

Accepted Manuscript

The Reality of Stock Market Jumps Diversification

Ke Chen, Luiz Vitiello, Stuart Hyde, Ser-Huang Poon

PII: S0261-5606(18)30239-0

DOI: <https://doi.org/10.1016/j.jimonfin.2018.04.008>

Reference: JIMF 1908

To appear in: *Journal of International Money and Finance*

Please cite this article as: K. Chen, L. Vitiello, S. Hyde, S-H. Poon, The Reality of Stock Market Jumps Diversification, *Journal of International Money and Finance* (2018), doi: <https://doi.org/10.1016/j.jimonfin.2018.04.008>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

The Reality of Stock Market Jumps Diversification

Ke Chen,^a Luiz Vitiello^b, Stuart Hyde^a and Ser-Huang Poon^{a,*}

April 24, 2018

a. Alliance Manchester Business School, Crawford House, University of Manchester, Oxford Road, Manchester M13 9PL, UK.

b. Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, UK

* Corresponding author: Tel: +44 161 275 0431, Fax: +44 161 275 4023.

E-mail addresses: Ke Chen (ke.chen@postgrad.mbs.ac.uk), Luiz Vitiello (lrviti@essex.ac.uk), Stuart Hyde (stuart.hyde@manchester.ac.uk), Ser-Huang Poon (ser-huang.poon@manchester.ac.uk).

The Reality of Stock Market Jumps Diversification

Abstract

We propose a non-parametric procedure for estimating systemic co-jumps and independent idiosyncratic jumps for 35 stock markets, and study news associated with these jumps as reported in Factiva and Bloomberg from 1988 to 2014. Our results suggest that it is important to distinguish between systemic co-jumps and idiosyncratic jumps. We find both types of jumps have important implications for home-bias investors, while idiosyncratic jumps have economically significant impact on portfolios weights for emerging markets. Our news analysis suggests systemic jumps are typically caused by currency crises, sectoral failure, liquidity issues, and deteriorating economic climate, while idiosyncratic jumps are usually caused by political unrest, currency instability, and large firm effects on small economies. In fact, many of the idiosyncratic jumps share the same origin although different stock markets experienced the impact differently at different times.

Keywords: Asset allocation, international portfolio diversification, home bias, systemic and idiosyncratic jumps, jump news.

JEL Classification: G11, G15.

The Reality of Stock Market Jumps Diversification

1 Introduction

In addition to comovement, spillover and occasional periods characterised by crisis and contagion, many stock markets witness large shocks that are local and contained within national boundaries. Mathematically, a jump-diffusion process provides a natural mechanism whereby such large movements can be modelled. However, identifying how jumps propagate across markets and separating single market events from regional or world-wide jumps is non trivial. Jumps, by definition, are rare events and difficult to forecast over short horizons, while long horizon jump estimates may not be efficient for use in short horizon portfolio rebalancing decisions. As the barrier to cross-boarder investment diminishes and the correlation between stock markets increases (Baele et al., 2007; Goetzmann et al., 2005; Longin and Solnik, 1995) the benefit of international diversification reduces and the impact of jumps can be more severe. Nevertheless, the recognition that stock market returns can jump together as well as separately plays an important role in cross-market asset allocation in the context of international investment. This is due to the inherent difficulty in hedging jump risk, and also to the well documented home bias effect i.e. the tendency of investors to invest in markets and companies close to where they live.¹

In this paper we examine the impact of jumps on international stock portfolios, extending the analysis of jumps in international markets by Asgharian and Nossman (2011) and Das and Uppal (2004) among others.² In particular, we make a distinction between systemic co-jumps and independent idiosyncratic jumps, and examine the impact of their

¹The home bias effect has been widely documented in regions in the US as well as stock markets in different countries (Bodnaruk, 2009; Cooper and Kaplanis, 1994; Coval and Moskowitz, 1999; Li, 2004; Tesar and Werner, 1995; Thapa and Poshawkale, 2012).

²Asgharian and Nossman (2011) study the risk spillover relationship using a stochastic volatility model with jumps in returns and volatility, i.e. a model that is heavily parameterised. Das and Uppal (2004), like our paper, use a jump diffusion model but with the assumption that all jumps are systematic co-jumps sharing the same jump intensity.

mis-specification on asset allocation decisions. To achieve this goal, we adopt a non-parametric approach to estimate the multivariate jump dependency and use the Markov Chain Monte Carlo (MCMC) procedure to estimate stock market return jumps.³

We successfully implemented our method using weekly returns on 35 MSCI stock indices over a 26-year period, which includes several important stock market events that have been widely covered by the media. Our findings suggest, congruous with the existent literature, that ignoring systemic and country specific idiosyncratic jumps has a negative impact on portfolio performance, and that the impact is most severe for emerging markets. We provide convincing evidence to show that the impact of idiosyncratic jumps is economically significant for a home biased portfolio for *both* developed and emerging markets investors.⁴

To better understand the causes of systemic and idiosyncratic jumps, we analyse the news archives in Factiva and Bloomberg over the period from 13 January 1988 to 9 July 2014. Our news analysis suggests systemic jumps are typically caused by currency crises, sectoral failure (e.g. dot-com), liquidity issues, sub-prime crisis and more generally a worsening inflationary economy. On the other hand, idiosyncratic jumps are often characterised by local political unrest, localised currency instability, and large firm effects on small economies. We also find that many supposedly idiosyncratic jumps actually originated from the same source and should really be classified as systemic risk in essence. This highlights the weakness of all mechanical quantitative analyses and the grossly underestimated impact of systemic jumps.

The remainder of this paper is organised as follows: Section 2 introduces the MCMC methodology used to estimate the univariate double exponential jump-diffusion model for each market, explains how the simulated jump distributions are used to estimate cross market jump dependency, and derive the optimal portfolio weights without imposing

³Kim et al. (1994) propose a similar (but different) framework to conduct a multivariate analysis to determine whether jumps in stock prices are the result of firm specific or systematic market factors and to examine the potential impact of jumps on diversification for 20 US stocks.

⁴We define a home biased portfolio as one with a zero weight on foreign markets.

any parametric restrictions. Section 3 presents the data and estimation results. Section 4 presents the optimal portfolio weights and the loss due to restrictive dependency assumptions and the resulting suboptimal portfolios. Section 5 studies the news associated with the systemic and idiosyncratic jumps and summarises the sources of both types of jumps. Finally, Section 6 discusses the results and concludes.

2 Jump Estimation and Portfolio Optimisation

This section presents an overview of portfolio optimisation in the presence of correlated systemic co-jumps and independent idiosyncratic jumps, and of the MCMC methodology used in the estimation.⁵

2.1 Utility Maximisation and Optimum Portfolio Weights

Many previous studies concern portfolio choice with jumps and high moments.⁶ Here, we adopt a very simple static approach. Assume that the stock price process $S_n(t)$, for $n = 1, \dots, N$, has three parts: a standard Brownian motion, $B_n(t)$, a systemic jump component governed by a compound Poisson process with constant intensity λ and jump size distribution J_n , and an idiosyncratic jump component governed by a compound Poisson process with individual intensity δ_n and independent jump size distribution I_n . If investors have a power utility function (Constant Relative Risk Aversion - CRRA) with risk aversion parameter γ , then the optimum portfolio weights for the N risky assets, $\boldsymbol{\omega} = [\omega_1, \dots, \omega_N]$, are determined by solving the following equation

$$(\boldsymbol{\alpha} - r_f) - \gamma \boldsymbol{\Omega} \boldsymbol{\omega} + \lambda E \left(\mathbf{J} (1 + \boldsymbol{\omega}' \mathbf{J})^{-\gamma} \right) + \Lambda = 0, \quad (1)$$

⁵Full details of the derivation of the model and of the estimation procedure are presented in the internet appendix.

⁶See e.g. Ait-Sahalia et al. (2009), Guidolin and Timmermann (2008), Jondeau and Rockinger (2006), Liu et al. (2003), Martellini and Ziemann (2010), and Wu (2003).

where r_f is the risk free rate, $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_N]$ is the drift of the risky assets, $\boldsymbol{\Omega}$ is the variance-covariance matrix of the diffusion part, $\mathbf{J} = (J_1, \dots, J_N)$ are the systematic jumps, and $\Lambda = [\delta_1 E [I_1 (1 + \omega_1 I_1)^{-\gamma}], \dots, \delta_N E [I_N (1 + \omega_N I_N)^{-\gamma}]]$ are the idiosyncratic jumps. If there are no systemic and idiosyncratic jumps i.e. $\mathbf{J} = 0$ and $\mathbf{I} = 0$, then the optimal weights in the above equation are the same as those in the traditional mean-variance model. We use the double exponential distribution to model the systemic and idiosyncratic jump sizes J_n and I_n .⁷ For a particular stock, n , let J_n and I_n have positive and negative jump sizes η_1 and η_2 , and probability of a positive jump p , then omitting the subscript n , $J \sim DE(\eta_{1,J}, \eta_{2,J}, p_J)$ and $I \sim DE(\eta_{1,I}, \eta_{2,I}, p_I)$. The double exponential density of a random variable $x \sim DE(\eta_1, \eta_2, p)$ is given by

$$f_{DE}(x; \eta_1, \eta_2, p) = \frac{p}{\eta_1} e^{-x/\eta_1} I_A(x \geq 0) + \frac{1-p}{\eta_2} e^{-x/\eta_2} I_A(x \leq 0), \quad (2)$$

where I_A is an indicator function equal to 1 if the event in $()$ is true.

2.2 Jump Estimation through MCMC

We assume that the information of stock n 's jumps contained in the time series of stock n 's returns is the same as that given by the N stock returns jointly, i.e. $f(J_n|r_n) = f(J_n|r_1, r_2, \dots, r_n, \dots, r_N)$. Based on this assumption, we perform the jump estimation in two steps. The first step is to estimate the double exponential jumps for each univariate stock return series using the Markov Chain Monte Carlo (MCMC) procedures.⁸ The jump estimate produced from the first step encompasses both the systemic and the idiosyncratic jumps since it is not possible to distinguish the two in the univariate setting. Hence, the

⁷In contrast to the Gaussian jump distribution, the exponential jump distribution accommodates longer tails and asymmetry between positive and negative jump distributions (see Kou, 2002).

⁸Most of the parameters in the jump models here have conjugate priors where the posterior and prior distributions belong to the same family of conjugate distributions. For a normal distribution, the conjugate prior and posterior distributions for the mean and variance are Normal-inverse-gamma distributions. For a Bernoulli distribution, the conjugate prior and posterior distributions for the probability are beta distributions. The prior distributions used in our estimation are $N - \Gamma^{-1}\{0, 10, 10, 20\}$ for $\{\alpha, \sigma^2\}$, $N - \Gamma^{-1}\{0, 10, 10, 30\}$ for $\{\theta, \delta^2\}$, and $Beta\{2, 20\}$ for $\{\lambda\}$. For the jump number and jump size, we use numerical integration based on the Griddy Gibbs method with 200 grid points.

jump intensity of the univariate estimation, λ_U , is the sum of the systemic and the idiosyncratic jump intensities. The advantage of the MCMC method is that apart from the jump parameters estimates, it produces a jump distribution, which can be used to estimate the cross sectional jump dependency between stocks in the second step via a bootstrap method.⁹ Hence, the second step is to estimate, non-parametrically, the cross sectional dependence of the jump processes given the exact timing and size of the jumps sampled from the jump distributions produced by the univariate MCMC procedures in the first step.

The MCMC method applied here is proposed by Carlin et al. (1992), and subsequently extended to include stochastic volatility with jumps by Eraker et al. (2003) and Eraker (2004). In the literature, one typical way of estimating a multivariate jump diffusion model is to specify the dependency of the co-jumps, e.g. as a multivariate normal distribution or some copula functions, and then estimate the parameters for the assumed dependence structure. Such a parametric multivariate approach, however, (i) imposes a strong prior in the estimation, which may bias the estimation results,¹⁰ and (ii) places a huge computational burden on the estimation. Even for the simplest multinormal distribution, the number of correlation parameters to be estimated is $\frac{1}{2}(N^2 - N)$ for N markets. To apply an approach such as moment matching, one would require many high moment conditions. Unless one imposes strong assumptions on the dependence structure, e.g. constant and same jump intensity across all stocks, the estimation is likely to be highly unstable.

⁹From the sample of jump distributions produced from the MCMC, the bootstrap process involves randomly picking the jump sample paths of any two return series, and checking for co-jumps. Repeating this sampling process enough times (5,000 in our case) and taking the average, one can obtain the estimates of co-jump statistics between any two stock return series.

¹⁰For example, Das and Uppal (2004) assume all jumps are co-jumps. As a result, the jump estimation for the US stock index changes depending on which group is used in the joint estimation. For instance, the jump intensity of the US stock market returns is 0.0501 per month when estimated together with the group of developed stock markets. However, when it is estimated together with the group of emerging markets, the jump intensity is just 0.0138, but the mean of the jump size doubles.

2.3 Portfolio Optimisation with Jumps

In order to calculate the last two jump terms in equation (1), a nonparametric approach using the jump samples drawn from the MCMC is applied as follows:

$$\begin{aligned} \lambda E \left[\mathbf{J} (1 + \boldsymbol{\omega}' \mathbf{J})^{-\gamma} \right] + \Lambda &= E \int \bar{\mathbf{J}} (1 + \boldsymbol{\omega}' \bar{\mathbf{J}})^{-\gamma} \mu(\bar{\mathbf{J}}) \\ &\approx \frac{1}{TM} \sum_{t=1}^T \sum_{i=1}^M \bar{\mathbf{J}}_i (1 + \boldsymbol{\omega}' \bar{\mathbf{J}}_i)^{-\gamma}, \end{aligned} \quad (3)$$

where the first equality is due to the fact that $\bar{\mathbf{J}} = (\bar{J}_1, \dots, \bar{J}_T)$, with jump measure $\mu(\bar{\mathbf{J}})$, encompasses both systemic co-jumps and independent idiosyncratic jumps. In other words, for the portfolio, it does not matter if jumps are aggregated separately as systematic and idiosyncratic jumps, or by univariate jumps without the systematic-idiosyncratic distinction so long as the portfolio weights are the same for both approaches. The second approximation is due to the discrete aggregation of each $\bar{\mathbf{J}}_i$ drawn from the MCMC sample. Equation (3) shows that for portfolio optimisation, there is no need to explicitly specify the jump dependence; it is implicit in the univariate jumps for the individual stock returns.

In order to report the jump dependence, we sample from the MCMC jump distributions to capture the joint dependence instead of assuming a specific form of cross sectional jumps dependence. Compared with the parametric multivariate approach, this nonparametric approach is much more stable as “it lets the data speak for itself”. Another advantage of our approach is that it can be easily extended to higher dimensions and accommodate more complex dependence structures. For example, it can still be applied when different subsets of stock markets experience co-jumps at different times, which is very difficult to model and estimate using the parametric approach.¹¹

¹¹One could also specify and estimate some copula function based on the sample of the jump process drawn from the MCMC procedures. However, since co-jumps are typically rare, any such estimation will be very unstable and different copula functions will produce very different results.

3 Data and Summary Statistics

Our data set consists of the Wednesday to Wednesday weekly continuously compounded returns of 35 MSCI stock market indices that are available in Datastream.¹² Working with weekly instead of daily prices helps to reduce the potential problem of non-synchronous timing of jumps that is due entirely to geographical time differences. Our sample period has 1,383 weeks from 13 January 1988 to 9 July 2014, which includes a number of well known events, such as the Iraqi invasion of Kuwait in 1990, the 9/11 terrorist attack in 2001, and the bankruptcy of Lehman Brothers in September 2008.¹³

Table 1 presents the summary statistics for the weekly returns on 35 MSCI stock market indices. The Latin American group has the highest average weekly return and standard deviation (averaging 0.245% and 5.219% respectively). Europe has an average return similar to that for the Far East, but with a smaller standard deviation. Similarly, Oceania has an average return closed to that for Asia, but with a smaller standard deviation. With respect to the individual markets, Portugal and Japan are the only countries with negative average returns, and only Argentina, Indonesia and Japan present positive skewness. Very high values of kurtosis are observed for Argentina, Indonesia, Malaysia and Jordan.¹⁴

¹²These weekly returns are measured in US\$ for the convenience of the asset allocation exercise later. We have reproduced the results using local currency returns. The conclusion is qualitatively similar.

¹³We have chosen to study MSCI indices since they represent the unconstrained investable equity asset class, and are based solely on tradable shares. Hence, our results more closely reflect practice and are less prone to thin trading problems.

¹⁴Our analysis is conducted on the sample from 13 January 1988 to 9 July 2014. Extending the sample to include the period up to 7 November 2017 yields qualitatively similar summary statistics. The mean return performance has worsened slightly for many markets but only noticeably for Greece. Throughout 2015, Greece defaulted on debt with the IMF and received bailout packages from the ECB. Between the end of our sample and February 2016, the stock market had fallen over 58%. The skewness statistics are largely unchanged for all countries with the exception of Hungary which became more negative despite a slightly improved average return performance. All the standard deviations and kurtosis remain of similar magnitude when the last three years of data is included. Importantly, therefore, the overall pattern between international stock markets return distributions, as summarised by these statistics, is stable. Further, an analysis of the pairwise correlations between stock returns is practically unchanged between the estimation sample and the extended sample. On this basis, given the stability of the out-of-sample period, we suggest that the general findings of our analysis continue to hold. However, it is clear that Greece, due to the large negative mean return after the sovereign default in 2015, would most likely drop out of all optimal portfolios and consequently Greeks will have an even greater incentive to “go abroad”.

[Table 1 about here]

The mean and standard error for all parameters estimated are presented in Table 2. The mean returns of the diffusion part, α , are significantly positive and the associated variance rate of the diffusion part, σ , is significantly higher for emerging markets. For all markets $p < 0.5$ which means that negative jumps are more likely than positive jumps. The jump sizes, η_1 and η_2 , respectively for positive and negative jumps are similar for all markets, but tend to be higher for emerging markets.

[Table 2 about here]

In Table 3 the cross correlations for the diffusion components are presented for eight markets, viz. Canada, Germany, Hong Kong, Japan, UK, USA, Brazil and Greece.¹⁵ The highest correlation coefficients are observed between the US and Canada and among the European markets, in particular between Germany and France, and between the UK and France. The lowest correlation is that between the US and Jordan, noting that all selected markets have a low correlation with Jordan. The pairwise correlation is much lower among emerging markets.

[Table 3 about here]

Given the sample of jump distributions produced from the MCMC and the bootstrap procedures, the jump and co-jump statistics are calculated. Table 4 reports the jump and co-jump intensities for selected markets. For instance, the jump intensity for the USA and Canada are 0.0812 and 0.0831 respectively, and the co-jump intensity between these two markets is 0.0188.¹⁶ In general, the developed and open markets such as Canada, Germany, Hong Kong, UK, and USA have higher jump and co-jump intensities. Greece

¹⁵From here on, we show the results for eight markets only to conserve space. Results for all markets are available on request.

¹⁶The co-jump between a country and itself is equivalent to its univariate jump intensity. Note that the univariate jump intensities reported in Table 4 is calculated by a bootstrap method using the jump distribution drawn from the MCMC procedure. Hence, they are slightly different from those reported in Table 2.

and, especially, Japan have fewer jumps and co-jumps. Brazil has a lot of jumps but fewer co-jumps.

[Table 4 about here]

Table 5 presents the conditional co-jump probability,

$$Co - Jump(i, j) = \frac{\lambda_U(i, j)}{\lambda_U(i)}, \quad (4)$$

where $\lambda_U(i, j)$ is the co-jump intensity between markets i and j and $\lambda_U(i)$ is the jump intensity of market i . The conditional jump probability in (4) and reported in Table 5 are not symmetrical, since the conditioning variable is different. For instance, 14% of the jumps in Hong Kong are co-jumps with Japan, but only 8% of jumps in Japan are co-jumps with Hong Kong.¹⁷ This table shows that the stock market jumps in Japan are largely idiosyncratic jumps.

[Table 5 about here]

4 The Impact of Jumps on Asset Allocation

In this section, we report the portfolio weights when equation (1) is optimised using a constant risk free interest rate of 3% per annum, an investment horizon of one year, and a risk aversion parameter of 3. Three distributional assumptions are tested viz. a mean variance (MV) model, a systemic co-jump model (SJ), and a double exponential model (SJII-DE) that makes no assumptions about jump dependency. Table 6 reports results for selected markets. Each cell in Table 6 contains the optimal weight for the risky portfolio of two assets, vis-à-vis the risk free rate, for investor in country i with foreign asset j from the three models. For instance, consider the first row. Here, a

¹⁷Our full set of results (not presented here) show that, in general, the co-jump probability tends to be higher between developed markets than that between emerging markets, which is probably due to the fact that developed stock markets are more homogeneous and integrated, while emerging stock markets tend to be driven by idiosyncratic events.

Canadian investor is mixing Canadian stocks with those in a foreign market.¹⁸ When she combines Canadian stocks with Argentinian stocks, the optimal weight for the risky portfolio comprising those two assets is 57% according to the MV model, 52% according to the SJ model, and 48% according to the SJJJ-DE model. In general, the investment in risky assets decreases when jump is considered, consistent with the results obtained by Das and Uppal (2004). When the co-jump assumption is relaxed, the jump estimation is more accurate and the investment weight in risky assets is further reduced. To gauge the economic significance of the investment choices, we calculate the CEQ (Certainty Equivalent) for the optimal weights in Table 6 using the mean variance portfolio as the base case. The CEQ is the additional dollar amount of initial investment needed for the mean variance portfolio in order to produce the same amount of utility as compared with the portfolio that contains jumps. The results, presented in Table 7, show that all the CEQs are positive meaning that both jump models dominate the MV model. Moreover, the CEQ of our SJJJ-DE model strongly dominates the SJ model highlighting the problem introduced by the co-jump restriction.

[Table 6, Table 7 and Figure 1 about here]

To facilitate visual comparison, Figure 1 presents, from a US investor's perspective only (a) the results from Table 6, and (b) the results from Table 7. As before Figure 1(a) shows jump estimation brings down investment weight on risk assets portfolio. Figure 1(b) shows jump models dominate MV base case, and the double exponential jump specification with non-parametric dependence measure dominates the systematic co-jump model.

Next we examine the CEQ of the portfolio of two risky assets, viz. domestic and foreign stocks against the home biased portfolio with zero weight on the foreign stock

¹⁸The "foreign markets" in the top row are arranged in the order of their respective time zones.

as the base case.¹⁹ The results in Table 8 show that from the US investor's perspective, removing the home bias can produce up to 276 basis point (bps) in CEQ when Danish (225 bps), Swiss (132 bps), Chilean (148 bps) or Mexican (276 bps) stocks are included as the foreign component of the two-asset portfolio. The recognition of jumps increase investment weights of the foreign stock and generate CEQ by as much as 39 basis point in the case of Indonesia (39 bps), Argentina (28 bps), Brazil (23 bps), Malaysia (11 bps) and Mexico (14 bps). The greater impact is observed among countries that have many idiosyncratic jumps such as Argentina (32 bps), Brazil (21 bps), and producing a CEQ in the magnitude of between 21 to 39 basis points.

[Table 8 about here]

We deduce from Table 8 that the home bias problem is most acute when the home stock market performs poorly, while a good jump model is particularly important when the home market is characterised by many idiosyncratic jumps. Indeed, in the case of Greece, the loss in CEQ due to home bias is between 17.5% to 23% (or 1741 to 2317 basis points), while CEQ loss due to jump omission is between 14 to 42 basis points. In the case of Brazil with low correlation and low co-jump intensity, the loss in CEQ due to home bias is between 29% to 33% (or 2864 to 3269 basis points), while CEQ loss due to jump omission is between 25 to 65 basis points.

5 News Items Associated with Stock Markets Jumps

From the jump distributions and jump estimates produced in the previous section, for each of the 1383 weeks in our sample period, we count the number of stock markets that have experienced a jump. Then, for weeks where at least one stock market jump is observed, we search news archives for local and global news that might be associated

¹⁹We also calculate the optimal weights for the domestic and the foreign markets (results not presented here due to space restrictions). Although the figures are slightly different from those in Table 6, the pattern is similar. It is important to highlight that the optimal weight of the foreign stock is never zero and is in fact nowhere close to zero.

with the jumps.²⁰ It is important to note that news survey is a qualitative and subjective study of historical events. There are two types of potential biases. First, there are many news items each day, some of which are potentially very important, but we only select the news that appears to match the dates and stock markets concerned. Second, when we cannot find any news that matches the jump event (e.g. in the case of Jordan), it may be due to the lack of reporting or bias in the news coverage rather than the absence of news itself. With this caveat in mind, we proceed to analyse the jumps related news below.

5.1 Systemic Jumps

A summary of the jump count exercise is presented in Table 9. The most striking, but perhaps not surprising, finding from the news search exercise is that all European stock markets should really be treated as one single market and it is best to reclassify European systemic jumps as idiosyncratic to Europe. The reason being there are many weeks when a jump is estimated in five or more European stock markets, yet no relevant news can be traced, suggesting that these weeks are not likely to be systematically important. This is the case especially from 2009 onwards, suggesting that the European markets are more fully integrated after the subprime crisis. The group of Asian stock markets, to a lesser extent, exhibit a similar trend of integration over the same period.

[Table 9 about here]

From the weekly aggregate jump size, we select the ten weeks with the most negative total jump size (%), and the ten weeks with the most positive total jump size (%). Table 10, Panel A reports the news associated with the top ten worst weeks and Panel B reports the news associated with the top ten best weeks. It is clear from Panel A that the worst weeks are concentrated in the subprime financial crisis. Five of the ten worst weeks,

²⁰The primary source for news items include Factiva and Bloomberg with some additional items sourced from Cam Harvey's web site, Google and wiki searches. Interestingly, a number of our key dates also match those in Aggarwal et al. (1999).

including the worst week, over the 26-year sample period are all clustered in October and November 2008. The repercussion of the subprime crisis lingered on producing two further systemic negative jumps in 2009 and in 2011. The European solvency crisis triggered by the insurance sector ranked 5th, and the Iraqi's invasion of Kuwait ranked 7th. The news leading to the top ten weeks of systemic up-jumps reported in Panel B is, on the other hand, more diverse, and the positive jump sizes and jump count are much smaller than those for the top ten worst weeks. While Obama's election in November 2008 brought on the greatest global market rallies, even a liquidity upsurge during the Chinese New Year in 1998 managed to trigger the third largest positive systematic up-jump.

[Table 10 about here]

We identify, over the 26-year sample period, six main causes of international stock market systemic jumps. The first and most important cause of systemic jump is *bank and financial system failure*. During the subprime crisis, stock markets around the world remained in an agitated state in just about every week from 16 July 2008 to 28 January 2009. For example, in the week ending 8 October 2008, stock return jumps are detected for 34 out of 35 stock markets. In the weeks following, 11 and up to 28 stock markets experience co-jumps every week. Of the 35 stock markets in our sample, none escapes the impact of the crisis. The subprime crisis is unique in terms of both the scale and the prolonged nature of its impact. In one sense, it is all the possible crises rolled into one; stocks, bonds, credit and money markets failed simultaneously in the US and Europe led to severe liquidity shortages and worsening of the global economies. In contrast, the Asian flu characterised by the Thai baht devaluation in July 1997 and the Hong Kong dollar devaluation in October 1997 was confined mostly to Asia.

The other five causes for the other shorter, but not necessarily less grave, stock market crises are *international political conflicts*, *worsening economic conditions*, *liquidity drain out*, *currency collapse* and *sector failures*. While there have been numerous wars and political conflicts in our sample period, none causes international stock markets to respond

in the same manner as the Iraqi's invasion of Kuwait in 1990 and the 9/11 terrorist attacks in 2001, these two events have the potential of destabilising international politics and global economies. In the last two decades, with the greater uniformity in macroeconomic policy, news about global inflation, unemployment and GDP is the root cause of 14 international stock market co-jumps.²¹ Although liquidity is never the source of the crisis, it increasingly becomes the immediate cause of or contributor to sudden market collapse. Liquidity crisis may be localised, e.g. a failed takeover, or of a broader nature, e.g. the stock markets collapse in October 1989. The most notable global currency events associated with systemic jumps include the Exchange Rate Mechanism crisis in 1992, the devaluation of Hong Kong dollar in 1997, and the devaluation of the Brazilian Real in 1999 (that severely affected its trading partners e.g., Netherlands, US and Italy). Sector failures include the dot-com bubble burst in 2001, the European insurers insolvency in 2002, and the Japanese banking sector failure in 2007.

Many studies have examined how jumps might spill over causing contagion in international stock markets.²² Our news analysis revealed that stock market turbulence travels by three usual routes: *trade links*, *cross-border or cross-markets risk-return relationships*, and *liquidity spiral*.²³ Being one of the largest global economies, US macro news releases are linked to 8 systemic events.²⁴ When the Fed raises the base rate, it triggers funds flow from equity into bonds and from low yield countries into US. Similarly, when crisis erupts, uncertainty and “flight to quality” drives funds from equity to bonds and gold, and from higher risk emerging markets to lower risk developed markets. Finally, liquidity

²¹For the remainder of this section, we classify the 80 weeks where five or more stock markets simultaneously record a jump as systemic jump weeks in order to focus on the more important international events. Indeed, we find such a classification is reliable, especially when the stock markets concerned spread across different continents.

²²See e.g. Asgharian, 2006; Asgharian and Nossman, 2011; Bae et al., 2003; Karolyi, 2003.

²³Similarly, Lahaye et al. (2011) argue trade links are important drivers of co-jumps in exchange rates while Caporin et al. (2017) demonstrate systemic co-jumps in US equity markets are linked to financial news, specifically liquidity and changes in the variance risk premium.

²⁴This is consistent with Lahaye et al. (2011) who provide initial evidence for the links between US macro news and both jumps and co-jumps in US stock returns and exchange rates and Chatrath et al. (2014) who document the importance of both US and non-US news for jumps in exchange rates.

drainage is triggered in the most unprescribed manner. In 1989, the failure of a large takeover bid caused the junk bond market and all stocks with a high takeover premium to collapse causing an illiquidity spiral which, in turn, affected unrelated, more liquid, better performing securities. Fund redemption and fire sales mean developed stock markets and markets that are not involved in the first round of financial crisis, may fall victims of the second round contagion.

5.2 Idiosyncratic Jumps

For simplicity, we focus our analysis of idiosyncratic jumps on the 272 weeks where a jump is recorded for only one stock market. Of the 35 stock markets, Jordan has the largest number of idiosyncratic jumps (41), followed by Indonesia (29) and Argentina (27). The news associated with idiosyncratic jumps are more diverse and colourful; one may conclude that “no two countries are the same”. First of all, we are not able to trace any news related to Jordan. In Argentina, the presidency of Carlos Saul Menem from 1989 to 1999 accounts for 16 of the 27 Argentinian idiosyncratic jumps with issues ranging from the government running out of money, on-going dispute over the Falkland Islands, a drug scandal and even the saga about his marriage and politically active wife. Under President Cristina Fernandez de Kirchner, the devaluation of peso and the nationalisation of Argentina’s largest energy company account for two further idiosyncratic jumps.

Brazil and Mexico have 12 and 14 idiosyncratic jumps respectively, and both countries are plagued by weak and unstable currencies during our sample period. During the period 1986 to 1993 Brazil had problems containing inflation, while Mexico had the additional problem of a strong dependence on the US economy and record unemployment. Among this Latin America group, Chile has the fewest number of jumps (3), one of which is driven by local political events, coinciding with the assassination of the political advisor of General Augusto Pinochet.

In contrast, idiosyncratic jumps in the US (6) and Canada (4) are non-political. In the

US, they are caused by unexpected rate moves, whereas in Canada, they are due to tech firm profit warnings, and commodity news – oil price increases and metal price drops. No news items are identified for the sole New Zealand stock market jump, while one of the two Australian stock market jumps coincides with an earthquake and the subsequent power blackout.

With respect to the Asian markets, all three idiosyncratic jumps in Japan are positive jumps associated with the government stimulus package, bridge bank reform and a strengthening yen while Korea has eight stock market jumps, all associated with news about its economy, currency, debt and the fortune of its flagship companies. Taiwan and Hong Kong have 17 and 6 idiosyncratic jumps respectively. Both share a common tie with China. Consequently, any political dispute with China has a substantial impact on their stock markets. Aside from that, like the other stock markets, they are affected by rate cuts, the general economic outlook and US economic developments. Singapore has four stock market jumps but no associated stock market news.

The remaining Asian markets are similarly impacted by political events. The Philippines, Malaysia, Indonesia and Thailand, have 10, 14, 29 and 8 stock market idiosyncratic jumps respectively with half of the Philippines' stock market jumps being associated with political events (withdrawal of a US army base, the end of Aquino's term, the impeachment of Estrada and the appointment of Airroya). The Kuala Lumpur stock market rallied when the Prime Minister Mahathir Mohamad returned to work after an illness, whereas Indonesia stock market's rises and falls following Timor violence, the Jakarta exchange bombing and Bali terrorist attack. Apart from these political events they are all plagued by troubled credit ratings, government overspending, weak currencies and their sensitive relationship with the IMF.

Three of the 11 Turkish stock market jumps are associated with political news (Greek Cypriot accord, formation of coalition cabinet and the Kurdish-Iraq conflict). After politics, the stock market's fortune is tied to the strength of Lira, the Turkish vulnerable

credit rating, and the government inflation and economic policy.

Similar causes are behind many of the stock market jumps in Europe. While most of the 12 idiosyncratic stock market jumps in Finland cannot be traced to news items, EU membership was associated with the positive jump in November 1992 with a rate cut and a rise in unemployment are most probably the cause of two other jumps. In some economies there is greater evidence of the influence of large firms or sectors. Ireland has 10 stock market idiosyncratic jumps, four of which are tied to profit warnings of its largest drug company, Elan Corp. The impact of the subprime crisis and the European sovereign debt crisis on the Irish banking sector may explain the negative jump in April 2009, while a short selling ban coincides with the negative jump in January 2009. One of the 5 jumps in Austria seems to be associated with the controversial costly expansion of Erste bank, one of the largest financial services based in Austria. While Belgium has four jumps, three of which are associated with corporate news. The Netherlands also has five idiosyncratic jumps but only one appears to be directly related to corporations, with those firms doing business with US facing weaker prospects due to a weaker dollar.

Both Greece and the UK markets exhibit three idiosyncratic jumps; the Greek events seem to be related to election and foreign inflow after measures introduced to provide tax break and safe haven. One of the three UK stock market jumps coincides with a weakened pound. Italy, Norway, and Portugal each have two idiosyncratic jumps. The Italian stock market jumps are associated with rate rise and US inflation, the Norwegian jumps are connected to crude oil prices, and no news item can be traced to the two Portuguese idiosyncratic jumps. France, Germany, Spain, and Switzerland, all have only one idiosyncratic stock market jump. The French's idiosyncratic jump appears to be triggered by a surprise left wing victory in the parliamentary election in May 1997. No news can be traced to the German jump while the Spanish positive jump coincides with a successful sovereign bond sale, whereas the Swiss negative jump coincides with a lower than expected profits for one of its largest corporations, Swiss Re. We do not detect any

idiosyncratic stock market jumps for Denmark and Sweden.

The analysis above suggests that the common causes of stock market idiosyncratic jumps are *unstable non-primary currencies* (Argentina, Brazil, Mexico, Malaysia, Thailand and Turkey), *local political uncertainty* (Chile, the Philippines, Hong Kong), and *small economies' exposure to big local firms* (Finland, Sweden, and Ireland).

5.3 Time delays in the spread of systemic jumps

The impact of a systemic jump may take several weeks to reach different markets. For instance, the Russian default in 1998 appears as idiosyncratic jumps in Brazil and Mexico (12 August), Spain (26 August) and the US and Ireland (2 September). Similarly, the jump caused by the Asian crisis in 1997 originated in Thailand (2 July), traveled to Singapore (3 September) and Hong Kong (15 and 22 October) before reaching the Philippines (17 December). Qualitative analysis of news allows us to identify cases where two or more stock market jumps are triggered by or originate from the same source even though the jumps do not occur in the same week. All quantitative analyses, including our own in the previous sections, would classify such jump events as uncorrelated idiosyncratic jumps. To investigate further, we group the news items and stock market jumps together if they were related to the same source. Table 11 shows that the top ten systemic events are all negative events. The subprime crisis tops the list affecting all 35 stock markets and generates negative jumps over one year. The second worst event is the Asian flu affecting 16, mostly Asian, stock markets over a four year period.²⁵ The Kuwait invasion is third, producing an impact lasting over one month and affecting 22 out of 35 stock markets. The uncertainty surrounding various stimulus programmes during the global financial crisis lasted ten months, affecting 30 out of 35 stock markets. The insolvency

²⁵The duration of Asian flu is difficult to pin point as all the stock markets in that region were very volatility from 1994 to 1998. The first sign of troubles was noted on 12 July 1994 when there were massive withdrawals by foreign institutional investors triggered big falls in stock prices in Malaysia and Singapore. This is followed by a continuous period of sporadic co-jumps involving 5 to 12 Asian markets till the Thai baht devalued on 2 July 1997, and Hong Kong dollar devalued in October 1997. The last episode of substantial co-jumps involving Taiwan, Singapore, Philippines, Malaysia, Hong Kong, Indonesia and Thailand was observed on January 7, 1998.

triggered by European insurers affects 17 European stock markets for one week, while the Sovereign debt crisis affected 18 stock markets over four months. The Chinese recession coincided with the Russian crisis affected 15 stock markets for a two week period while the impact due to the Brazilian devaluation, the 911 terrorist attacks and the tech bubble are wide spread but short-lived; all dissipated within one week.

[Table 11 and Figure 2 about here]

In Figure 2, we present the impact of the top ten events by country. Most stock markets lost 10% to 20% in these top ten events with Europe bearing the brunt of the post subprime financial instability. The market that is least affected by the systemic events is Japan, followed by Chile and Greece. But, the key message in this figure is that none of the 35 stock markets is completely immune from the world's woe; systemic risk is more widespread than any quantitative methods can detect and will affect every stock market sooner or later.

6 Discussion and Conclusion

In this paper we estimate individual stock market jumps using a double exponential jump diffusion model and a Monte Carlo Markov Chain (MCMC) procedure. We estimate jump dependency in two steps. First, a MCMC is applied to weekly market returns of 35 MSCI stock indices from 13 January 1988 to 9 July 2014, categorized in two groups: developed and emerging markets. The sampled paths of the univariate jump components are then used to study jump dependence between markets. We justify and explain in detail the merit of such a non-parametric approach for handling jumps.

Consistent with Das and Uppal (2004), our results suggest that it is important to distinguish between systemic co-jumps and independent idiosyncratic jumps in stock market returns. However, when we restrict the modelling assumptions to systemic common jumps, we find no significant difference in portfolio choice and CEQ against the

mean-variance approach. By allowing idiosyncratic jumps, we find economically significant improvement in portfolios of emerging markets. For home biased portfolios, both systemic and idiosyncratic jumps are important, affecting portfolio choice in emerging and developed markets alike. However, it is important to recognise that jump models are prone to model mis-specification as time evolves. This is because, jumps, by definition, are rare events and their occurrence or absence in a particular sample period will greatly influence the estimation and parameter estimates. Moreover, as our news analysis shows, many so called idiosyncratic jumps in different markets are triggered by the same source. This makes the measure of jump dependency very unstable depending on the data frequency and sample period.

Our intuition is supported by a comprehensive and qualitative analysis of news associated with stock markets jumps archived in Factiva and Bloomberg with some additional items sourced from Cam Harvey's web site, Google and wiki searches. Our qualitative analysis of jump news suggests that bank and financial system failure, international political conflicts, worsening economic conditions, liquidity reduction, currency collapse and sector failures are the common causes of systemic stock market jumps, whereas unstable currencies, local political uncertainty and small economies' exposure to big local firms are the main causes of idiosyncratic jumps. Our research on actual events that triggered stock markets jumps has dispelled many myths and misconceptions about systemic and idiosyncratic jumps. Lee (2012) claims that US jumps are mostly attributed to events like Federal Reserve announcements or initial job claims which are mainly idiosyncratic from a global perspective or are due to clearly idiosyncratic firm-specific events, such as earnings reports. We find 86% of the jumps estimated in the US are systematic jumps. This provides further evidence beyond Lahaye et al. (2011) and Chatrath et al. (2014) that US macro news is connected with co-jumps in international stock markets. News and company earnings in the US carry information beyond the country with repercussions for the global economy. Bekaert et al. (1998) claim emerging markets returns have

significant skewness and kurtosis and these markets are more likely to experience shocks induced by regulatory changes, currency devaluation, and political crisis. Our results show developed markets e.g. Austria, Norway, and Belgium are among the markets that are most affected by (negative) jumps together with Turkey, Greece, and Ireland. On the other hand, emerging markets e.g. Thailand, Jordan, Chile, and Malaysia are among the markets that are least affected by (negative) jumps together with the US, Hong Kong, and Japan. We do find emerging markets to have lesser co-jumps than developed markets.

We also find that 860 weeks (62%) of our 26-year sample period have no jump estimated in any of the 35 markets. But when there is a jump, 15% (80) of these are likely to be systemic.²⁶ Jumps, systemic and idiosyncratic, are latent variables. Different data frequencies and sample periods will lead to very different conclusions. Moreover, if we use our qualitative analysis by grouping jumps triggered by the same source as co-jumps then systemic risk markedly increase. The facts that the subprime crisis lasted one year, the Asian flu lasted four years, and the long period of uncertainty due to the implementation of government stimulus programme that lasted ten months, serve to illustrate the point that robotic measurement of co-jump could be quite misleading. Many so-called idiosyncratic jumps in fact originate from the same source but impact on different stock markets at different times and levels. Given the prevalence of single-country equity funds (e.g. long/short US equity) and the huge amount of research effort devoted to stock market jumps, our finding is economically important.

²⁶Pukthuanthong and Roll (2015) posit that jumps rarely happen within the same calendar months in two countries. The authors argue that this implies that jumps also do not happen during shorter intervals within the month, such as during the same week, on the same day, or at the same time of day. Our conclusion here suggests otherwise.

References

- [1] Aggarwal R., Inclan, C., Leal, R., 1999. Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis* 34, 33-55.
- [2] Ait-Sahalia, Y., Cacho-Diaz, J., Hurd, T.R., 2009. Portfolio choice with jumps: A closed form solution. *Annals of Applied Probability* 9, 356-584.
- [3] Asgharian, H., 2006. Jump spillover in international equity markets. *Journal of Financial Econometrics* 4, 167-203.
- [4] Asgharian, H., Nossman, M., 2011. Risk contagion among international stock markets. *Journal of International Money and Finance* 30, 22-38.
- [5] Bae, K.-H., Karolyi, G.A., Stulz, R.M., 2003. A new approach to measuring financial contagion. *Review of Financial Studies* 16, 717-763.
- [6] Baele, L., Pungulescu, C., Ter Horst, J., 2007. Model uncertainty, financial market integration and the home bias puzzle. *Journal of International Money and Finance* 26, 606-630.
- [7] Bekaert, G., C. Erb, C. Harvey, Viskanta T., 1998. The distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management*, Winter, 102-16.
- [8] Bodnaruk, A., 2009. Proximity always matters: Local bias when the set of local companies changes. *Review of Finance* 13, 629-656.
- [9] Caporin, M., Kolokolov, A., Renò, R., 2017. Systemic co-jumps. *Journal of Financial Economics*, forthcoming.
- [10] Carlin, B., Polson, N., Stoffer, D., 1992. A monte carlo approach to nonnormal and nonlinear state-space modeling. *Journal of the American Statistical Association* 87, 493-500.
- [11] Chatrath, A., Miao, H., Ramchander, S., Villupuram, S., 2014. Currency jumps, cojumps and the role of macro news. *Journal of International Money and Finance* 40, 42-62.

- [12] Cooper, I., Kaplanis, E., 1994. Home bias in equity portfolios, inflation hedging, and international capital market equilibrium. *Review of Financial Studies* 7, 45-60.
- [13] Coval, J.D., Moskowitz, T.J., 1999. Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance* 54, 2045-2073.
- [14] Das, S. R., Uppal, R., 2004. Systemic risk and international portfolio choice. *Journal of Finance* 59, 2809-2834.
- [15] Eraker, B., Johannes, M., Polson, N., 2003. The impact of jumps in volatility and returns. *Journal of Finance* 58, 1269-1300.
- [16] Eraker, B., 2004. Do stock prices and volatility jumps? Reconciling evidence from spot and option prices. *Journal of Finance* 59, 1367-403.
- [17] Goetzmann, W., Li, L., Rouwenhorst, G., 2005. Long-term global market correlations. *Journal of Business* 78, 1-38.
- [18] Guidolin, M., Timmermann, A., 2008. International market allocation under regime switching, skew and kurtosis preferences. *Review of Financial Studies* 21, 889-935.
- [19] Jondeau, E., Rockinger, M., 2006. Optimal portfolio allocation under high moments. *European Financial Management* 12, 29-55.
- [20] Karolyi, G.A., 2003. Does international financial contagion really exist? *International Finance* 6, 179-199.
- [21] Kim, M.-J., Oh, Y.-H., Brooks, R., 1994. Are jumps in stock returns diversifiable? Evidence and implications for option pricing. *Journal of Financial and Quantitative Analysis* 29, 609-631.
- [22] Kou, S. G., 2002. A jump-diffusion model for option pricing. *Management Science* 48, 1086-1101.
- [23] Lahaye, J., Laurent, S., Neely, C.J., 2011. Jumps, cojumps and macro announcements. *Journal of Applied Econometrics* 26, 893-921.

- [24] Lee, S., 2012. Jumps and information flow in financial markets. *Review of Financial Studies* 25, 439-79.
- [25] Li, K. (2004) Confidence in the familiar: an international perspective. *Journal of Financial and Quantitative Analysis* 39, 47-68.
- [26] Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960-1990? *Journal of International Money and Finance* 14, 3-26.
- [27] Liu, J., Longstaff, F., Pan, J., 2003. Dynamic asset allocation with event risk. *Journal of Finance* 58, 231-259.
- [28] Martellini, L., Ziemann, V., 2010. Improved estimates of higher-order comoments and implications for portfolio selection. *Review of Financial Studies* 23, 1467-1502.
- [29] Pukthuanthong, K., Roll, R., 2015. Internationally correlated jumps. *Review of Asset Pricing Studies* 5, 92-111.
- [30] Tesar, L.L., Werner, I., 1995. Home bias and high turnover. *Journal of International Money and Finance* 14, 467-492.
- [31] Thapa, C., Poshakwale, S.S., 2012. Country-specific equity market characteristics and foreign equity portfolio allocation. *Journal of International Money and Finance* 31, 189-211.
- [32] Wu, L., 2003. Jumps and dynamic asset allocation. *Review of Quantitative Finance and Accounting* 20, 207-243.

Table 1: Summary statistics for weekly returns on MSCI stock indices over the period from 13 January 1988 to 9 July 2014

		Mean (%)	StDev (%)	Min (%)	Max (%)	Skew	Kurt
Latin America	Argentina	0.237	6.880	-36.267	80.522	0.904	16.787
	Brazil	0.223	6.321	-50.690	20.828	-1.251	7.985
	Chile	0.204	3.358	-32.503	13.991	-0.703	7.821
	Mexico	0.316	4.317	-37.314	18.852	-0.650	6.481
	<i>Average</i>	<i>0.245</i>	<i>5.219</i>				
North America	Canada	0.134	2.718	-19.440	10.129	-0.720	4.231
	USA	0.149	2.252	-16.748	10.344	-0.650	4.639
	<i>Average</i>	<i>0.141</i>	<i>2.485</i>				
Oceania	Australia	0.126	2.977	-25.243	16.354	-0.719	6.291
	New Zealand	0.028	3.049	-21.486	15.426	-0.435	3.241
	<i>Average</i>	<i>0.077</i>	<i>3.013</i>				
Europe	Austria	0.063	3.693	-23.064	16.471	-0.878	4.754
	Belgium	0.104	3.092	-22.777	14.376	-0.824	5.315
	Denmark	0.219	2.899	-20.586	14.205	-0.808	4.404
	Finland	0.122	4.522	-23.387	23.279	-0.495	3.283
	France	0.129	3.103	-17.581	12.829	-0.531	2.899
	Germany	0.134	3.280	-17.504	13.977	-0.714	3.268
	Greece	0.009	4.773	-24.403	18.527	-0.296	1.646
	Ireland	0.038	3.587	-22.748	19.965	-0.592	5.025
	Italy	0.037	3.546	-18.936	14.839	-0.373	2.417
	Netherlands	0.127	2.885	-17.827	14.028	-0.682	4.347
	Norway	0.141	3.773	-28.906	22.350	-0.829	5.844
	Portugal	-0.012	3.161	-21.307	11.086	-0.434	2.778
	Spain	0.102	3.434	-17.091	13.805	-0.362	2.060
	Sweden	0.185	3.773	-21.159	15.361	-0.580	2.980
	Switzerland	0.177	2.516	-13.648	10.307	-0.434	1.931
UK	0.090	2.598	-15.220	11.564	-0.444	3.267	
<i>Average</i>	<i>0.104</i>	<i>3.415</i>					
Far East	Hong Kong	0.149	3.356	-22.551	14.033	-0.662	3.698
	Indonesia	0.155	6.092	-41.066	80.034	0.982	28.342
	Japan	-0.006	2.994	-15.057	14.618	0.035	1.670
	Korea	0.108	4.842	-40.257	30.023	-0.516	7.026
	Malaysia	0.116	3.793	-37.052	29.692	-0.754	16.692
	Philippines	0.122	4.116	-20.671	24.657	-0.148	3.551
	Singapore	0.122	3.095	-17.047	18.391	-0.287	3.564
	Taiwan	0.084	4.478	-22.225	23.106	-0.279	2.592
	Thailand	0.093	4.777	-22.879	24.785	-0.075	2.814
	<i>Average</i>	<i>0.105</i>	<i>4.171</i>				
Asia	Jordan	0.001	2.607	-31.144	14.144	-1.499	19.162
	Turkey	0.123	7.047	-32.332	28.959	-0.298	2.125
	<i>Average</i>	<i>0.062</i>	<i>4.827</i>				

The stock returns are calculated using Wednesday to Wednesday closing values. Average returns and average standard deviations are reported for each region.

Table 2: Univariate jump diffusion model estimation for weekly returns on MSCI stock indices over the period from 13 January 1988 to 9 July 2014

		α (%)	σ (%)	η_1 (%)	η_2 (%)	p	λ
Latin America	Argentina	.496 (.192)	.187 (.014)	9.904 (4.209)	8.545 (1.825)	.213 (.088)	.085 (.022)
	Brazil	.585 (.180)	.167 (.012)	8.101 (5.776)	8.754 (2.110)	.140 (.086)	.063 (.021)
	Chile	.269 (.115)	.077 (.005)	7.246 (3.392)	7.111 (2.552)	.313 (0.129)	.042 (.016)
	Mexico	.496 (.129)	.088 (.007)	6.252 (3.098)	6.994 (1.677)	.227 (.101)	.069 (.020)
North America	Canada	.385 (.110)	.065 (.006)	5.856 (3.334)	5.252 (1.159)	.214 (.096)	.079 (.025)
	USA	.189 (.086)	.036 (.003)	4.694 (1.403)	4.434 (1.014)	.346 (.108)	.085 (.020)
Oceania	Australia	.464 (.116)	.069 (.006)	7.298 (2.824)	5.381 (0.996)	.192 (.077)	.095 (.022)
	New Zealand	.291 (.105)	.064 (.005)	6.179 (3.318)	6.052 (1.842)	.229 (.122)	.051 (.018)
Europe	Austria	.635 (.139)	.086 (.007)	6.923 (2.681)	7.064 (1.139)	.178 (.070)	.123 (.024)
	Belgium	0.496 (.123)	.064 (.006)	6.286 (1.793)	5.861 (0.880)	.220 (.068)	.134 (.026)
	Denmark	.509 (.111)	.066 (.005)	7.447 (4.257)	5.882 (1.240)	.139 (.073)	.071 (.020)
	Finland	.331 (.166)	.154 (.012)	8.685 (5.809)	7.875 (1.859)	.132 (.081)	.062 (.021)
	France	.287 (.128)	0.078 (.006)	5.713 (1.857)	5.697 (1.163)	.293 (.101)	.100 (.024)
	Germany	.464 (.130)	.080 (.006)	6.722 (2.526)	6.418 (1.247)	.203 (.076)	.100 (.023)
	Greece	.268 (.180)	.174 (.015)	7.707 (4.235)	7.298 (1.487)	.137 (.073)	.086 (.025)
	Ireland	.326 (.131)	.081 (.007)	7.714 (2.209)	7.016 (1.155)	.270 (.078)	.130 (.024)
	Italy	.281 (.130)	.081 (.007)	6.415 (2.027)	5.590 (0.956)	.252 (.080)	.118 (.025)
	Netherlands	.347 (.127)	.069 (.006)	5.558 (1.686)	5.433 (0.965)	.265 (.086)	.119 (.026)
	Norway	.715 (.149)	.095 (.008)	7.744 (2.826)	7.059 (1.127)	.168 (.062)	.121 (.025)
	Portugal	.331 (.123)	.079 (.006)	7.686 (4.416)	5.549 (1.116)	.100 (.065)	.082 (.022)
	Spain	.235 (.146)	.110 (.009)	6.247 (2.434)	6.064 (1.576)	.304 (.121)	.074 (.024)
	Sweden	.388 (.155)	.122 (.009)	7.627 (3.542)	7.206 (1.868)	.217 (.105)	.065 (.023)
	Switzerland	.312 (.103)	.049 (.004)	5.759 (2.424)	4.221 (0.911)	.212 (.089)	.084 (.023)
	UK	.250 (.105)	.051 (.005)	4.795 (1.449)	4.754 (0.945)	.300 (.095)	.109 (.028)
Far East	Hong Kong	.185 (.112)	.061 (.004)	6.671 (2.418)	5.414 (1.572)	.341 (.129)	.063 (.020)
	Indonesia	.649 (.165)	.139 (.010)	9.499 (3.859)	8.187 (1.959)	.258 (.105)	.074 (.020)
	Japan	.090 (.104)	.069 (.004)	10.671 (6.653)	5.934 (2.334)	.246 (.122)	.027 (.013)
	Korea	.425 (.159)	.134 (0.009)	9.693 (4.155)	8.788 (2.377)	.330 (.120)	.060 (.020)
	Malaysia	.325 (.095)	.043 (.003)	6.163 (3.370)	3.965 (0.924)	.226 (.111)	.066 (.020)
	Philippines	.368 (.142)	.101 (.008)	6.416 (3.506)	6.326 (1.786)	.273 (.131)	.060 (.023)
	Singapore	.326 (.108)	.059 (.005)	6.940 (2.612)	4.910 (1.088)	.239 (.080)	.087 (.023)
	Taiwan	.209 (.145)	.099 (.008)	6.836 (2.545)	4.866 (1.182)	.248 (.104)	.075 (.025)
Asia	Thailand	.366 (.142)	.130 (.008)	10.875 (6.203)	8.564 (4.037)	.295 (.149)	.031 (.014)
	Jordan	.159 (.103)	.049 (.004)	4.683 (1.310)	5.388 (1.336)	.439 (.121)	.089 (.023)
	Turkey	.795 (.222)	.243 (.019)	8.836 (4.010)	9.906 (1.938)	.188 (.089)	.092 (.024)

The jumps have a double exponential distribution with positive jump size η_1 and negative jump size η_2 , p probability of an up jump and jump intensity λ ; α and σ are the drift and variance rates of the diffusion part.

Table 3: Cross correlations of weekly returns on MSCI stock indices over the period from 13 January 1988 to 9 July 2014

		Canada	Germany	HK	Japan	UK	USA	Brazil	Greece
Latin America	Argentina	0.30	0.24	0.24	0.15	0.24	0.27	0.27	0.22
	Brazil	0.42	0.40	0.30	0.25	0.37	0.40	1.00	0.28
	Chile	0.45	0.39	0.37	0.23	0.39	0.41	0.40	0.30
	Mexico	0.51	0.46	0.40	0.30	0.45	0.53	0.48	0.28
North America	Canada	1.00	0.65	0.47	0.38	0.66	0.75	0.42	0.41
	USA	0.75	0.67	0.46	0.36	0.67	1.00	0.40	0.35
Oceania	Australia	0.64	0.60	0.52	0.43	0.63	0.55	0.38	0.41
	New Zealand	0.44	0.45	0.40	0.33	0.49	0.39	0.30	0.34
Europe	Austria	0.55	0.70	0.37	0.39	0.62	0.48	0.35	0.54
	Belgium	0.57	0.76	0.37	0.38	0.71	0.57	0.32	0.49
	Denmark	0.54	0.68	0.38	0.39	0.66	0.49	0.33	0.47
	Finland	0.54	0.61	0.38	0.33	0.58	0.54	0.34	0.36
	France	0.65	0.87	0.45	0.44	0.80	0.67	0.41	0.51
	Germany	0.65	1.00	0.45	0.44	0.75	0.67	0.40	0.52
	Greece	0.41	0.52	0.29	0.31	0.44	0.35	0.28	1.00
	Ireland	0.53	0.65	0.38	0.38	0.69	0.54	0.31	0.46
	Italy	0.56	0.74	0.41	0.39	0.68	0.54	0.33	0.46
	Netherlands	0.66	0.85	0.45	0.44	0.81	0.67	0.37	0.50
	Norway	0.64	0.65	0.41	0.39	0.66	0.53	0.40	0.44
	Portugal	0.45	0.62	0.33	0.32	0.54	0.39	0.35	0.48
	Spain	0.57	0.78	0.43	0.41	0.70	0.57	0.42	0.50
	Sweden	0.64	0.75	0.46	0.41	0.71	0.65	0.41	0.44
Switzerland	0.56	0.77	0.38	0.42	0.72	0.58	0.33	0.49	
UK	0.66	0.75	0.49	0.44	1.00	0.67	0.37	0.44	
Far East	Hong Kong	0.47	0.45	1.00	0.37	0.49	0.46	0.30	0.29
	Indonesia	0.25	0.22	0.35	0.19	0.21	0.19	0.22	0.22
	Japan	0.38	0.44	0.37	1.00	0.44	0.36	0.25	0.31
	Korea	0.38	0.42	0.47	0.41	0.39	0.37	0.26	0.29
	Malaysia	0.32	0.28	0.44	0.26	0.28	0.27	0.16	0.22
	Philippines	0.28	0.28	0.38	0.24	0.28	0.26	0.21	0.23
	Singapore	0.50	0.51	0.66	0.43	0.53	0.48	0.31	0.37
	Taiwan	0.28	0.34	0.40	0.28	0.28	0.30	0.19	0.22
	Thailand	0.36	0.35	0.48	0.31	0.34	0.31	0.25	0.25
Asia	Jordan	0.13	0.15	0.12	0.13	0.11	0.09	0.11	0.12
	Turkey	0.31	0.34	0.22	0.19	0.31	0.29	0.26	0.32

Table 4: Jump and co-jump intensities ($\times 10^{-2}$) for weekly returns on MSCI stock indices over the period from 13 January 1988 to 9 July 2014

		Canada	Germany	HK	Japan	UK	USA	Brazil	Greece
Latin America	Argentina	1.25	1.22	1.35	0.65	1.13	1.10	1.85	1.02
	Brazil	1.17	1.21	1.26	0.62	1.20	1.17	9.23	0.90
	Chile	0.86	0.79	0.86	0.46	0.76	0.74	1.04	0.61
	Mexico	1.40	1.31	1.36	0.62	1.16	1.30	1.72	0.92
North America	Canada	8.31	1.84	1.32	0.58	1.75	1.88	1.17	1.05
	USA	1.88	1.74	1.19	0.60	1.70	8.12	1.17	0.85
Oceania	Australia	1.54	1.43	1.25	0.53	1.46	1.30	1.01	0.92
	New Zealand	0.90	0.81	0.86	0.40	0.84	0.90	0.82	0.59
Europe	Austria	2.18	2.31	1.57	0.72	1.90	1.78	1.46	1.61
	Belgium	2.06	2.54	1.51	0.72	2.34	2.08	1.46	1.33
	Denmark	1.25	1.36	0.97	0.44	1.21	1.03	0.84	0.90
	Finland	1.51	1.67	1.15	0.66	1.39	1.49	1.09	0.99
	France	1.80	2.45	1.19	0.56	2.04	1.78	1.25	1.06
	Germany	1.84	7.79	1.27	0.62	1.95	1.74	1.21	1.13
	Greece	1.05	1.13	1.03	0.47	0.96	0.85	0.90	6.76
	Ireland	1.93	1.89	1.39	0.63	1.94	1.83	1.19	1.17
	Italy	1.48	1.86	1.07	0.57	1.58	1.27	1.05	1.01
	Netherlands	2.27	2.82	1.54	0.74	2.46	2.07	1.53	1.34
	Norway	1.96	1.93	1.32	0.69	1.84	1.57	1.25	1.14
	Portugal	1.10	1.28	0.88	0.40	1.11	0.97	0.87	0.91
	Spain	1.48	1.89	1.10	0.57	1.56	1.39	1.18	1.06
	Sweden	1.46	1.73	1.04	0.56	1.40	1.43	0.97	0.88
Switzerland	1.20	1.63	0.99	0.43	1.38	1.35	0.95	0.77	
UK	1.75	1.95	1.17	0.56	7.58	1.70	1.20	0.96	
Far East	Hong Kong	1.32	1.27	8.35	0.64	1.17	1.19	1.26	1.03
	Indonesia	1.79	1.56	2.17	0.92	1.44	1.49	1.68	1.26
	Japan	0.58	0.62	0.64	4.48	0.56	0.60	0.62	0.47
	Korea	1.14	1.02	1.28	0.63	0.94	1.04	0.94	0.83
	Malaysia	1.19	1.20	1.89	0.76	0.98	1.28	1.34	0.96
	Philippines	0.88	0.72	1.21	0.53	0.77	0.78	1.04	0.64
	Singapore	1.60	1.55	2.31	0.76	1.40	1.57	1.29	1.13
	Taiwan	1.16	1.28	1.46	0.67	1.05	1.22	1.26	1.00
Thailand	1.06	1.00	1.60	0.67	0.85	1.02	1.11	0.79	
Asia	Jordan	1.40	1.24	1.22	0.65	1.30	1.21	1.13	1.00
	Turkey	1.25	1.22	1.16	0.54	1.12	1.34	1.26	0.89

Table 5: Proportion of co-jump to total jumps

	Conditioning Country							
	Canada	Germany	HK	Japan	UK	USA	Brazil	Greece
Canada		0.22	0.16	0.07	0.21	0.23	0.14	0.13
Germany	0.24		0.16	0.08	0.25	0.22	0.16	0.14
Hong Kong	0.16	0.15		0.08	0.14	0.14	0.15	0.12
Japan	0.13	0.14	0.14		0.12	0.13	0.14	0.10
UK	0.23	0.26	0.15	0.07		0.22	0.16	0.13
USA	0.23	0.21	0.15	0.07	0.21		0.14	0.10
Brazil	0.13	0.13	0.14	0.07	0.13	0.13		0.10
Greece	0.16	0.17	0.15	0.07	0.14	0.13	0.13	

This table is not meant to be symmetrical. For instance, 14% of the jumps in Hong Kong are co-jumps with Japan, but only 8% of jumps in Japan are co-jumps with Hong Kong.

Table 6: Optimal weight for risky asset portfolio vis-a-vis the risk free investment

Model	Argentina	Brazil	Chile	Mexico	Canada	USA	Australia	New Zealand	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand	Jordan	Turkey
MV	0.57	0.51	0.74	0.63	0.77	0.58	0.42	0.50	0.55	0.84	0.53	0.53	0.57	0.56	0.50	0.47	0.47	0.58	0.53	0.35	0.54	0.55	0.85	0.50	0.64	0.60	0.34	0.56	0.62	0.63	0.61	0.58	0.56	0.35	0.54
SJ	0.52	0.47	0.69	0.56	0.74	0.54	0.40	0.47	0.52	0.78	0.51	0.54	0.53	0.47	0.45	0.44	0.44	0.55	0.50	0.32	0.51	0.81	0.47	0.62	0.59	0.32	0.52	0.60	0.61	0.58	0.55	0.54	0.33	0.51	
SJIJ-DE	0.48	0.44	0.64	0.53	0.70	0.49	0.34	0.42	0.46	0.74	0.45	0.49	0.48	0.42	0.38	0.39	0.39	0.48	0.46	0.27	0.45	0.48	0.77	0.42	0.56	0.48	0.27	0.47	0.51	0.54	0.52	0.49	0.48	0.20	0.47
MV	0.53	0.46	0.72	0.64	0.56	0.77	0.52	0.30	0.37	0.41	0.77	0.43	0.43	0.39	0.34	0.33	0.33	0.45	0.46	0.19	0.40	0.46	0.80	0.35	0.58	0.53	0.21	0.46	0.55	0.55	0.52	0.47	0.47	0.23	0.45
SJ	0.51	0.43	0.68	0.58	0.53	0.73	0.48	0.28	0.35	0.38	0.72	0.40	0.41	0.36	0.31	0.31	0.31	0.42	0.43	0.17	0.38	0.43	0.77	0.33	0.54	0.51	0.19	0.43	0.53	0.52	0.50	0.44	0.45	0.20	0.42
SJIJ-DE	0.42	0.38	0.62	0.53	0.48	0.70	0.44	0.23	0.29	0.33	0.68	0.35	0.37	0.31	0.25	0.25	0.25	0.38	0.38	0.12	0.33	0.40	0.75	0.30	0.49	0.39	0.13	0.37	0.42	0.45	0.44	0.37	0.37	0.09	0.37
MV	0.57	0.55	0.76	0.72	0.64	0.84	0.56	0.34	0.46	0.55	0.92	0.52	0.58	0.58	0.44	0.41	0.40	0.60	0.57	0.27	0.51	0.61	0.92	0.48	0.51	0.24	0.48	0.52	0.54	0.49	0.48	0.47	0.27	0.53	
SJ	0.54	0.51	0.71	0.66	0.62	0.81	0.53	0.31	0.42	0.54	0.87	0.49	0.56	0.54	0.42	0.39	0.38	0.57	0.53	0.24	0.49	0.59	0.87	0.46	0.48	0.22	0.45	0.49	0.51	0.47	0.46	0.45	0.25	0.50	
SJIJ-DE	0.46	0.46	0.67	0.62	0.56	0.76	0.49	0.26	0.37	0.46	0.83	0.44	0.51	0.49	0.37	0.32	0.32	0.51	0.48	0.20	0.44	0.54	0.84	0.42	0.41	0.17	0.41	0.41	0.41	0.42	0.40	0.39	0.14	0.45	
MV	0.13	0.09	0.41	0.33	0.34	0.60	0.25	-0.01	0.05	0.18	0.54	0.09	0.23	0.21	-0.01	0.02	0.01	0.27	0.16	-0.10	0.13	0.21	0.58	0.21	0.24	0.09	0.03	0.16	0.15	0.22	0.07	0.06	-0.16	0.05	
SJ	0.12	0.06	0.35	0.21	0.32	0.57	0.23	-0.02	0.04	0.17	0.50	0.08	0.21	0.19	-0.02	0.01	0.00	0.25	0.14	-0.12	0.12	0.19	0.56	0.19	0.22	0.08	0.02	0.12	0.07	0.17	0.06	0.05	-0.18	0.04	
SJIJ-DE	0.04	0.01	0.33	0.24	0.27	0.52	0.18	-0.07	-0.02	0.10	0.46	0.03	0.17	0.13	-0.06	-0.05	-0.04	0.18	0.08	-0.16	0.07	0.15	0.51	0.17	-0.01	-0.02	0.05	0.07	0.15	0.00	0.00	-0.28	0.00		
MV	0.43	0.36	0.62	0.50	0.50	0.72	0.44	0.28	0.34	0.37	0.61	0.33	0.35	0.35	0.33	0.32	0.32	0.39	0.34	0.22	0.35	0.31	0.67	0.48	0.45	0.21	0.38	0.48	0.47	0.45	0.42	0.40	0.19	0.36	
SJ	0.38	0.32	0.58	0.46	0.47	0.69	0.42	0.27	0.32	0.35	0.56	0.31	0.34	0.33	0.32	0.31	0.31	0.37	0.32	0.21	0.33	0.29	0.65	0.46	0.43	0.19	0.36	0.47	0.45	0.44	0.40	0.38	0.17	0.34	
SJIJ-DE	0.35	0.30	0.55	0.42	0.42	0.65	0.38	0.23	0.28	0.31	0.54	0.29	0.30	0.30	0.28	0.28	0.27	0.33	0.29	0.17	0.30	0.26	0.62	0.42	0.34	0.15	0.33	0.39	0.39	0.38	0.35	0.34	0.07	0.30	
MV	0.81	0.74	0.95	0.75	0.77	0.81	0.68	0.75	0.77	1.02	0.76	0.77	0.77	0.77	0.76	0.74	0.73	0.78	0.78	0.62	0.77	0.74	0.97	0.72	0.84	0.86	0.60	0.79	0.87	0.87	0.82	0.81	0.81	0.61	0.78
SJ	0.79	0.69	0.87	0.68	0.74	0.76	0.64	0.72	0.73	0.94	0.71	0.74	0.73	0.72	0.71	0.70	0.74	0.74	0.74	0.59	0.73	0.70	0.93	0.69	0.81	0.83	0.57	0.75	0.84	0.82	0.78	0.77	0.77	0.56	0.73
SJIJ-DE	0.72	0.68	0.84	0.67	0.70	0.73	0.59	0.67	0.69	0.91	0.70	0.70	0.70	0.68	0.66	0.66	0.66	0.70	0.71	0.54	0.70	0.68	0.90	0.65	0.76	0.74	0.52	0.71	0.76	0.77	0.73	0.72	0.72	0.46	0.70
MV	0.47	0.65	0.67	0.51	0.74	0.48	0.18	0.30	0.43	0.86	0.41	0.46	0.46	0.29	0.26	0.24	0.24	0.49	0.44	0.04	0.36	0.54	0.84	0.36	0.55	0.46	0.09	0.42	0.51	0.48	0.49	0.42	0.41	0.12	0.41
SJ	0.43	0.59	0.60	0.47	0.69	0.43	0.15	0.30	0.38	0.79	0.38	0.43	0.43	0.26	0.23	0.21	0.21	0.45	0.40	0.01	0.33	0.51	0.79	0.32	0.51	0.41	0.06	0.37	0.43	0.44	0.46	0.39	0.38	0.09	0.36
SJIJ-DE	0.34	0.56	0.56	0.44	0.68	0.40	0.11	0.20	0.32	0.77	0.32	0.38	0.38	0.21	0.15	0.16	0.16	0.40	0.35	-0.02	0.29	0.47	0.77	0.30	0.46	0.30	0.01	0.31	0.36	0.37	0.40	0.30	0.30	-0.03	0.31
MV	0.30	0.29	0.58	0.58	0.50	0.76	0.42	0.10	0.19	0.33	0.77	0.27	0.40	0.39	0.14	0.14	0.43	0.34	-0.03	0.29	0.43	0.78	0.33	0.44	0.28	-0.01	0.26	0.33	0.32	0.39	0.25	0.25	-0.03	0.21	
SJ	0.29	0.26	0.55	0.53	0.47	0.72	0.39	0.09	0.17	0.30	0.72	0.25	0.38	0.36	0.13	0.13	0.41	0.32	-0.04	0.28	0.40	0.76	0.32	0.42	0.27	-0.02	0.25	0.31	0.31	0.38	0.24	0.24	-0.05	0.19	
SJIJ-DE	0.21	0.21	0.51	0.48	0.42	0.68	0.35	0.05	0.12	0.25	0.68	0.21	0.34	0.31	0.07	0.09	0.35	0.28	-0.07	0.23	0.36	0.73	0.28	0.37	0.17	-0.06	0.19	0.23	0.25	0.32	0.18	0.18	-0.14	0.15	

This table presents the optimal weight of the risk asset portfolio vis-a-vis the risk free investment for investor from country in row i with foreign asset in column j using the Mean Variance (MV), Systemic Jump (SJ) and Systemic and Idiosyncratic Jumps with double exponential jump size (SJIJ-DE) models.

Table 7: Certainty equivalent for risky asset portfolio with mean variance portfolio as the base case

$\times 10^{-3}$	Model	Argentina	Brazil	Chile	Mexico	Canada	USA	Australia	New Zealand	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand	Jordan	Turkey
Canada	SJ	0.28	0.58	0.16	0.41	0.06	0.06	0.04	0.06	0.05	0.23	0.05	0.04	0.05	0.06	0.03	0.04	0.04	0.07	0.10	0.05	0.04	0.11	0.06	0.03	0.03	0.03	0.04	0.07	0.05	0.04	0.04	0.07	0.04	0.03	0.10
	SJJJ-DE	2.56	2.06	0.57	1.36	0.35	0.35	0.30	0.59	0.49	0.55	0.61	0.33	0.43	0.39	0.59	0.36	0.47	0.53	0.35	0.37	0.34	0.33	0.33	0.35	0.36	3.68	0.32	0.71	1.08	0.56	0.39	0.69	0.69	0.72	0.82
Germany	SJ	0.43	0.20	0.15	0.50	0.05	0.08	0.09	0.04	0.05	0.04	0.21	0.05	0.05	0.04	0.03	0.04	0.06	0.10	0.03	0.05	0.08	0.07	0.04	0.10	0.03	0.03	0.07	0.05	0.04	0.06	0.04	0.05	0.05	0.08	
	SJJJ-DE	2.58	2.34	0.66	1.44	0.43	0.49	0.49	0.43	0.60	0.45	0.62	0.68	0.44	0.44	0.58	0.54	0.42	0.54	0.49	0.43	0.40	0.44	0.44	0.45	0.51	3.87	0.53	0.75	1.27	0.63	0.48	0.77	0.83	0.79	0.88
Hong Kong	SJ	0.06	0.27	0.16	0.39	0.03	0.06	0.05	0.09	0.02	0.15	0.06	0.05	0.10	0.06	0.02	0.05	0.05	0.10	0.07	0.10	0.07	0.03	0.03	0.15	0.02	0.13	0.05	0.06	0.07	0.04	0.05	0.05	0.04	0.04	0.12
	SJJJ-DE	2.75	2.18	0.53	1.36	0.36	0.38	0.32	0.40	0.66	0.54	0.48	0.59	0.38	0.51	0.37	0.59	0.39	0.48	0.61	0.35	0.36	0.40	0.37	0.27	0.27	3.80	0.39	0.64	1.13	0.53	0.37	0.68	0.71	0.67	0.87
Japan	SJ	0.01	0.43	0.25	1.05	0.04	0.03	0.04	0.00	0.02	0.01	0.18	0.04	0.03	0.03	0.01	0.01	0.01	0.02	0.06	0.01	0.01	0.06	0.02	0.01	0.05	0.08	0.03	0.19	0.39	0.20	0.01	0.00	0.02	0.04	
	SJJJ-DE	2.36	2.31	0.35	1.39	0.32	0.22	0.31	0.15	0.59	0.47	0.49	0.56	0.27	0.53	0.19	0.42	0.26	0.49	0.63	0.16	0.22	0.42	0.20	0.14	0.39	3.78	0.71	1.15	0.48	0.35	0.62	0.60	0.56	0.69	
UK	SJ	0.26	0.52	0.12	0.26	0.03	0.04	0.04	0.01	0.05	0.04	0.17	0.01	0.02	0.04	0.02	0.01	0.02	0.04	0.08	0.02	0.02	0.01	0.06	0.03	0.02	0.07	0.01	0.04	0.03	0.01	0.01	0.02	0.01	0.03	0.06
	SJJJ-DE	2.47	2.39	0.35	1.26	0.35	0.21	0.26	0.15	0.61	0.44	0.40	0.52	0.27	0.45	0.18	0.59	0.21	0.50	0.56	0.15	0.28	0.40	0.16	0.27	0.27	3.89	0.14	0.64	1.07	0.49	0.31	0.56	0.62	0.55	0.75
USA	SJ	0.02	0.69	0.27	0.43	0.06	0.09	0.04	0.09	0.06	0.27	0.15	0.05	0.08	0.05	0.05	0.07	0.13	0.03	0.04	0.10	0.08	0.04	0.06	0.04	0.06	0.07	0.03	0.09	0.07	0.10	0.05	0.06	0.06	0.07	0.16
	SJJJ-DE	2.57	2.29	0.57	1.41	0.35	0.32	0.28	0.64	0.45	0.49	0.60	0.32	0.49	0.28	0.57	0.33	0.45	0.63	0.20	0.27	0.33	0.20	0.21	0.38	4.13	0.22	0.79	1.06	0.54	0.40	0.60	0.69	0.67	0.90	
Brazil	SJ	0.21	0.85	1.31	0.58	0.69	0.67	0.25	0.00	0.23	0.71	0.52	0.63	0.20	0.44	0.13	0.78	0.55	0.27	0.60	0.53	0.47	0.33	0.52	0.27	0.66	0.43	0.69	0.53	0.45	0.47	0.20	0.46	0.07	0.70	
	SJJJ-DE	3.77	2.40	0.75	2.06	2.29	2.24	2.07	2.30	2.27	2.47	2.23	2.16	2.34	2.09	2.35	2.24	2.28	2.15	2.40	2.21	1.95	2.11	2.39	2.18	5.08	2.31	2.37	2.93	2.31	2.25	2.47	2.36	2.49	2.53	
Greece	SJ	0.02	0.44	0.11	0.39	0.06	0.05	0.05	0.01	0.03	0.04	0.19	0.05	0.02	0.04	0.02	0.01	0.04	0.04	0.01	0.01	0.06	0.04	0.02	0.06	0.01	0.01	0.01	0.05	0.01	0.02	0.02	0.01	0.02	0.03	
	SJJJ-DE	2.46	2.09	0.44	1.42	0.39	0.28	0.30	0.23	0.55	0.46	0.51	0.56	0.31	0.44	0.48	0.23	0.50	0.50	0.20	0.27	0.41	0.23	0.18	0.37	3.60	0.19	0.74	1.12	0.51	0.32	0.65	0.76	0.58	0.81	

This table presents the certainty equivalent (CEQ) for the Systemic Jump (SJ), and Systemic and Idiosyncratic Jump with double exponential jump size (SJJJ-DE) models relative to the mean variance model.

Table 8: Certainty equivalent with home biased portfolio as the base case

$\times 10^{-2}$	Model	Argentina	Brazil	Chile	Mexico	Canada	USA	Australia	New Zealand	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand	Jordan	Turkey
Canada	MV	1.08	0.95	1.90	3.57	1.20	0.43	0.52	0.37	0.31	2.94	0.41	0.41	0.48	0.34	0.54	0.55	0.36	0.43	1.06	0.33	1.15	2.03	0.31	0.84	0.23	0.86	0.44	0.37	0.63	0.48	0.38	0.35	0.65	0.83	
	SJ	1.10	0.99	1.91	3.60	1.21	0.44	0.52	0.38	0.31	2.96	0.42	0.42	0.49	0.35	0.54	0.55	0.36	0.44	1.07	0.34	1.16	2.04	0.32	0.84	0.23	0.87	0.45	0.37	0.64	0.48	0.38	0.35	0.65	0.84	
	SJLJ-DE	1.34	1.17	1.96	3.71	1.24	0.47	0.55	0.44	0.35	2.99	0.47	0.45	0.53	0.38	0.59	0.40	0.48	1.10	0.36	1.19	2.06	0.34	0.88	0.62	0.89	0.51	0.49	0.69	0.52	0.44	0.42	0.72	0.92		
Germany	MV	1.36	1.32	2.30	4.05	0.80	1.46	0.68	0.65	0.45	3.64	0.55	0.53	0.83	1.04	0.50	0.66	1.73	0.45	1.45	2.69	0.45	1.06	0.40	1.07	0.57	0.58	0.80	0.67	0.50	0.54	0.81	0.98			
	SJ	1.39	1.33	2.32	4.10	0.81	1.47	0.70	0.66	0.45	3.67	0.56	0.55	0.53	0.83	1.05	0.51	0.68	1.73	0.46	1.46	2.70	0.46	1.07	0.41	1.07	0.58	0.58	0.81	0.68	0.50	0.55	0.82	0.99		
	SJLJ-DE	1.62	1.53	2.37	4.19	0.84	1.50	0.73	0.70	0.72	3.71	0.62	0.59	0.57	0.89	1.10	0.55	0.72	1.79	0.50	1.49	2.76	0.50	1.11	0.80	1.12	0.65	0.70	0.86	0.72	0.57	0.63	0.89	1.07		
Hong Kong	MV	1.25	1.28	2.12	3.74	0.81	1.47	0.64	0.64	0.40	3.14	0.62	0.71	0.70	0.44	0.53	0.52	0.64	0.76	0.93	0.51	1.33	2.27	0.44	0.24	0.99	0.47	0.40	0.62	0.44	0.40	0.41	0.77	1.06		
	SJ	1.25	1.30	2.13	3.77	0.81	1.48	0.65	0.64	0.41	3.16	0.63	0.72	0.70	0.45	0.53	0.52	0.64	0.77	0.94	0.51	1.34	2.28	0.45	0.24	0.99	0.47	0.41	0.62	0.45	0.41	0.41	0.78	1.07		
	SJLJ-DE	1.52	1.50	2.16	3.88	0.85	1.50	0.68	0.67	0.46	3.19	0.69	0.75	0.75	0.48	0.60	0.56	0.69	0.81	0.97	0.54	1.38	2.29	0.47	0.61	1.02	0.53	0.51	0.68	0.48	0.47	0.47	0.85	1.14		
Japan	MV	1.83	2.06	3.37	5.56	1.92	2.96	1.68	0.29	4.09	1.03	5.31	1.28	1.79	1.75	0.41	0.31	0.36	1.58	1.62	0.32	1.15	2.95	4.27	1.04	2.04	0.61	1.12	0.79	1.14	1.53	0.74	0.90	0.43	1.45	
	SJ	1.83	2.09	3.40	5.67	1.92	2.96	1.68	0.29	4.09	1.03	5.33	1.28	1.79	1.75	0.41	0.31	0.36	1.58	1.63	0.32	1.15	2.96	4.27	1.04	2.05	0.61	1.13	0.80	1.17	1.54	0.74	0.90	0.43	1.46	
	SJLJ-DE	2.08	2.30	3.42	5.72	1.95	2.98	1.72	0.30	0.54	1.07	5.36	1.33	1.82	1.80	0.43	0.35	0.38	1.64	1.69	0.34	1.17	2.99	4.29	1.05	2.08	0.98	1.20	0.91	1.19	1.56	0.80	0.96	0.48	1.54	
UK	MV	1.31	1.25	2.42	4.35	0.90	2.00	0.69	0.33	0.19	0.29	4.39	0.57	0.78	0.70	0.21	0.36	0.33	0.65	0.71	0.81	0.39	1.95	3.31	1.09	0.26	0.63	0.49	0.41	0.72	0.63	0.36	0.42	0.48	0.97	
	SJ	1.32	1.28	2.43	4.38	0.91	2.01	0.70	0.33	0.19	0.30	4.41	0.57	0.78	0.71	0.21	0.36	0.33	0.65	0.72	0.82	0.39	1.95	3.32	1.09	0.26	0.63	0.49	0.41	0.72	0.63	0.36	0.42	0.49	0.98	
	SJLJ-DE	1.56	1.48	2.46	4.49	0.94	2.02	0.73	0.35	0.25	0.34	4.43	0.62	0.81	0.75	0.23	0.42	0.35	0.71	0.77	0.83	0.41	1.98	3.33	1.12	0.63	0.65	0.55	0.52	0.76	0.66	0.42	0.49	0.53	1.05	
USA	MV	0.76	0.63	1.48	2.76	0.19	0.24	0.53	0.32	0.20	2.25	0.19	0.21	0.19	0.25	0.71	0.65	0.18	0.26	1.07	0.21	0.59	1.32	0.35	0.47	0.08	0.93	0.22	0.21	0.42	0.26	0.21	0.21	0.55	0.60	
	SJ	0.76	0.67	1.50	2.80	0.20	0.25	0.54	0.33	0.21	2.30	0.21	0.22	0.20	0.26	0.72	0.65	0.19	0.27	1.07	0.21	0.60	1.32	0.35	0.41	0.08	0.93	0.23	0.22	0.42	0.26	0.22	0.21	0.56	0.61	
	SJLJ-DE	1.04	0.86	1.54	2.90	0.23	0.28	0.56	0.39	0.25	2.30	0.25	0.24	0.23	0.28	0.76	0.68	0.23	0.31	1.09	0.23	0.63	1.34	0.37	0.50	0.47	0.95	0.30	0.32	0.47	0.29	0.27	0.29	0.61	0.69	
Brazil	MV	2.72	3.45	4.94	2.34	2.99	2.29	2.10	1.99	2.12	4.67	2.20	2.25	2.25	1.98	2.05	2.03	2.25	2.23	2.58	2.05	2.91	3.85	2.05	2.65	1.95	2.35	2.21	2.18	2.35	2.31	2.09	2.12	2.33	2.49	
	SJ	2.81	3.55	5.08	2.36	3.13	2.33	2.12	2.01	2.16	4.76	2.27	2.32	2.34	2.03	2.07	2.11	2.32	2.25	2.65	2.08	2.95	3.93	2.12	2.72	2.01	2.37	2.30	2.27	2.40	2.38	2.12	2.17	2.38	2.57	
	SJLJ-DE	3.13	3.71	5.24	2.56	3.22	2.53	2.33	2.22	2.37	4.92	2.43	2.47	2.47	2.20	2.29	2.27	2.48	2.44	2.83	2.28	3.12	4.07	2.29	2.87	2.46	2.58	2.47	2.47	2.58	2.55	2.34	2.37	2.58	2.74	
Greece	MV	2.00	2.10	3.32	5.27	1.84	2.68	1.57	0.68	0.71	1.09	4.90	1.29	1.65	1.63	0.66	0.68	1.49	1.65	0.92	1.16	2.65	3.79	1.04	1.91	0.82	0.83	1.18	1.03	1.34	1.40	0.99	1.03	0.90	1.68	
	SJ	2.01	2.14	3.33	5.31	1.85	2.69	1.58	0.68	0.71	1.09	4.92	1.29	1.65	1.64	0.66	0.68	1.50	1.65	0.93	1.16	2.66	3.79	1.04	1.91	0.83	0.83	1.19	1.03	1.34	1.40	0.99	1.03	0.90	1.68	
	SJLJ-DE	2.25	2.33	3.37	5.42	1.88	2.71	1.61	0.70	0.77	1.13	4.96	1.34	1.68	1.68	0.70	0.70	1.54	1.70	0.95	1.19	2.69	3.81	1.06	1.95	1.19	0.85	1.25	1.15	1.39	1.44	1.04	1.10	0.96	1.75	

This table presents the certainty equivalent (CEQ) for the three models, viz. Mean Variance (MV), Systemic Jump (SJ), and Systemic and Idiosyncratic Jump with double exponential jump size (SJLJ-DE) models against the home biased portfolio consists of home stock market and risk free investment as the base case.

Table 9: Summary of jump count exercise

Number of jumps in the same week:	0	1	2	3	4	≥ 5
Number of weeks (over a total of 1383 weeks)	860	272	96	50	25	80
% of occurrence	62%	20%	7%	4%	2%	6%

Table 10: News items associated with top ten worst and best weeks

No	Date	Total Ave	Panel A: Top ten worst weeks
34	08/10/2008	-214.4	-6.3 Mass downgrades, Icelandic bank nationalised, European governments matched guarantees
28	12/11/2008	-121.1	-4.3 US Stocks Tumble on economic concern as President-elect Barack Obama tries to stimulate growth
25	10/08/2011	-82.2	-3.3 S&P downgraded US to AA+
24	22/10/2008	-80.6	-3.4 World wide panic; property collapsed when share collateral tanked; currency and commodities plunge; carry trade turn toxic
17	24/07/2002	-75.9	-4.5 European insurers losses due to losses from their bond and stock investment threaten solvency
23	14/01/2009	-74.8	-3.3 Asian stocks fell with global economic slowdown. US jobs lost highest since 1993, oil price near \$40 a barrel
15	08/08/1990	-48.0	-3.2 Iraq invaded Kuwait
12	29/10/2008	-40.5	-3.4 Nationalization of Fortis and Bradford & Bingley's
11	01/10/2008	-39.2	-3.6 US lawmakers rejected \$700 billion bail out
15	18/02/2009	-38.4	-2.6 Obama's \$787 billion stimulus bill failed to raise hope
No	Date	Total Ave	Panel B: Top ten best weeks
24	05/11/2008	97.6	4.1 Stock markets rally ahead of Obama's election
16	12/10/2011	41.4	2.6 Stocks surge on Europe's debt-crisis response
7	04/02/1998	34.1	4.9 CNY in Asia, falling rates and firmer currencies, Korean debt rescheduled, Indonesia & Thailand financial reforms, strong foreign fund inflow
7	19/03/2003	28.3	4.0 Investors believed market oversold. Bush omitted all mention of Iraq in a scheduled speech five months after Sept 11
10	21/10/1998	26.1	2.6 Confidence returns Europe after US led interest rate cuts
10	16/10/2002	25.7	2.6 Upbeat company earnings reports amidst high vol period with Bali bombing and potential Iraq war
9	30/11/2011	23.2	2.6 Upbeat US economic news and co-ordinated move by central banks to add liquidity to the global financial system
8	06/05/2009	22.7	2.8 Surprise increases in US home sales and construction spending, and slowing job losses
8	25/03/2009	20.3	2.5 Geithner's plan to buy \$1 trillion toxic assets from banks
6	10/12/2008	19.6	3.3 US stimulus to fight and a bailout of the flagging US auto sector

“No” is the number of stock markets affected, “Total” is the aggregate jump size (%) of all markets where a jump is detected, “Ave” is “Total” divided by the number of affected markets.

Table 11: News Items Related to Top Ten Events

No	Date	Total	Ave	Associated news items
35	2007 Nov 21–2008 Nov 19	-575.8	-2.4	Subprime
16	1994 Jan 12–1998 Jan 7	-180.8	-4.0	Asian flu
22	1990 Aug 8–1990 Sep 26	-108.9	-2.6	Iraq invasion of Kuwait
30	2009 Jan 14–2009 Oct 28	-102.8	-0.2	Stimulus program
17	2002 Jul 24	-75.9	-4.5	European insurers insolvency
28	2011 Aug 10–2011 Dec 14	-69.2	-2.4	Sovereign debt crisis
15	1998 Aug 12–1998 Aug 26	-44.9	-2.4	China recession and Russian crisis
11	1999 Jan 13	-36.3	-3.3	Brazilian devaluation
14	2001 Sep 12	-35.0	-2.5	911 terrorists attack
17	2001 Mar 14	-34.9	-2.1	Tech bubble

“No” is the number of stock markets affected, “Total” is the aggregate jump size (%) of all markets where a jump is detected, “Ave” is “Total” divided by the number of affected markets.

Figure 1: Optimal Weight and CEQ from the perspective of an American investor

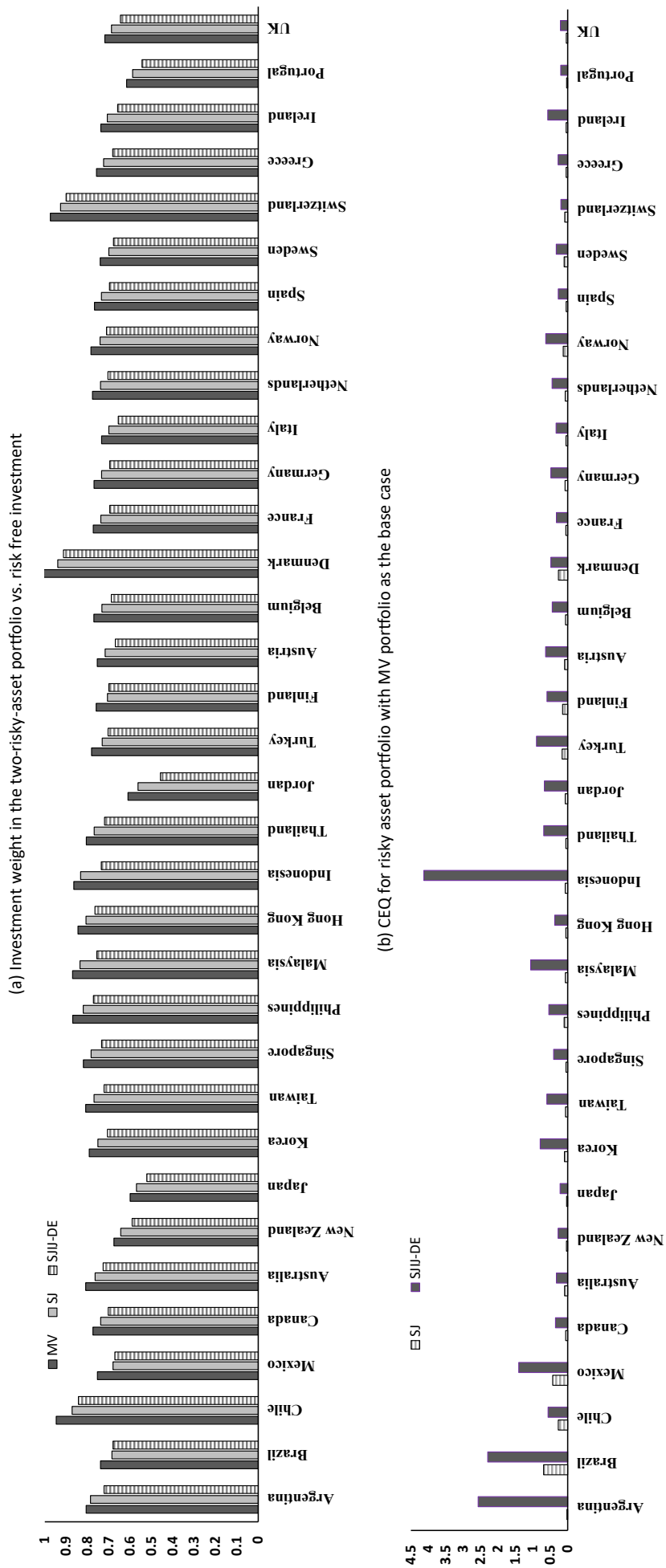
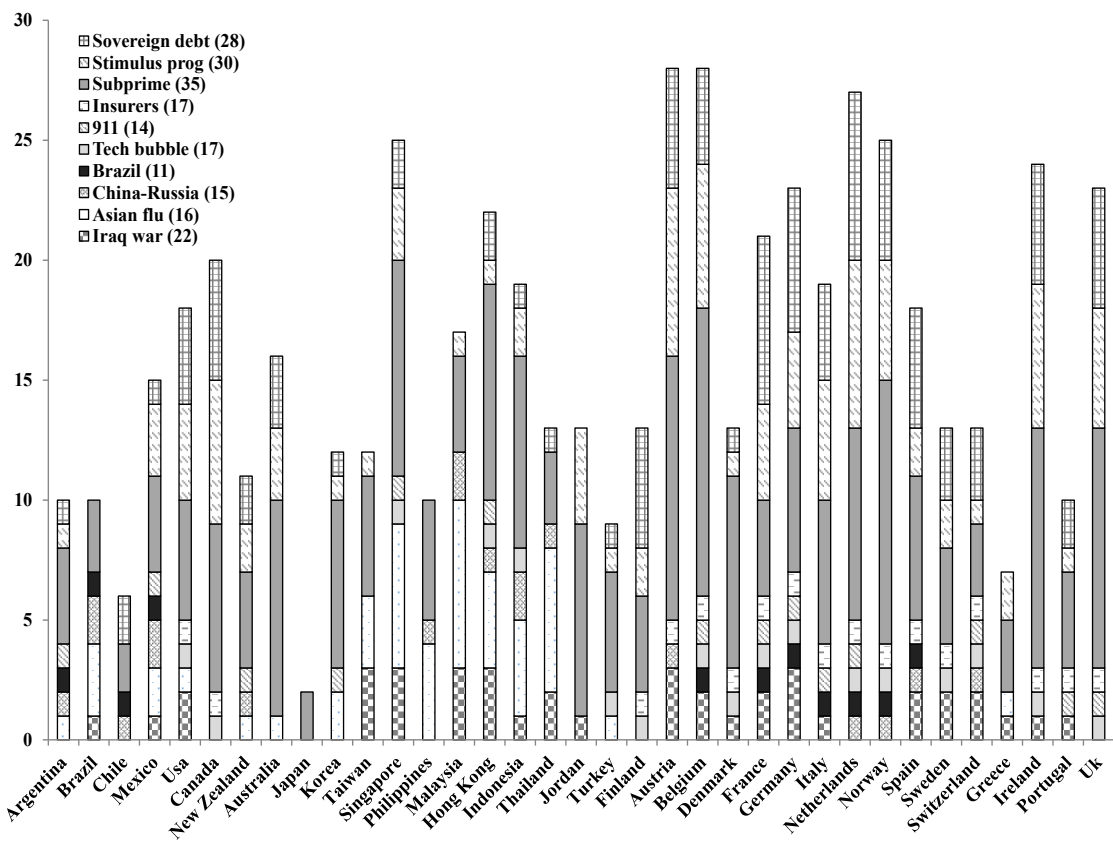


Figure 2: Impact (% loss) of top ten events represented by systemic co-jumps by country



Highlights

- Cohesive zone simulation of the fracture of ice cylinders
- Tensile and compressive uniaxial tests are reproduced
- Samples with up to 4000 grains are modeled with custom implementation of the finite element method with adaptive time step adjustment
- Relationship between the grain size and the fracture strength is investigated
- The model applies to the mechanics of ice by accounting for microscopic damage between grains

ACCEPTED MANUSCRIPT