Commonality in International Equity Jump Risk

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January 2020

Abstract

We study equity return jump risk for a large sample of emerging and developed markets, by using an analytical framework that endogenously differentiates between jumps and smooth variability. We find that jump risks exhibit strong commonality: The first principal component of jump risks explains over 60% of their variation. That factor has a correlation with the VIX of over 0.7. Thus, fluctuations in risk perceptions and global uncertainty might be responsible for most of the variation in international jump risks. Jump risks are heterogeneous across equity markets in terms of their expected size and frequency. Average jump sizes tend to be larger, while jump frequency tends to be lower for emerging markets than for developed markets. Jumps contribution to total return variability is typically higher for emerging than for developed markets and also spikes at times of heightened jump risk.

EFM Classification: 330, 370, 630

*This research was supported by Tubitak 1001 Grant No: 117K085.

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Domestic and international equity returns are characterized by jumps—price moves that are too large to be attributed to smooth return variation. Even though jumps are not frequent events, they represent an important portion of realized returns and contribute significantly to observed volatilities.[1] Understanding the nature and drivers of jump risk is critical for the ability of investors to manage risk of stock portfolios. Time-varying jump risk affects the whole return distribution; thus, elevated jump risk could require a risk premium, even if jumps end up not materializing. Furthermore, if jump risk is priced in international equity markets, a common time-varying component across countries could also generate return correlation across countries, with crucial implications for the diversification potential of an international portfolio.

We study jump risk of international equity index returns by using the discrete-time GARCH-Jump model of Maheu and McCurdy (2004). The conditional jump intensity process in that model is autoregressive, which allows us to examine statistically the time-varying and persistent nature of jump risk.

Three novel results arise from our analysis of 38 emerging and developed equity markets, over the 1990–2015 period. First, we find that there are important differences across international markets in terms of jump characteristics. While the expected daily jump size is -0.43%, it can be as large as -3.5% (the case of Brazil). The median expected number of jumps differs greatly across countries as well. It is between 0.1 and 0.3 per day for the majority of markets but for some, such as Greece, Hungary, and Japan, jumps are expected 4 to 5 times more often. Given that in some markets jumps have high expected magnitudes, whereas in others more frequent jumps are expected, in which markets are jumps more prevalent? We examine the contribution of jumps to total return variability in each market to answer this. In Brazil, jumps are responsible for about 10% of total return variance, whereas in Ireland they account for about 60%. In general, the contribution of

[1] Eraker et al. (2003) show that the jump component of returns require a bigger risk premium than do smooth components. Kapadia and Zekhnini (2019) argue that total annual return of a typical US stock is attributable to cumulative returns from the few days with realized jumps. Maheu and McCurdy (2004) document that jumps are responsible for a sizable portion of conditional return volatility of US stocks. Especially at times of heightened jump risk, jumps can account for up to 90% of total volatility.

jumps to total return variability is higher in a typical emerging market than a developed one. The jump contribution to return variability varies through time and tends to increase simultaneously for emerging and developed markets.

Second, we establish that despite the cross-sectional heterogeneity in jump risk among international equity markets, there is significant commonality in the time-series dimension. Using principal component analysis, we find that the first principal component of jump risks accounts for more than 61% of the jump risk variation. The first five components together explain about 80% of the jump risk variation over the full sample period. Equity jump risks co-vary more strongly than equity returns themselves. For example, the first principal component for international equity returns captures only about 49% of the common variability. The first principal component of jump risks has pronounced time-series dynamic, with peaks coinciding with identifiable historical financial episodes. For instance, its highest value is observed on Oct 14, 2008, the heart of the 2008 financial crisis. While many of the individual jump risk series peaked around the same date, for others the highest values were attained during idiosyncratic events. For example, Turkey's highest jump risk was on April 7, 1994, coinciding with its currency and stock market crisis, while Thailand's was on Feb 6, 1998, in the midst of the Asian financial crisis.

Third, to understand the nature of the first principal component, we examine its relationship with various macro and financial variables. We find that the first principal component of jump risks has a correlation of 0.74 with the VIX index. This finding is similar to that of Longstaff et al. (2011) who document similar commonality in the sovereign CDS market. Their first principal component has a correlation of 0.61 with the VIX index. The VIX is usually interpreted as a market proxy for risk aversion and uncertainty. Bekaert et al. (2013) document the impact of US monetary policy shocks on the VIX and its components, while Bruno and Shin (2015) show the significant relationship between the leverage of the US broker dealer sector and the VIX index. Our evidence suggests that the global risk factor in international jump risks is similarly driven by fluctuations in global risk aversion.

The paper is organized, as follows. The main dataset we employ and its characteristics are described in Section 2. Section 1 provides details of our analytical framework. The estimation results and analysis of heterogeneity of jump risks are the focus of Section 3. We discuss our results on commonality of jump risks in Section 4. Section 5 concludes.

1 Model Description

The GARCH-Jump mixed model of returns (a modification of Maheu and McCurdy (2004)'s model) is a discrete-time model, in which variation in returns and volatilities has two distinct components—normal (smooth) variation and jumps. An autoregressive specification of the conditional jump intensity allows to account for the empirically-observed clustering of jumps.

1.1 Model Setup

We consider a stock return process, evolving in discrete time. The innovations of this process have two components: (i) normal variation, captured by term $\epsilon_{1,t}$, which can be viewed as driven by ordinary information flow, causing smooth changes in equity prices, and (ii) jump-related variation, captured by the term $\epsilon_{2,t}$, which could be thought of as being a result of abrupt changes in the information set. The equity return process at time t is specified as:

$$r_t = \mu + \epsilon_{1,t} + \epsilon_{2,t}, \tag{1}$$

where

$$
\begin{aligned}
\epsilon_{1,t} &\overset{iid}{\sim} N(0,\sigma_t) \\
\epsilon_{2,t} &= J_t - E\left(J_t|F_{t-1}\right) \\
J_t &= \sum_{j=0}^{N_t} Y_{t,j} \\
Y_{t,j} &\overset{iid}{\sim} N(\theta,\delta), \text{ for all } t \text{ and } j \in [0,N_t] \\
N_t|F_{t-1} &\sim Poisson(\lambda_t) \\
\lambda_t &= E\left(N_t|F_{t-1}\right) \\
\sigma_t^2 &= \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2,
\end{aligned}
$$

where $\epsilon_{t-1} = \epsilon_{1,t-1} + \epsilon_{2,t-1}$ is the total innovation at time $t-1$. The most important parameter is λ_t which represents the conditional jump intensity at time t and gives the expected number of jumps at time t, given the information at time $t-1$. The conditional jump intensity has an autoregressive process, allowing for the expected number of jumps to vary through time and capturing the empirically-observed tendency of jumps to cluster:

$$\lambda_t = \phi_0 + \phi_1\lambda_{t-1} + \phi_2\xi_{t-1}. \tag{2}$$

The term ξ_{t-1} is the so-called "intensity residual", reflecting the revision in the conditional forecast of the number of jumps. It could be interpreted as the portion of the jump intensity affected by a surprise news arrival:

$$
\begin{aligned}
\xi_{t-1} &= E\left(N_{t-1}|F_{t-1}\right) - E\left(N_{t-1}|F_{t-2}\right) &(3)\\
&= \sum_{j=1}^{\infty} jP\left(N_{t-1} = j|F_{t-1}\right) - \lambda_{t-1}. &(4)
\end{aligned}
$$

The expectation $E\left(N_{t-1}|F_{t-1}\right)$ represents an *ex-post* inference on the number of jumps in period $t-1$, updated with contemporaneous (i.e., $t-1$) information, while $E\left(N_{t-1}|F_{t-2}\right)$ is the forecast for the number of jumps made at time $t-2$. The updated conditional probability of N_t, $P\left(N_{t-1} = j|F_{t-1}\right)$, is obtained through a Bayesian updating of the exante probability. We describe this posterior probability in (7) below.

The model setup in (1) implies that the total conditional variance of the return process can be expressed as:

$$\begin{aligned} \text{var}(r_t|F_{t-1}) &= \text{var}(\epsilon_{1,t}|F_{t-1}) + \text{var}(\epsilon_{2,t}|F_{t-1}) \\ &= \sigma_t^2 + \lambda_t \left(\theta^2 + \delta^2\right). \end{aligned} \tag{5}$$

Specifically, (5) implies that the conditional variance for the jump innovation component (second term on the right) contributes to the return variance and varies with the conditional intensity λ_t: the higher the expected number of jumps, the greater the contribution of the conditional jump innovation variance for the total conditional return variance. We emphasize the important observation that jumps do not need to be realized, in order to affect the conditional return variance. On the contrary, the variation in jump *expectation*, i.e. λ_t, has an impact on the return distribution. For example, the conditional variance, $\text{var}(r_t|F_{t-1})$, increases with the expected jump size θ and jump size variance δ^2.

1.2 Model Estimation

The GARCH-Jump model is estimated using the method of maximum likelihood. The conditional density of returns, as well as the updated jump probability, are described below. Conditional on information at time $t-1$, the return density can be written as:

$$f\left(r_t \mid F_{t-1}\right) = \sum_{j=1}^{\infty} \frac{exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi\sigma_t^2\left(1+j\delta^2\right)}} exp\left(\frac{\left(r_t-\mu_t-j\theta+\lambda_t\theta\right)^2}{2\sigma_t^2\left(1+j\delta^2\right)}\right) \tag{6}$$

The infinite sum above can be truncated to obtain an approximation of the density in (6), during the likelihood maximization process. Since the conditional volatility and intensity, as well as the number of jumps, are unobserved processes/variables, the conditional density is not available in closed form. All parameters—of the Poisson jump process, the jump size distribution, and the conditional variance process—are estimated jointly via numeric optimization of the likelihood function.

The ex-post probability of the number of jumps, updated with current information, is obtained using Bayes' theorem, as:

$$P\left(N_t = j \mid F_t\right) = \frac{\frac{exp(-\lambda_t)\lambda_t^j}{j!} \frac{1}{\sqrt{2\pi\sigma_t^2(1+j\delta^2)}} exp\left(\frac{(r_t-\mu_t-j\theta+\lambda_t\theta)^2}{2\sigma_t^2(1+j\delta^2)}\right)}{f\left(r_t \mid F_{t-1}\right)}. \tag{7}$$

This filter could be used in jump occurrence identification and determining the ex-post (observed) number of jumps. Jumps could be identified as the realized returns on the days for which $P\left(N_t = j \mid F_t\right)$ takes a value in excess of an exogenous threshold such as 0.9.

2 Data

Our sample consists of daily US-dollar denominated index return data for 38 markets—15 emerging markets and 23 developed markets.[2] The emerging markets (EM) are: Argentina, Brazil, Chile, Greece, Hungary, India, Indonesia, Mexico, Peru, Poland, Russia, South Africa, Taiwan, Thailand, Turkey. The developed markets (DM) are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, United Kingdom, and United States. The data spans the period from January 2, 1990 to December 31, 2015. A small number of countries have return data series starting later than January 1990.[3] The index price data is obtained from Thomson Reuters' Datastream.

Descriptive statistics for the index returns in our sample are reported in Table 1. EM average daily return and volatility are larger than those of DM (0.02% versus 0.01% for

[2]Our classification of countries into emerging and developed markets categories follows that of S&P Dow Jones Indices.

[3]India starts on Jan 3, 1991, Hungary and Poland on Dec 9, 1991, South Africa on Jul 3, 1995, Russia on Jul 11, 2000, and New Zealand on Dec 27, 2000.

average daily return and 2.2% versus 1.5% for average daily volatility). The average skewness of EM returns, in contrast is lower than DM's average skewness (-0.382 versus -0.201). We also observe that EM returns tend to be more autocorrelated than DM returns on average, perhaps a reflection of differences in average market liquidity (0.054 versus 0.006 for average lag-1 autocorrelation coefficient).

3 Estimation Results

This section provides a discussion of the maximum-likelihood estimation results for the GARCH-Jump model described in the previous section. For expositional brevity, we do not report the parameter estimates for each country. Rather, in Table 2, averages of the coefficient estimates over all markets, and over EM and DM separately, are reported. We also utilize figures to compare specific estimated quantities across markets.

Parameter estimates summarized in Table 2 suggest that all model coefficients are highly significant across markets. Turning first to the parameters of the jump intensity processes, we observe that the estimate of ϕ_1 has an average of 0.96, indicating that jump intensities tend to be very persistent. This evidence is consistent with Maheu and McCurdy (2004)'s and Rangel (2011)'s. The estimate of ϕ_2, with an average of 0.58 across countries, suggests that around 58 percent of the forecast error (difference between expected and ex-post number of jumps at time $t-1$) is made up for in the intensity value at time t. This is indicative of a model that is able to react relatively quickly to the arrival of new information relevant for the jump process.

The parameters of the GARCH volatility models in (1) are also highly significant: equity market volatility is very persistent, with an average β estimate of almost 0.9. This evidence suggests that introducing jump dynamics into the return process does not subsume the conditional volatility dynamics: normal equity return variations have the usual cluster structure.

3.1 Expected Jump Size

The average value for the expected jump size θ is -0.43% across the whole sample of markets and a bit higher, at -0.36%, for EM. An overwhelming majority of countries have significantly negative expected jump size—80% of EM and all DM (bottom panel of Table 2, and columns 4 and 6, respectively). Finally, the results in Table 2 suggest that jump sizes vary, as indicated by the estimated standard deviations δ of the jump size distributions for each country. The average δ estimate is 1.1 percent, with the EM average close to twice as large as the DM average.

Figure 1 plots the θ estimates for each country, in percentages. There is a substantial heterogeneity in the average jump size, somewhat greater for EM than for DM. Expected jump size estimates range from -3.5% daily for Brazil through -1.5% daily for Mexico and South Korea, to -0.3% daily for Chile and Denmark. We emphasize that direct comparisons of the expected jump magnitudes across countries are to be made with caution. Our model identifies jumps endogenously by decomposing return variation into normal and jump-related components. Thus, for a given return to be identified as a jump, it has to be an "abnormal" return relative to normal (smooth) variation for that specific market. That is, a return that constitutes a jump for market X may be normal variation for market Y. Equity markets with large normal variation would naturally have large expected jump sizes. Conversely, markets characterized by low normal variation could have lower expected jump magnitudes.

3.2 Expected Number of Jumps

The autoregressive structure of the jump intensity in (2) allows us to compute the time-series of conditional jump intensity, λ_t. The conditional intensity in period t, of course, represents the expected number of jumps for that period, given information at time $t-1$. It is our proxy for jump risk.

Figure 2 plots the time-series medians of the expected number of jumps for each market. The number of jumps expected on a typical day exhibits substantial variation across markets. Greece, Hungary, Taiwan, Denmark, and Japan stand out as the markets with the highest median expected number of jumps, in the range of $0.4 - 0.5$ per day.

We should again note that jump risks are identified for each market separately and endogenously. Thus, the nature of jumps can differ across markets. An ordinary DM jump might not stand out and be considered as a jump in a typical EM, given the more volatile nature of EM returns. Such differences also emerge in our estimation results. For example, a market with a very large negative expected jump magnitude, such as Brazil (around -3.5%), has a low expected daily incidence of jumps (around 0.1): jumps are large in absolute sense and rare. In contrast, the average jump magnitude for Denmark is lower than -0.5%. This, together with an expected number of jumps in the range of 0.4, suggests that the Danish market is characterized by expected jumps that are relatively more frequent and smaller in magnitude. Finally, the case of Greece is an interesting one, as it brings together one of the smallest expected jump sizes (-0.06%) with the largest number of jumps expected on a typical day (0.56). Combined with a relatively high standard deviation of the jumps size of 1.8% (unreported result), this evidence is indicative of a market in which jumps, both negatively- and positively-signed, are frequent.

For all markets, jump risk (expected number of jumps) exhibits pronounced variation through time. Figure 3 plots the cross-sectional medians of 21-day moving averages of jump intensities. Medians are computed separately for the groups of 15 EM and 23 DM. In general, jump risks for a typical emerging and developed market have remarkably consistent time-series dynamic. The correlation between the two series of cross-sectional medians is 0.63. In instances where jump risks spike, the median DM jump risk exceeds its EM counterpart, sometimes substantially. We tentatively ascribe this to the relative magnitudes of normal variability characterizing the typical DM and EM. Figure 4 documents that the time series median EM GARCH volatility exceeds the median DM GARCH volatility at almost all times over the 1990-2015 period. The large normal variability of the return process in the typical EM implies that relatively few returns stand out as jumps (and are endogenously identified by our model as such), in contrast to a typical DM. An analogy one could consider is temperature comparison between a country close to the Arctic circle and a tropical country. What constitutes "cold" differs in the two countries: a day of -10°C would be unheard of in the latter, whereas it would not make the news in the former.

3.3 Contribution of Jumps to Total Return Variability

The degree to which jumps contribute to the total return variability can be determined by computing the proportion of the estimated variance of the jump innovation, $\mathrm{var}(\varepsilon_{2,t} \mid F_{t-1})$, to the total variance, $\mathrm{var}(r_t \mid F_{t-1})$, using the relationship in equation 5. Figure 5 plots the average proportion of variance due to jumps for each market. We observe that jumps contribution to total variability varies substantially across countries: from as little as about 10% for Brazil, up to almost 60% for Ireland, related to the interplay between expected jump size θ, expected number of jumps λ_t, and normal return variation σ_t, as we explained above.

One could also reasonably expect that the proportion of variance due to jumps is not constant through time. Indeed, periods of arrivals of important macroeconomic and financial information and/or fluctuations in investor risk appetite are characterized by outsize influence of jumps on the conditional variance. This argument is illustrated by Figure 6, which plots the cross-sectional median 21-day moving average proportion of variability due to jumps, separately for EM and DM. Several features of the dynamics become apparent. First, the proportion of total return variability due to jumps varies substantially: from about 10% (a bit higher for EM) to about 70%. The proportion increases around periods of market distress, e.g., LTCM/Russia crisis of 1998 and financial crisis of 2008-2009. Second, jumps contribution to the total return variability is in general higher for EM than DM. This is consistent with the common characterization of EMs as less liquid and more volatile compared to DMs. Third, while EM and DM's proportions of return variability due to jumps tend to increase together, in some instances EM's proportion remains elevated, while DM's has decreased. This seems to be attributable to the dynamics of the jump risk λ_t and also evident in Figure 3, especially around 1998-1999 and 2008-2009. After it peaks, jump risk for EM tends to decrease somewhat more slowly than for DM. This is also consistent with the average estimated values of the ϕ_2 coefficient in Table 2. While DM's average estimate of ϕ_2 suggests that on average about 65% of λ_t's forecast error is made up for in the next period, for EM the corresponding value is 47%. That is, EM jump risks tend to respond more slowly to changes in the information set than DM jump risks. As we argue in Section 4, fluctuations (and possible EM versus DM heterogeneity) in global risk aversion and willingness for liquidity provision could be some of the underlying drivers for the jump risk dynamics.

In Section 4, we investigate jump risk in greater depth, focusing on its commonality across markets.

4 Commonality in Jump Risk

Is equity return jump risk market-specific or is it driven by common factors? Has the degree of commonality increased through time? In this section, we discuss the evidence of commonality in international equity jump risks, based on principal component analysis (PCA).

4.1 Principal Component Analysis

Our proxy for jump risk at time t is the expected number of jumps, i.e., the conditional intensity at time t, estimated from the model in Section 1.1. Since the daily returns we use in our analysis are recorded in different geographical areas, they, as well as daily quantities, such as the conditional intensities, lack time synchronicity. To ensure comparability of daily jump risks at time t, we perform the analysis in this section using their two-day moving averages.[4] We continue to refer to the non-synchronicity-adjusted intensities as "jump risks" or "intensities".

First, we compute the correlation matrix of intensities (unreported).[5] Pairwise correlations tend to be large, reaching values in excess of 0.8 in some cases. For example, the correlation between intensities of the United States and the United Kingdom is 0.85 and that between intensities of France and Belgium is 0.91. All pairwise jump risk correlations are positive, with an average of 0.58. The average pairwise correlation for the whole sample of countries is 0.47. With this evidence in mind, we now turn to PCA of the jump risks.

Panel A of Table 3 reports summary PCA results for the full sample period.[6] We observe that there is strong commonality in the dynamics of jump risks. The first principal component (PC1) explains 61.6% of the variation of jump risks, when we include all markets. The first five components together explain about 80% of the variation.[7] Commonality is stronger among DM jump risks, for which PC1 accounts for 68.6% of the variation, compared to 46% in the case of EM. In the latter, 15.2% and 10.6% of additional jump risk variation are explained by the second and third components, respectively, suggesting further heterogeneity of EM jump risk.

Commonality of jump risks strengthened during the recent financial crisis period. PCA performed for the 2007-2010 period (Panel B) indicates that PC1 now explains 80.8% of the jump risk variation in the whole sample. Similarly, its role increased for both DM and EM: 87.1% and 67.7% explained variation, respectively. This finding supports and extends the evidence in numerous studies, such as Longin and Solnik (2001), that international equity return correlations increase during bear markets and crisis periods.

[4]This approach has a parallel in the literature on international equity return modeling, where two-day moving average return is used as the non-synchronicity-adjusted return (e.g., Forbes and Rigobon (2002)).

[5]We perform augmented Dickey-Fuller tests for all intensity series and verify that none of them is non-stationary.

[6]In order to obtain the longest time-series of data for the PCA, we exclude New Zealand and Russia, since their return series have a late start.

[7]As a robustness check, we perform PCA using monthly conditional jump intensities. The conditional intensity in month t is defined as the average conditional daily intensity within that month. PC1 of the monthly jump risks explains about 64 percent of the variation. These results are available upon request.

Finally, for the purpose of comparison, panel C of Table 3 reports PCA results for the equity returns of the markets in our sample. The first component explains about 49% of the variability of stock returns, while the first five components together explain about 66%. The comparison allows us to emphasize the crucial distinction between realized and expected quantities: while expected jump risks are very correlated, realizations do not need to be. This argument has important implications for international investors. Jump risks being highly correlated implies that the diversification potential of an international portfolio is in fact not as high as one would suspect by only analyzing realized returns and/or realized jumps. We further discuss this topic in the next subsection.

The weighting vectors for the first two principal components are plotted in Figure 7. All weights (loadings) are positive: both EM and DM jump risks load positively on the first principal component—a global jump risk factor. The second principal component seems to capture the EM/DM distinction. All EM, as well as several Far East Asian economies (Hong Kong, Japan, and Singapore), load positively on it, while most DM weights are negative.

In conclusion, we establish that there is a global jump risk factor explaining much of the variation in international markets' jump risks. Preliminary evidence suggests time variation in the proportion of explained variability: it increased substantially during the 2008-2009 financial crisis. Our analysis below focuses on understanding the behavior of that risk factor.

4.2 The Global Jump Risk Factor

Figure 8 plots the time series of the global jump risk factor (PC1), where the factor's observations are averages of the daily values within each month. Gray bands denote ten major events that affected U.S. and/or global financial markets during the sample period. These events are, in chronological order: Kuwait invasion and oil price shock (August 1990), U.S. Treasury bond sell-off (March 1994), Russian crisis (August 1998), terrorist attack in the U.S (September 2001), stock market crash in the U.S. (Jul 2002), subprime mortgage crisis in the U.S. (Aug 2007), liquidity crisis (September 2008), U.S. equity market flash crash (May 2010), European sovereign debt crisis (August 2011), and U.S. Treasury flash crash (October 2014). We observe that many of the spikes in the global jump risk factor occur simultaneously with these events, when changes in global uncertainty and risk aversion, funding and liquidity shocks, and the consequent need for rebalancing of international portfolios are likely to affect market participants' expectations about asset values.

To investigate further, we compute the correlation of the global jump risk factor with variables capturing fluctuations in uncertainty and risk aversion. Table 4 reports the daily correlation matrix of PC1, VIX, variance risk premium, TED spread, spread between U.S. corporate high-yield bond yield to worst and 10-year Treasury yield, 3-month T-Bill yield, and the S&P 500 return, for the period Jan 20, 2000 – Dec 31, 2015.[8] We observe that the jump risk factor is highly correlated with VIX (correlation of 0.74) and moderately correlated with the TED spread and the high-yield corporate spread variable (correlation of about 0.5 for the latter two). This evidence is reminiscent of the finding of Pan and Singleton (2008) and Longstaff et al. (2011) in the context of sovereign credit risk. These two papers document that sovereign risks have strong commonality, with the first principal component of CDS spreads being highly correlated with VIX (correlation coefficient of about 0.6).

That the jump risk factor is strongly correlated with VIX is not surprising. A large volume of literature highlights the importance of VIX as a factor capturing uncertainty and risk aversion for understanding global financial cycles (Rey (2015)), monetary policy decision (Bekaert et al. (2013), capital flows (Forbes and Warnock (2012) and Bruno and Shin (2015), among others), and asset prices (Bao et al. (2011) and Brunnermeier et al.

[8]We follow Bollerslev et al. (2009) in computing the daily variance risk premium as the difference in the squared daily VIX levels and the total realized variation of S&P 500 return over the previous month. Daily realized variance data is from the Oxford-Man Institute Realized Library. The yield spread between U.S. corporate high-yield bonds and 10-year Treasuries is taken from Bloomberg (CSI BARC Index).

(2008), among others). It is, nevertheless, remarkable that jump risks of equity markets with very disparate geographies and development level would co-move to the extent that they do. Certainly, our evidence does not suggest that VIX is the factor driving jump risks of international equity returns. Rather, we conjecture that both jump risks' PC1 and VIX proxy for a risk factor related to the risk aversion and/or willingness for liquidity provision of global market players.

The dynamics of the global jump risk factor allows us also to make a contribution to the debate on the existence and time-varying nature of the benefits of international diversification. Bekaert et al. (2009) find no evidence for across-board increase in international correlations, except for European markets, during the 1980-2005 period and argue that benefits to diversification do exist. Pukthuanthong and Roll (2014) make a similar argument about diversification, based on realized equity return jumps being mostly idiosyncratic. Our findings compel us to make a different conclusion. While return realizations and realized jumps may be only weakly correlated across equity markets, *expectations* for jumps (i.e., jump risks) are highly correlated. That jump risks co-move strongly, especially during crisis periods, makes a strong case for a claim that the diversification potential of an international portfolio is not as high as would seem, based on realized quantities. This is, in fact, consistent with a "Peso problem": the mere possibility and anticipation that jumps may occur simultaneously could have implications for asset values.[9]

Finally, we provide evidence consistent with increasing market integration over the past two decades. In Figure 9, we plot time series of the proportion of variability explained by PC1. The PCA is performed for a moving window of 5 years, using all markets in the sample, as well as only DM. The first moving window is the period Jan 3, 1990 – Dec 31, 1994, the second one is Jan 2, 1991 – Dec 31, 1995, and so on. As in the previous section, two-day averages of the conditional intensities are used, in order to account for trading non-synchronicity. The graph suggests that the proportion of variability PC1 explains has been increasing steadily from about 25% in the early 1990s up to mid-60%

[9] See, for example, Veronesi (2004) and the references therein.

in the last five-year period. This increased commonality is consistent with decreasing diversification potential over time, as also argued by Christoffersen et al. (2012).

Crisis periods correspond to strengthening of jump risk commonality: the proportion of explained variability shot up around both the dot-com bust in 2000-2001 and the credit and liquidity crisis of 2008-2009. For the PCA based only on the group of DM, PC1's explained variability during the latter crisis period reached close to 90%: a sign of sharp deterioration in diversification benefits within DM. We do observe a slight decline in commonality after the financial crisis, suggesting somewhat of a reversal or levelling-off in the long-term trend.

5 Conclusion

We study jump risk in international equity returns, using a sample of 15 emerging and 23 developed markets. We use a modeling framework that endogenously differentiates between abrupt return movements (jumps) and normal variation in returns which itself could include large returns that are not jumps but arise during periods of high volatility. Our most important finding is that international jump risks are very correlated across markets and have a distinct factor structure. Principal component analysis shows that about 60% of jump risk variation across countries is attributable to a single factor and that factor is highly correlated with the VIX index. Thus, local equity jump risks seem to be driven to a large extent by changes in risk perceptions of global market participants: the common component peaks in times of large uncertainty and risk aversion. Commonality in international jump risks has increased over time, reaching about 65% explained variation due to the first principal component in the most recent five-year period.

We also establish that jumps are heterogeneous in terms of their expected jump magnitudes, as well as expected frequency. EM jumps tend to have larger magnitudes but are not necessarily more frequent. Consequently, a larger portion of a typical EM's total return variability could be attributed to jumps, compared to a typical DM's.

Our findings are all new to the literature and have important contribution to the debate on diversification benefits of international equities. The long sample period covers time stretches of abundant liquidity and investor confidence, as well uncertainty and increased risk aversion, thus validating the generality of our results. The evidence for time-variation and commonality of jump risks could potentially have asset-pricing implications: increases in jump risk could require compensation in the form of a risk premium.

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Figures and Tables

Table 1: Descriptive Statistics

The table reports summary statistics for the daily USD-denominated equity index returns of the markets in the sample. The sample period is Jan 2, 1990 – Dec 31, 2015. The means, standard deviations, minima, and maxima of returns are expressed in percentages.

Country	Mean	Std	Min	Max	Skewness	Kurtosis	Lag-1 Corr
Emerging Markets							
Argentina	0.009	2.931	-53.53	24.78	-1.592	36.08	0.005
Brazil	0.029	4.572	-71.20	72.18	0.580	95.52	-0.141
Chile	0.036	1.289	-14.96	16.95	0.082	21.86	0.030
Greece	-0.006	2.047	-22.92	21.55	-0.107	11.73	0.089
Hungary	0.034	1.984	-20.53	15.51	-0.368	12.29	0.060
India	0.020	1.712	-15.67	18.52	-0.336	11.88	0.098
Indonesia	0.005	2.202	-39.80	22.37	-1.599	47.00	0.115
Mexico	0.036	1.920	-22.87	19.93	-0.376	17.92	0.081
Peru	0.065	1.640	-14.37	13.70	-0.042	10.86	0.185
Poland	0.034	2.159	-18.54	14.78	-0.220	9.56	0.066
Russia	0.035	2.370	-21.88	25.38	-0.352	15.30	0.021
S. Africa	0.015	1.693	-23.13	11.57	-0.890	14.93	0.038
Taiwan	-0.011	1.765	-10.73	12.84	-0.194	6.94	0.034
Thailand	-0.003	1.762	-15.67	15.24	-0.002	10.10	0.095
Turkey	0.022	3.079	-26.24	20.05	-0.315	9.11	0.034
Average, EM	**0.021**	**2.208**	**-26.14**	**21.69**	**-0.382**	**22.07**	**0.054**
Developed Markets							
Australia	0.015	1.327	-15.28	13.69	-0.421	12.22	0.051
Austria	-0.002	1.605	-12.66	14.19	-0.170	11.27	0.067
Belgium	0.015	1.384	-15.62	11.44	-0.339	11.25	0.032

Table 1 continued

Country	Mean	Std	Min	Max	Skewness	Kurtosis	Lag-1 Corr
Canada	0.015	1.309	-13.27	9.66	-0.740	12.64	0.020
Denmark	0.034	1.359	-13.46	11.22	-0.252	9.53	0.013
Finland	0.017	2.093	-20.49	17.22	-0.290	9.80	-0.001
France	0.014	1.478	-11.51	12.13	-0.012	8.72	-0.022
Germany	0.014	1.548	-13.87	13.93	-0.061	8,77	-0.027
Hong Kong	0.026	1.506	-13.71	15.98	-0.069	11.94	0.025
Ireland	0.006	1.639	-19.04	14.38	-0.561	12.70	0.016
Israel	0.035	1.561	-12.94	12.17	-0.324	9.05	-0.035
Italy	0.001	1.638	-11.10	12.42	-0.118	7.58	0.004
Japan	-0.012	1.619	-13.90	13.67	0.041	8.13	-0.067
Netherlands	0.017	1.398	-11.45	11.18	-0.091	9.08	-0.038
N. Zealand	0.024	1.100	-6.05	5.92	-0.362	5.58	0.012
Norway	0.011	1.745	-15.06	14.81	-0.462	10.67	0.000
Singapore	0.014	1.327	-10.40	11.42	-0.044	9.92	0.088
S. Korea	0.000	1.892	-15.47	21.57	-0.108	11.91	0.043
Spain	0.013	1.608	-11.55	14.68	0.002	8.92	0.021
Sweden	0.022	1.782	-10.48	15.50	0.049	7.99	0.011
Switzerland	0.029	1.240	-8.71	10.23	0.018	7.90	-0.032
United Kingdom	0.010	1.246	-10.46	12.11	-0.057	11.62	0.002
United States	0.027	1.136	-9.47	10.96	-0.239	11.64	-0.054
Average, DM	**0.015**	**1.502**	**-12.87**	**13.06**	**-0.201**	**9.949**	**0.006**

Table 2: Maximum-Likelihood Estimates of the Jump-GARCH Model

The table reports summaries of the maximum-likelihood estimates for the GARCH-Jump model parameters. The entries in columns (1), (3), and (5) are averages of the parameter estimates. The entries in columns (2), (4), and (6) are proportions of countries for which the respective parameter is significantly positive or negative. Significance is identified on the basis of 5% significance level. A (+) or (–) sign after a percentage denotes that significance is determined according to a one-sided test in the respective direction. E.g., "92% (–)" means that for 92% of countries the respective parameter is significantly negative. When a sign is missing after a percentage, the respective hypothesis test is for parameter positivity.

	Average, ALL (1)	Proportion of significant parameters, ALL (2)	Average, EM (3)	Proportion of significant parameters, EM (4)	Average, DM (5)	Proportion of significant parameters, DM (6)
$\mu \times 100$	0.028	53% (+)	0.044	80% (+)	0.016	35%
GARCH process parameters						
ω	0.000	100%	0.000	100%	0.000	100%
α	0.038	100%	0.066	100%	0.019	100%
β	0.895	100%	0.811	100%	0.948	100%
Conditional intensity process parameters						
ϕ_0	0.020	100%	0.014	100%	0.023	100%
ϕ_1	0.962	100%	0.968	100%	0.959	100%
ϕ_2	0.577	100%	0.466	100%	0.650	100%
Jump-size distribution parameters						
$\theta \times 100$	-0.427	92% $(-)$	-0.364	80%	-0.467	100% $(-)$
$\delta \times 100$	1.107	92%	1.481	93%	0.863	91%

Table 3: Principal Component Analysis

The table reports results from principal component analysis (PCA) for the jump risks for the full sample period (panel A) and the 2007-2010 period (panel B), and equity returns for the full sample period (panel C). Two-day moving averages of intensities and returns are used, in order to account for trading non-synchronicity. Since New Zealand and Russia's return time series start late, these two countries are excluded from the PCA.

Principal Component	Variation, All Markets		Variation, DM		Variation, EM	
	Explained	Cumulative	Explained	Cumulative	Explained	Cumulative
Panel A. Jump Risks, Full Period						
First	61.6%	61.6%	68.6%	68.6%	46.0%	46.0%
Second	8.3%	69.9%	6.6%	75.2%	15.2%	61.2%
Third	4.5%	74.3%	4.6%	79.8%	10.6%	71.8%
Fourth	3.0%	77.3%	2.8%	82.6%	6.6%	78.4%
Fifth	2.8%	80.1%	2.4%	85.0%	4.1%	82.5%
Panel B. Jump Risks, 2007 – 2010 Period						
First	80.8%	80.8%	87.1%	87.1%	67.7%	67.7%
Second	6.1%	86.9%	3.4%	90.5%	17.0%	84.7%
Third	3.0%	89.9%	2.0%	92.5%	5.8%	90.5%
Fourth	1.5%	91.4%	1.5%	94.0%	2.5%	93.0%
Fifth	1.4%	92.8%	1.1%	95.1%	1.6%	94.6%
Panel C. Equity Returns, Full Period						
First	48.8%	48.8%	52.6%	52.6%	40.0%	40.0%
Second	5.3%	54.1%	7.5%	60.1%	11.1%	51.1%
Third	4.7%	58.8%	5.9%	66.0%	10.5%	61.6%
Fourth	3.9%	62.7%	4.6%	70.6%	7.4%	69.0%
Fifth	3.1%	65.8%	4.1%	74.7%	5.2%	74.2%

Table 4: Jump Risk Factor and Global Risk Aversion

The table reports the correlations of the first principal component of jump risks with VIX, variance risk premium, TED spread, spread between U.S. corporate high-yield bond yield to worst and 10-year Treasuries, 3-month T-Bill, and U.S. equity market return. Correlations are computed using daily data over the period Jan 20, 2000–Dec 31, 2015.

	Global Jump Risk Factor	VIX	Variance Risk Premium	TED Spread	High-Yield Corporate Spread	3-Month T-Bill	U.S. Equity Market Return
Global Jump Risk Factor	1						
VIX	0.736	1					
Variance Risk Premium	0.099	0.486	1				
TED Spread	0.543	0.489	0.002	1			
High-Yield Corporate Spread	0.519	0.876	0.403	0.462	1		
3-Month T-Bill	-0.046	-0.129	-0.104	0.240	-0.069	1	
U.S. Equity Market Return	-0.022	-0.140	-0.279	-0.065	-0.030	-0.011	1

Figure 1: Expected Jump Size, θ

The figure plots the estimates of the expected jump size θ for each equity market, in percentage. The estimates are obtained through maximum-likelihood estimation of the Jump-GARCH model in (1).

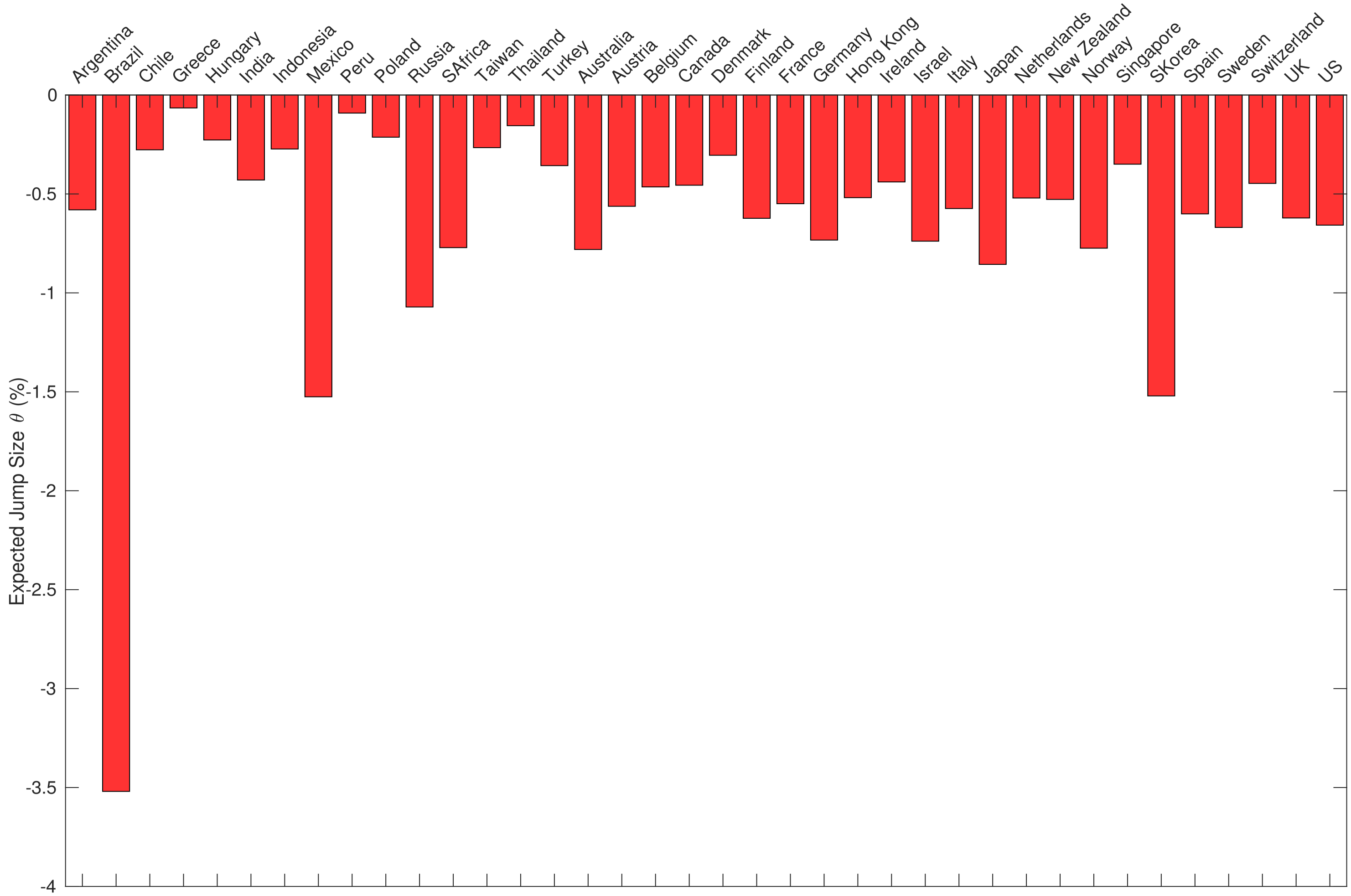

Figure 2: Expected Number of Jumps, λ_t

The figure plots the time-series median expected number of jumps λ_t for each equity market. The time-series median is based on the fitted conditional jump intensities, estimated from the Jump-GARCH model in (1).

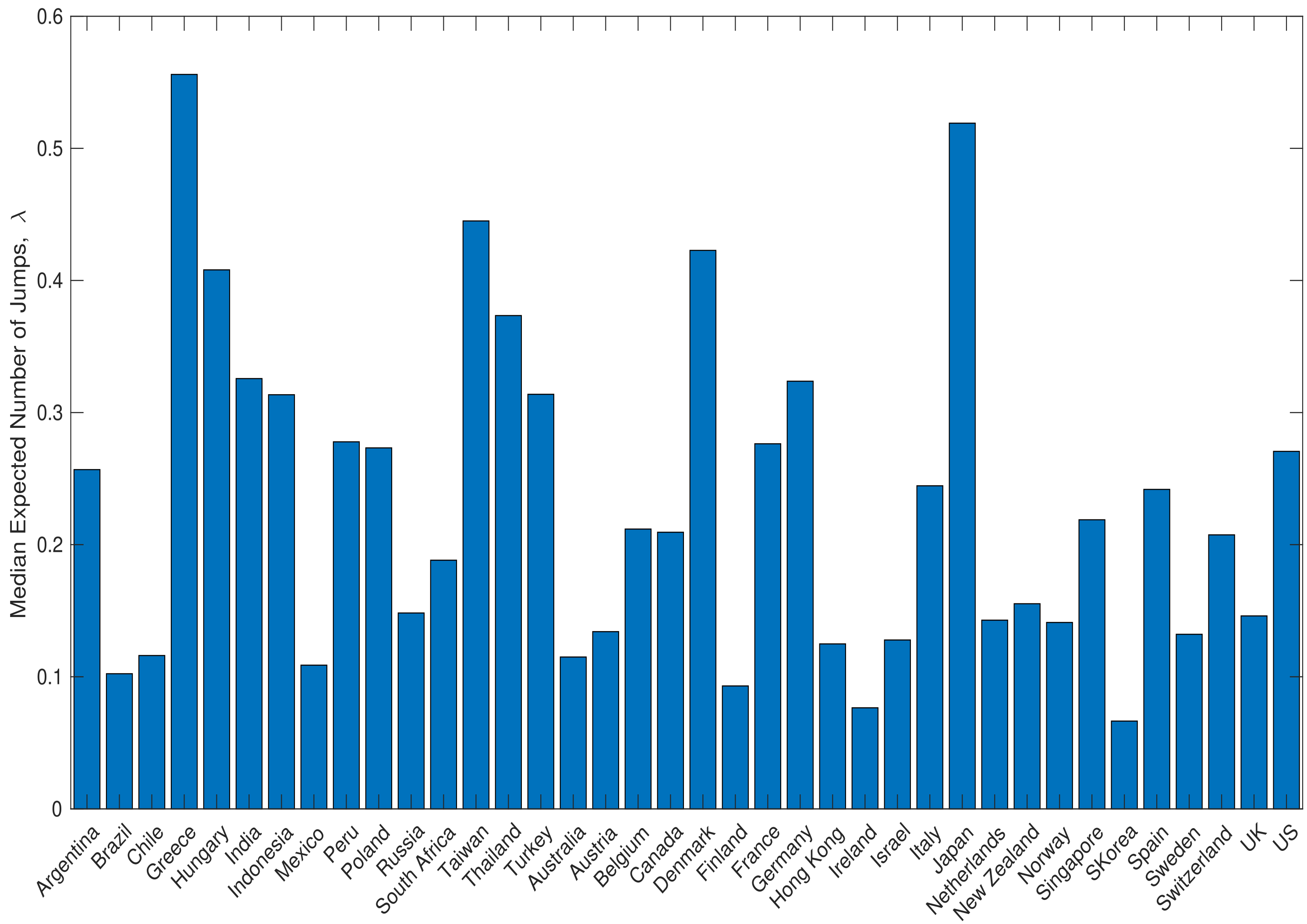

Figure 3: Time-Series Dynamics of the Expected Number of Jumps, λ_t

The figure plots the cross-sectional median of the 21-day moving average expected numbers of jumps, λ_t. EM refers to emerging markets, DM refers to developed markets.

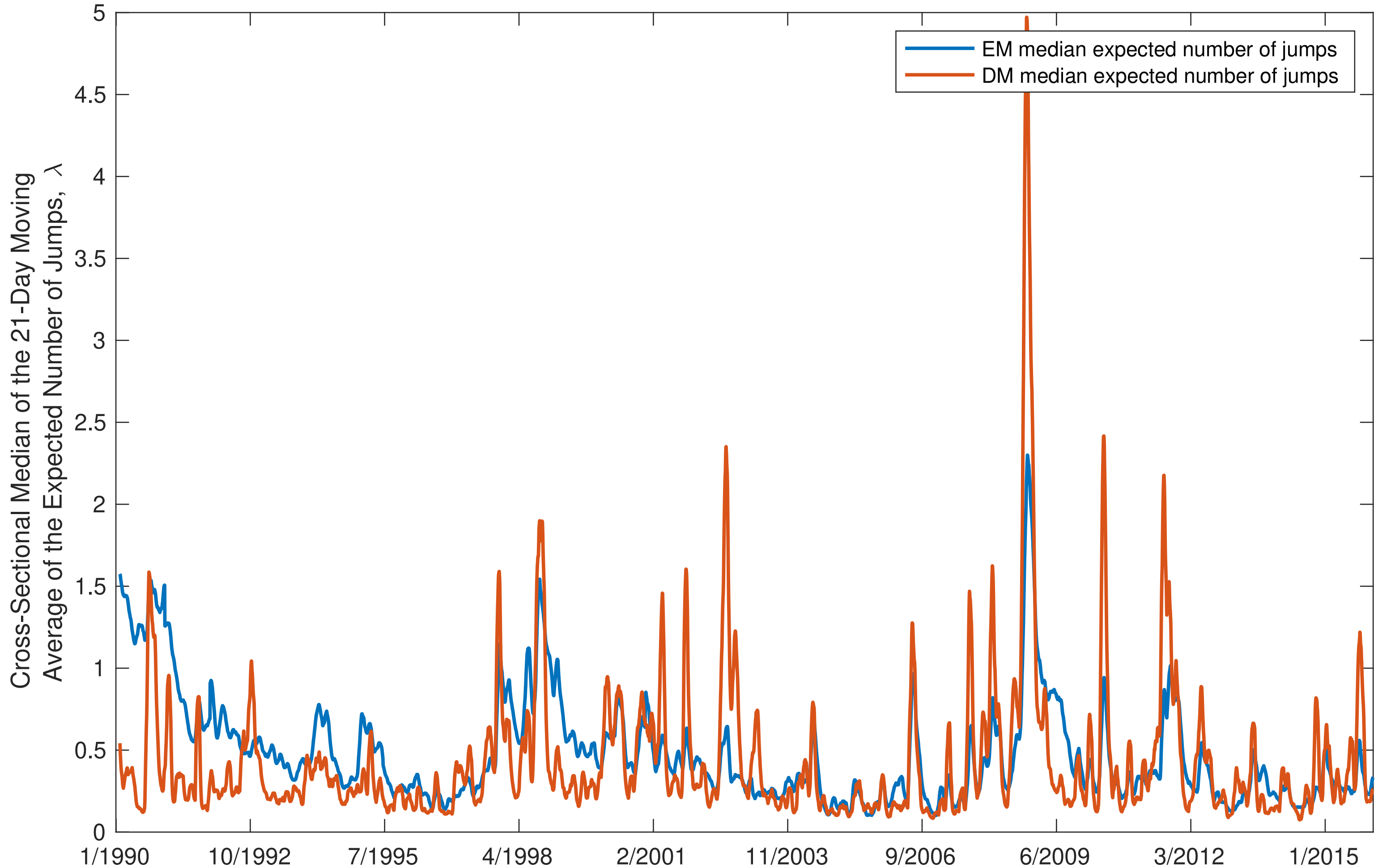

Figure 4: Time-Series Dynamics of the GARCH Conditional Volatility, σ_t

The figure plots the cross-sectional median of the 21-day moving average GARCH volatility, σ_t, expressed in percentage. EM refers to emerging markets, DM refers to developed markets.

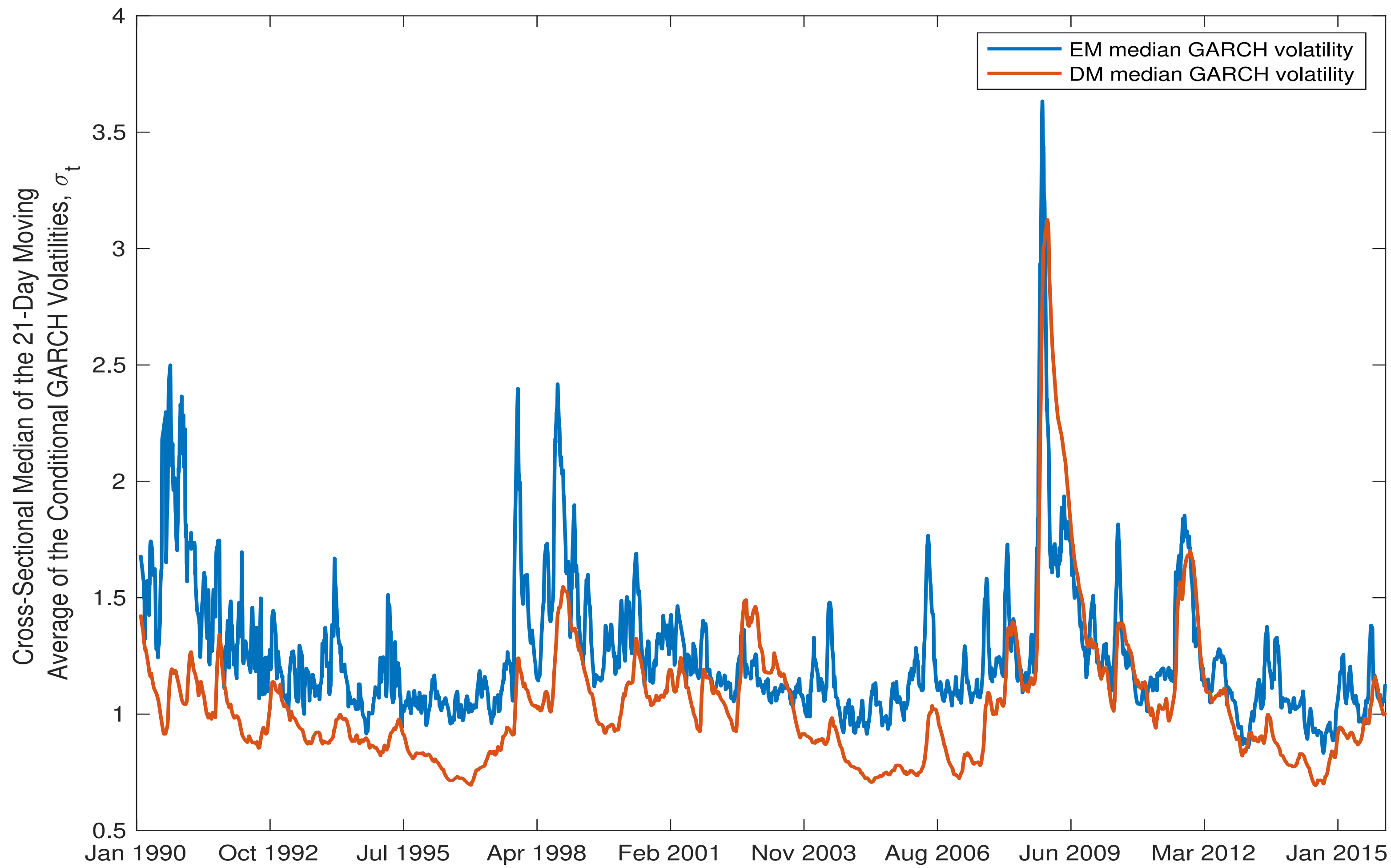

Figure 5: Proportion of Total Return Variability Due to Jumps

The figure plots the average proportion of return variability due to jumps, for each market. The proportion is defined as the ratio of $\text{var}(\varepsilon_{2,t} \mid F_{t-1})$ and $\text{var}(r_t \mid F_{t-1})$, using the relationship in equation 5.

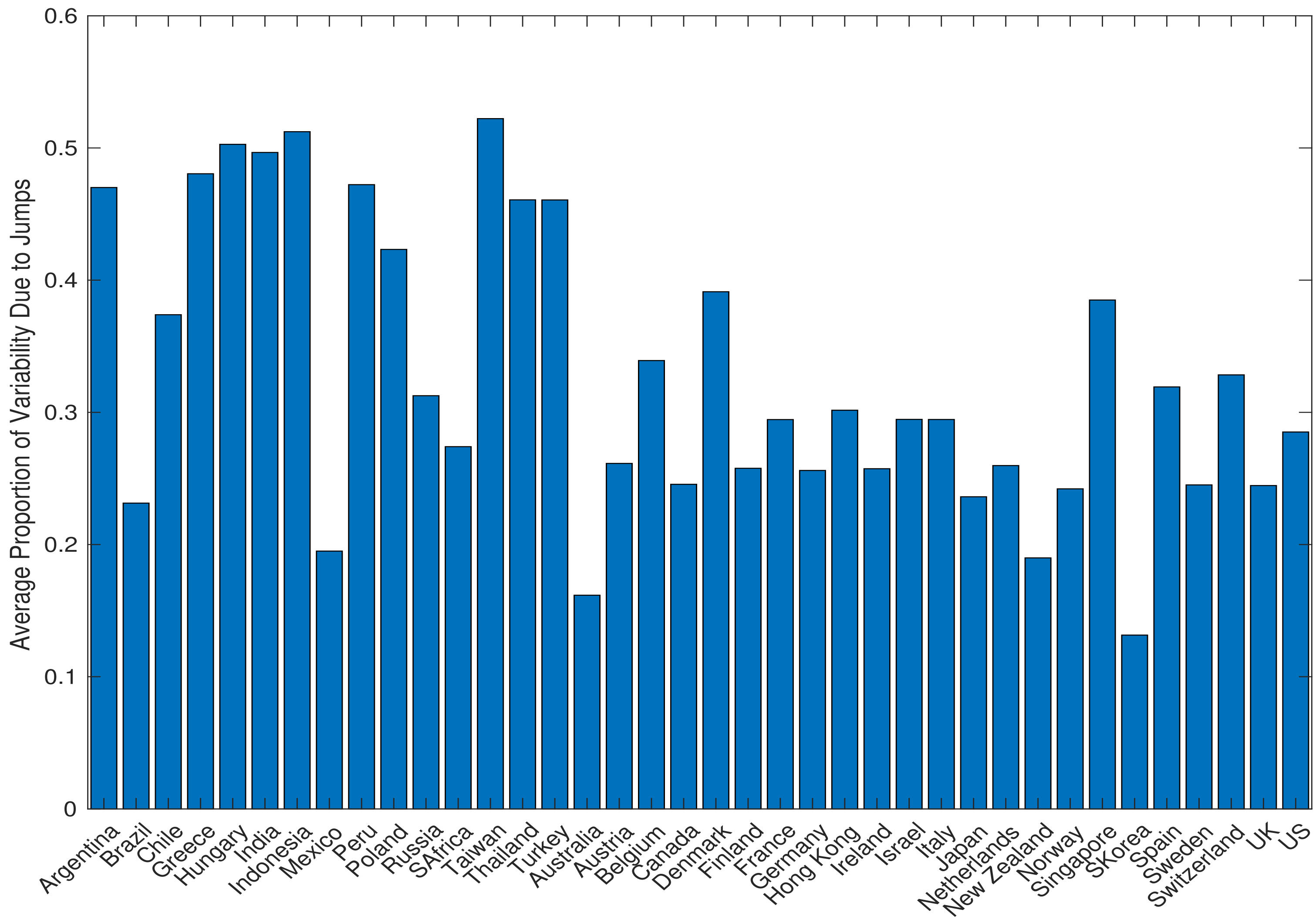

Figure 6: Time-Series Dynamics of the Proportion of Total Return Variability Due to Jumps

The figure plots the cross-sectional median of the 21-day moving average proportion of return variability due to jumps, for EM and DM. The proportion is defined as the ratio of $\text{var}(\varepsilon_{2,t} \mid F_{t-1})$ and $\text{var}(r_t \mid F_{t-1})$, using the relationship in equation 5.

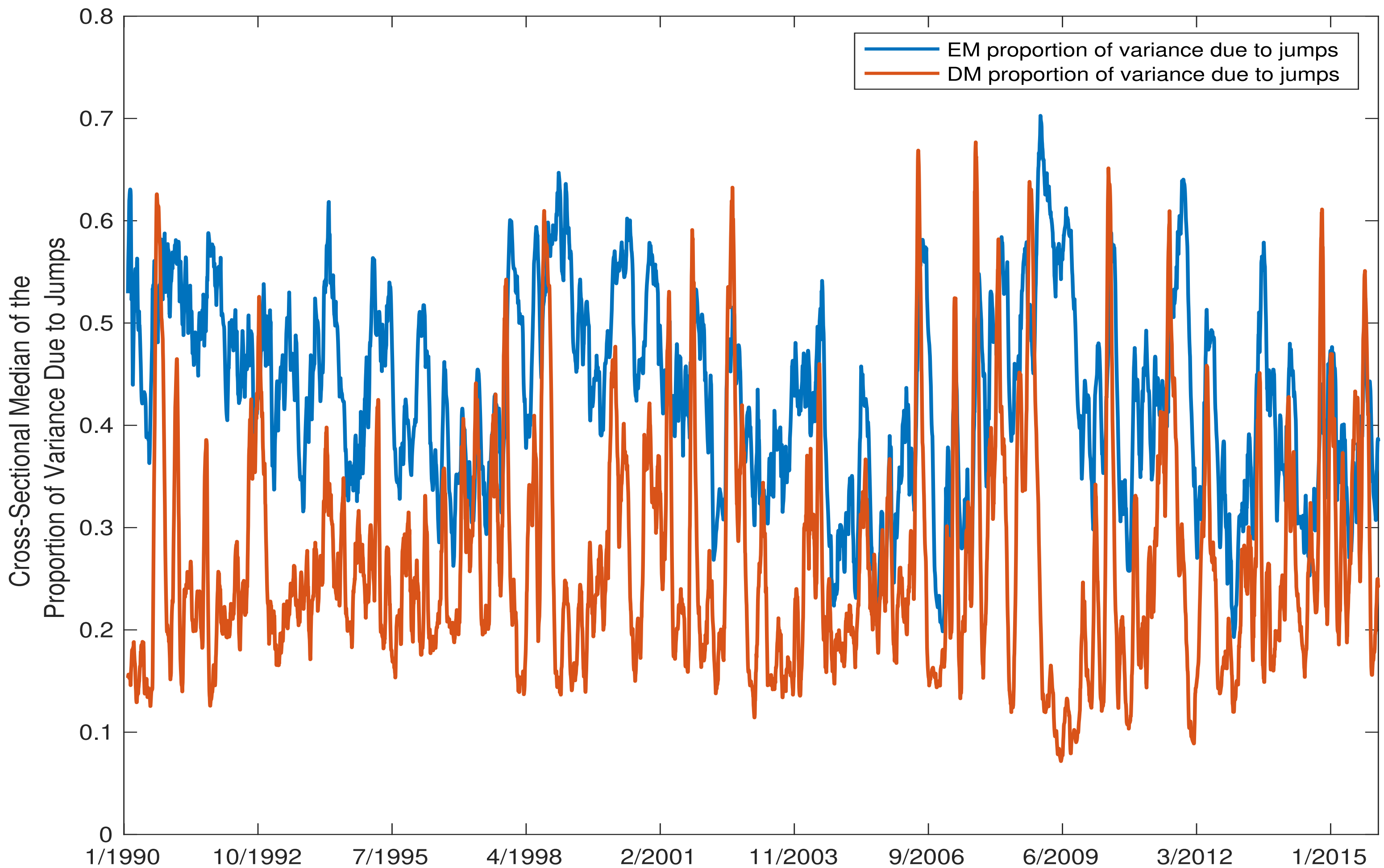

Figure 7: Loadings on the First Two Principal Components

The figure plots the loadings of markets' jump risks on the first two principal components, in Panels A and B. The PCA is performed using the two-day moving averages of conditional intensities, in order to account for trading non-synchronicity. Russia and New Zealand's intensities are not used in the PCA, due to the late start of these countries' return time series.

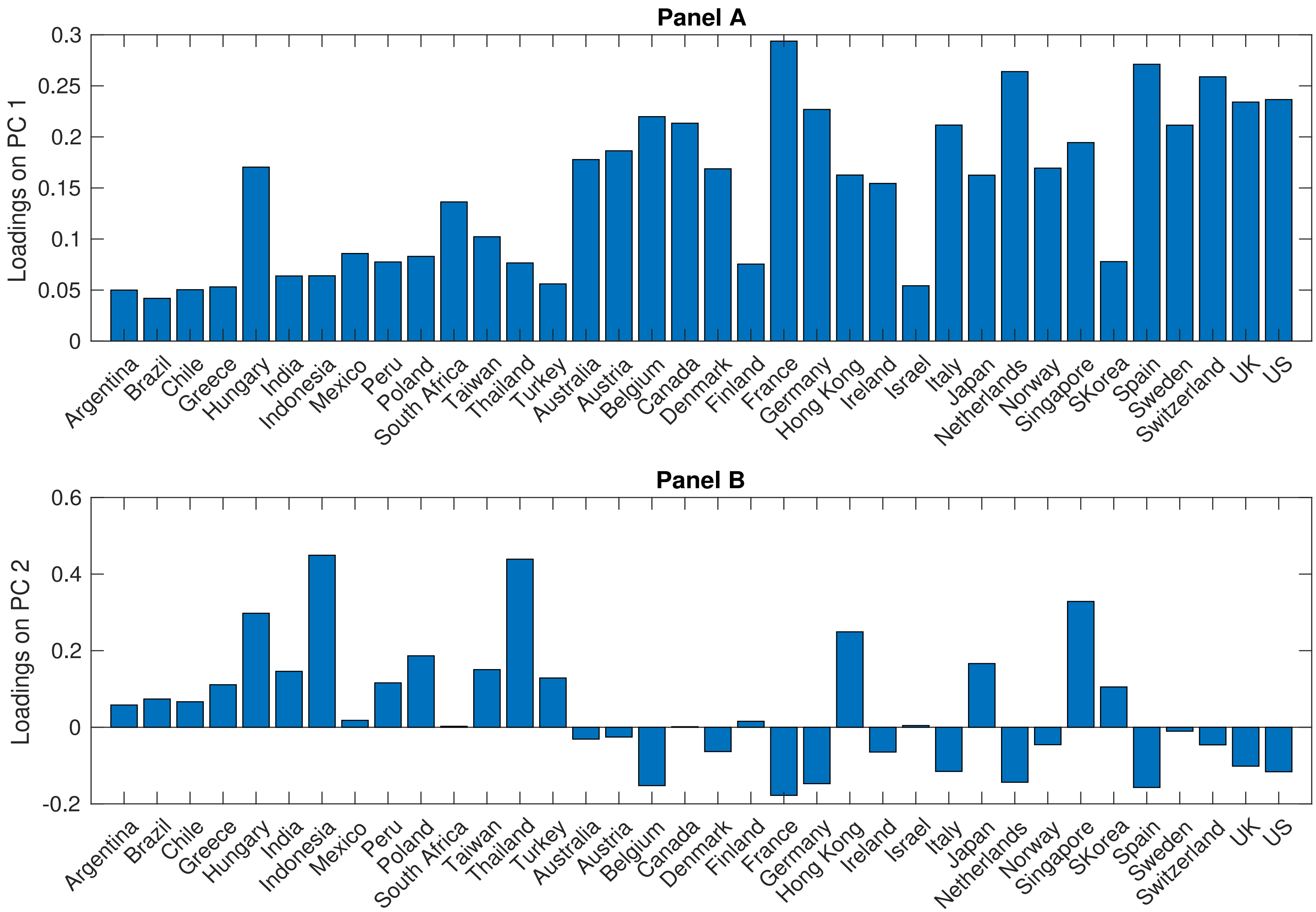

Figure 8: PC1 During Equity Crisis Periods

The figure plots the first principal component's time-series evolution. In order to ensure the longest possible PC1 time series, the PCA is performed for conditional intensities of the DM countries only (except New Zealand). Gray bands denote ten large stock market crisis periods. In chronological order, these are: Aug, 1990 (Kuwait invasion and oil price shock), Mar 1994 (U.S. Treasury bond sell-off in U.S.), Aug 1998 (Russian crisis), Sep 2001 (terrorist attack in U.S), Jul 2002 (stock market crash in U.S.), Aug 2007 (subprime mortgage crisis), Sep 2008 (liquidity crisis), May 2010 (equity market flash crash), Aug 2011 (European sovereign debt crisis), and Oct 2014 (U.S. Treasury flash crash).

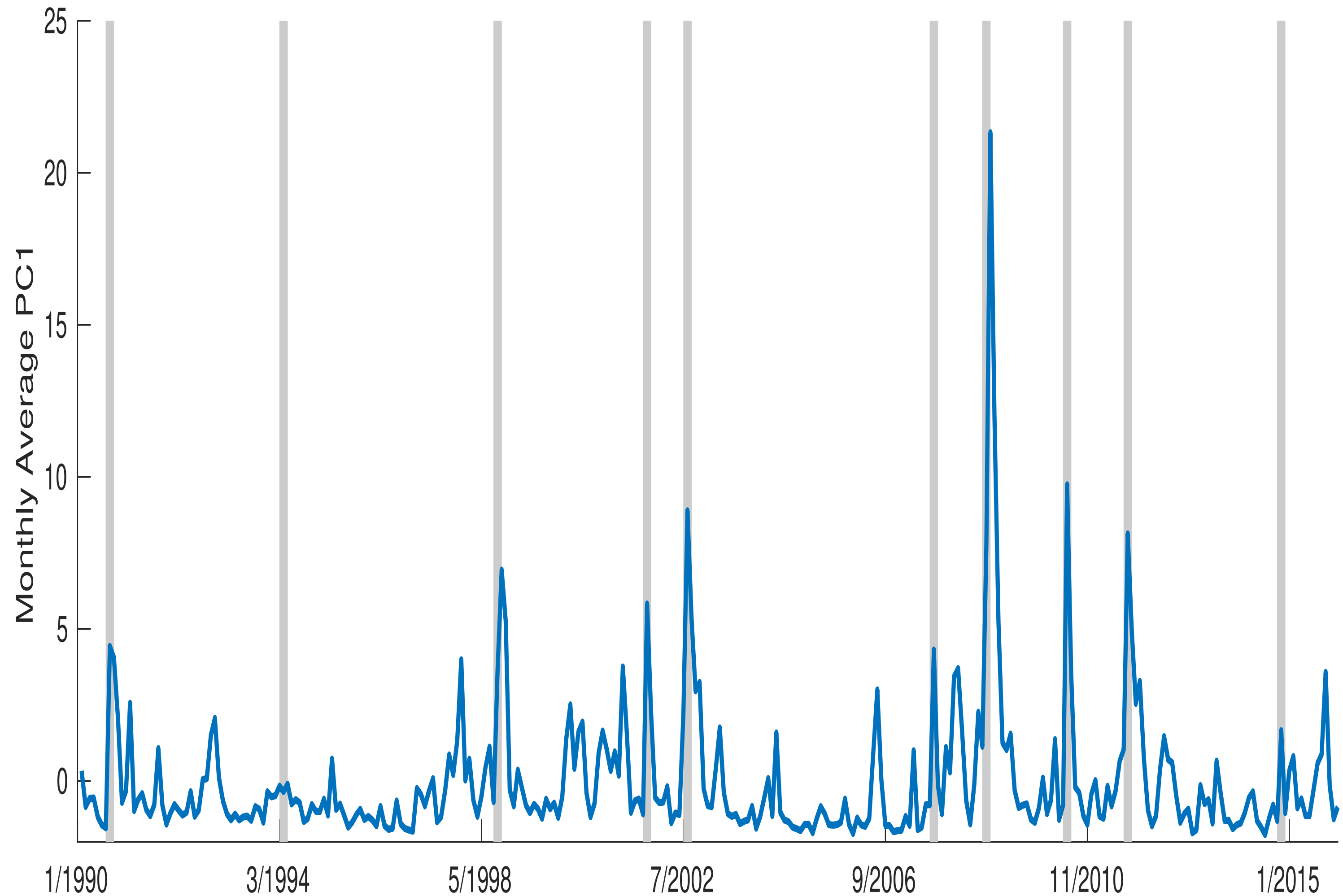

Figure 9: Time Series of the Proportion of Explained Variability of PC1

The figure plots the time series of the proportion of explained variability of PC1, where PCA for the conditional intensities is performed using five-year moving windows. The first moving window is for the period Jan 3, 1990–Dec 31, 1994, second one is for the period Jan 2, 1991–Dec 31, 1995, and so on. Conditional intensities are two-day moving averages.