehat{\beta}_{IT,HK}$	-0,218	-89,004	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	-0,070	*0,107*	0,000	*0,023*	0,477
$\widehat{\beta}_{JP,HK}$	-0,042	-0,565	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,060	*0,040*	0,059	*0,040*	-0,004
$\widehat{\beta}_{UK,FR,JP}$	-0,127	-1,230	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,138	*0,358*	0,000	*0,232*	-0,237
$\widehat{\beta}_{UK,FR,HK}$	-0,099	-29,963	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,445	*0,599*	0,000	*0,417*	-0,594
$\widehat{\beta}_{UK,GE,IT}$	0,791	4,905	$\hat{\tau}_{US\vert UK,\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,476	*0,143*	0,506	*0,194*	-0,110
$\widehat{\beta}_{UK,GE,JP}$	0,274	1,805	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	0,070	*0,458*	0,000	*0,324*	0,125
$\widehat{\beta}_{UK,GE,HK}$	-0,140	16,191	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,097	*0,539*	1,000	*0,480*	0,681
$\widehat{\beta}_{UK,IT,JP}$	0,018	-13,167	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,206	*0,508*	0,000	*0,321*	-0,135
$\widehat{\beta}_{UK,IT,HK}$	0,251	29,179	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,043	*0,298*	0,000	*0,177*	-0,019
$\widehat{\beta}_{UK,JP,HK}$	-0,121	-16,448	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,000	*0,120*	0,000	*0,050*	0,040
$\widehat{\beta}_{FR,GE,JP}$	-0,075	0,741	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},JP,\overline{HK}}$	0,038	*0,292*	0,000	*0,195*	0,021
$\widehat{\beta}_{FR,GE,HK}$	-0,189	-30,740	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},\overline{JP},HK}$	0,463	*0,497*	0,000	*0,389*	-0,724
$\widehat{\beta}_{FR,IT,JP}$	0,106	28,577	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,JP,\overline{HK}}$	0,762	*0,558*	1,000	*0,396*	0,099
$\widehat{\beta}_{FR,IT,HK}$	-0,309	57,791	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,\overline{JP},HK}$	0,050	*0,369*	0,000	*0,232*	-0,034
$\widehat{\beta}_{FR,JP,HK}$	-0,420	-90,369	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},JP,HK}$	-0,013	*0,215*	0,000	*0,116*	0,117
$\widehat{\beta}_{GE,IT,JP}$	-0,265	-1,899	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,JP,\overline{HK}}$	-0,150	*0,928*	0,000	*0,428*	0,556
$\widehat{\beta}_{GE,IT,HK}$	0,119	28,352	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,\overline{JP},HK}$	0,098	*0,423*	0,000	*0,344*	-0,008
$\widehat{\beta}_{GE,JP,HK}$	0,148	0,551	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},JP,HK}$	0,216	*0,463*	0,000	*0,424*	0,086
$\widehat{\beta}_{IT,JP,HK}$	0,366	89,505	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,JP,HK}$	0,574	*0,452*	0,500	*0,399*	-0,050
$\widehat{\beta}_{UK,FR,JP,HK}$	0,689	164,443	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},JP,HK}$	0,359	*0,590*	1,000	*0,486*	0,320
$\widehat{\beta}_{UK,GE,IT,JP}$	-0,015	13,826	$\hat{\tau}_{US\vert UK,\overline{FR},GE,IT,JP,\overline{HK}}$	0,371	*0,772*	0,000	*0,463*	-0,006
$\widehat{\beta}_{UK,GE,JP,HK}$	0,127	-1,455	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},JP,HK}$	0,095	*0,382*	0,000	*0,286*	-0,124
$\widehat{\beta}_{UK,IT,JP,HK}$	-0,614	-147,81	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,JP,HK}$	-0,190	*0,584*	0,000	*0,189*	0,495
$\widehat{\beta}_{GE,IT,JP,HK}$	0,250	3,500	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,JP,HK}$	0,599	*0,706*	1,000	*0,457*	0,478

Table 11: **Results of indicator regression using linear and logit model with response variable France. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%**

Regression coefficient			**Tail dependence**	**Probability**				**T-stat**
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-5,259	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,005	*0,001*	
$\widehat{\beta}_{US}$	0,013	0,806	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,013	*0,015*	0,012	*0,011*	-0,265
$\widehat{\beta}_{UK}$	0,169	3,638	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,169	*0,064*	0,165	*0,065*	-0,095
$\widehat{\beta}_{GE}$	0,278	4,283	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,278	*0,069*	0,274	*0,072*	-0,117
$\widehat{\beta}_{IT}$	0,159	3,584	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,159	*0,052*	0,158	*0,052*	-0,109
$\widehat{\beta}_{JP}$	0,009	0,576	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,009	*0,010*	0,009	*0,009*	0,231
$\widehat{\beta}_{HK}$	0,007	0,424	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},HK}$	0,007	*0,011*	0,008	*0,009*	0,057
$\widehat{\beta}_{US,UK}$	0,018	-0,557	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,200	*0,102*	0,202	*0,103*	0,201
$\widehat{\beta}_{US,GE}$	0,057	-0,430	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,349	*0,142*	0,354	*0,153*	0,264
$\widehat{\beta}_{US,IT}$	0,306	0,776	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,479	*0,179*	0,477	*0,200*	0,224
$\widehat{\beta}_{UK,GE}$	0,082	-2,517	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,529	*0,136*	0,536	*0,141*	-0,134
$\widehat{\beta}_{UK,IT}$	0,408	-0,859	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,736	*0,137*	0,751	*0,145*	0,007
$\widehat{\beta}_{UK,JP}$	0,150	0,308	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,328	*0,221*	0,324	*0,216*	0,078
$\widehat{\beta}_{UK,HK}$	0,026	-0,226	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},HK}$	0,202	*0,172*	0,194	*0,175*	-0,079
$\widehat{\beta}_{GE,IT}$	0,052	-2,620	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},\overline{HK}}$	0,490	*0,131*	0,497	*0,138*	-0,251
$\widehat{\beta}_{GE,JP}$	-0,001	-0,516	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,\overline{HK}}$	0,286	*0,184*	0,286	*0,184*	0,024
$\widehat{\beta}_{GE,HK}$	-0,058	-0,706	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},HK}$	0,227	*0,250*	0,221	*0,238*	0,035
$\widehat{\beta}_{IT,JP}$	-0,078	-0,948	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,JP,\overline{HK}}$	0,090	*0,240*	0,114	*0,216*	0,400
$\widehat{\beta}_{IT,HK}$	0,213	0,740	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},HK}$	0,379	*0,216*	0,375	*0,218*	-0,247
$\widehat{\beta}_{JP,HK}$	0,067	1,771	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,HK}$	0,084	*0,045*	0,077	*0,045*	-0,456
$\widehat{\beta}_{US,UK,GE}$	0,070	0,815	$\hat{\tau}_{FR\|US,UK,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,688	*0,229*	0,685	*0,242*	0,055
$\widehat{\beta}_{US,UK,IT}$	-0,176	-0,231	$\hat{\tau}_{FR\|US,UK,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,898	*0,265*	0,870	*0,255*	-0,218
$\widehat{\beta}_{US,GE,IT}$	-0,269	-0,746	$\hat{\tau}_{FR\|US,\overline{UK},GE,IT,\overline{JP},\overline{HK}}$	0,597	*0,271*	0,597	*0,268*	0,152
$\widehat{\beta}_{UK,GE,IT}$	-0,232	2,031	$\hat{\tau}_{FR\|\overline{US},UK,GE,IT,\overline{JP},\overline{HK}}$	0,916	*0,042*	0,907	*0,051*	-0,043
$\widehat{\beta}_{UK,GE,JP}$	-0,020	0,179	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,\overline{HK}}$	0,667	*0,337*	0,667	*0,323*	-0,041
$\widehat{\beta}_{UK,GE,HK}$	0,358	2,308	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},HK}$	0,862	*0,292*	0,875	*0,273*	0,112
$\widehat{\beta}_{UK,IT,JP}$	-0,204	-0,587	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,JP,\overline{HK}}$	0,613	*0,358*	0,612	*0,356*	-0,193
$\widehat{\beta}_{UK,IT,HK}$	-0,437	-1,842	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},HK}$	0,545	*0,293*	0,550	*0,301*	0,086
$\widehat{\beta}_{UK,JP,HK}$	-0,453	-17,804	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,HK}$	-0,024	*0,089*	0,000	*0,054*	0,159
$\widehat{\beta}_{GE,IT,JP}$	0,219	16,074	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,JP,\overline{HK}}$	0,638	*0,640*	1,000	*0,471*	-0,074
$\widehat{\beta}_{GE,IT,HK}$	-0,077	-0,110	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},HK}$	0,575	*0,327*	0,583	*0,323*	0,258
$\widehat{\beta}_{GE,JP,HK}$	0,324	0,120	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,HK}$	0,626	*0,297*	0,667	*0,305*	0,188
$\widehat{\beta}_{IT,JP,HK}$	-0,068	-1,679	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,JP,HK}$	0,310	*0,305*	0,312	*0,315*	0,367
$\widehat{\beta}_{UK,GE,JP,HK}$	-0,278	14,017	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,HK}$	0,660	*0,225*	0,645	*0,234*	-0,136
$\widehat{\beta}_{UK,IT,JP,HK}$	0,739	18,855	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,JP,HK}$	0,707	*0,307*	0,667	*0,328*	-0,219
$\widehat{\beta}_{GE,IT,JP,HK}$	-0,376	-15,170	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,JP,HK}$	0,671	*0,352*	0,637	*0,335*	-0,124

Table 12: **Results of indicator regression using linear and logit model with response variable Germany. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%.**

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,915	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$			0,007	*0,001*	
$\widehat{\beta}_{US}$	0,084	2,218	$\hat{\tau}_{GE\|US,\overline{UK},\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,084	*0,027*	0,063	*0,024*	-2,166**
$\widehat{\beta}_{UK}$	0,195	3,350	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,195	*0,073*	0,173	*0,074*	-1,787*
$\widehat{\beta}_{FR}$	0,369	4,103	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,369	*0,075*	0,308	*0,078*	-2,721**
$\widehat{\beta}_{IT}$	0,165	2,981	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,165	*0,054*	0,126	*0,052*	-2,474**
$\widehat{\beta}_{JP}$	0,046	1,638	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},\overline{IT},JP,\overline{HK}}$	0,046	*0,021*	0,036	*0,019*	-1,525
$\widehat{\beta}_{HK}$	0,037	1,376	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},\overline{IT},\overline{JP},HK}$	0,037	*0,022*	0,028	*0,017*	-0,987
$\widehat{\beta}_{US,UK}$	-0,138	-2,881	$\hat{\tau}_{GE\|US,UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,141	*0,075*	0,097	*0,074*	-1,119
$\widehat{\beta}_{US,FR}$	0,127	-0,739	$\hat{\tau}_{GE\|US,\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,580	*0,182*	0,661	*0,190*	1,389
$\widehat{\beta}_{US,IT}$	-0,195	-2,035	$\hat{\tau}_{GE\|US,\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,054	*0,139*	0,148	*0,124*	1,218
$\widehat{\beta}_{UK,FR}$	0,061	-1,692	$\hat{\tau}_{GE\|\overline{US},UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,625	*0,116*	0,700	*0,122*	1,913*
$\widehat{\beta}_{UK,IT}$	0,047	-1,012	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},IT,\overline{JP},\overline{HK}}$	0,407	*0,157*	0,600	*0,192*	2,265**
$\widehat{\beta}_{UK,JP}$	-0,093	-1,695	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},\overline{IT},JP,\overline{HK}}$	0,147	*0,212*	0,165	*0,214*	0,394
$\widehat{\beta}_{UK,HK}$	-0,193	-4,010	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},\overline{IT},\overline{JP},HK}$	0,039	*0,101*	0,015	*0,091*	-0,099
$\widehat{\beta}_{FR,IT}$	-0,117	-2,002	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,IT,\overline{JP},\overline{HK}}$	0,418	*0,111*	0,542	*0,130*	2,317**
$\widehat{\beta}_{FR,JP}$	0,149	-0,134	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,\overline{IT},JP,\overline{HK}}$	0,564	*0,332*	0,667	*0,332*	0,474
$\widehat{\beta}_{FR,HK}$	0,036	-0,582	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,\overline{IT},\overline{JP},HK}$	0,442	*0,428*	0,496	*0,400*	0,260
$\widehat{\beta}_{IT,JP}$	-0,276	-18,560	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},IT,JP,\overline{HK}}$	-0,066	*0,209*	0,000	*0,109*	0,238
$\widehat{\beta}_{IT,HK}$	0,017	-0,481	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},IT,\overline{JP},HK}$	0,219	*0,204*	0,261	*0,207*	0,146
$\widehat{\beta}_{JP,HK}$	-0,055	-1,727	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},\overline{IT},JP,HK}$	0,027	*0,030*	0,026	*0,025*	-0,265
$\widehat{\beta}_{US,UK,FR}$	-0,278	0,437	$\hat{\tau}_{GE\|US,UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,420	*0,168*	0,470	*0,210*	0,569
$\widehat{\beta}_{US,UK,IT}$	0,639	5,058	$\hat{\tau}_{GE\|US,UK,\overline{FR},IT,\overline{JP},\overline{HK}}$	0,797	*0,155*	0,941	*0,151*	0,935
$\widehat{\beta}_{UK.FR,JP}$	-0,147	-0,407	$\hat{\tau}_{GE\|\overline{US},UK,FR,\overline{IT},JP,\overline{HK}}$	0,580	*0,283*	0,562	*0,285*	-0,411
$\widehat{\beta}_{UK,FR,HK}$	0,134	2,973	$\hat{\tau}_{GE\|\overline{US},UK,FR,\overline{IT},\overline{JP},HK}$	0,639	*0,281*	0,647	*0,313*	-0,108
$\widehat{\beta}_{UK,IT,JP}$	0,235	17,101	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},IT,JP,\overline{HK}}$	0,318	*0,526*	0,248	*0,388*	-0,480
$\widehat{\beta}_{UK,IT,HK}$	0,038	1,926	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},IT,\overline{JP},HK}$	0,305	*0,321*	0,313	*0,291*	0,038
$\widehat{\beta}_{UK,JP,HK}$	0,335	5,066	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},\overline{IT},JP,HK}$	0,270	*0,177*	0,286	*0,187*	0,231
$\widehat{\beta}_{FR,IT,JP}$	-0,043	1,392	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,IT,JP,\overline{HK}}$	0,293	*0,504*	0,000	*0,368*	-0,380
$\widehat{\beta}_{FR,IT,HK}$	-0,030	-0,791	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,IT,\overline{JP},HK}$	0,477	*0,281*	0,423	*0,259*	-0,042
$\widehat{\beta}_{FR,JP,HK}$	-0,205	-0,378	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,\overline{IT},JP,HK}$	0,376	*0,234*	0,350	*0,252*	0,140
$\widehat{\beta}_{GE,JP,HK}$	0,435	18,468	$\hat{\tau}_{GE\|\overline{US},\overline{UK},\overline{FR},IT,JP,HK}$	0,367	*0,329*	0,228	*0,345*	-0,155
$\widehat{\beta}_{UK,FR,JP,HK}$	0,412	15,237	$\hat{\tau}_{GE\|\overline{US},UK,FR,\overline{IT},JP,HK}$	1,079	*0,135*	1,000	*0,077*	-0,552
$\widehat{\beta}_{UK,IT,JP,HK}$	-0,820	-36,106	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},IT,JP,HK}$	0,111	*0,376*	0,000	*0,245*	-0,190

Table 13: Results of indicator regression using linear and logit model with response variable Italy. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,564	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$			0,010	*0,002*	
$\widehat{\beta}_{US}$	0,052	1,469	$\hat{\tau}_{IT\|US,\overline{UK},\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,052	*0,026*	0,043	*0,022*	-1,153
$\widehat{\beta}_{UK}$	0,089	1,764	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,089	*0,054*	0,057	*0,044*	-1,456
$\widehat{\beta}_{FR}$	0,265	3,391	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,265	*0,085*	0,236	*0,089*	-0,560
$\widehat{\beta}_{GE}$	0,199	2,993	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,199	*0,065*	0,172	*0,066*	-0,581
$\widehat{\beta}_{JP}$	0,028	0,874	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},\overline{GE},JP,\overline{HK}}$	0,028	*0,016*	0,024	*0,014*	-0,043
$\widehat{\beta}_{HK}$	0,038	1,270	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{JP},HK}$	0,038	*0,020*	0,036	*0,018*	-0,050
$\widehat{\beta}_{US,UK}$	-0,177	-3,156	$\hat{\tau}_{IT\|US,UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	-0,036	*0,053*	0,011	*0,015*	1,001
$\widehat{\beta}_{US,FR}$	0,377	0,685	$\hat{\tau}_{IT\|US,\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,693	*0,209*	0,727	*0,215*	0,416
$\widehat{\beta}_{US,GE}$	-0,190	-2,135	$\hat{\tau}_{IT\|US,\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,061	*0,084*	0,096	*0,065*	0,522
$\widehat{\beta}_{UK,FR}$	0,260	0,092	$\hat{\tau}_{IT\|\overline{US},UK,FR,\overline{GE},\overline{JP},\overline{HK}}$	0,615	*0,118*	0,664	*0,126*	0,933
$\widehat{\beta}_{UK,GE}$	-0,049	-0,939	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},GE,\overline{JP},\overline{HK}}$	0,240	*0,122*	0,322	*0,151*	1,070
$\widehat{\beta}_{UK,JP}$	0,061	0,399	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},\overline{GE},JP,\overline{HK}}$	0,178	*0,201*	0,178	*0,227*	0,340
$\widehat{\beta}_{UK,HK}$	0,226	0,998	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},\overline{GE},\overline{JP},HK}$	0,354	*0,182*	0,370	*0,230*	0,442
$\widehat{\beta}_{FR,GE}$	-0,067	-2,002	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,GE,\overline{JP},\overline{HK}}$	0,397	*0,113*	0,455	*0,127*	0,980
$\widehat{\beta}_{FR,JP}$	-0,107	-0,778	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,\overline{GE},JP,\overline{HK}}$	0,186	*0,311*	0,254	*0,400*	0,475
$\widehat{\beta}_{FR,HK}$	0,308	0,629	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,\overline{GE},\overline{JP},HK}$	0,611	*0,419*	0,674	*0,353*	0,168
$\widehat{\beta}_{GE,JP}$	-0,267	-17,89	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},GE,JP,\overline{HK}}$	-0,040	*0,084*	0,000	*0,036*	0,408
$\widehat{\beta}_{GE,HK}$	0,070	-0,510	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},GE,\overline{JP},HK}$	0,308	*0,245*	0,308	*0,278*	-0,019
$\widehat{\beta}_{JP,HK}$	-0,012	-0,506	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},\overline{GE},JP,HK}$	0,054	*0,037*	0,051	*0,032*	-0,260
$\widehat{\beta}_{US,UK,FR}$	-0,388	0,122	$\hat{\tau}_{IT\|US,UK,FR,\overline{GE},\overline{JP},\overline{HK}}$	0,478	*0,204*	0,451	*0,222*	-0,484
$\widehat{\beta}_{US,UK,GE}$	0,787	5,247	$\hat{\tau}_{IT\|US,UK,\overline{FR},GE,\overline{JP},\overline{HK}}$	0,712	*0,209*	0,663	*0,246*	-0,534
$\widehat{\beta}_{US,FR,GE}$	-0,229	-0,331	$\hat{\tau}_{IT\|US,\overline{UK},FR,GE,\overline{JP},\overline{HK}}$	0,407	*0,186*	0,379	*0,198*	-0,521
$\widehat{\beta}_{UK,FR,JP}$	-0,003	-0,704	$\hat{\tau}_{IT\|\overline{US},UK,FR,\overline{GE},JP,\overline{HK}}$	0,593	*0,314*	0,616	*0,298*	-0,343
$\widehat{\beta}_{UK,FR,HK}$	-0,493	-2,544	$\hat{\tau}_{IT\|\overline{US},UK,FR,\overline{GE},\overline{JP},HK}$	0,694	*0,300*	0,738	*0,307*	0,033
$\widehat{\beta}_{UK,GE,JP}$	0,175	16,251	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},GE,JP,\overline{HK}}$	0,237	*0,391*	0,248	*0,365*	-0,228
$\widehat{\beta}_{UK,GE,HK}$	0,201	1,996	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},GE,\overline{JP},HK}$	0,775	*0,410*	0,953	*0,371*	0,004
$\widehat{\beta}_{UK,JP,HK}$	-0,270	-1,845	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},\overline{GE},JP,HK}$	0,159	*0,170*	0,167	*0,171*	0,069
$\widehat{\beta}_{FR,GE,JP}$	0,048	1,533	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,GE,JP,\overline{HK}}$	0,100	*0,250*	0,000	*0,212*	-0,264
$\widehat{\beta}_{FR,GE,HK}$	-0,234	-0,933	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,GE,\overline{JP},HK}$	0,579	*0,361*	0,568	*0,327*	0,191
$\widehat{\beta}_{FR,JP,HK}$	-0,222	-1,405	$\hat{\tau}_{IT\|\overline{US},\overline{UK},FR,\overline{GE},JP,HK}$	0,298	*0,210*	0,252	*0,242*	0,061
$\widehat{\beta}_{GE,JP,HK}$	0,472	18,142	$\hat{\tau}_{IT\|\overline{US},\overline{UK},\overline{FR},GE,JP,HK}$	0,529	*0,397*	0,453	*0,393*	-0,157
$\widehat{\beta}_{UK,FR,JP,HK}$	0,854	20,574	$\hat{\tau}_{IT\|\overline{US},UK,FR,\overline{GE},JP,HK}$	1,022	*0,277*	1,000	*0,202*	-0,215
$\widehat{\beta}_{UK,GE,JP,HK}$	-0,940	-35,91	$\hat{\tau}_{IT\|\overline{US},UK,\overline{FR},GE,JP,HK}$	0,022	*0,276*	0,000	*0,182*	-0,004

Table 14: **Results of indicator regression using linear and logit model with response variable Japan. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%**

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,674	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$			0,025	*0,003*	
$\widehat{\beta}_{US}$	0,048	0,555	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,048	*0,024*	0,042	*0,019*	-0,562
$\widehat{\beta}_{UK}$	0,128	1,661	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,128	*0,055*	0,118	*0,057*	-0,684
$\widehat{\beta}_{FR}$	0,051	0,478	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	0,051	*0,048*	0,039	*0,040*	-0,429
$\widehat{\beta}_{GE}$	0,145	1,835	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,145	*0,059*	0,137	*0,063*	0,139
$\widehat{\beta}_{IT}$	0,020	-0,176	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{HK}}$	0,020	*0,034*	0,021	*0,028*	0,355
$\widehat{\beta}_{HK}$	0,278	2,702	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},HK}$	0,278	*0,045*	0,275	*0,045*	-0,773
$\widehat{\beta}_{US,UK}$	-0,163	-1,898	$\hat{\tau}_{JP\|US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,014	*0,089*	0,034	*0,063*	0,765
$\widehat{\beta}_{US,FR}$	-0,198	-1,566	$\hat{\tau}_{JP\|US,\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	-0,099	*0,193*	0,015	*0,168*	0,837
$\widehat{\beta}_{US,GE}$	-0,176	-2,591	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,017	*0,060*	0,020	*0,015*	0,035
$\widehat{\beta}_{US,IT}$	0,343	2,877	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},\overline{GR},IT,\overline{HK}}$	0,412	*0,197*	0,397	*0,246*	-0,446
$\widehat{\beta}_{UK,FR}$	0,030	0,104	$\hat{\tau}_{JP\|\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,210	*0,126*	0,193	*0,156*	0,367
$\widehat{\beta}_{UK.GE}$	-0,127	-1,540	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{HK}}$	0,146	*0,108*	0,152	*0,113*	-0,236
$\widehat{\beta}_{UK,IT}$	0,063	0,792	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{HK}}$	0,211	*0,145*	0,198	*0,200*	0,253
$\widehat{\beta}_{UK,HK}$	0,106	-0,464	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},HK}$	0,512	*0,147*	0,556	*0,174*	0,843
$\widehat{\beta}_{FR,GE}$	-0,005	-0,152	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	0,191	*0,090*	0,180	*0,105*	-0,422
$\widehat{\beta}_{FR,IT}$	-0,073	-0,330	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{HK}}$	-0,002	*0,056*	0,024	*0,029*	0,461
$\widehat{\beta}_{FR,HK}$	0,315	1,112	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},HK}$	0,644	*0,224*	0,650	*0,252*	0,452
$\widehat{\beta}_{GE,IT}$	-0,152	-1,713	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{HK}}$	0,013	*0,052*	0,023	*0,030*	-0,091
$\widehat{\beta}_{GE,HK}$	-0,099	-1,400	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},HK}$	0,324	*0,206*	0,369	*0,283*	0,252
$\widehat{\beta}_{IT,HK}$	-0,061	-0,332	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,HK}$	0,237	*0,153*	0,186	*0,142*	-0,340
$\widehat{\beta}_{US,UK,FR}$	0,200	2,587	$\hat{\tau}_{JP\|US,UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,097	*0,132*	0,148	*0,194*	-0,068
$\widehat{\beta}_{US,UK,GE}$	0,085	1,818	$\hat{\tau}_{JP\|US,UK,\overline{FR},GE,\overline{IT},\overline{HK}}$	-0,060	*0,139*	0,021	*0,133*	0,540
$\widehat{\beta}_{US,UK,IT}$	-0,196	-2,611	$\hat{\tau}_{JP\|US,UK,\overline{FR},\overline{GE},IT,\overline{HK}}$	0,243	*0,302*	0,078	*0,436*	0,273
$\widehat{\beta}_{US,FR,GE}$	0,066	-0,074	$\hat{\tau}_{JP\|US,\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	-0,069	*0,099*	0,006	*0,050*	0,448
$\widehat{\beta}_{US,GE,IT}$	0,040	1,300	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},GE,IT,\overline{HK}}$	0,269	*0,257*	0,170	*0,418*	0,307
$\widehat{\beta}_{UK,FR,HK}$	-0,434	-2,015	$\hat{\tau}_{JP\|\overline{US},UK,FR,\overline{GE},\overline{IT},HK}$	0,474	*0,359*	0,476	*0,353*	-0,519
$\widehat{\beta}_{UK,GE,IT}$	-0,020	0,142	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},GE,IT,\overline{HK}}$	0,057	*0,133*	0,065	*0,236*	0,452
$\widehat{\beta}_{UK,GE,HK}$	0,336	2,204	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},GE,\overline{IT},HK}$	0,767	*0,269*	0,790	*0,283*	0,075
$\widehat{\beta}_{UK,IT,HK}$	-0,172	-1,167	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},IT,HK}$	0,361	*0,266*	0,342	*0,286*	-0,131
$\widehat{\beta}_{FR,GE,HK}$	-0,018	0,060	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,\overline{IT},HK}$	0,667	*0,252*	0,723	*0,249*	0,281
$\widehat{\beta}_{FR,IT,HK}$	0,059	0,513	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},IT,HK}$	0,589	*0,250*	0,573	*0,271*	-0,188
$\widehat{\beta}_{GE,IT,HK}$	0,046	0,937	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,IT,HK}$	0,177	*0,339*	0,140	*0,258*	-0,015

Table 15: **Results of indicator regression using linear and logit model with response variable Hong Kong. The number of variables is reduced by the conditional probability described in section 2.3.1. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%**

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,830	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$			0,021	*0,003*	
$\hat{\beta}_{US}$	0,055	0,797	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,055	*0,024*	0,046	*0,018*	-1,280
$\hat{\beta}_{UK}$	0,126	1,845	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,126	*0,057*	0,121	*0,057*	-0,341
$\hat{\beta}_{FR}$	0,033	0,475	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP}}$	0,033	*0,035*	0,034	*0,022*	-0,063
$\hat{\beta}_{GE}$	0,051	0,946	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,051	*0,051*	0,053	*0,047*	0,474
$\hat{\beta}_{IT}$	0,100	1,560	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP}}$	0,100	*0,047*	0,094	*0,045*	-0,437
$\hat{\beta}_{JP}$	0,248	2,685	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP}$	0,248	*0,040*	0,241	*0,040*	-0,871
$\hat{\beta}_{US,UK}$	-0,108	-1,268	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,073	*0,108*	0,079	*0,096*	0,752
$\hat{\beta}_{US,FR}$	-0,055	-0,809	$\hat{\tau}_{HK\|US,\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP}}$	0,033	*0,236*	0,033	*0,258*	0,923
$\hat{\beta}_{US,GE}$	0,075	0,565	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,181	*0,146*	0,179	*0,147*	0,357
$\hat{\beta}_{US,IT}$	-0,192	-2,294	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GR},IT,\overline{JP}}$	-0,037	*0,154*	0,023	*0,108*	0,669
$\hat{\beta}_{UK,FR}$	-0,047	-0,539	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{JP}}$	0,112	*0,118*	0,114	*0,112*	0,120
$\hat{\beta}_{UK,GE}$	-0,085	-1,204	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	0,091	*0,081*	0,096	*0,080*	-0,129
$\hat{\beta}_{UK,IT}$	0,118	-0,153	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{JP}}$	0,343	*0,163*	0,359	*0,205*	0,301
$\hat{\beta}_{UK,JP}$	0,146	-0,543	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,519	*0,160*	0,539	*0,177*	0,662
$\hat{\beta}_{FR,GE}$	0,047	0,385	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{JP}}$	0,130	*0,080*	0,117	*0,082*	-0,669
$\hat{\beta}_{FR,IT}$	0,028	0,026	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{JP}}$	0,160	*0,105*	0,146	*0,110*	-0,281
$\hat{\beta}_{FR,JP}$	0,358	1,287	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},JP}$	0,639	*0,237*	0,650	*0,243*	0,473
$\hat{\beta}_{GE,IT}$	-0,018	-0,594	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{JP}}$	0,132	*0,097*	0,128	*0,098*	-0,208
$\hat{\beta}_{GE,JP}$	-0,117	-1,366	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},JP}$	0,181	*0,164*	0,173	*0,164*	-0,172
$\hat{\beta}_{IT,JP}$	0,128	-0,120	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,JP}$	0,476	*0,231*	0,573	*0,291*	0,526
$\hat{\beta}_{US,UK,FR}$	0,149	1,685	$\hat{\tau}_{HK\|US,UK,FR,\overline{GE},\overline{IT},\overline{JP}}$	0,154	*0,164*	0,162	*0,229*	-0,059
$\hat{\beta}_{US,UK,GE}$	0,064	0,380	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	0,178	*0,171*	0,146	*0,244*	-0,311
$\hat{\beta}_{US,UK,IT}$	-0,171	-0,720	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},IT,\overline{JP}}$	-0,073	*0,255*	0,017	*0,235*	0,441
$\hat{\beta}_{US,FR,GE}$	-0,162	-1,265	$\hat{\tau}_{HK\|US,\overline{UK},FR,GE,\overline{IT},\overline{JP}}$	0,044	*0,116*	0,061	*0,117*	0,120
$\hat{\beta}_{US,GE,IT}$	0,200	2,128	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,IT,\overline{JP}}$	0,271	*0,254*	0,327	*0,424*	0,554
$\hat{\beta}_{UK,FR,JP}$	-0,498	-2,124	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},\overline{IT},JP}$	0,365	*0,303*	0,322	*0,284*	-0,788
$\hat{\beta}_{UK,GE,IT}$	-0,054	0,196	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,IT,\overline{JP}}$	0,236	*0,175*	0,225	*0,209*	0,035
$\hat{\beta}_{UK,GE,JP}$	0,366	2,487	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,\overline{IT},JP}$	0,733	*0,283*	0,735	*0,271*	-0,077
$\hat{\beta}_{UK,IT,JP}$	-0,273	-1,319	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},IT,JP}$	0,591	*0,322*	0,531	*0,349*	-0,613
$\hat{\beta}_{FR,GE,JP}$	-0,054	-0,239	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,\overline{IT},JP}$	0,565	*0,246*	0,585	*0,264*	-0,004
$\hat{\beta}_{FR,IT,JP}$	-0,018	0,742	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},IT,JP}$	0,876	*0,275*	0,944	*0,191*	0,191
$\hat{\beta}_{GE,IT,JP}$	0,184	0,663	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,IT,JP}$	0,575	*0,449*	0,486	*0,429*	-0,356

C Multivariate tail dependence – PCA

Table 16: **Results of indicator regression using linear and logit model with response variable US. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%.**

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,716				0,024	*0,003*	
$\widehat{\beta}_{UK}$	0,233	2,235	$\hat{t}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,233	*0,057*	0,185	*0,060*	-2,863**
$\widehat{\beta}_{FR}$	0,056	1,021	$\hat{t}_{US\vert \overline{UK},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,056	*0,052*	0,063	*0,037*	0,575
$\widehat{\beta}_{GE}$	0,123	1,443	$\hat{t}_{US\vert \overline{UK},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,123	*0,057*	0,093	*0,048*	-1,260
$\widehat{\beta}_{IT}$	0,050	0,809	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,050	*0,048*	0,052	*0,036*	0,229
$\widehat{\beta}_{JP}$	0,027	0,263	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,027	*0,022*	0,031	*0,016*	0,436
$\widehat{\beta}_{HK}$	0,053	0,685	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,053	*0,028*	0,046	*0,021*	-0,632
$\widehat{\beta}_{UK,FR}$	-0,046	-0,842	$\hat{t}_{US\vert UK,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,243	*0,088*	0,214	*0,101*	-0,766
$\widehat{\beta}_{UK,IT}$	-0,005	-0,559	$\hat{t}_{US\vert UK,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,277	*0,100*	0,226	*0,127*	-0,809
$\widehat{\beta}_{UK,JP}$	-0,211	-1,891	$\hat{t}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,049	*0,099*	0,043	*0,060*	0,043
$\widehat{\beta}_{UK,HK}$	-0,044	-0,184	$\hat{t}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,241	*0,107*	0,273	*0,139*	0,865
$\widehat{\beta}_{FR,GE}$	-0,003	-0,559	$\hat{t}_{US\vert \overline{UK},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,176	*0,084*	0,141	*0,078*	-1,232
$\widehat{\beta}_{FR,IT}$	0,092	0,445	$\hat{t}_{US\vert \overline{UK},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,198	*0,086*	0,192	*0,085*	-0,321
$\widehat{\beta}_{GE,IT}$	0,092	0,131	$\hat{t}_{US\vert \overline{UK},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,265	*0,070*	0,209	*0,081*	-1,540
$\widehat{\beta}_{IT,JP}$	0,365	2,052	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,443	*0,185*	0,356	*0,210*	-0,830
$\widehat{\beta}_{IT,HK}$	-0,209	-1,508	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	-0,106	*0,079*	0,023	*0,027*	2,175**
$\widehat{\beta}_{JP,HK}$	-0,022	-0,153	$\hat{t}_{US\vert \overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,058	*0,039*	0,051	*0,028*	-0,359
$\widehat{\beta}_{UK,IT,JP}$	-0,114	0,006	$\hat{t}_{US\vert UK,\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,345	*0,136*	0,310	*0,171*	-0,529

Table 17: Results of indicator regression using linear and logit model with response variable UK. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,799				0,008	*0,001*	
$\widehat{\beta}_{US}$	0,097	1,961	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,097	*0,029*	0,055	*0,023*	-3,867**
$\widehat{\beta}_{FR}$	0,243	3,336	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,243	*0,068*	0,188	*0,064*	-2,456**
$\widehat{\beta}_{GE}$	0,162	2,441	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,162	*0,057*	0,086	*0,044*	-3,253**
$\widehat{\beta}_{IT}$	0,083	1,625	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,083	*0,040*	0,040	*0,024*	-1,997**
$\widehat{\beta}_{JP}$	0,035	1,252	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,035	*0,020*	0,028	*0,013*	-0,890
$\widehat{\beta}_{HK}$	0,052	1,748	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,052	*0,024*	0,045	*0,019*	-1,170
$\widehat{\beta}_{US,FR}$	0,053	-0,675	$\hat{\tau}_{UK\|US,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,393	*0,118*	0,456	*0,153*	1,280
$\widehat{\beta}_{US,IT}$	-0,046	-0,852	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,135	*0,107*	0,112	*0,091*	-0,032
$\widehat{\beta}_{FR,GE}$	0,034	-1,374	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,438	*0,089*	0,402	*0,103*	-1,338
$\widehat{\beta}_{FR,IT}$	0,144	-0,107	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,470	*0,096*	0,514	*0,113*	1,183
$\widehat{\beta}_{FR,JP}$	0,149	-0,129	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,426	*0,121*	0,416	*0,186*	0,222
$\widehat{\beta}_{FR,HK}$	-0,007	-1,344	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,287	*0,194*	0,257	*0,205*	0,107
$\widehat{\beta}_{GE,IT}$	0,109	0,268	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,354	*0,098*	0,386	*0,128*	0,515
$\widehat{\beta}_{GE,HK}$	-0,039	-1,796	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,174	*0,163*	0,083	*0,105*	-0,752
$\widehat{\beta}_{IT,HK}$	0,019	-0,222	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,155	*0,133*	0,161	*0,131*	0,563
$\widehat{\beta}_{JP,HK}$	0,059	-0,226	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,145	*0,056*	0,117	*0,052*	-2,157**
$\widehat{\beta}_{FR,GE,HK}$	0,103	2,390	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},\overline{JP},HK}$	0,547	*0,148*	0,646	*0,193*	1,241
$\widehat{\beta}_{FR,JP,HK}$	-0,313	-1,378	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},JP,HK}$	0,217	*0,152*	0,176	*0,132*	-0,394

Table 18: Results of indicator regression using linear and logit model with response variable Germany. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			Tail dependence	Probability				T-stat
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,748				0,009	*0,001*	
$\widehat{\beta}_{US}$	0,069	1,923	$\hat{\tau}_{GE\mid US,\overline{UK},\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,069	*0,029*	0,056	*0,025*	-1,910*
$\widehat{\beta}_{UK}$	0,166	2,843	$\hat{\tau}_{GE\mid \overline{US},UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,166	*0,063*	0,129	*0,058*	-2,523**
$\widehat{\beta}_{FR}$	0,395	4,109	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,395	*0,069*	0,346	*0,071*	-3,121**
$\widehat{\beta}_{IT}$	0,129	2,225	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,129	*0,045*	0,074	*0,038*	-3,313**
$\widehat{\beta}_{JP}$	0,027	1,037	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},\overline{FR},\overline{IT},JP,\overline{HK}}$	0,027	*0,022*	0,024	*0,014*	-0,298
$\widehat{\beta}_{HK}$	0,032	0,487	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},FR,\overline{IT},\overline{JP},HK}$	0,032	*0,027*	0,014	*0,008*	-0,846
$\widehat{\beta}_{US,UK}$	-0,064	-1,734	$\hat{\tau}_{GE\mid US,UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,171	*0,082*	0,152	*0,076*	-0,978
$\widehat{\beta}_{US,FR}$	-0,020	-1,536	$\hat{\tau}_{GE\mid US,\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,445	*0,181*	0,437	*0,187*	0,191
$\widehat{\beta}_{US,IT}$	0,082	-0,152	$\hat{\tau}_{GE\mid US,\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,281	*0,122*	0,320	*0,166*	0,696
$\widehat{\beta}_{UK,FR}$	0,042	-1,759	$\hat{\tau}_{GE\mid \overline{US},UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,603	*0,090*	0,610	*0,109*	0,120
$\widehat{\beta}_{UK,IT}$	0,131	-0,059	$\hat{\tau}_{GE\mid \overline{US},UK,\overline{FR},IT,\overline{JP},\overline{HK}}$	0,427	*0,099*	0,565	*0,140*	1,917*
$\widehat{\beta}_{UK,JP}$	-0,036	-1,048	$\hat{\tau}_{GE\mid \overline{US},UK,\overline{FR},\overline{IT},JP,\overline{HK}}$	0,157	*0,123*	0,128	*0,113*	-0,322
$\widehat{\beta}_{FR,IT}$	-0,129	-1,744	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},FR,IT,\overline{JP},\overline{HK}}$	0,395	*0,090*	0,460	*0,107*	1,566
$\widehat{\beta}_{FR,JP}$	-0,005	-0,973	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},FR,\overline{IT},JP,\overline{HK}}$	0,418	*0,159*	0,360	*0,178*	-0,581
$\widehat{\beta}_{JP,HK}$	0,002	-0,204	$\hat{\tau}_{GE\mid \overline{US},\overline{UK},\overline{FR},\overline{IT},JP,HK}$	0,061	*0,038*	0,031	*0,020*	-1,013
$\widehat{\beta}_{US,UK,FR}$	0,113	2,770	$\hat{\tau}_{GE\mid US,UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,702	*0,137*	0,866	*0,121*	2,330**
$\widehat{\beta}_{UK.FR,JP}$	0,024	1,093	$\hat{\tau}_{GE\mid \overline{US},UK,FR,\overline{IT},JP,\overline{HK}}$	0,614	*0,110*	0,635	*0,149*	0,394

Table 19: Results of indicator regression using linear and logit model with response variable Italy. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			**Tail dependence**	**Probability**				**T-stat**
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-4,516				0,011	*0,002*	
$\widehat{\beta}_{US}$	0,040	0,887	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,040	*0,027*	0,026	*0,017*	-1,057
$\widehat{\beta}_{UK}$	0,086	1,498	$\hat{\tau}_{IT\mid \overline{US},UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,086	*0,053*	0,047	*0,034*	-1,382
$\widehat{\beta}_{FR}$	0,315	3,358	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,315	*0,081*	0,239	*0,082*	-2,674**
$\widehat{\beta}_{GE}$	0,158	2,456	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,158	*0,061*	0,113	*0,054*	-2,064**
$\widehat{\beta}_{JP}$	0,024	0,831	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},\overline{GE},JP,\overline{HK}}$	0,024	*0,017*	0,024	*0,014*	0,016
$\widehat{\beta}_{HK}$	0,060	1,450	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},FR,\overline{GE},\overline{JP},HK}$	0,060	*0,025*	0,045	*0,019*	-1,804*
$\widehat{\beta}_{US,UK}$	-0,049	-0,189	$\hat{\tau}_{IT\mid US,UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,077	*0,069*	0,090	*0,054*	0,213
$\widehat{\beta}_{US,FR}$	0,166	0,406	$\hat{\tau}_{IT\mid US,\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,521	*0,134*	0,534	*0,185*	0,259
$\widehat{\beta}_{US,GE}$	0,023	-0,121	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,221	*0,095*	0,215	*0,116*	-0,021
$\widehat{\beta}_{UK,FR}$	0,127	-0,264	$\hat{\tau}_{IT\mid \overline{US},UK,FR,\overline{GE},\overline{JP},\overline{HK}}$	0,528	*0,105*	0,519	*0,123*	-0,158
$\widehat{\beta}_{UK,GE}$	0,153	0,269	$\hat{\tau}_{IT\mid \overline{US},UK,\overline{FR},GE,\overline{JP},\overline{HK}}$	0,396	*0,104*	0,427	*0,134*	0,482
$\widehat{\beta}_{UK,JP}$	-0,022	-0,385	$\hat{\tau}_{IT\mid \overline{US},UK,\overline{FR},\overline{GE},JP,\overline{HK}}$	0,088	*0,128*	0,071	*0,105*	0,060
$\widehat{\beta}_{UK,HK}$	0,057	-0,025	$\hat{\tau}_{IT\mid \overline{US},UK,\overline{FR},\overline{GE},\overline{JP},HK}$	0,203	*0,107*	0,169	*0,121*	-0,247
$\widehat{\beta}_{FR,GE}$	-0,117	-1,773	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},FR,GE,\overline{JP},\overline{HK}}$	0,355	*0,094*	0,384	*0,107*	0,669
$\widehat{\beta}_{FR,JP}$	-0,008	-0,831	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},FR,\overline{GE},JP,\overline{HK}}$	0,331	*0,145*	0,239	*0,188*	-0,495
$\widehat{\beta}_{GE,JP}$	-0,088	-0,843	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},GE,JP,\overline{HK}}$	0,094	*0,110*	0,112	*0,084*	0,308
$\widehat{\beta}_{GE,HK}$	0,026	-0,616	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},GE,\overline{JP},HK}$	0,244	*0,125*	0,227	*0,157*	0,292
$\widehat{\beta}_{JP,HK}$	-0,024	-0,654	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},\overline{GE},JP,HK}$	0,061	*0,040*	0,053	*0,031*	-0,530
$\widehat{\beta}_{UK,FR,JP}$	0,168	1,245	$\hat{\tau}_{IT\mid \overline{US},UK,FR,\overline{GE},JP,\overline{HK}}$	0,690	*0,181*	0,718	*0,218*	0,087
$\widehat{\beta}_{UK,GE,JP}$	-0,251	-0,950	$\hat{\tau}_{IT\mid \overline{US},UK,\overline{FR},GE,JP,\overline{HK}}$	0,060	*0,180*	0,162	*0,177*	0,824
$\widehat{\beta}_{GE,JP,HK}$	0,033	0,567	$\hat{\tau}_{IT\mid \overline{US},\overline{UK},\overline{FR},GE,JP,HK}$	0,190	*0,197*	0,210	*0,183*	0,531

Table 20: Results of indicator regression using linear and logit model with response variable Japan. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%

Regression coefficient			**Tail dependence**	**Probability**				**T-stat**
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,679				0,025	*0,003*	
$\widehat{\beta}_{US}$	0,062	0,850	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,062	*0,024*	0,056	*0,019*	-0,835
$\widehat{\beta}_{UK}$	0,147	1,472	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,147	*0,055*	0,099	*0,042*	-2,119**
$\widehat{\beta}_{FR}$	0,076	1,167	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	0,076	*0,055*	0,075	*0,046*	-0,298
$\widehat{\beta}_{GE}$	0,116	1,558	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,116	*0,064*	0,107	*0,059*	-0,348
$\widehat{\beta}_{IT}$	0,071	0,918	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{HK}}$	0,071	*0,037*	0,059	*0,030*	-0,905
$\widehat{\beta}_{HK}$	0,285	2,638	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},HK}$	0,285	*0,042*	0,261	*0,043*	-2,815**
$\widehat{\beta}_{US,UK}$	-0,154	-2,062	$\hat{\tau}_{JP\|US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,054	*0,079*	0,032	*0,057*	-0,381
$\widehat{\beta}_{US,FR}$	-0,024	-0,618	$\hat{\tau}_{JP\|US,\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	0,114	*0,166*	0,093	*0,152*	0,050
$\widehat{\beta}_{US,GE}$	-0,130	-1,778	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,048	*0,065*	0,045	*0,043*	-0,126
$\widehat{\beta}_{UK,FR}$	-0,104	-0,983	$\hat{\tau}_{JP\|\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,119	*0,118*	0,117	*0,110*	0,277
$\widehat{\beta}_{UK.GE}$	-0,027	-0,547	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{HK}}$	0,236	*0,101*	0,232	*0,126*	-0,048
$\widehat{\beta}_{UK,IT}$	-0,038	-0,958	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{HK}}$	0,180	*0,144*	0,096	*0,145*	-0,715
$\widehat{\beta}_{FR,GE}$	-0,038	-0,822	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	0,154	*0,093*	0,145	*0,089*	-0,071
$\widehat{\beta}_{FR,IT}$	-0,070	-0,878	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{HK}}$	0,078	*0,074*	0,078	*0,050*	-0,182
$\widehat{\beta}_{FR,HK}$	0,177	-0,035	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},HK}$	0,538	*0,176*	0,523	*0,225*	0,161
$\widehat{\beta}_{GE,IT}$	-0,143	-1,659	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{HK}}$	0,043	*0,070*	0,054	*0,054*	0,096
$\widehat{\beta}_{GE,HK}$	0,039	-0,521	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},HK}$	0,440	*0,190*	0,499	*0,243*	0,641
$\widehat{\beta}_{IT,HK}$	-0,100	-0,586	$\hat{\tau}_{JP\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,HK}$	0,257	*0,131*	0,330	*0,160*	0,975
$\widehat{\beta}_{US,UK,FR}$	0,223	2,709	$\hat{\tau}_{JP\|US,UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,226	*0,146*	0,241	*0,194*	0,240
$\widehat{\beta}_{US,FR,GE}$	0,028	0,944	$\hat{\tau}_{JP\|US,\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	0,090	*0,087*	0,085	*0,078*	-0,203
$\widehat{\beta}_{UK,FR,IT}$	0,041	1,006	$\hat{\tau}_{JP\|\overline{US},UK,FR,\overline{GE},IT,\overline{HK}}$	0,124	*0,106*	0,126	*0,099*	0,029
$\widehat{\beta}_{FR,GE,IT}$	0,055	1,111	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,IT,\overline{HK}}$	0,068	*0,092*	0,092	*0,069*	0,549
$\widehat{\beta}_{FR,GE,HK}$	-0,028	0,551	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,\overline{IT},HK}$	0,627	*0,141*	0,702	*0,174*	0,678

Table 21: **Results of indicator regression using linear and logit model with response variable Hong Kong. The number of variables is reduced by the principal component analysis described in section 2.3.2. Note: * denotes 10% significant difference between the models and ** denotes significant difference at 5%**

Regression coefficient			**Tail dependence**	**Probability**				**T-stat**
	Linear	Logit		Linear	*SE*	Logit	*SE*	
c		-3,808				0,022	*0,003*	
$\widehat{\beta}_{US}$	0,034	0,308	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,034	*0,022*	0,029	*0,013*	-0,306
$\widehat{\beta}_{UK}$	0,150	1,884	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,150	*0,052*	0,127	*0,048*	-1,211
$\widehat{\beta}_{FR}$	0,091	1,208	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP}}$	0,091	*0,052*	0,069	*0,039*	-1,081
$\widehat{\beta}_{GE}$	0,059	0,797	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,059	*0,051*	0,047	*0,031*	-0,402
$\widehat{\beta}_{IT}$	0,099	1,252	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP}}$	0,099	*0,045*	0,072	*0,033*	-1,569
$\widehat{\beta}_{JP}$	0,259	2,645	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},JP}$	0,259	*0,037*	0,238	*0,037*	-2,475**
$\widehat{\beta}_{US,UK}$	-0,149	-1,429	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,035	*0,109*	0,045	*0,064*	0,356
$\widehat{\beta}_{US,GE}$	0,086	0,959	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,179	*0,117*	0,149	*0,122*	-0,405
$\widehat{\beta}_{UK,FR}$	-0,181	-1,651	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{JP}}$	0,059	*0,113*	0,086	*0,080*	0,648
$\widehat{\beta}_{UK,GE}$	-0,111	-1,213	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	0,097	*0,105*	0,088	*0,074*	-0,110
$\widehat{\beta}_{UK,IT}$	0,022	-0,301	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{JP}}$	0,270	*0,118*	0,274	*0,141*	0,434
$\widehat{\beta}_{UK,JP}$	0,031	-0,749	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,440	*0,124*	0,493	*0,148*	1,187
$\widehat{\beta}_{FR,GE}$	-0,044	-0,623	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{JP}}$	0,105	*0,082*	0,081	*0,059*	-0,528
$\widehat{\beta}_{FR,IT}$	0,024	0,053	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{JP}}$	0,213	*0,099*	0,215	*0,110*	0,157
$\widehat{\beta}_{FR,JP}$	0,176	0,134	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},JP}$	0,525	*0,128*	0,545	*0,165*	0,318
$\widehat{\beta}_{GE,IT}$	-0,010	-0,294	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{JP}}$	0,147	*0,093*	0,114	*0,089*	-0,740
$\widehat{\beta}_{US,UK,GE}$	-0,116	-0,680	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	-0,047	*0,103*	0,040	*0,037*	1,189
$\widehat{\beta}_{UK,FR,GE}$	0,209	1,891	$\hat{\tau}_{HK\|\overline{US},UK,FR,GE,\overline{IT},\overline{JP}}$	0,171	*0,091*	0,180	*0,088*	0,183

D Multivariate tail dependence – full model

In the Tables 22 - 28, we present the results of the indicator regression using the full set of variables, that is, performing regression without any variables selection.

Table 22: Results of the indicator regression using the full set of explanatory variables. The response variable is US.

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-3,801	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,022	*0,003*
$\widehat{\beta}_{UK}$	0,278	2,845	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,278	*0,069*	0,278	*0,069*
$\widehat{\beta}_{FR}$	0,048	0,805	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,048	*0,048*	0,048	*0,048*
$\widehat{\beta}_{GE}$	0,212	2,488	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,212	*0,081*	0,212	*0,081*
$\widehat{\beta}_{IT}$	0,093	1,523	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,093	*0,056*	0,093	*0,056*
$\widehat{\beta}_{JP}$	0,049	0,835	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,049	*0,021*	0,049	*0,021*
$\widehat{\beta}_{HK}$	0,045	0,756	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,045	*0,027*	0,045	*0,027*
$\widehat{\beta}_{UK,FR}$	0,050	-0,360	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,375	*0,190*	0,375	*0,190*
$\widehat{\beta}_{UK,GE}$	-0,365	-3,479	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,125	*0,126*	0,125	*0,128*
$\widehat{\beta}_{UK,IT}$	-0,371	-18,13	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,000	*0,215*	0,000	*0,147*
$\widehat{\beta}_{UK,JP}$	-0,077	-0,978	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,250	*0,270*	0,250	*0,256*
$\widehat{\beta}_{UK,HK}$	0,077	-0,206	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,400	*0,250*	0,400	*0,251*
$\widehat{\beta}_{FR,GE}$	0,026	-0,409	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,286	*0,126*	0,286	*0,126*
$\widehat{\beta}_{FR,IT}$	0,132	0,492	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,273	*0,141*	0,273	*0,141*
$\widehat{\beta}_{FR,JP}$	-0,097	-15,41	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,000	*0,554*	0,000	*0,279*
$\widehat{\beta}_{FR,HK}$	0,907	19,806	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP},HK}$	1,000	*0,759*	1,000	*0,452*
$\widehat{\beta}_{GE,IT}$	-0,305	-17,78	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,000	*0,020*	0,000	*0,022*
$\widehat{\beta}_{GE,JP}$	-0,261	-17,09	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	0,000	*0,061*	0,000	*0,030*
$\widehat{\beta}_{GE,HK}$	0,242	0,556	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,500	*0,346*	0,500	*0,265*
$\widehat{\beta}_{IT,JP}$	0,191	0,749	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,333	*0,347*	0,333	*0,332*
$\widehat{\beta}_{IT,HK}$	-0,138	-16,04	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,000	*0,130*	0,000	*0,065*
$\widehat{\beta}_{JP,HK}$	-0,036	-0,563	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,059	*0,040*	0,059	*0,040*
$\widehat{\beta}_{UK,FR,GE}$	0,052	1,063	$\hat{\tau}_{US\vert UK,FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,300	*0,158*	0,300	*0,158*
$\widehat{\beta}_{UK,FR,IT}$	-0,007	15,377	$\hat{\tau}_{US\vert UK,FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,222	*0,136*	0,222	*0,135*
$\widehat{\beta}_{UK,FR,JP}$	-0,251	-1,507	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,000	*0,353*	0,000	*0,185*
$\widehat{\beta}_{UK,FR,HK}$	-1,404	-37,41	$\hat{\tau}_{US\vert UK,FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,000	*0,809*	0,000	*0,413*
$\widehat{\beta}_{UK,GE,IT}$	1,208	37,432	$\hat{\tau}_{US\vert UK,\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,750	*0,286*	0,750	*0,256*
$\widehat{\beta}_{UK,GE,JP}$	0,164	1,612	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	0,000	*0,500*	0,000	*0,242*
$\widehat{\beta}_{UK,GE,HK}$	-0,132	-0,620	$\hat{\tau}_{US\vert UK,\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,358	*0,991*	0,188	*0,439*
$\widehat{\beta}_{UK,IT,JP}$	-0,164	-0,606	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,000	*0,536*	0,000	*0,248*
$\widehat{\beta}_{UK,IT,HK}$	0,016	15,495	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,000	*0,395*	0,000	*0,157*
$\widehat{\beta}_{UK,JP,HK}$	-0,337	-16,45	$\hat{\tau}_{US\vert UK,\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,000	*0,072*	0,000	*0,037*
$\widehat{\beta}_{FR,GE,IT}$	0,169	16,168	$\hat{\tau}_{US\vert\overline{UK},FR,GE,IT,\overline{JP},\overline{HK}}$	0,375	*0,186*	0,375	*0,186*
$\widehat{\beta}_{FR,GE,JP}$	0,023	15,010	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},JP,\overline{HK}}$	0,000	*0,356*	0,000	*0,166*
$\widehat{\beta}_{FR,GE,HK}$	-1,481	-37,77	$\hat{\tau}_{US\vert\overline{UK},FR,GE,\overline{IT},\overline{JP},HK}$	0,000	*0,693*	0,000	*0,402*
$\widehat{\beta}_{FR,IT,JP}$	0,584	32,368	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,JP,\overline{HK}}$	1,000	*0,635*	1,000	*0,372*
$\widehat{\beta}_{FR,IT,HK}$	-1,087	-21,10	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},IT,\overline{JP},HK}$	0,000	*0,446*	0,000	*0,236*
$\widehat{\beta}_{FR,JP,HK}$	-0,917	-20.00	$\hat{\tau}_{US\vert\overline{UK},FR,\overline{GE},\overline{IT},JP,HK}$	0,000	*0,276*	0,000	*0,162*
$\widehat{\beta}_{GE,IT,JP}$	2,031	0,000	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,JP,\overline{HK}}$	2,010	*0,992*	0,000	*0,377*
$\widehat{\beta}_{GE,IT,HK}$	-0,149	14,733	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,IT,\overline{JP},HK}$	0,000	*0,619*	0,000	*0,315*
$\widehat{\beta}_{GE,JP,HK}$	-0,252	-0,749	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},GE,\overline{IT},JP,HK}$	0,000	*0,625*	0,000	*0,395*
$\widehat{\beta}_{IT,JP,HK}$	0,295	16,545	$\hat{\tau}_{US\vert\overline{UK},\overline{FR},\overline{GE},IT,JP,HK}$	0,500	*0,506*	0,500	*0,387*
$\widehat{\beta}_{UK,FR,GE,IT}$	-0,590	-33,70	$\hat{\tau}_{US\vert UK,FR,GE,IT,\overline{JP},\overline{HK}}$	0,630	*0,067*	0,630	*0,067*
$\widehat{\beta}_{UK,FR,GE,JP}$	0,149	0,804	$\hat{\tau}_{US\vert UK,FR,GE,\overline{IT},JP,\overline{HK}}$	0,000	*0,350*	0,000	*0,225*

$\widehat{\beta}_{UK,FR,GE,HK}$	1,445	38,169	$\hat{\tau}_{US\|UK,FR,GE,\overline{IT},\overline{JP},HK}$	0,000	*0,520*	0,000	*0,229*
$\widehat{\beta}_{UK,FR,IT,JP}$	0,041	-14,20	$\hat{\tau}_{US\|UK,FR,\overline{GE},IT,JP,\overline{HK}}$	0,500	*0,514*	0,500	*0,397*
$\widehat{\beta}_{UK,FR,IT,HK}$	1,362	22,394	$\hat{\tau}_{US\|UK,FR,\overline{GE},IT,\overline{JP},HK}$	0,000	*0,419*	0,000	*0,197*
$\widehat{\beta}_{UK,FR,JP,HK}$	0,209	15,710	$\hat{\tau}_{US\|UK,FR,\overline{GE},\overline{IT},JP,HK}$	-1,455	*1,126*	0,000	*0,371*
$\widehat{\beta}_{UK,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{US\|UK,\overline{FR},GE,IT,JP,\overline{HK}}$	2,684	*1,199*	0,000	*0,476*
$\widehat{\beta}_{UK,GE,IT,HK}$	-0,711	-33,33	$\hat{\tau}_{US\|UK,\overline{FR},GE,IT,\overline{JP},HK}$	0,000	*0,815*	0,000	*0,460*
$\widehat{\beta}_{UK,GE,JP,HK}$	0,392	17,281	$\hat{\tau}_{US\|UK,\overline{FR},GE,\overline{IT},JP,HK}$	0,000	*0,539*	0,000	*0,205*
$\widehat{\beta}_{UK,IT,JP,HK}$	0,077	0,472	$\hat{\tau}_{US\|UK,\overline{FR},\overline{GE},IT,JP,HK}$	0,000	*0,615*	0,000	*0,285*
$\widehat{\beta}_{FR,GE,IT,JP}$	-2,513	-2,120	$\hat{\tau}_{US\|\overline{UK},FR,GE,IT,JP,\overline{HK}}$	0,382	*1,071*	1,000	*0,474*
$\widehat{\beta}_{FR,GE,IT,HK}$	1,285	22,009	$\hat{\tau}_{US\|\overline{UK},FR,GE,IT,\overline{JP},HK}$	0,000	*0,494*	0,000	*0,204*
$\widehat{\beta}_{FR,GE,JP,HK}$	1,490	37,960	$\hat{\tau}_{US\|\overline{UK},FR,GE,\overline{IT},JP,HK}$	0,000	*0,466*	0,000	*0,170*
$\widehat{\beta}_{FR,IT,JP,HK}$	0,430	3,036	$\hat{\tau}_{US\|\overline{UK},FR,\overline{GE},IT,JP,HK}$	0,500	*0,512*	0,500	*0,396*
$\widehat{\beta}_{GE,IT,JP,HK}$	-1,018	35,404	$\hat{\tau}_{US\|\overline{UK},\overline{FR},GE,IT,JP,HK}$	1,000	*0,882*	1,000	*0,450*
$\widehat{\beta}_{UK,FR,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{US\|UK,FR,GE,IT,JP,\overline{HK}}$	0,500	*0,231*	0,500	*0,228*
$\widehat{\beta}_{UK,FR,GE,IT,HK}$	-0,507	11,632	$\hat{\tau}_{US\|UK,FR,GE,IT,\overline{JP},HK}$	0,400	*0,122*	0,400	*0,122*
$\widehat{\beta}_{UK,FR,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{US\|UK,FR,GE,\overline{IT},JP,HK}$	0,250	*0,329*	0,250	*0,260*
$\widehat{\beta}_{UK,FR,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{US\|UK,FR,\overline{GE},IT,JP,HK}$	0,000	*0,433*	0,000	*0,176*
$\widehat{\beta}_{UK,GE,IT,JP,HK}$	-0,021	-1,389	$\hat{\tau}_{US\|UK,\overline{FR},GE,IT,JP,HK}$	1,034	*1,454*	1,000	*0,482*
$\widehat{\beta}_{FR,GE,IT,JP,HK}$	0,000	-85,98	$\hat{\tau}_{US\|\overline{UK},FR,GE,IT,JP,HK}$	0,000	*0,491*	0,000	*0,267*
$\widehat{\beta}_{UK,FR,GE,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{US\|UK,FR,GE,IT,JP,HK}$	0,583	*0,166*	0,583	*0,166*

Table 23: **Results of the indicator regression using the full set of explanatory variables. The response variable is UK.**

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-5,008	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,007	*0,001*
$\widehat{\beta}_{US}$	0,103	2,845	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,103	*0,030*	0,103	*0,030*
$\widehat{\beta}_{FR}$	0,200	3,622	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,200	*0,074*	0,200	*0,074*
$\widehat{\beta}_{GE}$	0,212	3,696	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,212	*0,073*	0,212	*0,073*
$\widehat{\beta}_{IT}$	0,071	2,443	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,071	*0,042*	0,071	*0,042*
$\widehat{\beta}_{JP}$	0,030	1,532	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,030	*0,017*	0,030	*0,017*
$\widehat{\beta}_{HK}$	0,034	1,676	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,034	*0,020*	0,034	*0,020*
$\widehat{\beta}_{US,FR}$	0,447	-0,360	$\hat{\tau}_{UK\|US,FR,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,750	*0,281*	0,750	*0,246*
$\widehat{\beta}_{US,GE}$	-0,190	-3,479	$\hat{\tau}_{UK\|US,\overline{FR},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,125	*0,137*	0,125	*0,137*
$\widehat{\beta}_{US,IT}$	-0,175	-17,85	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,000	*0,241*	0,000	*0,154*
$\widehat{\beta}_{US,JP}$	0,034	-0,978	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,167	*0,170*	0,167	*0,167*
$\widehat{\beta}_{US,HK}$	0,196	-0,206	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},\overline{IT},\overline{JP},HK}$	0,333	*0,248*	0,333	*0,244*
$\widehat{\beta}_{FR,GE}$	0,000	-2,667	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,412	*0,118*	0,412	*0,118*
$\widehat{\beta}_{FR,IT}$	0,195	-1,191	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,467	*0,131*	0,467	*0,131*
$\widehat{\beta}_{FR,JP}$	0,437	0,547	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,667	*0,387*	0,667	*0,314*
$\widehat{\beta}_{FR,HK}$	0,766	17,276	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},\overline{JP},HK}$	1,000	*0,776*	1,000	*0,418*
$\widehat{\beta}_{GE,IT}$	-0,172	-3,211	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	0,111	*0,110*	0,111	*0,110*
$\widehat{\beta}_{GE,JP}$	-0,075	-1,829	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	0,167	*0,168*	0,167	*0,167*
$\widehat{\beta}_{GE,HK}$	-0,247	-17,93	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,000	*0,372*	0,000	*0,247*
$\widehat{\beta}_{IT,JP}$	0,232	0,340	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,333	*0,369*	0,333	*0,325*
$\widehat{\beta}_{IT,HK}$	0,227	0,196	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,333	*0,211*	0,333	*0,210*
$\widehat{\beta}_{JP,HK}$	0,071	-0,056	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,135	*0,056*	0,135	*0,056*
$\widehat{\beta}_{US,FR,GE}$	-0,343	1,063	$\hat{\tau}_{UK\|US,FR,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,429	*0,189*	0,429	*0,189*
$\widehat{\beta}_{US,FR,IT}$	-0,442	15,089	$\hat{\tau}_{UK\|US,FR,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,400	*0,253*	0,400	*0,245*
$\widehat{\beta}_{US,FR,JP}$	0,000	0,000	$\hat{\tau}_{UK\|US,FR,\overline{GE},\overline{IT},JP,\overline{HK}}$	1,250	*0,836*	0,900	*0,442*
$\widehat{\beta}_{US,FR,HK}$	-1,746	-37,41	$\hat{\tau}_{UK\|US,FR,\overline{GE},\overline{IT},\overline{JP},HK}$	0,000	*0,959*	0,000	*0,467*
$\widehat{\beta}_{US,GE,IT}$	1,151	38,125	$\hat{\tau}_{UK\|US,\overline{FR},GE,IT,\overline{JP},\overline{HK}}$	1,000	*0,242*	1,000	*0,198*
$\widehat{\beta}_{US,GE,JP}$	-0,480	16,253	$\hat{\tau}_{UK\|US,\overline{FR},GE,\overline{IT},JP,\overline{HK}}$	-0,367	*0,712*	1,000	*0,347*
$\widehat{\beta}_{US,GE,HK}$	-0,109	0,840	$\hat{\tau}_{UK\|US,\overline{FR},GE,\overline{IT},\overline{JP},HK}$	0,000	*0,408*	0,000	*0,193*
$\widehat{\beta}_{US,IT,JP}$	-0,295	-0,893	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},IT,JP,\overline{HK}}$	0,000	*0,600*	0,000	*0,186*
$\widehat{\beta}_{US,IT,HK}$	0,105	16,883	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},IT,\overline{JP},HK}$	0,563	*0,901*	0,728	*0,429*
$\widehat{\beta}_{US,JP,HK}$	-0,468	-17,37	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},\overline{IT},JP,HK}$	0,000	*0,273*	0,000	*0,195*
$\widehat{\beta}_{FR,GE,IT}$	0,294	3,701	$\hat{\tau}_{UK\|\overline{US},FR,GE,IT,\overline{JP},\overline{HK}}$	0,800	*0,085*	0,800	*0,085*
$\widehat{\beta}_{FR,GE,JP}$	-0,303	0,107	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},JP,\overline{HK}}$	0,500	*0,321*	0,500	*0,289*
$\widehat{\beta}_{FR,GE,HK}$	-0,298	0,027	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},\overline{JP},HK}$	0,667	*0,364*	0,667	*0,321*
$\widehat{\beta}_{FR,IT,JP}$	-0,165	15,281	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},IT,JP,\overline{HK}}$	1,000	*0,709*	1,000	*0,277*
$\widehat{\beta}_{FR,IT,HK}$	-0,894	-18,61	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},IT,\overline{JP},HK}$	0,600	*0,312*	0,600	*0,289*
$\widehat{\beta}_{FR,JP,HK}$	-1,537	-37,16	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},\overline{IT},JP,HK}$	0,000	*0,297*	0,000	*0,142*
$\widehat{\beta}_{GE,IT,JP}$	0,045	0,203	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,IT,JP,\overline{HK}}$	0,343	*0,992*	0,138	*0,398*
$\widehat{\beta}_{GE,IT,HK}$	0,374	18,138	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,IT,\overline{JP},HK}$	0,500	*0,508*	0,500	*0,390*
$\widehat{\beta}_{GE,JP,HK}$	0,641	18,613	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,\overline{IT},JP,HK}$	0,667	*0,399*	0,667	*0,328*
$\widehat{\beta}_{IT,JP,HK}$	-0,166	-1,122	$\hat{\tau}_{UK\|\overline{US},\overline{FR},\overline{GE},IT,JP,HK}$	0,500	*0,525*	0,500	*0,386*
$\widehat{\beta}_{US,FR,GE,IT}$	-0,432	-34,40	$\hat{\tau}_{UK\|US,FR,GE,IT,\overline{JP},\overline{HK}}$	0,919	*0,045*	0,919	*0,045*
$\widehat{\beta}_{US,FR,GE,JP}$	0,795	0,000	$\hat{\tau}_{UK\|US,FR,GE,\overline{IT},JP,\overline{HK}}$	0,865	*1,073*	1,000	*0,459*
$\widehat{\beta}_{US,FR,GE,HK}$	1,016	43,482	$\hat{\tau}_{UK\|US,FR,GE,\overline{IT},\overline{JP},HK}$	0,041	*1,161*	0,999	*0,472*
$\widehat{\beta}_{US,FR,IT,JP}$	-0,171	-15,42	$\hat{\tau}_{UK\|US,FR,\overline{GE},IT,JP,\overline{HK}}$	0,500	*0,542*	0,500	*0,390*
$\widehat{\beta}_{US,FR,IT,HK}$	0,600	24,928	$\hat{\tau}_{UK\|US,FR,\overline{GE},IT,\overline{JP},HK}$	-0,311	*1,128*	0,987	*0,475*
$\widehat{\beta}_{US,FR,JP,HK}$	1,145	12,483	$\hat{\tau}_{UK\|US,FR,\overline{GE},\overline{IT},JP,HK}$	-0,289	*1,213*	0,000	*0,372*

$\widehat{\beta}_{US,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{UK\|US,\overline{FR},GE,IT,JP,\overline{HK}}$	0,489	*1,247*	1,000	*0,481*
$\widehat{\beta}_{US,GE,IT,HK}$	0,000	-33,50	$\hat{\tau}_{UK\|US,\overline{FR},GE,IT,\overline{JP},HK}$	1,581	*1,147*	0,975	*0,397*
$\widehat{\beta}_{US,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,\overline{FR},GE,\overline{IT},JP,HK}$	-0,248	*1,011*	0,197	*0,429*
$\widehat{\beta}_{US,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,\overline{FR},\overline{GE},IT,JP,HK}$	0,000	*0,686*	0,000	*0,219*
$\widehat{\beta}_{FR,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{UK\|\overline{US},FR,GE,IT,JP,\overline{HK}}$	1,000	*0,263*	1,000	*0,163*
$\widehat{\beta}_{FR,GE,IT,HK}$	0,056	-0,656	$\hat{\tau}_{UK\|\overline{US},FR,GE,IT,\overline{JP},HK}$	0,818	*0,116*	0,818	*0,117*
$\widehat{\beta}_{FR,GE,JP,HK}$	0,670	17,954	$\hat{\tau}_{UK\|\overline{US},FR,GE,\overline{IT},JP,HK}$	0,600	*0,269*	0,600	*0,253*
$\widehat{\beta}_{FR,IT,JP,HK}$	1,166	20,922	$\hat{\tau}_{UK\|\overline{US},FR,\overline{GE},IT,JP,HK}$	0,667	*0,429*	0,667	*0,322*
$\widehat{\beta}_{GE,IT,JP,HK}$	-1,149	-35,92	$\hat{\tau}_{UK\|\overline{US},\overline{FR},GE,IT,JP,HK}$	0,129	*1,331*	0,000	*0,474*
$\widehat{\beta}_{US,FR,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{UK\|US,FR,GE,IT,JP,\overline{HK}}$	1,000	*0,245*	1,000	*0,101*
$\widehat{\beta}_{US,FR,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,FR,GE,IT,\overline{JP},HK}$	1,000	*0,081*	1,000	*0,039*
$\widehat{\beta}_{US,FR,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,FR,GE,\overline{IT},JP,HK}$	1,000	*0,877*	1,000	*0,339*
$\widehat{\beta}_{US,FR,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,FR,\overline{GE},IT,JP,HK}$	0,000	*0,973*	0,000	*0,364*
$\widehat{\beta}_{US,GE,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|US,\overline{FR},GE,IT,JP,HK}$	0,000	*1,107*	0,000	*0,438*
$\widehat{\beta}_{FR,GE,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{UK\|\overline{US},FR,GE,IT,JP,HK}$	0,714	*0,263*	0,714	*0,251*
$\widehat{\beta}_{US,FR,GE,IT,JP,HK}$	-0,455	6,517	$\hat{\tau}_{UK\|US,FR,GE,IT,JP,HK}$	1,000	*0,097*	1,000	*0,050*

Table 24: **Results of the indicator regression using the full set of explanatory variables. The response variable is France.**

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-5,271	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$			0,005	*0,001*
$\widehat{\beta}_{US}$	0,011	0,805	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,011	*0,011*	0,011	*0,011*
$\widehat{\beta}_{UK}$	0,161	3,622	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,161	*0,069*	0,161	*0,069*
$\widehat{\beta}_{GE}$	0,278	4,315	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,278	*0,070*	0,278	*0,070*
$\widehat{\beta}_{IT}$	0,170	3,687	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,170	*0,051*	0,170	*0,051*
$\widehat{\beta}_{JP}$	0,010	0,696	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,010	*0,010*	0,010	*0,010*
$\widehat{\beta}_{HK}$	0,000	-12,30	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},\overline{JP},HK}$	0,000	*0,000*	0,000	*0,000*
$\widehat{\beta}_{US,UK}$	0,058	-0,360	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},\overline{JP},\overline{HK}}$	0,231	*0,121*	0,231	*0,121*
$\widehat{\beta}_{US,GE}$	0,074	-0,409	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},\overline{JP},\overline{HK}}$	0,364	*0,165*	0,364	*0,165*
$\widehat{\beta}_{US,IT}$	0,247	0,492	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},IT,\overline{JP},\overline{HK}}$	0,429	*0,234*	0,429	*0,234*
$\widehat{\beta}_{US,JP}$	-0,022	-13,80	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},JP,\overline{HK}}$	0,000	*0,049*	0,000	*0,027*
$\widehat{\beta}_{US,HK}$	0,189	15,375	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},\overline{JP},HK}$	0,200	*0,254*	0,200	*0,234*
$\widehat{\beta}_{UK,GE}$	0,061	-2,667	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,500	*0,144*	0,500	*0,144*
$\widehat{\beta}_{UK,IT}$	0,368	-1,191	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},\overline{HK}}$	0,700	*0,153*	0,700	*0,153*
$\widehat{\beta}_{UK,JP}$	0,229	0,547	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,400	*0,252*	0,400	*0,249*
$\widehat{\beta}_{UK,HK}$	0,089	12,845	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},\overline{JP},HK}$	0,250	*0,321*	0,250	*0,259*
$\widehat{\beta}_{GE,IT}$	-0,063	-3,201	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},\overline{HK}}$	0,385	*0,144*	0,385	*0,144*
$\widehat{\beta}_{GE,JP}$	-0,002	-0,657	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,\overline{HK}}$	0,286	*0,187*	0,286	*0,186*
$\widehat{\beta}_{GE,HK}$	0,056	12,558	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},\overline{JP},HK}$	0,333	*0,360*	0,333	*0,315*
$\widehat{\beta}_{IT,JP}$	-0,180	-16,68	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,JP,\overline{HK}}$	0,000	*0,391*	0,000	*0,229*
$\widehat{\beta}_{IT,HK}$	0,163	13,186	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,\overline{JP},HK}$	0,333	*0,219*	0,333	*0,216*
$\widehat{\beta}_{JP,HK}$	0,076	14,503	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},\overline{IT},JP,HK}$	0,086	*0,048*	0,086	*0,048*
$\widehat{\beta}_{US,UK,GE}$	0,106	1,063	$\hat{\tau}_{FR\|US,UK,GE,\overline{IT},\overline{JP},\overline{HK}}$	0,750	*0,259*	0,750	*0,263*
$\widehat{\beta}_{US,UK,IT}$	-0,016	15,782	$\hat{\tau}_{FR\|US,UK,\overline{GE},IT,\overline{JP},\overline{HK}}$	1,000	*0,318*	1,000	*0,203*
$\widehat{\beta}_{US,UK,JP}$	-0,448	-3,809	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},JP,\overline{HK}}$	0,000	*0,514*	0,000	*0,294*
$\widehat{\beta}_{US,UK,HK}$	-0,508	-32,29	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},\overline{JP},HK}$	0,000	*0,386*	0,000	*0,272*
$\widehat{\beta}_{US,GE,IT}$	0,283	17,149	$\hat{\tau}_{FR\|US,\overline{UK},GE,IT,\overline{JP},\overline{HK}}$	1,000	*0,185*	1,000	*0,147*
$\widehat{\beta}_{US,GE,JP}$	-0,277	39,966	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},JP,\overline{HK}}$	0,073	*0,647*	1,000	*0,391*
$\widehat{\beta}_{US,GE,HK}$	-0,608	-32,64	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},\overline{JP},HK}$	0,000	*0,408*	0,000	*0,296*
$\widehat{\beta}_{US,IT,JP}$	0,263	30,066	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},IT,JP,\overline{HK}}$	0,500	*0,513*	0,500	*0,389*
$\widehat{\beta}_{US,IT,HK}$	-0,424	-15,36	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},IT,\overline{JP},HK}$	0,356	*0,997*	0,650	*0,451*
$\widehat{\beta}_{US,JP,HK}$	-0,264	-17,58	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},\overline{IT},JP,HK}$	0,000	*0,287*	0,000	*0,191*
$\widehat{\beta}_{UK,GE,IT}$	-0,023	3,701	$\hat{\tau}_{FR\|\overline{US},UK,GE,IT,\overline{JP},\overline{HK}}$	0,952	*0,050*	0,952	*0,050*
$\widehat{\beta}_{UK,GE,JP}$	-0,070	0,107	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,\overline{HK}}$	0,667	*0,332*	0,667	*0,314*
$\widehat{\beta}_{UK,GE,HK}$	0,356	4,458	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},\overline{JP},HK}$	1,000	*0,324*	1,000	*0,219*
$\widehat{\beta}_{UK,IT,JP}$	-0,258	14,587	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,JP,\overline{HK}}$	0,500	*0,495*	0,500	*0,390*
$\widehat{\beta}_{UK,IT,HK}$	-0,352	-14,18	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,\overline{JP},HK}$	0,600	*0,320*	0,600	*0,299*
$\widehat{\beta}_{UK,JP,HK}$	-0,564	-32,21	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},\overline{IT},JP,HK}$	0,000	*0,046*	0,000	*0,055*
$\widehat{\beta}_{GE,IT,JP}$	0,320	30,186	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,JP,\overline{HK}}$	0,532	*0,896*	1,000	*0,461*
$\widehat{\beta}_{GE,IT,HK}$	0,063	-12,29	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,\overline{JP},HK}$	0,667	*0,369*	0,667	*0,322*
$\widehat{\beta}_{GE,JP,HK}$	0,250	-13,16	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,\overline{IT},JP,HK}$	0,667	*0,335*	0,667	*0,310*
$\widehat{\beta}_{IT,JP,HK}$	0,261	2,172	$\hat{\tau}_{FR\|\overline{US},\overline{UK},\overline{GE},IT,JP,HK}$	0,500	*0,536*	0,500	*0,396*
$\widehat{\beta}_{US,UK,GE,IT}$	-0,797	-35,09	$\hat{\tau}_{FR\|US,UK,GE,IT,\overline{JP},\overline{HK}}$	0,919	*0,046*	0,919	*0,046*
$\widehat{\beta}_{US,UK,GE,JP}$	0,000	0,000	$\hat{\tau}_{FR\|US,UK,GE,\overline{IT},JP,\overline{HK}}$	0,170	*1,014*	1,000	*0,467*
$\widehat{\beta}_{US,UK,GE,HK}$	1,485	0,000	$\hat{\tau}_{FR\|US,UK,GE,\overline{IT},\overline{JP},HK}$	1,808	*1,104*	0,000	*0,460*
$\widehat{\beta}_{US,UK,IT,JP}$	0,406	-11,61	$\hat{\tau}_{FR\|US,UK,\overline{GE},IT,JP,\overline{HK}}$	1,000	*0,556*	1,000	*0,276*
$\widehat{\beta}_{US,UK,IT,HK}$	0,000	80,851	$\hat{\tau}_{FR\|US,UK,\overline{GE},IT,\overline{JP},HK}$	0,156	*1,155*	1,000	*0,453*
$\widehat{\beta}_{US,UK,JP,HK}$	0,603	60,840	$\hat{\tau}_{FR\|US,UK,\overline{GE},\overline{IT},JP,HK}$	-0,381	*0,988*	0,000	*0,375*

$\widehat{\beta}_{US,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{FR\|US,\overline{UK},GE,IT,JP,\overline{HK}}$	1,112	*1,168*	1,000	*0,462*
$\widehat{\beta}_{US,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,\overline{UK},GE,IT,\overline{JP},HK}$	0,438	*1,109*	0,000	*0,471*
$\widehat{\beta}_{US,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,\overline{UK},GE,\overline{IT},JP,HK}$	-0,229	*0,929*	0,001	*0,374*
$\widehat{\beta}_{US,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,\overline{UK},\overline{GE},IT,JP,HK}$	0,500	*0,513*	0,500	*0,395*
$\widehat{\beta}_{UK,GE,IT,JP}$	0,000	-14,22	$\hat{\tau}_{FR\|\overline{US},UK,GE,IT,JP,\overline{HK}}$	1,000	*0,265*	1,000	*0,118*
$\widehat{\beta}_{UK,GE,IT,HK}$	-0,427	-5,087	$\hat{\tau}_{FR\|\overline{US},UK,GE,IT,\overline{JP},HK}$	0,900	*0,098*	0,900	*0,088*
$\widehat{\beta}_{UK,GE,JP,HK}$	-0,328	13,013	$\hat{\tau}_{FR\|\overline{US},UK,GE,\overline{IT},JP,HK}$	0,600	*0,258*	0,600	*0,250*
$\widehat{\beta}_{UK,IT,JP,HK}$	0,494	16,674	$\hat{\tau}_{FR\|\overline{US},UK,\overline{GE},IT,JP,HK}$	0,667	*0,381*	0,667	*0,323*
$\widehat{\beta}_{GE,IT,JP,HK}$	-0,401	-0,193	$\hat{\tau}_{FR\|\overline{US},\overline{UK},GE,IT,JP,HK}$	1,000	*0,515*	1,000	*0,205*
$\widehat{\beta}_{US,UK,GE,IT,JP}$	0,111	-40,24	$\hat{\tau}_{FR\|US,UK,GE,IT,JP,\overline{HK}}$	1,000	*0,190*	1,000	*0,099*
$\widehat{\beta}_{US,UK,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,UK,GE,IT,\overline{JP},HK}$	1,000	*0,057*	1,000	*0,022*
$\widehat{\beta}_{US,UK,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,UK,GE,\overline{IT},JP,HK}$	1,000	*0,998*	1,000	*0,415*
$\widehat{\beta}_{US,UK,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,UK,\overline{GE},IT,JP,HK}$	0,761	*1,339*	1,000	*0,482*
$\widehat{\beta}_{US,GE,IT,JP,HK}$	-0,472	-59,19	$\hat{\tau}_{FR\|US,\overline{UK},GE,IT,JP,HK}$	0,000	*0,994*	0,000	*0,433*
$\widehat{\beta}_{UK,GE,IT,JP,HK}$	0,264	0,000	$\hat{\tau}_{FR\|\overline{US},UK,GE,IT,JP,HK}$	1,000	*0,224*	1,000	*0,094*
$\widehat{\beta}_{US,UK,GE,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{FR\|US,UK,GE,IT,JP,HK}$	1,000	*0,092*	1,000	*0,050*

Table 25: Results of the indicator regression using the full set of explanatory variables. The response variable is Germany.

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-5,008	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$			0,007	*0,002*
$\widehat{\beta}_{US}$	0,074	2,488	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,074	*0,030*	0,074	*0,030*
$\widehat{\beta}_{UK}$	0,212	3,696	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,212	*0,079*	0,212	*0,079*
$\widehat{\beta}_{FR}$	0,333	4,315	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,333	*0,076*	0,333	*0,076*
$\widehat{\beta}_{IT}$	0,170	3,424	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,170	*0,057*	0,170	*0,057*
$\widehat{\beta}_{JP}$	0,049	2,043	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},\overline{IT},JP,\overline{HK}}$	0,049	*0,022*	0,049	*0,022*
$\widehat{\beta}_{HK}$	0,023	1,271	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},\overline{IT},\overline{JP},HK}$	0,023	*0,016*	0,023	*0,016*
$\widehat{\beta}_{US,UK}$	-0,196	-3,479	$\hat{t}_{GE\mid US,UK,\overline{FR},\overline{IT},\overline{JP},\overline{HK}}$	0,091	*0,090*	0,091	*0,090*
$\widehat{\beta}_{US,FR}$	0,392	-0,409	$\hat{t}_{GE\mid US,\overline{UK},FR,\overline{IT},\overline{JP},\overline{HK}}$	0,800	*0,215*	0,800	*0,210*
$\widehat{\beta}_{US,IT}$	-0,245	-18,47	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},IT,\overline{JP},\overline{HK}}$	0,000	*0,239*	0,000	*0,195*
$\widehat{\beta}_{US,JP}$	-0,123	-17,09	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},\overline{IT},JP,\overline{HK}}$	0,000	*0,085*	0,000	*0,050*
$\widehat{\beta}_{US,HK}$	0,236	0,556	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},\overline{IT},\overline{JP},HK}$	0,333	*0,270*	0,333	*0,248*
$\widehat{\beta}_{UK,FR}$	0,038	-2,667	$\hat{t}_{GE\mid\overline{US},UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,583	*0,136*	0,583	*0,136*
$\widehat{\beta}_{UK,IT}$	-0,132	-3,211	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},IT,\overline{JP},\overline{HK}}$	0,250	*0,285*	0,250	*0,268*
$\widehat{\beta}_{UK,JP}$	-0,011	-1,829	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},\overline{IT},JP,\overline{HK}}$	0,250	*0,289*	0,250	*0,258*
$\widehat{\beta}_{UK,HK}$	-0,235	-17,52	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},\overline{IT},\overline{JP},HK}$	0,000	*0,229*	0,000	*0,129*
$\widehat{\beta}_{FR,IT}$	-0,119	-3,201	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,IT,\overline{JP},\overline{HK}}$	0,385	*0,144*	0,385	*0,144*
$\widehat{\beta}_{FR,JP}$	0,284	-0,657	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,\overline{IT},JP,\overline{HK}}$	0,667	*0,366*	0,667	*0,320*
$\widehat{\beta}_{FR,HK}$	0,643	16,989	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,\overline{IT},\overline{JP},HK}$	1,000	*0,691*	1,000	*0,408*
$\widehat{\beta}_{IT,JP}$	-0,219	-18,02	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},IT,JP,\overline{HK}}$	0,000	*0,347*	0,000	*0,259*
$\widehat{\beta}_{IT,HK}$	0,007	-1,073	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},IT,\overline{JP},HK}$	0,200	*0,201*	0,200	*0,205*
$\widehat{\beta}_{JP,HK}$	-0,042	-1,771	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},\overline{IT},JP,HK}$	0,030	*0,031*	0,030	*0,031*
$\widehat{\beta}_{US,UK,FR}$	-0,354	1,063	$\hat{t}_{GE\mid US,UK,FR,\overline{IT},\overline{JP},\overline{HK}}$	0,500	*0,230*	0,500	*0,229*
$\widehat{\beta}_{US,UK,IT}$	1,116	38,125	$\hat{t}_{GE\mid US,UK,\overline{FR},IT,\overline{JP},\overline{HK}}$	1,000	*0,201*	1,000	*0,208*
$\widehat{\beta}_{US,UK,JP}$	-0,005	1,612	$\hat{t}_{GE\mid US,UK,\overline{FR},\overline{IT},JP,\overline{HK}}$	0,000	*0,428*	0,000	*0,199*
$\widehat{\beta}_{US,UK,HK}$	-0,114	0,434	$\hat{t}_{GE\mid US,UK,\overline{FR},\overline{IT},\overline{JP},HK}$	0,000	*0,230*	0,000	*0,129*
$\widehat{\beta}_{US,FR,IT}$	-0,107	16,861	$\hat{t}_{GE\mid US,\overline{UK},FR,IT,\overline{JP},\overline{HK}}$	0,500	*0,225*	0,500	*0,220*
$\widehat{\beta}_{US,FR,JP}$	0,000	0,000	$\hat{t}_{GE\mid US,\overline{UK},FR,\overline{IT},JP,\overline{HK}}$	1,010	*0,854*	0,000	*0,452*
$\widehat{\beta}_{US,FR,HK}$	-1,702	-37,77	$\hat{t}_{GE\mid US,\overline{UK},FR,\overline{IT},\overline{JP},HK}$	0,000	*0,823*	0,000	*0,454*
$\widehat{\beta}_{US,IT,JP}$	0,294	33,071	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},IT,JP,\overline{HK}}$	0,000	*0,579*	0,000	*0,199*
$\widehat{\beta}_{US,IT,HK}$	0,481	17,066	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},IT,\overline{JP},HK}$	0,747	*0,912*	0,563	*0,464*
$\widehat{\beta}_{US,JP,HK}$	-0,217	-0,056	$\hat{t}_{GE\mid US,\overline{UK},\overline{FR},\overline{IT},JP,HK}$	0,000	*0,286*	0,000	*0,182*
$\widehat{\beta}_{UK,FR,IT}$	0,238	3,701	$\hat{t}_{GE\mid\overline{US},UK,FR,IT,\overline{JP},\overline{HK}}$	0,741	*0,096*	0,741	*0,096*
$\widehat{\beta}_{UK.FR,JP}$	-0,406	0,107	$\hat{t}_{GE\mid\overline{US},UK,FR,\overline{IT},JP,\overline{HK}}$	0,500	*0,313*	0,500	*0,289*
$\widehat{\beta}_{UK,FR,HK}$	-0,348	-0,378	$\hat{t}_{GE\mid\overline{US},UK,FR,\overline{IT},\overline{JP},HK}$	0,667	*0,367*	0,667	*0,317*
$\widehat{\beta}_{UK,IT,JP}$	-0,069	1,344	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},IT,JP,\overline{HK}}$	0,000	*0,534*	0,000	*0,225*
$\widehat{\beta}_{UK,IT,HK}$	0,289	17,732	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},IT,\overline{JP},HK}$	0,333	*0,333*	0,333	*0,314*
$\widehat{\beta}_{UK,JP,HK}$	0,290	18,207	$\hat{t}_{GE\mid\overline{US},UK,\overline{FR},\overline{IT},JP,HK}$	0,286	*0,191*	0,286	*0,191*
$\widehat{\beta}_{FR,IT,JP}$	1,104	35,715	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,IT,JP,\overline{HK}}$	1,603	*1,004*	1,000	*0,466*
$\widehat{\beta}_{FR,IT,HK}$	-0,558	-16,72	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,IT,\overline{JP},HK}$	0,500	*0,337*	0,500	*0,257*
$\widehat{\beta}_{FR,JP,HK}$	-0,891	-17,59	$\hat{t}_{GE\mid\overline{US},\overline{UK},FR,\overline{IT},JP,HK}$	0,400	*0,270*	0,400	*0,253*
$\widehat{\beta}_{IT,JP,HK}$	0,012	1,573	$\hat{t}_{GE\mid\overline{US},\overline{UK},\overline{FR},IT,JP,HK}$	0,000	*0,544*	0,000	*0,303*
$\widehat{\beta}_{US,UK,FR,IT}$	-0,478	-34,40	$\hat{t}_{GE\mid US,UK,FR,IT,\overline{JP},\overline{HK}}$	0,944	*0,039*	0,944	*0,039*
$\widehat{\beta}_{US,UK,FR,JP}$	1,520	33,247	$\hat{t}_{GE\mid US,UK,FR,\overline{IT},JP,\overline{HK}}$	1,808	*1,096*	1,000	*0,462*
$\widehat{\beta}_{US,UK,FR,HK}$	-0,251	7,840	$\hat{t}_{GE\mid US,UK,FR,\overline{IT},\overline{JP},HK}$	-1,249	*1,076*	0,000	*0,477*
$\widehat{\beta}_{US,UK,IT,JP}$	0,000	0,000	$\hat{t}_{GE\mid US,UK,\overline{FR},IT,JP,\overline{HK}}$	0,915	*1,022*	1,000	*0,444*
$\widehat{\beta}_{US,UK,IT,HK}$	0,000	0,000	$\hat{t}_{GE\mid US,UK,\overline{FR},IT,\overline{JP},HK}$	1,686	*1,027*	1,000	*0,279*

$\widehat{\beta}_{US,UK,JP,HK}$	0,000	0,000	$\hat{\tau}_{GE\|US,UK,\overline{FR},\overline{IT},JP,HK}$	-0,060	*0,843*	0,000	*0,456*
$\widehat{\beta}_{US,FR,IT,JP}$	-1,888	-52,62	$\hat{\tau}_{GE\|US,\overline{UK},FR,IT,JP,\overline{HK}}$	0,000	*0,823*	0,000	*0,372*
$\widehat{\beta}_{US,FR,IT,HK}$	1,397	26,556	$\hat{\tau}_{GE\|US,\overline{UK},FR,IT,\overline{JP},HK}$	1,027	*1,051*	0,999	*0,471*
$\widehat{\beta}_{US,FR,JP,HK}$	0,741	11,559	$\hat{\tau}_{GE\|US,\overline{UK},FR,\overline{IT},JP,HK}$	-0,199	*1,089*	0,000	*0,351*
$\widehat{\beta}_{US,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{GE\|US,\overline{UK},\overline{FR},IT,JP,HK}$	0,500	*0,544*	0,500	*0,392*
$\widehat{\beta}_{UK,FR,IT,JP}$	-0,724	-18,65	$\hat{\tau}_{GE\|\overline{US},UK,FR,IT,JP,\overline{HK}}$	0,750	*0,285*	0,750	*0,259*
$\widehat{\beta}_{UK,FR,IT,HK}$	0,188	-0,251	$\hat{\tau}_{GE\|\overline{US},UK,FR,IT,\overline{JP},HK}$	0,750	*0,162*	0,750	*0,162*
$\widehat{\beta}_{UK,FR,JP,HK}$	1,060	18,360	$\hat{\tau}_{GE\|\overline{US},UK,FR,\overline{IT},JP,HK}$	1,000	*0,258*	1,000	*0,142*
$\widehat{\beta}_{UK,IT,JP,HK}$	-0,343	-18,42	$\hat{\tau}_{GE\|\overline{US},UK,\overline{FR},IT,JP,HK}$	0,000	*0,646*	0,000	*0,331*
$\widehat{\beta}_{FR,IT,JP,HK}$	-0,130	-0,599	$\hat{\tau}_{GE\|\overline{US},\overline{UK},FR,IT,JP,HK}$	0,667	*0,479*	0,667	*0,328*
$\widehat{\beta}_{US,UK,FR,IT,JP}$	0,000	0,000	$\hat{\tau}_{GE\|US,UK,FR,IT,JP,\overline{HK}}$	0,750	*0,277*	0,750	*0,252*
$\widehat{\beta}_{US,UK,FR,IT,HK}$	0,000	0,000	$\hat{\tau}_{GE\|US,UK,FR,IT,\overline{JP},HK}$	1,000	*0,040*	1,000	*0,000*
$\widehat{\beta}_{US,UK,FR,JP,HK}$	0,000	0,000	$\hat{\tau}_{GE\|US,UK,FR,\overline{IT},JP,HK}$	1,000	*0,886*	1,000	*0,408*
$\widehat{\beta}_{US,UK,IT,JP,HK}$	-0,285	0,000	$\hat{\tau}_{GE\|US,UK,\overline{FR},IT,JP,HK}$	1,016	*1,347*	1,000	*0,344*
$\widehat{\beta}_{US,FR,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{GE\|US,\overline{UK},FR,IT,JP,HK}$	0,000	*0,946*	0,000	*0,366*
$\widehat{\beta}_{UK,FR,IT,JP,HK}$	0,000	0,000	$\hat{\tau}_{GE\|\overline{US},UK,FR,IT,JP,HK}$	0,714	*0,250*	0,714	*0,238*
$\widehat{\beta}_{UK,US,FR,IT,JP,HK}$	0,000	-9,538	$\hat{\tau}_{GE\|US,UK,FR,IT,JP,HK}$	1,000	*0,057*	1,000	*0,019*

Table 26: **Results of the indicator regression using the full set of explanatory variables. The response variable is Italy.**

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-4,603	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$			0,010	
$\widehat{\beta}_{US}$	0,044	1,523	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,044	*0,026*	0,044	*0,026*
$\widehat{\beta}_{UK}$	0,103	2,443	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,103	*0,059*	0,103	*0,059*
$\widehat{\beta}_{FR}$	0,286	3,687	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,286	*0,087*	0,286	*0,087*
$\widehat{\beta}_{GE}$	0,235	3,424	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,235	*0,073*	0,235	*0,073*
$\widehat{\beta}_{JP}$	0,020	0,721	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},JP,\overline{HK}}$	0,020	*0,015*	0,020	*0,015*
$\widehat{\beta}_{HK}$	0,045	1,558	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{JP},HK}$	0,045	*0,021*	0,045	*0,021*
$\widehat{\beta}_{US,UK}$	-0,147	-16,93	$\hat{\tau}_{IT\mid US,UK,\overline{FR},\overline{GE},\overline{JP},\overline{HK}}$	0,000	*0,000*	0,000	*0,000*
$\widehat{\beta}_{US,FR}$	0,420	0,492	$\hat{\tau}_{IT\mid US,\overline{UK},FR,\overline{GE},\overline{JP},\overline{HK}}$	0,750	*0,284*	0,750	*0,253*
$\widehat{\beta}_{US,GE}$	-0,279	-17,91	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},GE,\overline{JP},\overline{HK}}$	0,000	*0,020*	0,000	*0,000*
$\widehat{\beta}_{US,JP}$	0,103	0,749	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},\overline{GR},JP,\overline{HK}}$	0,167	*0,174*	0,167	*0,171*
$\widehat{\beta}_{US,HK}$	-0,089	-16,04	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},\overline{GE},\overline{JP},HK}$	0,000	*0,218*	0,000	*0,110*
$\widehat{\beta}_{UK,FR}$	0,194	-1,191	$\hat{\tau}_{IT\mid\overline{US},UK,FR,\overline{GE},\overline{JP},\overline{HK}}$	0,583	*0,136*	0,583	*0,136*
$\widehat{\beta}_{UK,GE}$	-0,214	-3,211	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},GE,\overline{JP},\overline{HK}}$	0,125	*0,138*	0,125	*0,138*
$\widehat{\beta}_{UK,JP}$	0,126	0,340	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},\overline{GE},JP,\overline{HK}}$	0,250	*0,270*	0,250	*0,250*
$\widehat{\beta}_{UK,HK}$	0,251	0,196	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},\overline{GE},\overline{JP},HK}$	0,400	*0,270*	0,400	*0,249*
$\widehat{\beta}_{FR,GE}$	-0,188	-3,201	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,GE,\overline{JP},\overline{HK}}$	0,333	*0,125*	0,333	*0,125*
$\widehat{\beta}_{FR,JP}$	-0,306	-17,37	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,\overline{GE},JP,\overline{HK}}$	0,000	*0,642*	0,000	*0,264*
$\widehat{\beta}_{FR,HK}$	0,669	16,924	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,\overline{GE},\overline{JP},HK}$	1,000	*0,484*	1,000	*0,267*
$\widehat{\beta}_{GE,JP}$	-0,255	-17,11	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},GE,JP,\overline{HK}}$	0,000	*0,056*	0,000	*0,039*
$\widehat{\beta}_{GE,HK}$	0,053	-1,073	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},GE,\overline{JP},HK}$	0,333	*0,365*	0,333	*0,317*
$\widehat{\beta}_{JP,HK}$	-0,035	-1,143	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},JP,HK}$	0,030	*0,030*	0,030	*0,030*
$\widehat{\beta}_{US,UK,FR}$	-0,500	14,173	$\hat{\tau}_{IT\mid US,UK,FR,\overline{GE},\overline{JP},\overline{HK}}$	0,400	*0,255*	0,400	*0,253*
$\widehat{\beta}_{US,UK,GE}$	1,008	36,362	$\hat{\tau}_{IT\mid US,UK,\overline{FR},GE,\overline{JP},\overline{HK}}$	0,750	*0,276*	0,750	*0,272*
$\widehat{\beta}_{US,UK,JP}$	-0,249	-1,810	$\hat{\tau}_{IT\mid US,UK,\overline{FR},GE,JP,\overline{HK}}$	0,000	*0,391*	0,000	*0,181*
$\widehat{\beta}_{US,UK,HK}$	-0,207	14,291	$\hat{\tau}_{IT\mid US,UK,\overline{FR},\overline{GE},\overline{JP},HK}$	0,000	*0,235*	0,000	*0,097*
$\widehat{\beta}_{US,FR,GE}$	-0,090	16,301	$\hat{\tau}_{IT\mid US,\overline{UK},FR,GE,\overline{JP},\overline{HK}}$	0,429	*0,210*	0,429	*0,210*
$\widehat{\beta}_{US,FR,JP}$	0,433	32,368	$\hat{\tau}_{IT\mid US,\overline{UK},FR,GE,JP,\overline{HK}}$	1,000	*0,549*	1,000	*0,338*
$\widehat{\beta}_{US,FR,HK}$	-1,375	-21,10	$\hat{\tau}_{IT\mid US,\overline{UK},FR,\overline{GE},\overline{JP},HK}$	0,000	*0,778*	0,000	*0,441*
$\widehat{\beta}_{US,GE,JP}$	-0,628	-3,218	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},GE,JP,\overline{HK}}$	-0,761	*0,834*	0,000	*0,356*
$\widehat{\beta}_{US,GE,HK}$	-0,009	15,559	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},GE,\overline{JP},HK}$	0,000	*0,539*	0,000	*0,249*
$\widehat{\beta}_{US,JP,HK}$	0,246	16,545	$\hat{\tau}_{IT\mid US,\overline{UK},\overline{FR},\overline{GE},JP,HK}$	0,333	*0,367*	0,333	*0,325*
$\widehat{\beta}_{UK,FR,GE}$	0,324	3,701	$\hat{\tau}_{IT\mid\overline{US},UK,FR,GE,\overline{JP},\overline{HK}}$	0,741	*0,085*	0,741	*0,085*
$\widehat{\beta}_{UK,FR,JP}$	-0,091	15,281	$\hat{\tau}_{IT\mid\overline{US},UK,FR,\overline{GE},JP,\overline{HK}}$	0,333	*0,396*	0,333	*0,323*
$\widehat{\beta}_{UK,FR,HK}$	-0,799	-17,92	$\hat{\tau}_{IT\mid\overline{US},UK,FR,\overline{GE},\overline{JP},HK}$	0,750	*0,370*	0,750	*0,312*
$\widehat{\beta}_{UK,GE,JP}$	-0,016	0,428	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},GE,JP,\overline{HK}}$	0,000	*0,491*	0,000	*0,192*
$\widehat{\beta}_{UK,GE,HK}$	0,526	18,831	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},GE,\overline{JP},HK}$	1,000	*0,569*	1,000	*0,410*
$\widehat{\beta}_{UK,JP,HK}$	-0,345	-1,122	$\hat{\tau}_{IT\mid\overline{US},UK,\overline{FR},\overline{GE},JP,HK}$	0,167	*0,184*	0,167	*0,171*
$\widehat{\beta}_{FR,GE,JP}$	0,208	16,886	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,GE,JP,\overline{HK}}$	0,000	*0,321*	0,000	*0,190*
$\widehat{\beta}_{FR,GE,HK}$	-0,434	-16,02	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,GE,\overline{JP},HK}$	0,667	*0,365*	0,667	*0,317*
$\widehat{\beta}_{FR,JP,HK}$	-0,429	-0,872	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},FR,\overline{GE},JP,HK}$	0,250	*0,304*	0,250	*0,257*
$\widehat{\beta}_{GE,JP,HK}$	-0,063	0,657	$\hat{\tau}_{IT\mid\overline{US},\overline{UK},\overline{FR},GE,JP,HK}$	0,000	*0,619*	0,000	*0,349*
$\widehat{\beta}_{US,UK,FR,GE}$	-0,277	-32,63	$\hat{\tau}_{IT\mid US,UK,FR,GE,\overline{JP},\overline{HK}}$	0,919	*0,041*	0,919	*0,041*
$\widehat{\beta}_{US,UK,FR,JP}$	0,563	-12,31	$\hat{\tau}_{IT\mid US,UK,FR,\overline{GE},JP,\overline{HK}}$	1,000	*0,599*	1,000	*0,315*
$\widehat{\beta}_{US,UK,FR,HK}$	0,000	0,000	$\hat{\tau}_{IT\mid US,UK,FR,\overline{GE},\overline{JP},HK}$	-1,105	*0,983*	0,000	*0,427*
$\widehat{\beta}_{US,UK,GE,JP}$	0,000	0,000	$\hat{\tau}_{IT\mid US,UK,\overline{FR},GE,JP,\overline{HK}}$	-0,150	*1,071*	0,000	*0,458*
$\widehat{\beta}_{US,UK,GE,HK}$	0,000	0,000	$\hat{\tau}_{IT\mid US,UK,\overline{FR},GE,\overline{JP},HK}$	1,320	*0,967*	1,000	*0,253*
$\widehat{\beta}_{US,UK,JP,HK}$	-2,981	-89,02	$\hat{\tau}_{IT\mid US,UK,\overline{FR},\overline{GE},JP,HK}$	-3,115	*1,049*	0,000	*0,346*

$\widehat{\beta}_{US,FR,GE,JP}$	0,000	0,000	$\hat{\tau}_{IT \mid US,\overline{UK},FR,GE,JP,\overline{HK}}$	0,003	*0,975*	1,000	*0,461*
$\widehat{\beta}_{US,FR,GE,HK}$	1,684	21,981	$\hat{\tau}_{IT \mid US,\overline{UK},FR,GE,\overline{JP},HK}$	0,973	*0,958*	0,816	*0,461*
$\widehat{\beta}_{US,FR,JP,HK}$	0,968	4,134	$\hat{\tau}_{IT \mid US,\overline{UK},FR,\overline{GE},JP,HK}$	1,000	*0,695*	1,000	*0,362*
$\widehat{\beta}_{US,GE,JP,HK}$	1,613	37,929	$\hat{\tau}_{IT \mid US,\overline{UK},\overline{FR},GE,JP,HK}$	1,000	*0,710*	1,000	*0,439*
$\widehat{\beta}_{UK,FR,GE,JP}$	0,173	0,181	$\hat{\tau}_{IT \mid \overline{US},UK,FR,GE,JP,\overline{HK}}$	0,600	*0,254*	0,600	*0,247*
$\widehat{\beta}_{UK,FR,GE,HK}$	-0,234	-2,043	$\hat{\tau}_{IT \mid \overline{US},UK,FR,GE,\overline{JP},HK}$	0,818	*0,131*	0,818	*0,131*
$\widehat{\beta}_{UK,FR,JP,HK}$	1,309	20,634	$\hat{\tau}_{IT \mid \overline{US},UK,FR,\overline{GE},JP,HK}$	1,000	*0,451*	1,000	*0,269*
$\widehat{\beta}_{UK,GE,JP,HK}$	-0,432	-17,90	$\hat{\tau}_{IT \mid \overline{US},UK,\overline{FR},GE,JP,HK}$	0,000	*0,387*	0,000	*0,179*
$\widehat{\beta}_{FR,GE,JP,HK}$	0,694	17,538	$\hat{\tau}_{IT \mid \overline{US},\overline{UK},FR,GE,JP,HK}$	0,500	*0,310*	0,500	*0,290*
$\widehat{\beta}_{US,UK,FR,GE,JP}$	0,000	0,000	$\hat{\tau}_{IT \mid US,UK,FR,GE,JP,\overline{HK}}$	1,000	*0,245*	1,000	*0,152*
$\widehat{\beta}_{US,UK,FR,GE,HK}$	0,000	0,000	$\hat{\tau}_{IT \mid US,UK,FR,GE,\overline{JP},HK}$	1,000	*0,055*	1,000	*0,032*
$\widehat{\beta}_{US,UK,FR,JP,HK}$	0,000	0,000	$\hat{\tau}_{IT \mid US,UK,FR,\overline{GE},JP,HK}$	-1,771	*1,290*	0,000	*0,484*
$\widehat{\beta}_{US,UK,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{IT \mid US,UK,\overline{FR},GE,JP,HK}$	-1,577	*1,267*	0,000	*0,486*
$\widehat{\beta}_{US,FR,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{IT \mid US,\overline{UK},FR,GE,JP,HK}$	3,541	*1,308*	1,000	*0,387*
$\widehat{\beta}_{UK,FR,GE,IT,HK}$	-0,751	-18,14	$\hat{\tau}_{IT \mid \overline{US},UK,FR,GE,JP,HK}$	0,625	*0,239*	0,625	*0,239*
$\widehat{\beta}_{US,UK,FR,GE,JP,HK}$	0,000	0,000	$\hat{\tau}_{IT \mid US,UK,FR,GE,JP,HK}$	0,875	*0,104*	0,875	*0,093*

Table 27: **Results of the indicator regression using the full set of explanatory variables. The response variable is Japan.**

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-3,692	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$			0,024	*0,003*
$\widehat{\beta}_{US}$	0,054	0,835	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,054	*0,023*	0,054	*0,023*
$\widehat{\beta}_{UK}$	0,103	1,532	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,103	*0,059*	0,103	*0,059*
$\widehat{\beta}_{FR}$	0,048	0,696	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	0,048	*0,047*	0,048	*0,047*
$\widehat{\beta}_{GE}$	0,161	2,043	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,161	*0,063*	0,161	*0,063*
$\widehat{\beta}_{IT}$	0,049	0,721	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{HK}}$	0,049	*0,036*	0,049	*0,036*
$\widehat{\beta}_{HK}$	0,276	2,727	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},HK}$	0,276	*0,043*	0,276	*0,043*
$\widehat{\beta}_{US,UK}$	-0,067	-0,978	$\hat{t}_{JP\mid US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{HK}}$	0,091	*0,093*	0,091	*0,093*
$\widehat{\beta}_{US,FR}$	-0,102	-15,406	$\hat{t}_{JP\mid US,\overline{UK},FR,\overline{GE},\overline{IT},\overline{HK}}$	0,000	*0,408*	0,000	*0,323*
$\widehat{\beta}_{US,GE}$	-0,216	-16,753	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{HK}}$	0,000	*0,068*	0,000	*0,022*
$\widehat{\beta}_{US,IT}$	0,097	0,749	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},\overline{GR},IT,\overline{HK}}$	0,200	*0,284*	0,200	*0,254*
$\widehat{\beta}_{US,HK}$	0,003	-0,563	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},HK}$	0,333	*0,252*	0,333	*0,245*
$\widehat{\beta}_{UK,FR}$	0,135	0,547	$\hat{t}_{JP\mid\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,286	*0,187*	0,286	*0,184*
$\widehat{\beta}_{UK.GE}$	-0,140	-1,829	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{HK}}$	0,125	*0,135*	0,125	*0,133*
$\widehat{\beta}_{UK,IT}$	0,098	0,340	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{HK}}$	0,250	*0,278*	0,250	*0,247*
$\widehat{\beta}_{UK,HK}$	0,246	-0,056	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},HK}$	0,625	*0,187*	0,625	*0,187*
$\widehat{\beta}_{FR,GE}$	-0,042	-0,657	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	0,167	*0,111*	0,167	*0,111*
$\widehat{\beta}_{FR,IT}$	-0,096	-15,292	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{HK}}$	0,000	*0,016*	0,000	*0,000*
$\widehat{\beta}_{FR,HK}$	0,677	17,835	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},HK}$	1,000	*0,332*	1,000	*0,167*
$\widehat{\beta}_{GE,IT}$	-0,210	-16,639	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{HK}}$	0,000	*0,000*	0,000	*0,000*
$\widehat{\beta}_{GE,HK}$	-0,104	-1,771	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},HK}$	0,333	*0,406*	0,333	*0,320*
$\widehat{\beta}_{IT,HK}$	-0,125	-1,143	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,HK}$	0,200	*0,192*	0,200	*0,163*
$\widehat{\beta}_{US,UK,FR}$	-0,171	-1,101	$\hat{t}_{JP\mid US,UK,FR,\overline{GE},\overline{IT},\overline{HK}}$	0,000	*0,244*	0,000	*0,076*
$\widehat{\beta}_{US,UK,GE}$	0,103	1,276	$\hat{t}_{JP\mid US,UK,\overline{FR},GE,\overline{IT},\overline{HK}}$	0,000	*0,295*	0,000	*0,227*
$\widehat{\beta}_{US,UK,IT}$	0,196	29,952	$\hat{t}_{JP\mid US,UK,\overline{FR},\overline{GE},IT,\overline{HK}}$	0,531	*0,657*	1,000	*0,455*
$\widehat{\beta}_{US,UK,HK}$	-0,616	-17,370	$\hat{t}_{JP\mid US,UK,\overline{FR},\overline{GE},\overline{IT},HK}$	0,000	*0,328*	0,000	*0,215*
$\widehat{\beta}_{US,FR,GE}$	0,097	15,366	$\hat{t}_{JP\mid US,\overline{UK},FR,GE,\overline{IT},\overline{HK}}$	0,000	*0,069*	0,000	*0,039*
$\widehat{\beta}_{US,FR,IT}$	0,201	30,289	$\hat{t}_{JP\mid US,\overline{UK},FR,\overline{GE},IT,\overline{HK}}$	0,250	*0,257*	0,250	*0,249*
$\widehat{\beta}_{US,FR,HK}$	-0,956	-19,998	$\hat{t}_{JP\mid US,\overline{UK},FR,\overline{GE},\overline{IT},HK}$	0,000	*0,796*	0,000	*0,439*
$\widehat{\beta}_{US,GE,IT}$	-0,168	-15,081	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},GE,IT,\overline{HK}}$	-0,233	*0,770*	0,000	*0,357*
$\widehat{\beta}_{US,GE,HK}$	-0,175	-0,392	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},GE,\overline{IT},HK}$	0,000	*0,482*	0,000	*0,240*
$\widehat{\beta}_{US,IT,HK}$	0,646	17,932	$\hat{t}_{JP\mid US,\overline{UK},\overline{FR},\overline{GE},IT,HK}$	1,000	*0,576*	1,000	*0,377*
$\widehat{\beta}_{UK,FR,GE}$	-0,043	0,107	$\hat{t}_{JP\mid\overline{US},UK,FR,GE,\overline{IT},\overline{HK}}$	0,222	*0,148*	0,222	*0,148*
$\widehat{\beta}_{UK,FR,IT}$	-0,211	13,201	$\hat{t}_{JP\mid\overline{US},UK,FR,\overline{GE},IT,\overline{HK}}$	0,125	*0,126*	0,125	*0,126*
$\widehat{\beta}_{UK,FR,HK}$	-1,484	-37,155	$\hat{t}_{JP\mid\overline{US},UK,FR,\overline{GE},\overline{IT},HK}$	0,000	*0,746*	0,000	*0,406*
$\widehat{\beta}_{UK,GE,IT}$	-0,061	-0,042	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},GE,IT,\overline{HK}}$	0,000	*0,581*	0,000	*0,247*
$\widehat{\beta}_{UK,GE,HK}$	0,457	18,613	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},GE,\overline{IT},HK}$	1,000	*0,371*	1,000	*0,218*
$\widehat{\beta}_{UK,IT,HK}$	-0,314	-1,122	$\hat{t}_{JP\mid\overline{US},UK,\overline{FR},\overline{GE},IT,HK}$	0,333	*0,412*	0,333	*0,321*
$\widehat{\beta}_{FR,GE,IT}$	0,091	15,252	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,GE,IT,\overline{HK}}$	0,000	*0,064*	0,000	*0,050*
$\widehat{\beta}_{FR,GE,HK}$	-0,349	-16,488	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,GE,\overline{IT},HK}$	0,667	*0,365*	0,667	*0,316*
$\widehat{\beta}_{FR,IT,HK}$	-0,494	-2,546	$\hat{t}_{JP\mid\overline{US},\overline{UK},FR,\overline{GE},IT,HK}$	0,333	*0,429*	0,333	*0,325*
$\widehat{\beta}_{GE,IT,HK}$	-0,047	0,187	$\hat{t}_{JP\mid\overline{US},\overline{UK},\overline{FR},GE,IT,HK}$	0,000	*0,616*	0,000	*0,324*
$\widehat{\beta}_{US,UK,FR,GE}$	0,079	0,447	$\hat{t}_{JP\mid US,UK,FR,GE,\overline{IT},\overline{HK}}$	0,000	*0,212*	0,000	*0,122*
$\widehat{\beta}_{US,UK,FR,IT}$	0,000	-43,088	$\hat{t}_{JP\mid US,UK,FR,\overline{GE},IT,\overline{HK}}$	0,333	*0,342*	0,333	*0,315*
$\widehat{\beta}_{US,UK,FR,HK}$	0,000	71,798	$\hat{t}_{JP\mid US,UK,FR,\overline{GE},\overline{IT},HK}$	-1,854	*1,318*	0,413	*0,358*
$\widehat{\beta}_{US,UK,GE,IT}$	0,000	0,000	$\hat{t}_{JP\mid US,UK,\overline{FR},GE,IT,\overline{HK}}$	0,000	*0,212*	0,000	*0,094*
$\widehat{\beta}_{US,UK,GE,HK}$	2,365	0,000	$\hat{t}_{JP\mid US,UK,\overline{FR},GE,\overline{IT},HK}$	2,453	*0,986*	0,000	*0,461*
$\widehat{\beta}_{US,UK,IT,HK}$	-2,520	-102,961	$\hat{t}_{JP\mid US,UK,\overline{FR},\overline{GE},IT,HK}$	-1,872	*1,267*	0,000	*0,457*
$\widehat{\beta}_{US,FR,GE,IT}$	0,037	0,000	$\hat{t}_{JP\mid US,\overline{UK},FR,GE,IT,\overline{HK}}$	0,000	*0,199*	0,000	*0,116*

$\widehat{\beta}_{US,FR,GE,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,\overline{UK},FR,GE,\overline{IT},HK}$	-0,628	*1,188*	0,000	*0,477*
$\widehat{\beta}_{US,FR,IT,HK}$	0,723	4,422	$\hat{\tau}_{JP\|US,\overline{UK},FR,\overline{GE},IT,HK}$	1,000	*0,711*	1,000	*0,376*
$\widehat{\beta}_{US,GE,IT,HK}$	0,759	48,406	$\hat{\tau}_{JP\|US,\overline{UK},\overline{FR},GE,IT,HK}$	1,000	*0,783*	1,000	*0,417*
$\widehat{\beta}_{UK,FR,GE,IT}$	0,249	1,814	$\hat{\tau}_{JP\|\overline{US},UK,FR,GE,IT,\overline{HK}}$	0,130	*0,071*	0,130	*0,070*
$\widehat{\beta}_{UK,FR,GE,HK}$	0,659	17,954	$\hat{\tau}_{JP\|\overline{US},UK,FR,GE,\overline{IT},HK}$	0,600	*0,269*	0,600	*0,249*
$\widehat{\beta}_{UK,FR,IT,HK}$	1,493	23,001	$\hat{\tau}_{JP\|\overline{US},UK,FR,\overline{GE},IT,HK}$	0,400	*0,345*	0,400	*0,297*
$\widehat{\beta}_{UK,GE,IT,HK}$	-0,389	-17,434	$\hat{\tau}_{JP\|\overline{US},UK,\overline{FR},GE,IT,HK}$	0,000	*0,686*	0,000	*0,329*
$\widehat{\beta}_{FR,GE,IT,HK}$	0,666	18,765	$\hat{\tau}_{JP\|\overline{US},\overline{UK},FR,GE,IT,HK}$	0,500	*0,333*	0,500	*0,292*
$\widehat{\beta}_{US,UK,FR,GE,IT}$	-0,190	12,961	$\hat{\tau}_{JP\|US,UK,FR,GE,IT,\overline{HK}}$	0,081	*0,045*	0,081	*0,045*
$\widehat{\beta}_{US,UK,FR,GE,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,UK,FR,GE,\overline{IT},HK}$	1,000	*0,993*	1,000	*0,471*
$\widehat{\beta}_{US,UK,FR,IT,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,UK,FR,\overline{GE},IT,HK}$	-2,110	*1,278*	0,000	*0,458*
$\widehat{\beta}_{US,UK,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,UK,\overline{FR},GE,IT,HK}$	0,463	*1,398*	0,000	*0,474*
$\widehat{\beta}_{US,FR,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,\overline{UK},FR,GE,IT,HK}$	1,501	*1,203*	1,000	*0,411*
$\widehat{\beta}_{UK,FR,GE,IT,HK}$	-0,941	-20,057	$\hat{\tau}_{JP\|\overline{US},UK,FR,GE,IT,HK}$	0,357	*0,179*	0,357	*0,179*
$\widehat{\beta}_{US,UK,FR,GE,IT,HK}$	0,000	0,000	$\hat{\tau}_{JP\|US,UK,FR,GE,IT,HK}$	0,538	*0,144*	0,538	*0,144*

Table 28: **Results of the indicator regression using the full set of explanatory variables. The response variable is Hong Kong.**

Regression coefficient			Tail dependence	Probability			
	Linear	Logit		Linear	*SE*	Logit	*SE*
c		-3,836	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$			0,021	*0,003*
$\widehat{\beta}_{US}$	0,044	0,756	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,044	*0,026*	0,044	*0,026*
$\widehat{\beta}_{UK}$	0,103	1,676	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,103	*0,058*	0,103	*0,058*
$\widehat{\beta}_{FR}$	0,000	-13,73	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP}}$	0,000	*0,000*	0,000	*0,000*
$\widehat{\beta}_{GE}$	0,071	1,271	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,071	*0,050*	0,071	*0,050*
$\widehat{\beta}_{IT}$	0,093	1,558	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,\overline{JP}}$	0,093	*0,049*	0,093	*0,049*
$\widehat{\beta}_{JP}$	0,248	2,727	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP}$	0,248	*0,040*	0,248	*0,040*
$\widehat{\beta}_{US,UK}$	0,019	-0,206	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},\overline{IT},\overline{JP}}$	0,167	*0,115*	0,167	*0,115*
$\widehat{\beta}_{US,FR}$	0,456	16,810	$\hat{\tau}_{HK\|US,\overline{UK},FR,\overline{GE},\overline{IT},\overline{JP}}$	0,500	*0,455*	0,500	*0,391*
$\widehat{\beta}_{US,GE}$	0,107	0,556	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,\overline{IT},\overline{JP}}$	0,222	*0,162*	0,222	*0,159*
$\widehat{\beta}_{US,IT}$	-0,137	-16,04	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GR},IT,\overline{JP}}$	0,000	*0,228*	0,000	*0,128*
$\widehat{\beta}_{US,JP}$	-0,006	-0,563	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GE},\overline{IT},JP}$	0,286	*0,196*	0,286	*0,191*
$\widehat{\beta}_{UK,FR}$	0,063	14,281	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},\overline{IT},\overline{JP}}$	0,167	*0,168*	0,167	*0,162*
$\widehat{\beta}_{UK,GE}$	-0,175	-16,8	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	0,000	*0,034*	0,000	*0,034*
$\widehat{\beta}_{UK,IT}$	0,204	0,196	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},IT,\overline{JP}}$	0,400	*0,252*	0,400	*0,248*
$\widehat{\beta}_{UK,JP}$	0,273	-0,056	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,625	*0,183*	0,625	*0,183*
$\widehat{\beta}_{FR,GE}$	0,019	13,993	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,\overline{IT},\overline{JP}}$	0,091	*0,094*	0,091	*0,094*
$\widehat{\beta}_{FR,IT}$	0,107	14,621	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},IT,\overline{JP}}$	0,200	*0,136*	0,200	*0,136*
$\widehat{\beta}_{FR,JP}$	0,502	15,938	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},\overline{IT},JP}$	0,750	*0,262*	0,750	*0,250*
$\widehat{\beta}_{GE,IT}$	-0,053	-1,073	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,IT,\overline{JP}}$	0,111	*0,114*	0,111	*0,114*
$\widehat{\beta}_{GE,JP}$	-0,153	-1,771	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,\overline{IT},JP}$	0,167	*0,175*	0,167	*0,176*
$\widehat{\beta}_{IT,JP}$	-0,008	-1,143	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},\overline{GE},IT,JP}$	0,333	*0,342*	0,333	*0,326*
$\widehat{\beta}_{US,UK,FR}$	-0,686	-33,32	$\hat{\tau}_{HK\|US,UK,FR,\overline{GE},\overline{IT},\overline{JP}}$	0,000	*0,245*	0,000	*0,167*
$\widehat{\beta}_{US,UK,GE}$	-0,170	-1,106	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,\overline{IT},\overline{JP}}$	0,000	*0,608*	0,000	*0,340*
$\widehat{\beta}_{US,UK,IT}$	-0,868	29,979	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},IT,\overline{JP}}$	-0,542	*0,902*	1,000	*0,465*
$\widehat{\beta}_{US,UK,JP}$	-0,682	-18,06	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},\overline{IT},JP}$	0,000	*0,467*	0,000	*0,354*
$\widehat{\beta}_{US,FR,GE}$	-0,698	-33,39	$\hat{\tau}_{HK\|US,\overline{UK},FR,GE,\overline{IT},\overline{JP}}$	0,000	*0,131*	0,000	*0,100*
$\widehat{\beta}_{US,FR,IT}$	-0,563	-17,70	$\hat{\tau}_{HK\|US,\overline{UK},FR,\overline{GE},IT,\overline{JP}}$	0,000	*0,204*	0,000	*0,150*
$\widehat{\beta}_{US,FR,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,\overline{UK},FR,\overline{GE},\overline{IT},JP}$	1,244	*0,983*	1,000	*0,431*
$\widehat{\beta}_{US,GE,IT}$	0,505	-31,50	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,IT,\overline{JP}}$	0,630	*0,941*	0,000	*0,429*
$\widehat{\beta}_{US,GE,JP}$	0,695	34,191	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,\overline{IT},JP}$	1,006	*0,860*	1,000	*0,446*
$\widehat{\beta}_{US,IT,JP}$	0,266	16,545	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},\overline{GE},IT,JP}$	0,500	*0,465*	0,500	*0,385*
$\widehat{\beta}_{UK,FR,GE}$	0,140	1,770	$\hat{\tau}_{HK\|\overline{US},UK,FR,GE,\overline{IT},\overline{JP}}$	0,222	*0,151*	0,222	*0,150*
$\widehat{\beta}_{UK,FR,IT}$	-0,270	-15,61	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},IT,\overline{JP}}$	0,300	*0,182*	0,300	*0,182*
$\widehat{\beta}_{UK,FR,JP}$	-1,190	-34,56	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},\overline{IT},JP}$	0,000	*0,446*	0,000	*0,269*
$\widehat{\beta}_{UK,GE,IT}$	0,257	16,885	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,IT,\overline{JP}}$	0,500	*0,515*	0,500	*0,387*
$\widehat{\beta}_{UK,GE,JP}$	0,298	17,360	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,\overline{IT},JP}$	0,667	*0,336*	0,667	*0,319*
$\widehat{\beta}_{UK,IT,JP}$	-0,414	-1,122	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},\overline{GE},IT,JP}$	0,500	*0,498*	0,500	*0,390*
$\widehat{\beta}_{FR,GE,IT}$	0,048	-13,72	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,IT,\overline{JP}}$	0,286	*0,190*	0,286	*0,189*
$\widehat{\beta}_{FR,GE,JP}$	-0,188	-14,59	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,\overline{IT},JP}$	0,500	*0,307*	0,500	*0,287*
$\widehat{\beta}_{FR,IT,JP}$	0,058	1,430	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,\overline{GE},IT,JP}$	1,000	*0,655*	1,000	*0,264*
$\widehat{\beta}_{GE,IT,JP}$	-0,672	15,892	$\hat{\tau}_{HK\|\overline{US},\overline{UK},\overline{FR},GE,IT,JP}$	-0,474	*0,892*	1,000	*0,461*
$\widehat{\beta}_{US,UK,FR,GE}$	0,705	33,579	$\hat{\tau}_{HK\|US,UK,FR,GE,\overline{IT},\overline{JP}}$	0,000	*0,207*	0,000	*0,116*
$\widehat{\beta}_{US,UK,FR,IT}$	1,435	3,005	$\hat{\tau}_{HK\|US,UK,FR,\overline{GE},IT,\overline{JP}}$	0,000	*0,479*	0,000	*0,198*
$\widehat{\beta}_{US,UK,FR,JP}$	0,615	17,909	$\hat{\tau}_{HK\|US,UK,FR,\overline{GE},\overline{IT},JP}$	-0,240	*1,117*	0,000	*0,365*
$\widehat{\beta}_{US,UK,GE,IT}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,IT,\overline{JP}}$	0,000	*0,192*	0,000	*0,150*
$\widehat{\beta}_{US,UK,GE,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,\overline{IT},JP}$	0,674	*1,162*	1,000	*0,456*

$\widehat{\beta}_{US,UK,IT,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,\overline{FR},\overline{GE},IT,JP}$	-0,864	*1,317*	1,000	*0,482*
$\widehat{\beta}_{US,FR,GE,IT}$	0,000	63,860	$\hat{\tau}_{HK\|US,\overline{UK},FR,GE,IT,\overline{JP}}$	0,000	*0,232*	0,000	*0,100*
$\widehat{\beta}_{US,FR,GE,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,\overline{UK},FR,GE,\overline{IT},JP}$	1,098	*1,041*	1,000	*0,475*
$\widehat{\beta}_{US,FR,IT,JP}$	-0,560	-17,37	$\hat{\tau}_{HK\|US,\overline{UK},FR,\overline{GE},IT,JP}$	0,500	*0,519*	0,500	*0,390*
$\widehat{\beta}_{US,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,\overline{UK},\overline{FR},GE,IT,JP}$	1,000	*0,813*	1,000	*0,377*
$\widehat{\beta}_{UK,FR,GE,IT}$	-0,297	-2,399	$\hat{\tau}_{HK\|\overline{US},UK,FR,GE,IT,\overline{JP}}$	0,310	*0,098*	0,310	*0,098*
$\widehat{\beta}_{UK,FR,GE,JP}$	0,587	16,617	$\hat{\tau}_{HK\|\overline{US},UK,FR,GE,\overline{IT},JP}$	0,600	*0,252*	0,600	*0,249*
$\widehat{\beta}_{UK,FR,IT,JP}$	0,897	18,332	$\hat{\tau}_{HK\|\overline{US},UK,FR,\overline{GE},IT,JP}$	0,667	*0,387*	0,667	*0,324*
$\widehat{\beta}_{UK,GE,IT,JP}$	-0,852	0,000	$\hat{\tau}_{HK\|\overline{US},UK,\overline{FR},GE,IT,JP}$	-0,779	*1,081*	1,000	*0,477*
$\widehat{\beta}_{FR,GE,IT,JP}$	0,928	0,000	$\hat{\tau}_{HK\|\overline{US},\overline{UK},FR,GE,IT,JP}$	1,000	*0,414*	1,000	*0,268*
$\widehat{\beta}_{US,UK,FR,GE,IT}$	-0,310	-16,22	$\hat{\tau}_{HK\|US,UK,FR,GE,IT,\overline{JP}}$	0,150	*0,057*	0,150	*0,057*
$\widehat{\beta}_{US,UK,FR,GE,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,FR,GE,\overline{IT},JP}$	1,000	*0,708*	1,000	*0,449*
$\widehat{\beta}_{US,UK,FR,IT,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,FR,\overline{GE},IT,JP}$	0,000	*0,629*	0,000	*0,248*
$\widehat{\beta}_{US,UK,GE,IT,JP}$	-0,093	0,000	$\hat{\tau}_{HK\|US,UK,\overline{FR},GE,IT,JP}$	-1,099	*1,347*	1,000	*0,484*
$\widehat{\beta}_{US,FR,GE,IT,JP}$	0,000	-31,34	$\hat{\tau}_{HK\|US,\overline{UK},FR,GE,IT,JP}$	1,109	*1,082*	0,912	*0,452*
$\widehat{\beta}_{UK,FR,GE,IT,JP}$	0,000	-33,74	$\hat{\tau}_{HK\|\overline{US},UK,FR,GE,IT,JP}$	0,625	*0,240*	0,625	*0,238*
$\widehat{\beta}_{US,UK,FR,GE,IT,JP}$	0,000	0,000	$\hat{\tau}_{HK\|US,UK,FR,GE,IT,JP}$	0,700	*0,178*	0,700	*0,178*