Jump Spillover in International Equity Markets

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Abstract

We study jump spillover effects between a number of country equity indices. In order to identify the latent historical jump times of each index, we use a Bayesian approach to estimate an event risk model on each index. We look at the simultaneous jump intensities of pairs of countries and the probabilities that jumps in large countries cause jumps in other countries. In all cases, we find significant evidence of jump spillover. We also find that jump spillover is particularly large between countries that belong to the same regions and have similar industry structures and market capitalizations. Most interestingly, we find that the sample correlations between the countries do not capture the jump spillover effects.

Keywords: Event risk; Spillover; Systemic risk; Stochastic volatility; Jump-diffusion; Markov Chain Monte Carlo.
JEL classifications: C13; C15.

1 Introduction

In the wake of events such as Black Monday, 1987, or, more recently, the attacks of September 11, 2001, that affected financial markets in many countries, there has been a growing interest in financial economics to allow for the presence of jumps in asset pricing models. Such models are often referred to as *event risk* models. A number of recent theoretical studies analyze the impact of event risk on strategic asset allocation (see e.g. Wu, 2003; Liu et al., 2003) and it is shown that the presence of jumps can dramatically affect optimal portfolio strategies. Other recent papers study the implications of event risk for option pricing and their ability to explain the observed volatility smiles which became particularly pronounced after the world wide crash of Black Monday (see e.g. Pan, 2002; Eraker et

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al., 2003). Efforts have also been made to take into account event risk in calculations of risk measures such as Value-at-Risk (VaR) (see e.g. Duffie and Pan, 2001; Gibson, 2001).

Most studies on event risk are, however, based on the US and relatively little focus has been directed towards other equity markets and the international aspects of jumps. An empirical study of jumps in different countries is interesting for at least two reasons. Firstly, because it can add insights about differences in stock price behavior around the world. Secondly, and more importantly, because it makes it possible to assess the likelihood of jump spillover; that is, to what extent jumps transmit across borders. Jump spillover can for example have important implications for international diversification (see e.g. Das and Uppal, 2004). If country equity indices do tend to jump simultaneously, the international diversification effect decreases since the dependence between international equity returns increases in periods of market stress. The main purpose of this paper is to estimate an event risk model for a number of country equity indices in order to identify the latent historical jump times of each country which we then use to quantify the degrees of jump spillover between different markets. We look at two forms of jump spillover. Firstly, we calculate the simultaneous jump intensities for pairs of countries and we test whether these simultaneous jump intensities are significant or not and we also look for factors that affect them. Secondly, we perform an analysis of conditional jump spillover to examine to what extent jumps in large markets increase the probability of jumps in other markets, or in a weaker form, cause unusually large negative returns in other markets.

To our knowledge, the issue of international jump spillover has not been addressed in this way by previous studies. However, the present paper does have similarities with other work. In a preliminary paper, Foresi et al. (1999) studies the diversification and contagion of jump risk. The main difference between our studies is that we focus on the analysis of actual jump times. Foresi et al. (1999) do not estimate any jump times or jump intensities but mainly compares predictions of theoretical results with some calculations on international equity returns data to get an idea of the relative magnitude between systemic and idiosyncratic jump risk. Our study is also related in spirit to the literature on contagion (see e.g. De Bandt and Hartmann, 2000; Forbes and Rigobon, 2002). This literature examines how large country-specific shocks (financial crises) are transmitted across borders to other countries, and often, significant evidence that financial crises are contagious is found. However, those studies differ from ours again in the sense that they do not use actual estimated jumps times, but instead look at changes in cross-market correlations, volatility spillover effects, changes in cointegration vectors between markets, or estimate explicitly specified transmission mechanisms (see Forbes and Rigobon (2002)). Finally, this paper is to some extent related to the literature on applications of copulas to finance which are methods for constructing multivariate distributions that can be used to study non-

Gaussian dependence structures between returns in the tails of the return distribution (see e.g. Hu, 2004).

To identify the historical jump times, we estimate a univariate jump-diffusion model with stochastic volatility on each index. The model, which falls into the class of models proposed by Duffie et al. (2000), is referred to as the stochastic volatility with correlated jumps (SVCJ) model and it assumes that jumps in returns and volatility arrive simultaneously and that the jump sizes are correlated. The primary reason for estimating such a relatively complex model, instead of simply looking at the historically largest price movements of each index, is that we in this way can separate returns that are actually jumps from large diffusive returns caused by periods of high volatility. Jumps in volatility allow for the rapid changes in volatility empirically found by for instance Bates (2000), Duffie et al. (2000), Pan (2002), and Eraker et al. (2003), and prevent estimated jump times to cluster. One reason for the relatively limited amount of empirical research on event risk is that the complexity of the models makes estimation comparatively difficult. Standard methods such as direct maximum likelihood (ML) and the generalized method of moments (GMM) are, if applicable at all, intractable (see e.g. Honoré, 1998). In this paper we use a relatively new approach for the estimation of event risk models based on Markov Chain Monte Carlo (MCMC) methods. The MCMC method to estimate stochastic volatility models was proposed by Jacquier et al. (1994) and the method was extended to models with jumps in returns and volatility by Eraker et al. (2003).[1] An advantage of the MCMC method compared to many alternative methods is that it also identifies the latent processes of the model; the jump times, jump sizes, and the spot volatility path, which is a merit that is crucial for our analysis.

In our empirical analysis we find strong evidence of international jump spillover. The estimated simultaneous jump intensities are in general significantly larger than the corresponding intensities under the null hypothesis that the different countries jump independently of each other. We find that the intensities are particularly large and significant for countries within approximately the same region and we also find that they are generally larger for countries with similar industry structures and market capitalizations. Most interestingly, however, we find that the historical sample correlations between the countries is not a good measure to capture the degree of jump spillover between the countries. This implies that the dependence between the different country equity indices' jump processes is quite different from the dependence between returns that are not jumps, implying for instance that mean-variance investors who use these correlations may have no protection against event risk.

[1] Other estimation methods include, for instance, the Efficient Method of Moments (EMM) of Gallant and Tauchen (1996), Simulated Maximum Likelihood (SML), the Spectral GMM (SGMM) of Chacko and Viceira (2003), and the Implied-State GMM (ISGMM) of Pan (2002).

In our empirical analysis of conditional jump spillover from large markets to other markets we also find strong evidence of jump spillover. A large majority of the estimated conditional jump spillover probabilities are significantly larger than the corresponding probabilities under the null hypothesis of independent jump processes. For most European countries, the lagged jump spillover effect from the US market is stronger than the spillover effect on the same day. This may be explained by the fact that only about 30 percent of the US and European market opening hours overlap. Of the European countries, Germany shows the smallest overall sensitivity to jumps in larger countries, and within North America, the jump spillover probability from the S&P to the Nasdaq and to Canada is very strong.

The rest of the paper is organized as follows: Section 2 presents the event risk model and the estimation method (further details on the estimation method can be found in Appendix A). Section 3 contains the empirical results. This includes a discussion of the parameter estimates, and most importantly, the analysis of jump spillover. Section 4 concludes the paper.

2 Event Risk Model and Estimation Methodology

The SVCJ model assumes that the logarithm of market index i, $S_{i,t}$, $i = 1, 2, ..., N$, solves the stochastic differential equation

$$\begin{pmatrix} d\ln\left(S_{i,t}\right) \\ dV_{i,t} \end{pmatrix} = \begin{pmatrix} \mu_i \\ \varkappa_i\left(\vartheta_i - V_{i,t-}\right) \end{pmatrix} dt + \sqrt{V_{i,t-}} \begin{pmatrix} dW^Y_{i,t} \\ \sigma_{V,i} dW^V_{i,t} \end{pmatrix} + \begin{pmatrix} \xi^Y_{i,t} \\ \xi^V_{i,t} \end{pmatrix} dN_{i,t}, \quad (1)$$

where $t-$ is the point in time that closest precedes time t, $W^Y_{i,t}$ and $W^V_{i,t}$ are standard one-dimensional wiener process with instantaneous correlation ρ_i, $N_{i,t}$ is a one-dimensional Poisson process with constant intensity λ_i, and $\xi^Y_{i,t}$ and $\xi^V_{i,t}$ are jump sizes. The jump size of spot volatility, $\xi^V_{i,t}$, is assumed to be exponentially distributed with mean μ^V_i, and to allow for the return and spot volatility jump sizes to be correlated, $\xi^Y_{i,t}$ is assumed to be conditionally normally distributed with conditional mean $\mu^Y_i + \rho^J_i \xi^V_{i,t}$ and standard deviation σ^Y_i. The correlation between the diffusive terms is allowed for in order to capture the important leverage effect between return and volatility. Typically this correlation is expected to be negative which induces negative skewness in returns (see Das and Sundaram, 1999). In what remains of this section, we will drop the subscript i.

Another possible model specification would be the stochastic volatility with independently arriving jumps (SVIJ) model, which also falls into the general class of models proposed by Duffie et al. (2000). The SVIJ model assumes different jump processes for returns and volatility. Although this model has been found to fit returns data slightly better than the SVCJ model, there is, to this date, no evidence of significant misspecification of the SVCJ model. We choose to work with the SVCJ specification in this paper since in an event risk study it simplifies the analysis, and if there are indeed jumps in volatility, it is in some sense more intuitive to assume that major events affect both return and volatility rather than assuming that some events affect only return and some events affect only volatility.

To estimate the SVCJ model with MCMC, equation (1) is discretized over a time interval Δ using an Euler discretization. The discretization interval is one day ($\Delta = 1$) and the discretized version of the model is

$$\begin{pmatrix} Y_{(t+1)\Delta} \\ V_{(t+1)\Delta} \end{pmatrix} = \begin{pmatrix} \mu \\ \alpha + (1/\Delta + \beta) V_{t\Delta} \end{pmatrix} \Delta + \sqrt{V_{t\Delta}\Delta} \begin{pmatrix} \varepsilon^Y_{(t+1)\Delta} \\ \sigma_V \varepsilon^V_{(t+1)\Delta} \end{pmatrix} + \begin{pmatrix} \xi^Y_{(t+1)\Delta} \\ \xi^V_{(t+1)\Delta} \end{pmatrix} J_{(t+1)\Delta}, \tag{2}$$

where $Y_{(t+1)\Delta} = \ln(S_{(t+1)\Delta}) - \ln(S_{t\Delta})$ is the log return, $J_{(t+1)\Delta} = 1$ indicates a jump arrival which occurs with probability $\Delta\lambda$, the drift parameters of the volatility process have been rewritten so that $\alpha = \varkappa\vartheta$, $\beta = -\varkappa$, and $\varepsilon^Y_{(t+1)\Delta}$ and $\varepsilon^V_{(t+1)\Delta}$ are standard normal stochastic variables with correlation coefficient ρ. The need for the continuous-time process to be discretized is a drawback of the MCMC method in the sense that it can potentially introduce discretization biases when low frequency data is used. However, in a simulation study, Eraker et al. (2003) show that the biases in MCMC estimates are very small for daily returns. In addition, the continuous-time specification—although it provides a nice foundation to stand on—is not critical for our empirical study.

The Markov Chain Monte Carlo (MCMC) method for inference and parameter estimation is a Bayesian and simulation based estimation method. While traditional methods treats parameters and latent variables as unknown constants, the Bayesian approach is to treat them as random variables. The foundation of Bayesian analysis is the joint distribution of the parameters and latent variables conditional on the data. This joint conditional distribution, referred to as the posterior distribution, is derived via Bayes' formula and is generally of the form

$$p(\Theta, V, J, \xi^V, \xi^Y | Y) \propto p(Y | \Theta, V, J, \xi^V, \xi^Y) p(\Theta, V, J, \xi^V, \xi^Y), \tag{3}$$

where Y is a $T \times 1$ vector of observations, V, J, ξ^V, and ξ^Y are, respectively, $T \times 1$ vectors of latent spot volatilities, jump times, return jumps sizes, and volatility jump sizes, Θ is a vector of parameters, $p(Y|\Theta, V, J, \xi^V, \xi^Y)$ is the likelihood of the data, and $p(\Theta, V, J, \xi^V, \xi^Y)$ is the prior distribution of the parameters and the latent variables. The Bayesian parameter point estimates of the parameters and the latent variables are typically taken as the respective posterior means. While knowledge about the normalizing constant is not required, the prior distribution of the parameters has to be specified unconditional of the data by the researcher (the prior distribution of the latent variables, conditional on Θ, is specified by the model assumptions.). It can be thought of as a natural way to impose non-sample information, if there is any, and to impose stationarity and non-negativity where it is needed. If there is no non-sample information to be imposed, the prior is usually chosen so that it is as uninformative as possible—typically with a very large variance over the relevant parameter space—which is what we do in this paper.[2]

The posterior distribution of equation (3) is extremely complex and non-standard with no existing closed form solution. Consequently, simulation-based methods have to be used to explore it. The MCMC method, which is discussed in more detail in Appendix A, generates a sequence of draws $\{\Theta^{(j)}, V^{(j)}, J^{(j)}, \xi^{V(j)}, \xi^{Y(j)}\}_{j=1}^{M}$, that is a Markov Chain with equilibrium distribution equal to the posterior distribution. Using this generated sample from the posterior distribution, the point estimates of Θ, V, J, ξ^V, and ξ^Y are then simply given by their respective posterior sample means.

In this paper we are particularly interested in estimating the latent historical jump times. The point estimate of J is

$$\hat{J} = \sum_{j=1}^{M} J^{(j)}.$$

It is important to note that this estimate will, unlike the "true" vector of jump times, not be a vector of ones and zeros. Rather, element t, $\hat{J}_t$, will be the posterior probability that a jump has occurred at time t. Following Johannes et al. (1999), a natural and simple approach to construct from $\hat{J}$ the vector of jump times is to assert that a jump has occurred if the estimated jump probability is sufficiently large; that is, greater than an appropriately chosen threshold value ℓ, so that

$$\hat{J}_t^* = \begin{cases} 1 \text{ if } \hat{J}_t > \ell, \\ 0 \text{ if } \hat{J}_t \leq \ell. \end{cases} \tag{4}$$

In our empirical study we choose ℓ so that the number of inferred jump times divided by the number of observations is roughly equal to the estimated jump intensity. For simplicity and for consistency, we use the same value of ℓ for all indices and we choose $\ell = 0.1702$ since it is the value that (it turns out) minimizes the average distance from the actual estimated intensities.[3]

More details on the MCMC algorithm used to estimate the SVCJ model can be found in Appendix A. Further details on the theory behind MCMC methods can be found in Johannes and Polson (2004).

[2] Alternatively, it can be chosen to be diffuse which means that it is completely uninformative. Diffuse priors, however, do not integrate to unity and they are therefore not well suited for all situations.

[3] The preliminary results of a forthcoming paper by the second co-author of this paper, which uses instead a multivariate version of the SVIJ model and thus avoids the issue of specifying such a threshold value, indicate that the simultaneous jump intensities using the approach of this paper are in fact correctly estimated.

3 Empirical Results

In this section we present and analyze our empirical results. After a presentation of the data set, we provide a short discussion on the parameter estimates. Then follows the analysis of jump spillover between pairs of countries. All tables and figures can be found Appendices C and D, respectively.

3.1 Data Set

The data is extracted from the EcoWin data base and consists of the daily log returns of $N = 14$ country equity indices between February 1, 1985, and April 28, 2004. The indices are selected based on data availability for the chosen window of time and they are, except for the US for which we include both the S&P (500) and the Nasdaq (100), the largest equity indices of Canada, UK, the Netherlands, Sweden, France, Germany, Denmark, Italy, Norway, Hong Kong, Japan, and Australia. Descriptive statistics for the data can be found in Table 1. We will refer to the indices by their respective country of origin except for the US where we distinguish between the S&P and the Nasdaq.[4]

In our study of jump spillover, it is important to take into account that financial markets in different time zones have different opening hours. The approximative opening hours for different regions are illustrated in Figure 1. The figure shows that the only overlap in opening hours is between North America and Europe. We will generally assume that the S&P is the internationally leading index. For this reason, when we examine jump spillover between countries that belong to different regions, we look at jumps in Europe that arrive on the same or on the day after jumps in the US, while we only look at jumps in Asia or Australia that arrive on days after jumps in the US. Due to relative efficiency of the equity markets involved in our study, it is rational to assume that jumps transfer very quickly across the markets, why we do not include any additional lead-lag effects.

It can be argued that the effects of differences in market opening hours can be avoided by using, for example, weekly data. However, lower frequency data would smooth out the effects of jumps and invalidate the assumption that at most one jump can occur per discretization interval. A better alternative would instead be to use higher frequency data such as hourly returns in order to really find out when in the day the jumps have occurred and how fast they are transmitted across borders. Unfortunately, high frequency data sets that go back sufficiently long in time are hard to obtain for more than perhaps a few international equity indices. Consequently, our best alternative is to use daily data, but taking into account our analysis that differences in market opening hours are present.

[4]To examine the quality of our estimates, we have also estimated the model on the same data sets as in Eraker et al. (2003) and on artificial data sets. The results are not included in the paper but are available upon request.

3.2 Parameter Estimates

The parameter estimates for the SVCJ model and for the different indices are presented in Table 2 for the North American and Asian countries and Australia, and in Table 3 for the European countries. To serve as illustrative examples, Figure 2 shows, together with the historical log returns, the estimated jump probabilities and the estimated spot volatility paths for the S&P, the UK, and Japan. The plots for the other countries have been omitted to save space, but are available upon request.

Since this paper is focused on the analysis of jumps, we begin by examining the estimates of the unconditional average sizes of jumps in returns, which for each country equals $\mu^Y + \rho^J \mu^V$. It should be noted that despite the fact that the estimate of μ^Y is positive for some countries, the total unconditional average jump size to return is negative for all indices. The reason is that whenever the estimate of μ^Y is positive, the estimate of ρ^J, which measures the dependency between the size of jumps in returns and the size of jumps in volatility, is negative. An effect of the negative jumps in returns is that the estimates of the drift parameters are strictly greater than the corresponding sample means for every index. For example, the estimated drift parameter of the S&P is approximately 15 % larger than the sample mean, and for Japan, the effect of jumps in returns has likely decreased the average return in the sample by so much that it is effectively equal to zero. This implies that jumps may constitute a relatively large component of expected return. Another implication may be that a traditional expected return estimate may be very sensitive to whether or not the estimation window contains any jumps or not.

The index that has the largest unconditional average size of jumps in returns is Australia where jumps in returns are on average -5.6212 %, closely followed by Hong Kong (-5.2867 %) and the S&P (-5.0368 %). The index that has the smallest unconditional average size of jumps in returns is Japan where jumps in returns are on average -0.7316 %, closely followed by Denmark (-0.7568 %), the UK (-1.1397 %), and Italy (-1.1470 %). As a simple measure of dependency between jump frequency and jump size, we calculate the cross-sectional correlation between the estimated jump intensities and the estimated unconditional average jump sizes of returns. This sample correlation is equal to -0.6133 which implies that countries with a high jump intensity generally have a smaller average jump size than countries with a low jump intensity. That is, some countries experience few but large jumps while other countries experience frequent but small jumps. The parameter λ, which is the arrival intensity of jumps, is estimated to values between $\lambda = 0.0033$ for Australia and $\lambda = 0.0271$ for Denmark. So, although jumps in the Danish market are approximately seven times more frequent than jumps in the Australian market, the average jump size of Australia is, coincidentally, about seven times larger than the average jump size of Denmark.

3.3 Jump Spillover

In this section we use our estimates of the historical jump times to analyze jump spillover effects. First, we look at the simultaneous jump intensities between pairs of countries, and second, we examine the conditional jump spillover probabilities that jumps in large countries cause jumps or unusually large negative returns in other countries.

While this section deals with jump spillover between pairs of countries, in Appendix B we perform a brief historical and descriptive study of the dates in our sample on which many countries have jumped simultaneously. Many of these dates coincide with important economical or political event, which indicate that the estimated jump times do make sense in that they seem to be consistent with the interpretation of jumps as event risk.

3.3.1 Simultaneous Jump Intensities

We start our study of jump spillover by taking a look at the simultaneous jump intensities between pairs of countries. We calculate the simultaneous jump intensity of two countries (indices) in a straightforward manner simply as the number of identified simultaneous jumps divided by the number of overlapping observations. The simultaneous jump intensity of a country (index) with itself is the number of jump times divided by the number of observations—a number which should be roughly consistent with the respective estimate of λ (for example by lying in the confidence interval of the corresponding estimate of λ in Table 2 or 3). When the two countries are either both North American or both non-North American, we define a simultaneous jump time as a date on which we have identified jumps in both countries. In the remaining cases we define a simultaneous jump time as a date on which we have estimated a jump in the North American country and a jump in the non-North American country on the day (of trade) after. The reason for this distinction is that the opening hours of the Asian and Australian markets do not overlap with the opening hours of the North American markets and that most of the market opening hours of the North American markets take place after the European markets have closed. Since the US equity market is the largest in the world, it is most natural to assume that the S&P is the internationally leading index. In addition, in Appendix B we find some evidence that there do seem to exist a lagged effect from the US market to other markets, but not in the opposite direction.

Table 4 reports the estimated simultaneous jump intensities and whether the estimated values are significant at the 95 (*) or 99 (**) percent level. The significance levels are obtained by testing if the estimated intensities are greater than what they would be under the null hypothesis that the different countries' jump processes are completely independent. Under the null hypothesis, the simultaneous jump intensity of two countries is estimated simply as the product of each country's ratio of the number of identified jumps to the number of observations.[5] For example, the simultaneous jump intensity of the S&P and the Nasdaq is under the null hypothesis equal to 0.0045 multiplied by 0.0072.

An initial observation is that the estimated simultaneous jump intensities are generally quite significant, which is evidence of the existence of systemic jump spillover. Another observation is that generally, the intensities are especially large and significant between countries of approximately the same time zones or regions. That is, between countries 1 to 3 (North American region), between countries 4 to 11 (European region), and between countries 12 to 14 (Asian and Australian region). For example, while, on average, the S&P and Canada jump simultaneously every 1.7 years, the UK and France jump simultaneously every 2.3 years, and Japan and Hong Kong jump simultaneously every 2.0 years, the S&P and UK only jump simultaneously every 6.6 years and the S&P and Japan only jump simultaneously every 3.6 years.

To formally test for this regional effect, we run a regression of the simultaneous jump intensities in excess of the corresponding intensities under the null hypothesis (excess simultaneous jump intensities henceforth) on a constant and a dummy variable. The dummy variable is equal to one if the corresponding simultaneous jump intensity is between two countries that belong to the same region and equal to zero otherwise. The reason why we use the excess intensities as the dependent variable in the regression is that we are interested in explaining the portions of the intensities that cannot be explained by the fact that counties sometimes jump simultaneously only by accident. A motivation for not including the null hypothesis intensities instead on the right hand side of the regression is to avoid the bias due to the errors-in-variables problem which arises when including estimated values as a regressor in a regression. That the left hand side of the regression contains measurement error should not, in theory, present such a problem, but it does imply that the usual OLS standard errors will be somewhat underestimated. Because the S&P and the Nasdaq are both indices belonging to the same country and therefore exhibit a very high degree of jump spillover, we omit the Nasdaq from this analysis. What remains is therefore 78 excess simultaneous jump intensity observations to be explained on the left hand side of the regression. To keep things simple, we estimate the regression with ordinary least squares (OLS) and perform no corrections of the standard errors. The result is that both coefficients are highly significant (see column R3 of Table 5). The t-statistic of the slope coefficient is

[5] All the test statistics we use in this section can be found in Hogg and Tanis (2001). The tests take into account that the estimated simultaneous jump intensities and the estimated conditional jump spillover probabilities are random under both the null and the alternative hypothesis. We have also tested the simultaneous jump intensities using bootstrap methods which resulted in even higher levels of significance.

6.0641, thus indicating that the regional factor is indeed an important factor that affects the degree of jump spillover between two countries.

The importance of the regional factor might not be surprising. In addition to having similar market opening hours, countries located in the same region are often similar in many more ways. They may for example have extensive links through trade and finance and have similar market structures. It is therefore interesting to examine if there are other factors as well, in addition to the regional factor, that can be used to explain the estimated simultaneous jump intensities. For this purpose, we regress the excess simultaneous jump intensities (still excluding the Nasdaq) on a constant, the regional dummy, and three additional factors: The first additional factor consists of the (absolute) size differences between the different countries' equity markets. As proxies for the sizes of the different countries' equity markets we use their weights in the April 11, 2002, MSCI All Country World Index Free (ACWI) index. We include this factor in order to examine if there is a tendency for jump spillover to be greater between, for instance, large and small countries. The second additional factor consists of the sample correlations calculated from the historical (log) returns of the different country indices. We include this factor in order to examine if countries whose returns are highly correlated are also highly dependent in the sense of a high degree of jump spillover. The third additional factor consists of the differences between the different countries' industry structures. To construct a proxy for this factor, we first calculate the countries' respective exposures (betas) to the ten MSCI World industry indices.[6] As a measure of the industry differences, for every pair of countries we then calculate the average absolute difference in exposures. We include this final factor to examine if a similar industry structure affects the degree of jump spillover between two countries.[7]

The OLS parameter estimates of the regression of the excess simultaneous jump intensities on the factors above are presented in column R1 of Table 5. We see that the regional effect is still significant and that there are also significant negative relations with the absolute size differences and the industry differences (especially when the sample correlations are omitted from the regression, see column R3 of Table 5), whereas there is no significant relation with the sample correlations. That the relation with the absolute size differences is negative indicates that the smaller is the difference in size between two countries, the larger is the degree of jump spillover.[8] To examine if there is any tendency that two

[6]We use daily return data between 02 January, 1995, and 1 November, 2004, and the industries are: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, IT, Materials, Telecommunications Services, Utilities.

[7]A potential fourth factor that would be interesting to include are the amounts of cross-listings between the different indices. However, since the data collection to construct this factor would be disproportionately time consuming and difficult, keeping in mind that this regression study is not the main focus of the paper, we do not include such a factor.

[8]It should be noted that this result is somewhat sensitive to the inclusion of the S&P (US) in the regression. The weight

large countries exhibit more jump spillover than two smaller countries, or vice versa, we include in the regression also a dummy variable for this, but we find no significant such relation (the results are not reported in Table 5 but are available upon request). Similarly, the negative relation with the industry differences indicates that countries with similar industry structures generally exhibit a higher than average degree of jump spillover. Perhaps most interesting, however, is that the sample correlations have no significant power in explaining the simultaneous jump intensities. Even if we do obtain a significant relationship when we run a regression of the excess intensities on the sample correlations alone (see column R4 of Table 5), the R^2 in such a regression is quite low; $R^2 = 0.0975$ compared to $R^2 = 0.4366$ when all factors are included. This implies that ordinary correlations are not sufficient to capture how different equity markets depend on each other in times of extreme event—in particular when the effect of the regional, absolute size difference, and industry difference factors are taken into account. An implication of this is that an investor with mean-variance preferences who disregards event risk and who uses sample correlations to form portfolios, may be exposed to more risk than expected because of the jump spillover and its (almost) independence with sample correlations.

3.3.2 Conditional Jump Spillover Probabilities

Next, we look at the conditional spillover probability that, given a jump in a chosen benchmark country, other countries jump on the same or on the following day—denoted by *same-day (conditional) jump spillover* and *next-day (conditional) jump spillover*. We examine three cases for the choice of benchmark country: (1) S&P, (2) UK, and (3) Japan. These choices are motivated by the fact that these are the major indices in their respective regions, and out of these, we still assume that the S&P is the internationally leading index. For case (1), we look at the same-day jump spillover to the remaining two North American countries and Europe and next-day jump spillover to Europe, Asia, and Australia. For case (2), we look at the same-day jump spillover to the other European countries and next-day jump spillover to Asia and Australia. Since the UK and the US market opening hours overlap, there is no real motivation for looking at same-day jump spillover from the UK to the US. Finally, for case (3), we look at the same-day jump spillover to the US, to Europe, and to Hong Kong and Australia.

Table 6 shows the estimated same-day and next-day (conditional) jump spillover probabilities. The same-day jump spillover probability for a country is estimated as the number of simultaneous jump times with the benchmark country divided by the number of jump times of the benchmark country. The next-day jump spillover probability is calculated in the same way but by using instead the number

of the US in the ACWI is by far the largest; 0.5347 compared to the second largest weight 0.0986 (the UK).

of jumps that occur on the day after jumps in the benchmark country. The table also shows which of these estimated probabilities that are significant at the 95 or 99 percent level. The significance levels are obtained by testing for equality of the estimated spillover probabilities with the corresponding probabilities under the null hypothesis of independent jump processes. Under the null hypothesis, the same-day and next-day jump spillover probabilities of a country are both estimated as the number of identified jumps divided by the number of observations.

The results show that all the estimated probabilities are significant, except for Japan, which, as could be expected, does not seem to have any significant effect on the North American indices. For most of the European countries (all except for Sweden) the next-day jump spillover effect from the S&P is greater than the same-day jump spillover effect. This may be due to fact that the largest portion of the activity on the US market takes place when the European markets are closed; only about 30 percent of the US and European market opening hours overlap. For the European indices, we again notice a region effect in that the same-day jump spillover effect from the UK is larger than the one from the S&P.[9] Of the European countries, Germany shows the smallest overall sensitivity to jumps in the S&P and the UK. Within North America, the jump spillover probability from the S&P to the other two indices is quite strong; 77.27 % for the Nasdaq and 50.00 % for Canada.

It may be possible that although jumps in the benchmark countries do not always cause jumps in other countries, they still affect considerably other markets. To analyze a weaker form of jump spillover, we look at the conditional probabilities that jumps in the benchmark countries merely results in unusually large negative returns in other countries and not necessarily jumps. For simplicity, we define an unusually large negative return as a return belonging to the lower decile of the historical returns of each index. These probabilities are estimated in the same fashion as above and we again test if they are greater than the corresponding probabilities under the null hypothesis of independence between the benchmark jumps and the unusually large negative returns. In this case, the probabilities under the null are simply equal to 10 %.

The result for this type of jump spillover is shown in Table 7. Firstly, it is easy to see that all values are considerably larger than the corresponding values in Table 6, and at the same time, almost the same pattern as above in terms of spillover and significance is present. Secondly, despite the, on average, stronger same-day jump spillover from the UK to the other European countries compared to the next-day jump spillover from the S&P, in this case the next-day effect from the S&P is larger, on

[9] It would be interesting to perform a regression study similar to the one in the previous analysis in order to examine factors that may help explain the estimated conditional jump spillover probabilities. However, the number of "observations" is considerably less in this case which makes such a study hard to carry out. It would, however, perhaps be interesting to look at the explanatory power of factors like benchmark country foreign investment and so forth.

average, than the same-day effect from the UK. On average, about 60% of the jumps in S&P cause strong reactions in the European markets.

4 Conclusion

In this paper we study jump spillover between a number of country equity indices. Our contribution is twofold: Firstly, we fit a stochastic volatility jump-diffusion model to each individual index and compare features of the different indices such as jump frequencies and jump magnitudes. This analysis is motivated by the fact that most previous empirical research of event risk models have focused mostly on the US markets and little is known about the impact of jumps in other markets. Secondly, we look at jump spillover effects between countries. This is the central issue of the paper, and to our knowledge, it has not been analyzed by previous studies.

To identify the historical jump times of the different indices, we use the stochastic volatility with correlated jumps (SVCJ) model. This model helps us to separate out returns that are related to sudden unexpected events (jumps) from large diffusive returns caused by periods of high volatility. We estimate the model with the MCMC method of Eraker et al. (2003). The advantage of this estimation method, compared to most other methods, is that it makes it possible to estimate the latent processes of the model; in particular the jump times.

Our study of jump spillover begins with an analysis of the simultaneous jump intensities of pairs of countries. We find that these intensities are generally quite significant, and in a regression study, we find that the (excess) simultaneous jump intensities are particularly large for pairs of countries that belong to approximately the same time zones or regions and have similar market capitalizations and industry structures. That is, two countries that belong to the same region and have similar equity market sizes and industry structures are likely to exhibit a relatively high degree of jump spillover. Perhaps most interestingly, however, we find that there is no strong relation between the historical sample correlations and the estimated simultaneous jump intensities. The R^2 in a regression of the (excess) simultaneous jump intensities on the historical sample correlations alone is quite low and the relation is highly insignificant when the other factors are included in the regression. That is, the return correlation between two countries estimated from historical returns is not likely to carry much information on the degree of dependence in terms of how often they jump simultaneously. For example, this implies that an international investor with mean-variance preferences who do not take into account jump spillover and who uses these correlations when selecting portfolios, may not even accidentally construct any hedge against event risk. Consequently, the risk of the portfolio position may be much greater than what is expected since ordinary correlations tells the investor little about the jump spillover dependencies in times of extreme events.

We end our study of jump spillover by looking at the conditional probabilities that jumps in large markets cause jumps or large price movements in other markets. We find that these estimated conditional jump spillover probabilities are also generally significantly larger than what they would be under the null hypothesis of no international jump spillover. Furthermore, we observe a lagged effect from the US to the other countries in our data set. For most of the European countries, jumps in the S&P are more likely to cause jumps in Europe, Asia, and Australia on the day after the US jump than on the same day. This effect is likely to be the result of differences in market opening hours.

References

Andersen, T., L. Benzoni, and J. Lund, 2002, An Empirical Investigation of Continuous-Time Equity Return Models, *Journal of Finance* 57, 1239-1284.

Akgiray, V. and G. Booth, 1988, Mixed Diffusion-Jump Process modeling of Exchange Rate Movements, *Review of Economics and Statistics Studies* 70, 631-637.

Bates, D, 1996, Jumps and Stochastic Volatility: Exchange Rate Processes Implicit in Deutsche Mark Options, *Review of Financial Studies* 9, 69-107.

Bates, D., 2000, Post-'87 Crash Fears in the S&P 500 Futures Option Market, *Journal of Econometrics* 94, 181-238.

Bakshi, G., C. Cao, and Z. Chen, 2003, Empirical Performance of Alternativ Option Pricing Models, *Journal of Finance* 52, 2003-2049.

Bekaert, G, C. Erb, C. Harvey, and T. Viskanta, 1998, Distribu- tional Characteristics of Emerging Market Returns and Asset Allocation, *Journal of Portfolio Management* 24, 102-116.

Cappuccio, N., D. Lubian, and D. Raggi, 2004, MCMC Bayesian Estimation of a Skew-GED Stochastic Volatility Model, *Studies in Nonlinear Dynamics and Econometrics* 8.

Chacko, G. and L.M. Viceira, 2003, Spectral GMM Estimation of Continuous-Time Processes, *Journal of Econometrics* 116, 259-292.

Chernov, M., R. Gallant, E. Ghysels, and G. Tauchen, 2003, Alternative Models for Stock Price Dynamics, *Journal of Econometrics* 116, 225-257.

Das, Sanjiv Ranjan, and Rangarajan K. Sundaram, 1999, Of Smiles and Smirks: A Term Structure Perspective, *Journal of Financial and Quantitative Analysis* 34, 211-239.

Das, S.R. and R. Uppal, 2004, Systemic Risk and International Portfolio Choice, Forthcoming in *Journal of Finance*.

De Bandt, O. and P. Hartmann, 2000, Systemic Risk: A Survey, Working Paper, European Central Bank.

Duffie, D., J. Pan, and K. Singleton, 2000, Transform Analysis and Asset Pricing for Affine Jump Diffusion, *Econometrica* 68, 1343-1376.

Duffie, D. and J. Pan, 2001, Analytical Value-At-Risk with Jumps and Credit Risk, *Finance and Stochastics* 5, 155-180.

Eraker, B., M. Johannes, and N. Polson, 2003, The Impact of Jumps in Volatility and Returns, *Journal of Finance* 58, 1269-1300.

Eraker, B., 2001, MCMC Analysis of Diffusion Models with Application to Finance, *Journal of Business & Economic Statistics* 19, 177-191.

Eraker, B., 2004, Do Stock Prices and Volatility Jump? Reconciling Evidence from Spot and Option Prices, *Journal of Finance* 59, 1367-1404.

Forbes, K. and R. Rigobon, 2002, No Contagion, Only Interdependence, Measuring Stock Market Comovements, *Journal of Finance* 55, 285-297.

D., S. Foresi, and L. Wu, 1999, Crashes, Contagion, and International Diversification Backus, Working Paper.

Gallant, R., and G. Tauchen, 1996, Which Moments to Match, *Econometric Theory* 12, 657-681.

Gibson, M., 2001, Incorporating Event Risk into Value-at-Risk, Finance and Economics Discussion Series 2001-17, Washington: Board of Governors of the Federal Reserve System.

Hammersley, J. and P. Clifford, 1970, Markov Fields on Finite Graphs and Lattices, Unpublished Manuscript.

Heston, S., 1993, A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options, *Review of Financial Studies* 6, 327-343.

Hogg R. and E. Tanis, 2001, *Probability and Statistical Inference*, Sixth Edition, Prentice Hall.

Honoré, P., 1998, Pitfalls in Estimating Jump-Diffusion Models, Working Paper, University of Aarhus.

Hu, L., 2004, Dependence Patterns across Financial Markets: a Mixed Copula Approach, Working Paper.

Jacquier, E., N. Polson, P. Rossi, 1994, Bayesian Analysis of Stochastic Volatility Models, *Journal of Business & Economic Statistics* 12, 371-390.

Jacquier, E., N. Polson, P. Rossi, 2002, Bayesian analysis of Stochastic Volatility Models with Fat-Taied and Correlated Errors, *Journal of Econometrics*, Forthcoming.

Jagannathan, R. and T. Ma, 2003, Risk Reduction in Large Portfolios: Why Imposing the Wrong Constraints Helps, *Journal of Finance* 58, 1651-1684.

Johannes, M. and N. Polson, 2004, MCMC Methods for Financial Econometrics, in Y. Aït-Sahalia and Lars Hansen, eds.: *Handbook of Financial Econometrics*, Elsevier, New York.

Johannes, M., R. Kumar, and N. Polson, 1999, State Dependent Jump Models: How do U.S. Equity Markets Jump?, Working Paper.

Jorion, P., 1988, On Jump Processes in the Foreign Exchange and Stock Markets, *The Review of Financial Studies* 1, 427-445.

Liu, J., F. Longstaff, and J. Pan, 2003, Dynamic Asset Allocation with Event Risk, *Journal of Finance* 58, 427-445.

Merton, R., 1976, Option Pricing When Underlying Stock Returns are Discontinuous, *Journal of Financial Economics* 3, 125-144.

Pan, J., 2002, The Jump-Risk Premia Implicit in Options: Evidence From an Integrated Time-Series Study, *Journal of Financial Economics* 63 3-50.

Press, S. J., 1967, A Compound Events Model for Security Prices, *Journal of Business* 40, 317-335.

Roll, R., 1989, The International Crash of October 1987, in R. Kamphuis (ed.) Black Moday and the Future of Financial Markets, Richard D. Irwin, Inc., Homewood, IL.

Wu, L. 2003, Jumps and Dynamic Asset Allocation, *Review of Quantitative Finance and Accounting* 20, 207-243.

Zhou, C., 1997, A Jump-Diffusion Approach to Modeling Credit Risk and Valuing Defaultable Securities, Finance and Economics Discussion Series 1997-15, Board of Governors of the Federal Reserve System (U.S.).

A MCMC estimation

The MCMC method draws from the Clifford-Hammersley theorem (Hammersley and Clifford, 1970) which states that a joint distribution $p(A, B|C)$ is completely characterized by the two conditional marginal distributions $p(A|B, C)$ and $p(B|A, C)$. This implies that a sample from the complete posterior of equation (3) can be obtained by drawing random numbers from a set of conditional marginals, which can be derived by using Bayes' formula. The marginals are lower in dimension and chosen so that they are as easy to sample from as possible. The MCMC algorithm used to estimate the SVCJ model is

For $j = 1, 2, ..., m, ..., M$:

(1) *Parameters*

Draw $\Theta_1^{(j)}$ from $p\left(\Theta_1^{(j)}|Y, \Theta_2^{(j-1)}, \Theta_3^{(j-1)}, ..., \Theta_K^{(j-1)}, V^{(j-1)}, J^{(j-1)}, \xi^{V(j-1)}, \xi^{Y(j-1)}\right)$

$\vdots$

Draw $\Theta_K^{(j)}$ from $p\left(\Theta_K^{(j)}|Y, \Theta_1^{(j)}, \Theta_2^{(j)}, ..., \Theta_{K-1}^{(j)}, V^{(j-1)}, J^{(j-1)}, \xi^{V(j-1)}, \xi^{Y(j-1)}\right)$

(2) *Jump times* For $t = 1, 2, ..., T$:

Draw $J_{\Delta t}^{(j)}$ from $p\left(J_{\Delta t}^{(j)} = 1|Y, \Theta^{(j)}, V^{(j-1)}, \xi^{V(j-1)}, \xi^{Y(j-1)}\right)$

(3) *Jump sizes* For $t = 1, 2, ..., T$:

Draw $\xi_{\Delta t}^{V(j)}$ from $p\left(\xi_{\Delta t}^{V(j)}|Y, \Theta^{(j)}, V^{(j-1)}, J_{\Delta t}^{(j)}, \xi_{\Delta t}^{Y(j-1)}\right)$

Draw $\xi_{\Delta t}^{Y(j)}$ from $p\left(\xi_{\Delta t}^{Y(j)}|Y, \Theta^{(j)}, V^{(j-1)}, J_{\Delta t}^{(j)}, \xi_{\Delta t}^{V(j)}\right)$

(4) *Spot volatilities*

Draw $V_{\Delta 1}^{(j)}$ from $p\left(V_{\Delta 1}^{(j)}|Y, \Theta^{(j)}, V_0^{(j)}, V_{\Delta 2}^{(j-1)}, J^{(j)}, \xi^{V,(j)}, \xi^{Y(j)}\right)$

$\vdots$

Draw $V_{\Delta T}^{(j)}$ from $p\left(V_{\Delta T}^{(j)}|Y, \Theta^{(j)}, V_{\Delta(T-1)}^{(j)}, V_{\Delta(T+1)}^{(j-1)}, J^{(j)}, \xi^{V(j)}, \xi^{Y(j)}\right)$

When we run the MCMC algorithm, we set $M = 100,000$ and we discard the first $m = 20,000$ iterations as burn-in. In the cases when the conditional marginals are standard distributions that can be easily sampled from, the corresponding MCMC draws are referred to a Gibbs steps. In the other cases when they are unknown distributions, so called Metropolis steps are necessary. Metropolis-Hastings algorithms are methods to generate random numbers from non-standard distributions and generally consists of at least two steps: First a draw from a proposal density and then a draw from a uniform distribution to decide whether to accept or reject the draw from the proposal. Whenever possible, we choose conjugate priors.[10] The (marginal) prior distributions we choose are: $\mu \sim \mathcal{N}(a, A)$, $(\alpha, \beta) \sim$

[10] A conjugate prior is a distribution under which the prior and posterior of a parameter is the same type of distribution, but with different hyperparameters.

$\mathcal{N}(b, B)$, $\sigma_V^2 \sim \mathcal{IW}(c, C)$, $\rho \sim \mathcal{U}(-1, 1)$, $\mu_V \sim \mathcal{IW}(d, D)$, $\mu_Y \sim \mathcal{N}(e, E)$, $\sigma_Y^2 \sim \mathcal{IW}(f, F)$, $\rho_J \sim \mathcal{N}(g, G)$, $\lambda \sim \beta(k, K)$. With these priors for the parameters, the only (marginal) posteriors that cannot be written as standard distributions are those of σ_V^2, ρ, and $V_{\Delta t}$, $t = 1, 2, ..., T$. We use an independence Metropolis-Hastings algorithm for σ_V^2 and random walk Metropolis-Hastings algorithms for ρ and $V_{\Delta t}$. Cappuccio et al. (2004) consider a novel Metropolis-Hastings algorithm in a related setting, but we find that our approach works well.

The posterior of σ_V^2, conditional on Y, V, J, ξ^Y, ξ^V, and$\Theta_{-\sigma_V^2}$, it can be showed using Bayes' formula, is proportional to

$$(\sigma_V^2)^{T/2} \exp\left\{-\frac{1}{2}\sum_{t=1}^{T} \frac{(V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta - \xi_{t\Delta}^V J_{t\Delta} - \rho\sigma_V(Y_{t\Delta} - \mu - \xi_{t\Delta}^Y J_{t\Delta}))^2}{(1-\rho^2)\sigma_V^2 V_{(t-1)\Delta}\Delta}\right\} (\sigma^2)^{\frac{c+2}{2}} \exp\left\{-\frac{1}{2}\frac{C}{\sigma^2}\right\},$$

which is a non-standard distribution. However, in the special case when $\rho = 0$ it is a one-dimensional inverted-Wishart distribution (which is the same thing as the inverted-gamma distribution). On account of this, we choose the proposal density to be $\mathcal{IW}(c^*, C^*)$, where

$$\begin{aligned} c^* &= c + T, \\ C^* &= C + \sum_{t=1}^{T} \frac{(V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{t-1}\Delta - \xi_{t\Delta}^V J_{t\Delta})^2}{V_{t-1}\Delta}, \end{aligned}$$

and where $c = 2.5$, and $C = 0.1$. Since the proposal is identical to the true posterior if there is no leverage effect, we hope that it is a reasonable approximation when $\rho \neq 0$. Indeed, when estimate the model on the different country equity indices, those with very little leverage effect such as Denmark have an acceptance ratio for this parameter almost equal to one, while countries like Japan which have quite a lot of leverage, have a significantly lower acceptance ratio of approximately 85 % to compensate for the difference between the true posterior and the proposal.

The posterior of ρ, conditional on Y, V, J, ξ^Y, ξ^V, and $\Theta_{-\rho}$, can in a similar fashion be derived as

$$\left(\frac{1}{\sqrt{1-\rho^2}}\right)^T \exp\left\{-\frac{1}{2(1-\rho^2)}\sum_{t=1}^{T} \frac{Y_{t\Delta} - \mu\Delta - \xi_{t\Delta}^Y J_{t\Delta} - \frac{\rho}{\sigma_V}(V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta - \xi_{t\Delta}^V J_{t\Delta})^{\;2}}{V_{(t-1)\Delta}\Delta}\right\} \mathbf{1}_{\{-1<\rho<1\}},$$

where $\mathbf{1}_{\{-1<\rho<1\}}$ is an indicator function that is equal to 1 when $|\rho| \leq 1$ and 0 otherwise. Since this distribution is not similar to any well known distribution, we choose a random walk Metropolis-Hastings algorithm in this case. We choose the t-distribution for the random walk disturbances with degrees of freedom and standard deviations that depend on the data set in question, usually around 6.5 to 10 and 0.015 to 0.4, respectively.

Similarly, the posterior of $V_{t\Delta}$ conditional on $Y, V_{-V_{t\Delta}}, J, \xi^Y, \xi^V$, and Θ, $t = 2, ..., T-1$, is proportional to

$$V_{t\Delta}^{-1} \exp\left\{ -\frac{1}{2} \sum_{i=0}^{1} \left(\frac{Y_{(t+i)\Delta} - \mu\Delta - \xi^Y_{(t+i)\Delta} J_{(t+i)\Delta} - \frac{\rho}{\sigma_V} \quad V_{(t+i)\Delta} - V_{(t-1+i)\Delta} - \alpha\Delta - \beta V_{(t-1+i)\Delta}\Delta - \xi^V_{(t+i)\Delta} J_{(t+i)\Delta}}{(1-\rho^2) V_{(t-1+i)\Delta}\Delta}^2 \right.\right.$$

$$\left.\left. + \frac{V_{(t+i)\Delta} - V_{(t-1+i)\Delta} - \alpha\Delta - \beta V_{(t-1+i)\Delta}\Delta - \xi^V_{(t+i)\Delta} J_{(t+i)\Delta}}{\sigma_V^2 V_{(t-1+i)\Delta}\Delta}^2 \right) \right\},$$

which also is extremely non-standard. We therefore again use random walk Metropolis-Hastings algorithms with t-distributed disturbances. The standard deviations have to be adjusted so that when $V_{t\Delta}$ is large, so is the standard error of corresponding the disturbance, and vice versa. For example, a preliminary estimate of V can be obtained half way into the burn-in period, or so, according to which the disturbance standard deviations can be adjusted. An average standard deviation that seems to work well is 0.25, together with 6.5 degrees of freedom.

All other posteriors are standard distributions that can be sampled by using standard statistical softwares such as the built in functions in Matlab. By Bayes' formula it can be showed that:

$\mu|_{Y,V,J,\xi^Y,\xi^V,\Theta_{-\mu}} \sim \mathcal{N}(a^*, A^*)$, where

$$\begin{aligned} a^* &= A^* \left(\frac{\Delta}{(1-\rho^2)} \sum_{t=1}^{T} \frac{e^{\mu}_{Y,t\Delta} - \frac{\rho}{\sigma_V} e^{\mu}_{V,t\Delta}}{V_{(t-1)\Delta}} + \frac{a}{A} \right), \\ A^* &= \left(\frac{\Delta^2}{(1-\rho^2)} \sum_{t=1}^{T} \frac{}{V_{(t-1)\Delta}} + \frac{1}{A} \right)^{-1}, \end{aligned}$$

$a = 0$, $A = 25$, $e^{\mu}_{Y,t\Delta} = Y_{t\Delta} - \xi^Y_{t\Delta} J_{t\Delta}$, and $e^{\mu}_{V,t\Delta} = V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta - \xi^V_{t\Delta} J_{t\Delta}$.

$(\alpha, \beta)|_{Y,V,J,\xi^Y,\xi^V,\Theta_{-(\alpha,\beta)}} \sim \mathcal{N}(b^*, B^*)$, where $\gamma = (\alpha\, \beta)^{\mathrm{T}}$ and

$$\begin{aligned} b^* &= B^* \left(B^{-1} b + \frac{1}{(1-\rho^2)\sigma_V^2} W^{\mathrm{T}} Q \right), \\ B^* &= \left(B^{-1} + \frac{1}{(1-\rho^2)\sigma_V^2} W^{\mathrm{T}} W \right)^{-1}, \\ Q &= \begin{pmatrix} \frac{V_{(1)} - V_{(0)} - \xi^V_{(1)} J_{(1)} - \rho\sigma_V e^{\gamma}_{Y(1)}}{\sqrt{V_{(0)}\Delta}} \\ \frac{V_{(2)} - V_{(1)} - \xi^V_{(2)} J_{(2)} - \rho\sigma_V e^{\gamma}_{Y(2)}}{\sqrt{V_{(1)}\Delta}} \\ \frac{V_{(3)} - V_{(2)} - \xi^V_{(3)} J_{(3)} - \rho\sigma_V e^{\gamma}_{Y(3)}}{\sqrt{V_{(2)}\Delta}} \\ \vdots \end{pmatrix}, \\ W &= \begin{pmatrix} \frac{1}{\sqrt{V_{(0)}\Delta}} & \sqrt{V_{(0)}\Delta} \\ \frac{1}{\sqrt{V_{(1)}\Delta}} & \sqrt{V_{(1)}\Delta} \\ \frac{1}{\sqrt{V_{(2)}\Delta}} & \sqrt{V_{(2)}\Delta} \\ \vdots & \vdots \end{pmatrix}, \end{aligned}$$

and $b = 0\mathbf{1}$, $B = \mathbf{I}$, $e^{\gamma}_{Y,t\Delta} = Y_{t\Delta} - \mu\Delta - \xi^{Y}_{t\Delta} J_{t\Delta}$. $\mathbf{1}$ denotes a vector of ones and $\mathbf{I}$ denotes the identity matrix, both with the appropriate dimension.

$\mu_V|_{Y,V,J,\xi^Y,\xi^V,\Theta_{-\mu_V}} \sim \mathcal{IW}(d^*, D^*)$, where

$$\begin{aligned} d^* &= d + 2T, \\ D^* &= D + 2\sum_{t=1}^{T} \xi^{V}_{t\Delta}, \end{aligned}$$

$d = 10$, and $D = 20$.

$\mu_Y|_{Y,V,J,\xi^Y,\xi^V,\Theta_{-\mu_Y}} \sim \mathcal{N}(e^*, E^*)$, where

$$\begin{aligned} e^* &= E^* \left(\sum_{t=1}^{T} \frac{\left(\xi^{Y}_{t\Delta} - \rho_J \xi^{V}_{t\Delta}\right)}{\sigma^2_Y} + \frac{e}{E} \right), \\ E^* &= \left(\frac{T}{\sigma^2_Y} + \frac{1}{E} \right)^{-1}, \end{aligned}$$

$e = 0$, and $E = 100$.

$\sigma^2_Y|_{Y,J,\xi^Y,\xi^V,\Theta_{-\sigma^2_Y}} \sim \mathcal{IW}(f^*, F^*)$,where

$$\begin{aligned} f^* &= f + T, \\ F^* &= F + \sum_{t=1}^{T} \left(\xi^{Y}_{t\Delta} - \mu_Y - \rho_J \xi^{V}_{t\Delta}\right)^2, \end{aligned}$$

$f = 10$, and $F = 40$.

$\mu_Y|_{Y,J,\xi^Y,\xi^V,\Theta_{-\rho_J}} \sim \mathcal{N}(g^*, G^*)$, where

$$\begin{aligned} g^* &= G^* \left(\frac{\sum_{t=1}^{T} \left(\xi^{Y}_{t\Delta} - \mu_Y\right) \xi^{V}_{t\Delta}}{\sigma^2_Y} + \frac{g}{G} \right), \\ G^* &= \left(\frac{\sum_{t=1}^{T} \left(\xi^{V}_{t\Delta}\right)^2}{\sigma^2_Y} + \frac{1}{G} \right)^{-1}, \end{aligned}$$

$g = 0$, and $G = 4$.

$\lambda|_J \sim B(k^*, K^*)$, where

$$\begin{aligned} k^* &= k + \sum_{t=1}^{T} J_{t\Delta}, \\ K^* &= K + T - \sum_{t=1}^{T} J_{t\Delta}, \end{aligned}$$

$k = 2$, and $K = 40$.

$p(J_{t\Delta} = 1|Y, V, \xi^Y, \xi^V, \Theta)$ is proportional to

$$\lambda \exp\left\{ -\frac{1}{2} \left(\frac{\left(Y_{t\Delta} - \mu\Delta - \xi^{Y}_{t\Delta} - \frac{\rho}{\sigma_V}(V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta - \xi^{V}_{t\Delta})\right)^2}{(1-\rho^2) V_{(t-1)\Delta}\Delta} + \frac{(V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta - \xi^{V}_{t\Delta})^2}{\sigma^2_V V_{(t-1)\Delta}\Delta} \right) \right\},$$

and $p(J_{t\Delta} = 0|Y, V, \xi^Y, \xi^V, \Theta)$ is proportional to

$$(1-\lambda)\exp\left\{-\frac{1}{2}\left(\frac{\left(Y_{t\Delta}-\mu\Delta-\frac{\rho}{\sigma_V}(V_{t\Delta}-V_{(t-1)\Delta}-\alpha\Delta-\beta V_{(t-1)\Delta}\Delta)\right)^2}{(1-\rho^2)V_{(t-1)\Delta}\Delta}+\frac{\left(V_{t\Delta}-V_{(t-1)\Delta}-\alpha\Delta-\beta V_{(t-1)\Delta}\Delta\right)^2}{\sigma_V^2 V_{(t-1)\Delta}\Delta}\right)\right\}.$$

$\xi^V_{t\Delta}|_{\xi^V_{t\Delta}>0,Y_{t\Delta},V_{t\Delta},V_{(t-1)\Delta},J_{t\Delta}=1,\xi^Y_{t\Delta},\Theta} \sim \mathcal{TN}(h, H)$, where $\mathcal{TN}$ is the truncated normal distribution, and

$$\begin{aligned}
h &= H\left(\frac{e^{\xi,V}_{V,t\Delta}-\rho\sigma_V e^{\xi,V}_{Y,t\Delta}}{(1-\rho^2)\sigma_V^2 V_{(t-1)\Delta}}+\frac{\rho_J\left(\xi^V_{t\Delta}-\mu_Y\right)}{\sigma_Y^2}-\frac{1}{\mu_V}\right),\\
H &= \left(\frac{1}{(1-\rho^2)\sigma_V^2 V_{(t-1)\Delta}}+\frac{\rho_J^2}{\sigma_Y^2}\right)^{-1},
\end{aligned}$$

$e^{\xi,V}_{V,t\Delta} = V_{t\Delta} - V_{(t-1)\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta$ and $e^{\xi,V}_{Y,t\Delta} = Y_{t\Delta} - \mu\Delta - \xi^Y_{t\Delta}$.

$\xi^Y_{t\Delta}|_{Y_{t\Delta},V_{t\Delta},V_{(t-1)\Delta},J_{t\Delta}=1,\xi^V_{t\Delta},\Theta} \sim \mathcal{N}(i, I)$, where

$$\begin{aligned}
i &= I\left(\frac{e^{\xi,Y}_{Y,t\Delta}-\frac{\rho}{\sigma_V}e^{\xi,Y}_{V,t\Delta}}{(1-\rho^2)V_{(t-1)\Delta}\Delta}+\frac{\mu_Y+\rho_J\xi^V_{t\Delta}}{\sigma_Y^2}\right),\\
I &= \left(\frac{1}{(1-\rho^2)V_{(t-1)\Delta}}+\frac{1}{\sigma_Y^2}\right)^{-1},
\end{aligned}$$

$e^{\xi,Y}_{V,t\Delta} = V_{t\Delta} - V_{(t-1)\Delta} - \xi^V_{t\Delta} - \alpha\Delta - \beta V_{(t-1)\Delta}\Delta$ and $e^{\xi,Y}_{Y,t\Delta} = Y_{t\Delta} - \mu\Delta$.

B Global Jumps

In this appendix we look at some of the identified jump times that are shared by several countries. Many of these simultaneous jumps can easily be related to important political or economical events, which is in line with the interpretation of jumps as event risk. However, since it is beyond the scope of this paper to provide a complete historical study of the background factors of jump occurrences, these brief discussions should mainly be taken as speculations. The purpose is rather to show that the estimated jump times do seem to make some economical sense.

October 19, 1987 This date is the well known world wide crash of Black Monday and we estimate that all countries in our data set jumped on this day. On the Friday before Black Monday, we identify jumps in the three North American indices, while the only non-North American index that jumped was Sweden.[11] On the day after Black Monday, we estimate jumps in six countries out of which none

[11] On Black Monday the DJIA 30 fell by 508 (22.6 %). Other country indices fell even more. For instance, in Hong Kong prices fell by 46 %. On the Friday before Black Monday, the DJIA for the first time fell by more than 100 points (108).

are North American. This indicates that there was a lagged effect from the US market to the other countries. A possible explanation for this delay is the differences in opening hours (for a full discussion on nature of the crash of Black Monday, see e.g. Roll, 1989).

October 13, 1989 On this Friday the thirteenth, the DJIA fell by almost 200 points points, which marked the start of the recession of 1990's and we estimate all three North American countries jumped. We again observe a lagged effect from the US market to other countries. On the Monday that followed this date, there were no identified jumps in the US, whereas there were identified jumps in most other countries.

August 6, 1990 On this date we have estimated jumps in a total of eight countries. The underlying trigger may have been that the UN on this date declared sanctions against Iraq following this country's invasion of Kuwait.[12]

August 19, 1991 On this date Soviet leader Mikhail Gorbachev was overthrown following a military coup which caused jumps in all indices except for the US indices. Possible explanations to this may be geographical closeness and worries concerning the new political climate in the the Soviet Union.

October 23, 1997 On this date the Asian crises reached Hong Kong which overnight had to dramatically raise its interest rates in order to protect its currency. This resulted in a 10 % fall in the Hong Kong stock market index which had substantial international effects.

October 27, 1997 On this Monday, all trading on the NYSE came to a halt twice and the DJIA plunged a total of a record breaking 554 points.[13] This crash is believed to mostly be a consequence of the Asian financial crises. Again we see a delayed effect from the US to the other indices in that we identify jumps the day after in six non-North American indices.

August 11, 1998 On this day the Russian market collapsed, which increased the fear of a financial meltdown of the Russian and Asian markets. Surrounding this date there are several other global jumps that also are likely to have been related to the financial situation in Russia.

January 4, 2000 On this date US President Bill Clinton reappointed US Federal Reserve Chairman Alan Greenspan for a fourth term. On account of fears of increases in the interest rate, the US and

[12] On the date of the invasion we estimate jumps in three European countries together with Japan

[13] As a consequence of Black Monday, in 1988 the NYSE introduced the so called *circuit-breaker rules* whereby all trading stops for one hour as soon as the DJIA drops by more than 550 points.

European markets responded negatively.

March 14, 2000 This date was approximately three month after the reappointment of US Federal Reserve Chairman Alan Greenspan and investors were surprised by, and responded negatively to reports of increased US inflation. The reports, among other issues, again raised concerns regarding the risk of interest rate increases. The Asian and Australian markets followed the nosedives taken by the US market and dropped largely on the Monday of April 14.

September 11, 2001 This is the date of the terrorist attacks to the World Trade Center and the Pentagon. The events took place before the US security markets opened, and therefore, the effects of the events did not show up as jump times in the US markets until they reopened on September 17. The Asian and Australian markets were also closed at the time of the events, why the jump in Japan occurs on September 12. The European markets, on the other hand, were opened at the time of the events, why there were jumps in these countries on September 11.

March 11, 2004 This final date of our study of simultaneous jump times was the day of the bombings of the central train station in Madrid. Spain is not included in this particular study but we estimate that three other European countries jumped on this day.

C Tables

Table 1: Descriptive Statistics

Descriptive statistics of the country equity indices included in our study. The data consists of daily percentage log returns for each country equity index from February 1, 1985, to April 28, 2004. The mean returns and standard deviations have been annualized through multiplication by 252 and $\sqrt{252}$, respectively.

	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max	Sample Size
S&P	9.5004	17.4651	-2.0522	46.2513	-22.8997	9.0952	4858
Nasdaq	12.726	29.4456	-0.0842	9.6428	-16.3460	17.2030	4856
Can	5.9976	13.8426	-1.1929	20.3630	-11.7948	8.6459	4849
UK	6.6276	15.0760	-0.9387	14.6655	-11.9142	5.6976	4967
Ger	8.2404	23.4879	-0.4566	8.5149	-13.7099	7.5527	4822
Swe	11.4156	20.7051	-0.1487	8.4220	-9.1437	9.8116	4821
Fra	8.6940	21.3861	-0.2830	7.0183	-9.8945	7.9658	4856
Den	8.3160	13.5886	-0.4989	8.3345	-7.7846	4.7633	4801
Net	6.9552	21.5036	-0.2834	11.0968	-12.7880	11.1785	4875
Nor	8.2152	19.5828	-1.4677	28.1679	-21.2188	10.4809	4824
Ita	8.4672	20.2273	-0.5312	7.1638	-10.0217	6.7361	4832
HK	11.5416	27.9264	-3.2788	76.4680	-40.5422	17.2471	4774
Aus	7.6356	15.0887	-6.2953	179.3222	-28.7585	6.0666	4939
Japan	0.0000	22.5116	0.0318	8.1657	-12.6558	12.4301	4759

Table 2: Parameter Estimates for North American, Asian, and Australian Indices

SVCJ model parameter estimates for the North American, Asian, and Australian equity indices. The data consists of daily percentage log returns from February 1, 1985, to April 28, 2004. Reported are also the posterior standard errors and the posterior confidence intervals for each parameter.

	S&P			Nasdaq			Canada		
	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval
μ	0.0432	0.0115	(0.0207, 0.0657)	0.0909	0.0179	(0.0556, 0.1259)	0.0527	0.0088	(0.0356, 0.0701)
ϑ	0.8112	0.0917	(0.6438, 1.0032)	1.5331	0.2474	(1.0890, 2.0679)	0.3735	0.0340	(0.3136, 0.4472)
$\varkappa$	0.0252	0.0034	(0.0187, 0.0322))	0.0142	0.0028	(0.0089, 0.0193)	0.0355	0.0047	(0.0267, 0.0456)
σ_V	0.1353	0.0103	(0.1155, 0.1553)	0.1341	0.0137	(0.1116, 0.1631)	0.0945	0.0097	(0.0754, 0.1133)
ρ	-0.5932	0.0509	(-0.6846, -0.4875)	-0.3759	0.0766	(-0.5175, -0.2243)	-0.1190	0.0637	(-0.2517, -0.0015)
μ_V	1.3649	0.3748	(0.7774, 2.2735)	3.0147	0.7168	(1.8700, 4.6589)	1.6539	0.4319	(1.0331, 2.6596)
μ_Y	-1.7780	1.0308	(-3.698, 0.1442)	-2.9182	1.0254	(-4.7817, -0.8881)	-1.4514	0.7069	(-2.8331, -0.0057)
σ_Y	1.9460	0.3600	(1.3876, 2.8037)	1.9554	0.3875	(1.3280, 2.8756)	1.8299	0.3225	(1.2949, 2.4972)
ρ_J	-2.2866	0.5093	(-3.6612, -1.5304)	-0.3388	0.3374	(-0.9895, 0.3414)	-1.0295	0.3257	(-1.6282, -0.2253)
λ	0.0056	0.0021	(0.0024, 0.0107)	0.0078	0.0021	(0.0042, 0.0124)	0.0070	0.0018	(0.0038, 0.0110)

	Japan			Hong Kong			Australia		
	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval
μ	0.0333	0.0148	(0.0046, 0.0626)	0.0924	0.0180	(0.0572, 0.1276)	0.0490	0.0102	(0.0290, 0.0690)
ϑ	0.8053	0.1453	(0.5903, 1.1592)	1.3824	0.1400	(1.1345, 1.6801)	0.5408	0.0303	(0.4839, 0.6028)
$\varkappa$	0.0314	0.0045	(0.0222, 0.0396)	0.0425	0.0081	(0.0274, 0.0584)	0.0543	0.0083	(0.0396, 0.0718)
σ_V	0.1452	0.0141	(0.1186, 0.1739)	0.1913	0.0173	(0.1574, 0.2272)	0.1217	0.0120	(0.0996, 0.1457)
ρ	-0.6711	0.0494	(-0.7690, -0.5749)	-0.3653	0.0602	(-0.4895, -0.2518)	-0.2769	0.0549	(-0.3800, -0.1676)
μ_V	1.7729	0.4303	(1.1330, 2.7659)	3.1766	1.2132	(1.4140, 5.9231)	2.0544	0.5339	(1.2511, 3.3144)
μ_Y	-0.3902	1.1601	(-3.8636, 1.2220)	0.6519	1.5067	(-2.3345, 3.2541)	-2.0143	1.1541	(-4.1692, 0.5087)
σ_Y	2.3739	0.5036	(1.6038, 3.5774)	2.8682	0.8727	(1.6062, 4.8165)	2.0757	0.4804	(1.4063, 3.1604)
ρ_J	-0.1925	0.7142	(-0.9772, 2.1037)	-1.8695	0.8834	(-3.9446, -0.7719)	-1.7557	0.3380	(-2.3885, -1.1474)
λ	0.0181	0.0051	(0.0092, 0.0286)	0.0124	0.0039	(0.0061, 0.0212)	0.0033	0.0011	(0.0015, 0.0059)

Table 3: Parameter Estimates for European Indices

SVCJ model parameter estimates for the European equity indices. The data consists of daily percentage log returns from February 1, 1985, to April 28, 2004. Reported are also the posterior standard errors and the posterior confidence intervals for each parameter.

	UK			DAX			CAC			AFGX		
	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval
μ	0.0440	0.0101	(0.0242, 0.0638)	0.0559	0.0153	(0.0258, 0.0860)	0.0518	0.0156	(0.0213, 0.0822)	0.0974	0.0133	(0.0714, 0.1234)
ϑ	0.4720	0.0417	(0.3984, 0.5599)	1.0947	0.1601	(0.7410, 1.3916)	1.1352	0.1852	(0.8476, 1.5964)	0.8085	0.1046	(0.6185, 1.0184)
$\varkappa$	0.0338	0.0044	(0.0261, 0.0425)	0.0219	0.0029	(0.0168, 0.0282)	0.0232	0.0035	(0.0166, 0.0305)	0.0313	0.0042	(0.0231, 0.0396)
σ_V	0.0843	0.0085	(0.0703, 0.1032)	0.1372	0.0141	(0.1086, 0.1665)	0.1236	0.0179	(0.0927, 0.1619)	0.1383	0.0143	(0.1114, 0.1679)
ρ	-0.4257	0.0809	(-0.5806, -0.2770)	-0.4798	0.0729	(-0.6334, -0.3383)	-0.4751	0.0637	(-0.6010, -0.3447)	-0.3235	0.0642	(-0.4451, -0.1945)
μ_V	2.1674	0.5831	(1.3576, 3.6605)	2.9725	0.8244	(1.7016, 4.9213)	2.6515	1.0697	(1.2804, 5.4150)	2.5607	0.5432	(1.6272, 3.7171)
μ_Y	0.6832	0.7928	(-0.8978, 2.2414)	-1.3264	1.5380	(-4.2398, 1.7404)	-3.1803	1.9002	(-6.6777, 0.6459)	-3.1279	0.8529	(-4.7838, -1.4801)
σ_Y	2.0970	0.3537	(1.4843, 2.8483)	3.4050	0.5628	(2.4657, 4.6712)	2.2909	0.4563	(1.4898, 3.2213)	2.1775	0.3428	(1.6130, 2.9254)
ρ_J	-0.8411	0.2468	(-1.4129, -0.4535)	-0.4223	0.3431	(-1.0604, 0.2326)	-0.0918	0.6150	(-1.9744, 0.8627)	0.2111	0.2198	(-0.2088, 0.667)
λ	0.0063	0.0020	(0.0032, 0.0111)	0.0073	0.0028	(0.0034, 0.0148)	0.0057	0.0026	(0.0016, 0.0115)	0.0086	0.0025	(0.0045, 0.0141)

	Denmark			Netherlands			Norway			Italy		
	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval	Posterior Mean	Posterior Std.Dev.	Posterior 95% Conf. Interval
μ	0.0490	0.0091	(0.0309, 0.0668)	0.0589	0.0130	(0.0334, 0.0843)	0.0809	0.0133	(0.0550, 0.1071)	0.0398	0.0145	(0.0112, 0.0681)
ϑ	0.3033	0.0383	(0.2347, 0.3840)	0.6707	0.0883	(0.5026, 0.8411)	0.8390	0.0704	(0.7106, 0.9872)	0.7519	0.0845	(0.5931, 0.9223)
$\varkappa$	0.0648	0.0092	(0.0473, 0.0840)	0.0270	0.0028	(0.0216, 0.0326)	0.0559	0.0078	(0.0412, 0.0706)	0.0316	0.0036	(0.0254, 0.0393)
σ_V	0.1292	0.0120	(0.1069, 0.1533)	0.1051	0.0103	(0.0858, 0.1246)	0.1786	0.0178	(0.1467, 0.2142)	0.1141	0.0140	(0.0857, 0.1401)
ρ	-0.0374	0.0602	(-0.1587, 0.0766)	-0.4308	0.0747	(-0.5788, -0.2844)	-0.2493	0.0527	(-0.3522, -0.1475)	-0.4855	0.0710	(-0.6192, -0.3550)
μ_V	0.8528	0.1478	(0.5976, 1.1731)	2.8082	0.7402	(1.7356, 4.556)	3.2388	1.0225	(1.5546, 5.5067)	1.9947	0.4184	(1.3403, 2.9428)
μ_Y	-0.1769	0.4020	(-0.9660, 0.5660)	-1.4398	0.6180	(-2.6485, -0.2895)	-1.2886	1.7499	(-4.0204, 2.5360)	-2.0099	1.0780	(-4.4712, -0.0199)
σ_Y	1.7394	0.1928	(1.4013, 2.1527)	2.0430	0.3450	(1.4700, 2.7955)	2.7997	0.4999	(1.9346, 3.9094)	2.2465	0.3039	(1.7033, 2.8826)
ρ_J	-0.6800	0.3703	(-1.4055, 0.0469)	-0.4980	0.1675	(-0.8622, -0.2106)	-0.6814	0.5821	(-2.0557, -0.0175)	0.4326	0.3727	(-0.2358, 1.2841)
λ	0.0265	0.0058	(0.0164, 0.0392)	0.0097	0.0029	(0.0049, 0.0159)	0.0077	0.0025	(0.0037, 0.0138)	0.0131	0.0035	(0.0074, 0.0207)

Table 4: Estimated Simultaneous Jump Intensities

Estimated simultaneous jump intensities between pairs of countries. For two given countries, the intensity is estimated as the number of simultaneous jumps divided by the number of overlapping observations. For a single country, the intensity is simply the number of jump times divided by the number of observations. (**) denotes a one-sided significance at the 99 percent level and (*) denotes a one-sided significance at the 95 percent level.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. S&P	0.0045													
2. Nasdaq	0.0035**	0.0072												
3. Can	0.0023**	0.0027**	0.0078											
4. UK	0.0006*	0.0006*	0.0008*	0.0077										
5. Ger	0.0006	0.0008*	0.0006	0.0013**	0.0071									
6. Swe	0.0006*	0.0008*	0.0006*	0.0019**	0.0013**	0.0095								
7. Fra	0.0006*	0.0006	0.0006	0.0017**	0.0015**	0.0017**	0.0062							
8. Den	0.0015**	0.0015**	0.0015*	0.0021**	0.0030**	0.0025**	0.0021**	0.0279						
9. Net	0.0006*	0.0008*	0.0004	0.0021**	0.0017**	0.0010**	0.0025**	0.0033**	0.0115					
10. Nor	0.0015**	0.0015**	0.0017**	0.0013**	0.0015**	0.0013**	0.0019**	0.0025**	0.0015**	0.0070				
11. Ita	0.0008*	0.0008	0.0013*	0.0012**	0.0015**	0.0011**	0.0013**	0.0019**	0.0015**	0.0017**	0.0141			
12. HK	0.0015**	0.0013*	0.0019**	0.0008*	0.0013**	0.0009	0.0013*	0.0019**	0.0011*	0.0017**	0.0017**	0.0101		
13. Aus	0.0012**	0.0010*	0.0012**	0.0010**	0.0015**	0.0008*	0.0008*	0.0015**	0.0008*	0.0013**	0.0010*	0.0017**	0.0028	
14. Jap	0.0011*	0.0013*	0.0013*	0.0013*	0.0011*	0.0007*	0.0009*	0.0020*	0.0017**	0.0011*	0.0013*	0.0020**	0.0015**	0.0130

Table 5: Regression Results

OLS parameter estimates of regressions of the simultaneous jump intensities (the off-diagonal elements in Table 4 excluding the Nasdaq) in excess over the corresponding intensities under the null hypothesis of no jump spillover (the diagonal elements in Table 4 pairwise multiplied together) on a number of factors. The first regression, regression R1, is unconstrained, whereas in the remaining regressions, one or more factors have been excluded by asuming that the corresponding slope coefficients are equal to 0. Reported in parenthesis are the t-statistics calculated using the usual OLS standard errors without any corrections.

	R1	R2	R3	R4
Constant	0.0015 (8.3351)	0.0013 (12.9712)	0.0011 (16.3739)	0.0009 (5.6733)
Regional Dummy	0.0007 (4.8496)	0.0006 (6.6407)	0.0006 (6.0641)	
Abs. Size Diff.	-0.0006 (-1.8938)	-0.0007 (-2.6956)		
Correlations	-0.0005 (-0.9850)			0.0011 (2.8835)
Industry Diff.	-0.0003 (-2.5666)	-0.0002 (-2.4420)		
R^2	0.4366	0.4295	0.3232	0.0975

Table 6: Conditional Jump Spillover Probabilities

Estimated jump spillover probabilities from chosen benchmark countries to other countries. For a given non-benchmark country, the jump spillover probability is estimated as the number of the country's jumps that occur, depending on which is meaningful, either simultaneously as, or on the day following a benchmark country jump, divided by the number of jump times of the benchmark country. (**) denotes a one-sided significance at the 99 percent level and (*) denotes a one-sided significance at the 95 percent level.

	Benchmark				
	S&P		UK		Japan
	Same-Day	Next-Day	Same-Day	Next-Day	Same-Day
S&P					0.0161
Nasdaq	0.7727**				0.0161
Can	0.5000**				0.0161
FTSE	0.1364**	0.1364**			0.0968**
Ger	0.0455*	0.1364**	0.1579**		0.0806**
Swe	0.1818**	0.1364**	0.2368**		0.0484**
Fra	0.0909**	0.1364**	0.2105**		0.0645**
Den	0.2727**	0.3182**	0.2632**		0.1452**
Net	0.0909**	0.1364**	0.2632**		0.1290**
Nor	0.0909**	0.3182**	0.1579**		0.0806**
Ita	0.0909**	0.1818**	0.1579**		0.0968**
HK		0.3182**		0.0526**	0.1452**
Aus		0.2727**		0.0526**	0.1129**
Nikkei		0.2273**		0.0789**	

Table 7: Conditional Probabilities of Spillover from Jumps to Return

Estimated probabilities that jumps in the chosen benchmark countries translate int unusually lare negative returns in other countries. We define an unusually large negative return of a given country as a historical return that belongs to the lowest decile of that country's data set. For a given non-benchmark country, the probability is estimated as the number of the country's unusually large negative returns that occur, depending on which is meaningful, either simultaneously as, or on the day following a benchmark country jump, divided by the number of jump times of the benchmark country. (**) denotes a one-sided significance at the 99 percent level and (*) denotes a one-sided significance at the 95 percent level.

	Benchmark				
	S&P		UK		Japan
	Same-Day	Next-Day	Same-Day	Next-Day	Same-Day
S&P					0.1774*
Nasdaq	0.8636**				0.1452
Can	0.9091**				0.2258**
FTSE	0.4091**	0.6818**			0.3548**
Ger	0.3636**	0.3182**	0.5000**		0.2903**
Swe	0.3636**	0.5909**	0.5789**		0.3226**
Fra	0.5000**	0.4545**	0.5263**		0.3226**
Den	0.4545**	0.7273**	0.3684**		0.2581**
Net	0.4091**	0.6364**	0.5526**		0.4194**
Nor	0.4545**	0.7727**	0.3684**		0.3710**
Ita	0.3182**	0.5000**	0.4737**		0.3548**
HK		0.5909**		0.2632**	0.3226**
Aus		0.6364**		0.2368**	0.2903**
Nikkei		0.5000**		0.2368**	

D Figures

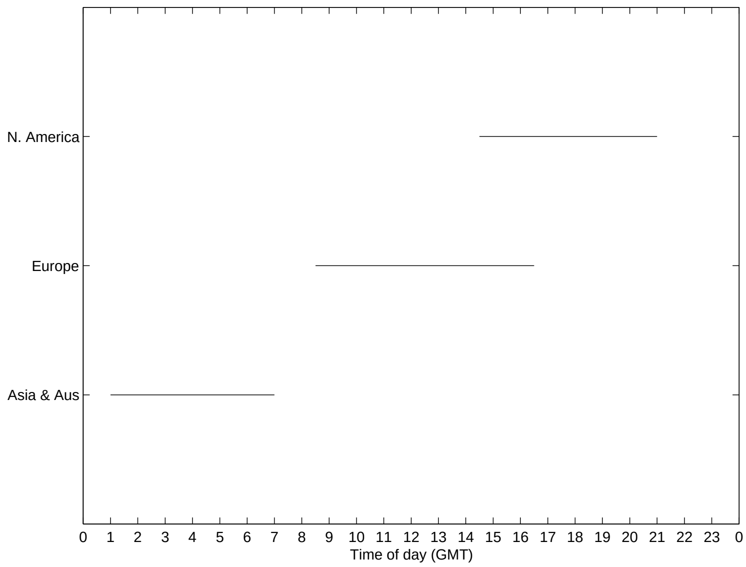

Figure 1: Approximate market opening hours in North America, Europe, and Asia and Australia.

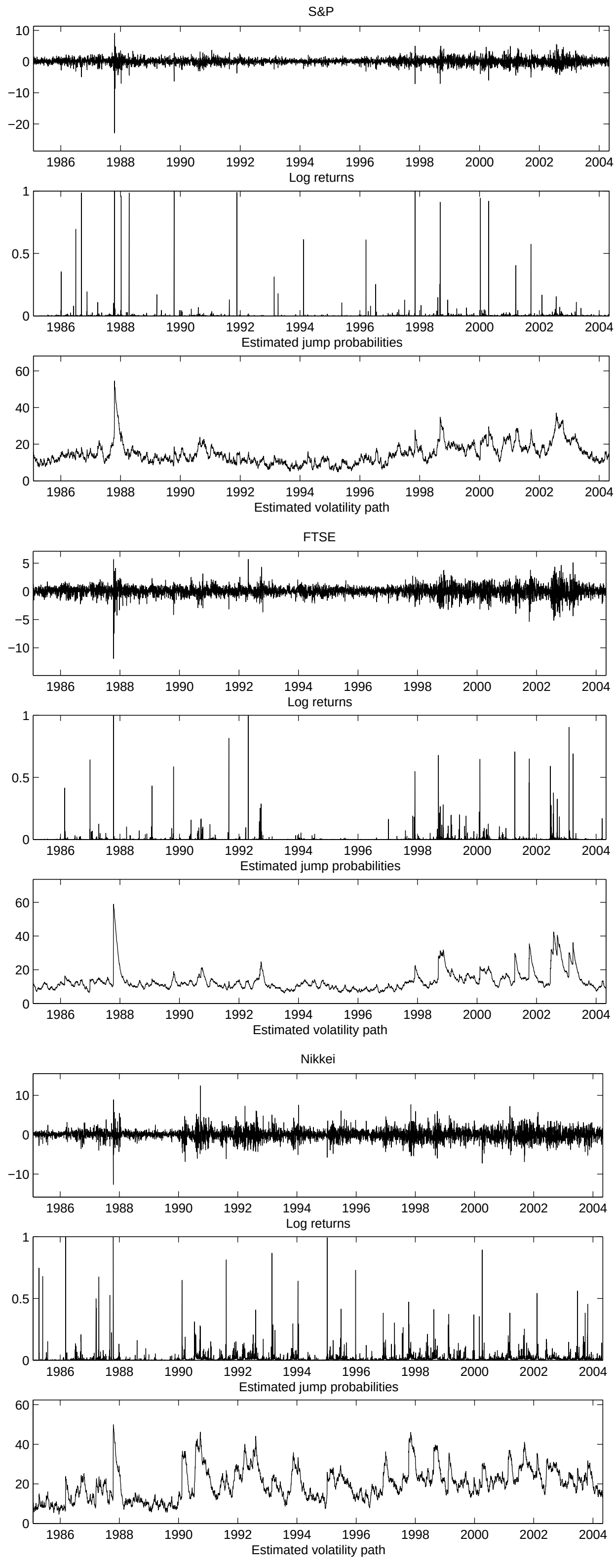

Figure 2: Historical percentage log returns together with estimated historical jump probabilities and estimated annualized historical percentage spot volatilities for the S&P, the UK, and Japan.