Internationally Correlated Jumps

by

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ABSTRACT

Stock returns are characterized by extreme observations, jumps that would not occur under the smooth variation typical of a Gaussian process. We find that jumps are prevalent in most countries. This has been noticed before in some countries, but there has been little investigation of whether the jumps are internationally correlated. Their possible inter-correlation is important for investors because international diversification is less effective when jumps are frequent, unpredictable and strongly correlated. Government fiscal and monetary authorities are also interested in jump correlations, which have implications for international policy coordination. We investigate using daily returns on broad equity indexes from 82 countries and for several competing statistical measures of jumps. Various jump measures are not in complete agreement but a general pattern emerges. Jumps are internationally correlated but not as much as returns. Although the smooth variation in returns is driven strongly by systematic global factors, jumps are more idiosyncratic.

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1. Introduction.

Stock returns exhibit jumps relative to the rather smooth variation typical of a Gaussian distribution.[1] Jumps might arise for a number of different reasons; to name a few: sudden changes in the parameters of the conditional return distribution, extreme events such as political upheavals in a particular country, shocks to some important factor such as energy prices, global perturbation of recessions.

The ubiquity of jumps has important implications for investors, who must rely on diversification for risk control. If jumps are idiosyncratic to particular firms or even countries, they might be only a second-order concern. But if jumps are broadly systematic, unpredictable, and highly correlated, diversification provides scant solace for even the best-diversified portfolio.

Jumps that affect broad markets are also headaches for policy makers such as finance ministers and central bankers. This is all the more true if jumps are significantly correlated internationally, for policy makers will then find it necessary, albeit difficult, to coordinate their reactions across countries.

Using various measures of jumps and data for 82 countries over several decades, we present evidence about the international co-movement of jumps. The general finding is that jumps are correlated across countries but they are less correlated than returns. Jumps are more idiosyncratic except for a few pairs of countries. Different measures of jumps are not in absolute agreement, so common prescriptions for investors and policy makers would be premature. The measures generally agree, however, that jumps are less systematic than the smooth (non-jump) component of country price indexes.

Little has been previously documented about the international nature of jumps. To this end, we provide a comparative summary statistics for various jump measures and countries. We also document calendar periods that had the most influence on jump correlations and compare them with the most influential periods for return correlations. This provides an intuitive depiction of the frequency and importance of jumps.

[1] See, inter alia, Chernov, et al. (2003), Eraker, et al. (2003), and Hung and Tauchen (2005).

2. Jump Measures.

Several different statistical measures of jumps have been proposed in previous literature. Although we do not pretend to study all such measures ever advanced, we hope to display the similarities and differences among some of the most prominent ones. This section presents some measures, provides their explicit form, and discusses their intuition, potential strengths and weaknesses.

In calculating these measures, we have undoubtedly taken some liberties with respect to the intentions of the originators. Scholars seem to focus exclusively on very high frequency data because asset prices are supposed to evolve in continuous time and jumps are envisioned as instantaneous discontinuities. The continuous smooth variation of price (or log price) and the instantaneous nature of jumps are taken to be literal features of reality. Hence, for a jump to be correlated across assets, it must happen at precisely the same instant. In real markets, this would undoubtedly be an event with vanishing probability.

It is less clear that non-mathematically inclined investors care all that much about whether jumps occur in two assets at the precise same instant. So long as jumps occur within whatever happens to be the investment review period, there are important implications for diversification. A few professional investment organizations monitor markets more or less continually, but the vast majority are less attentive; monthly rebalancing seems to be the norm except among hedge funds and investment banks. Consequently, we think it acceptable and even correct to think of jumps as being correlated across assets so long as they occur within the same finite time interval. Thus, the main liberty we take henceforth is to apply tests that were originally developed for continuous time to measurable calendar periods.

2.1. Barndorff-Nielsen and Shephard.

Barndorff-Nielson and Shephard (2006), hereafter BNS, develop a test statistic based on comparing bipower variation with squared variation. To understand their test, consider the following notation (that we will adopt throughout the paper.)

t, subscript for day
T_k, the number of days in subperiod k
K, the total number of available subperiods

$R_{i,t,k}$, the return (log price relative including dividends, if any)
for asset i on day t in subperiod k

The BNS bipower and squared variations are defined as follows:

$B_{i,k}$, bipower variation,

$$B_{i,k} = \frac{1}{T_k - 1} \sum_{t=2}^{T_k} | R_{i,t,k} || R_{i,t-1,k} |$$

$S_{i,k}$, squared variation

$$S_{i,k} = \frac{1}{T_k} \sum_{t=1}^{T_k} (R_{i,t,k})^2 .$$

BNS propose two variants of the quadratic versus bipower variation measure, a difference and a ratio. If the non-jump part of the process has constant drift and volatility, they show that $(\pi/2)B_{i,k}$ is asymptotically equal to the non-jump squared variation. Consequently, a test for the null hypothesis of no jumps can be based on $(\pi/2)B_{i,k} - S_{i,k}$, or $(\pi/2)B_{i,k}/Si_{,k} -1$. Under the null hypothesis, the standard deviations of this difference and ratio depend on the "quarticity" of the process, which they show can be estimated by

$$Q_{i,k} = \frac{1}{T_k - 3} \sum_{t=4}^{T_k} | R_{i,t,k} || R_{i,t-1,k} || R_{i,t-2,k} || R_{i,t-3,k} | .$$

Define the constant $\upsilon = (\pi^2/4) + \pi - 5$. Then the difference and ratio statistics,

$$G_{i,k} = \frac{(\pi/2)B_{i,k} - S_{i,k}}{\sqrt{\upsilon(\pi/2)^2 Q_{i,k}}} \text{, and}$$

$$H_{i,k} = \frac{(\pi/2)(B_{i,k}/S_{i,k}) - 1}{\sqrt{\upsilon Q_{i,k}/B_{i,k}^2}}$$

are both asymptotically unit normal.

These statistics have intuitive appeal because the squared variation ($S_{i,k}$) should be relatively small if there is smooth variation, as with the normal distribution. On the other hand, if the price jumps on some days, those jumps are magnified by squaring and the statistics above should be small. Small values of G and H relative to the unit normal reject the null hypothesis of no jumps.

From our perspective, these statistics also have the benefit that they can be computed sequentially over calendar periods of various lengths.[2] For example, beginning with daily observations, they can be computed monthly or semiannually for each asset. Subsequently, the resulting monthly or semiannual statistics can be correlated across assets to detect whether jumps are related. When the assets are broad country indexes, this provides the opportunity to test for internationally correlated jumps. For example, to check whether countries j and i exhibit correlated jumps, one can calculate the correlation over $k = 1,\ldots,K$ between $G_{i,k}$ and $G_{j,k}$.

2.2. Lee and Mykland.

Like BNS, Lee and Mykland (2008), (hereafter LM), base their test on bipower variation, but it is employed differently. Bipower variation is used as an estimate of the instantaneous variance of the continuous (non-jump) component of prices. LM recommend its computation with data preceding a particular return observation being tested for a jump and the resulting test statistic is something like $L = R_{i,t+1,k}/\sqrt{B_{i,k}}$. Under the null hypothesis of no jump at t+1, LM show that $L\sqrt{2/\pi}$ converges to a unit normal.[3] In addition, if there is a jump at t+1, $L\sqrt{2/\pi}$ is equal to a unit normal plus the jump scaled by the standard deviation of the continuous portion of the process.

LM stress that high-frequency data minimizes the likelihood that a jump will be misclassified. A test might fail to detect an actual jump at t+1 or it might spuriously "detect" one at t+1 even though it has not occurred. Over a sequence of periods, tests might also fail to detect any jumps even when one or more have occurred or they may falsely indicate that one or more have occurred. LM provide explicit expressions for the probabilities of such misclassifications.

Unfortunately, we do not possess international stock index data at frequencies higher than daily, so we will have to live with possible misclassifications. But since our purpose is mainly to find evidence about the international correlation of jumps rather than the unambiguous identification of a jump at a particular time, occasional misclassification is less of an issue. We also finesse the problem to some extent by using a non-parametric enumeration of the test statistic.

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[2] There is a caveat. BNS assume that the non-jump part of the process has constant mean and volatility, which rules out phenomena such as reductions in volatility with increasing prices, and vice versa. This should be only a minor annoyance, though, when the calendar period is fairly short.

[3] For short periods, the mean return is negligible and is ignored in the simplest version of the LM test.

Since the LM test statistic has the return in the numerator, it would not be appropriate to simply correlate it across countries. The resulting statistic would be polluted by the normal non-jump correlation of returns. Instead, we first identify periods when the statistic is significantly non-normal, thus indicating a likely jump. Using a simple contingency table test, we then ascertain whether these periods are related across each pair of countries.

2.3. Jiang and Oomen.

Jiang and Oomen (2008) (hereafter JO) devise a test inspired by the variance swap, a contract whose payoff depends on the realized squared returns of an asset at a particular frequency and over a specified horizon. They cite Neuberger (1994) for the continuous replication strategy using a "log contract." This leads to the idea of swap-based variation, defined during period k with our usual notation as

$$SW_{i,k} = \frac{1}{T_k}\sum_{t=1}^{T_k}(R_{i,t,k}^{ar} - R_{i,t,k}^{ln})$$

where the new superscripts "ar" and "ln" denote, respectively, the arithmetic return (P_t/P_{t-1}-1) and the log return $\ln(P_t/P_{t-1})$ with P_t as the price (or index value) at time t. The squared variation, already defined in section 2.1 when introducing the BNS statistic, is compared with the swap variation in several proposed test statistics based on $SW_{i,k} - S_{i,k}$, or $\ln(SW_{i,k}) - \ln(S_{i,k})$, or a ratio test based on $1 - S_{i,k}/SW_{i,k}$.[4]

JO argue that these statistics are more sensitive to jumps than the BNS and LM statistics described in sections 2.1 and 2.2 because they exploit the influence of jumps on the third and higher order moments rather than exclusively on the second moment. JO provide simulations that seem to demonstrate that their statistic performs comparatively well.

Their theorem 2.1, p. 354, states that any of the proposed test statistics are asymptotically normal with mean zero under the null hypothesis of no jumps during k. The variances of the tests are unknown but can by estimated by multi-power variations that are consistent and robust to jumps during the estimation period.

For our purpose of correlating jumps across international markets, we do not even need to estimate the variances of the JO tests provided that the variance is constant over time, (though

[4] Because JO intend their estimator for very high frequency data, the means are ignored. De-meaned data can be used for lower frequency data.

different across countries.) Also, to save space, we shall use just the second of JO's three proposed statistics, involving logs of SW and S, simply on the grounds that logs always seem to help calm things down.

2.4. Jacod and Todorov.

The tests devised by Jacod and Todorov (2009), hereafter JT, seem to perfectly fit our purpose here because they are explicitly intended to detect the <u>common</u> arrival of jumps in two time series. JT actually develop two statistics, one for the null hypothesis that jumps arrive at the same instant in both time series ("joint" jumps) and another for the null hypothesis that jumps arrive in both time series but not at the same instant ("disjoint" jumps.)

Within a finite subperiod k, the first JT test asks whether $R_{i,t,k}$ and $R_{j,t,k}$ ($i \neq j$) both experience a jump on the same date t, for at least one $t \in k$. Given a pair of countries, one can compute the first JT test for a sequence of subperiods, $k = 1,...,K$, and tabulate the frequency of common jumps. This provides a measure of jump co-movement frequency. One can also use the second test to measure the arrival frequency of disjoint jumps that arrive on different dates but both within the same subperiod k.

JT apply their tests to the DM/$ and ¥/$ exchange rates sampled at five-minute intervals within the 24-hour trading day, so they can be confident that two observations occur at almost the same moment, even though one transaction might take place in Tokyo and the other in Frankfurt.

From a practical standpoint, our international stock index data are only observed daily and, worse, during local trading hours. Unless two markets are open at the same time, there is a problem of synchronicity. In this case, if a common jump hits global stock markets late on a given calendar day t, it will affect the North and South American markets on t but will show up in Asia and Europe only on day t+1. Blindly applying the JT tests to such events would incorrectly reject the null hypothesis of common jumps between American and other markets and favor the null hypothesis of disjoint jumps. The common jump test would not fail if the jump arrives early on a calendar day, but it would obviously be weakened overall.

There is no apparent solution if we stick to daily data. We might garner some insight about the extent of the problem by comparing the results for pairs of countries whose markets are open roughly at the same time with country pairs having very different trading hours, but this faces another difficulty in that geographic neighbors might simply be subject to more common jumps.[5]

A possible resolution is to use two-day returns rather than daily returns. Since a jump is presumably a large event, it will be a significant component of any two-day return. So a jump arriving after Asian and European market have closed on day t will show up in their returns on day t+1, but a return spanning the period t <u>and</u> t+1 will contain the jump for all markets. However, this would induce serial dependence because successive two-day turns have one over-lapping day.

Moreover, such an approach might not be that relevant to most investors. Instead, a longer observation interval, such as monthly, could be chosen and the JT tests applied to a sequence of months. (The tests statistics can be calculated for intervals of any feasible length.) One null hypothesis would then be that no joint jump occurs in two countries occur on the same day within a month. The second null hypothesis would be that no jump occurs in both countries on different days within a month. Rejecting both nulls is investment relevant and will be adopted as our empirical work below.

The JT tests require that at least one jump occurs in both countries i and j in at least one interval k = 1,...,K. So, the first step in implementing their procedure is to throw out countries that never experience a jump during the sample. The BNS statistics could be used for this purpose. In other words, one could first compute the $G_{i,k}$ and $G_{j,k}$ (or $H_{i,k}$ and $H_{j,k}$) according to the expressions in section 2.1 above, check whether the means of both G's (or both H's) fall below some pre-specified threshold, such as the .01 fractile of the unit normal, and retain for the JT test only those pairs of countries for which the threshold is breached. For monthly periods, this approach seems unnecessary because failure to reject <u>both</u> the "joint" and the "disjoint" jump null hypotheses is tantamount to accepting the hypothesis that the month contains no jump of any kind.

For month k, the monthly return is simply the sum of daily (log) returns, which we now denote as $R_{i,k} = \sum_{t=1}^{T_k} R_{i,t,k}$, for country i and month k which contains T_k daily returns. Inserting our return notation in JT's functional representation, we first define a functional sum as

[5] Indeed, we find some empirical evidence later that this is true.

$$V\ (f,\lambda)=\sum_{m=1}^{[K/\lambda]} f\left(\sum_{l=\lambda(m-1)+1}^{\lambda m}(R_{i,l})\right)$$

for integer $\lambda \geq 1$, where [.] denotes the integer part or the argument and the function *f(x)* takes on two forms: a cross-product, $f_{i,j} = (x_i x_j)^2$ and a quartic, $g_i = x_i^4$. For $\lambda = 1$, *V(f,1)* is simply the sum of the functions of individual monthly returns. For $\lambda > 1$, JT recommend the choices of $\lambda = 2$ or $\lambda = 3$; we will adopt the former and retain it throughout because this maximizes the number of terms in the sum, i.e., in [K/λ]. Consequently, in our application of the JT tests, the second sum in *V(f,2)* will involve bi-monthly returns.

The JT test statistic for simultaneous ("joint") jumps is given by

$$\Phi_{i,j}^{(J)}=\frac{V(f_{i,j},2)}{V(f_{i,j},1)},$$

and for "disjoint" jumps (non-simultaneous ones), the statistic is

$$\Phi_{i,j}^{(D)}=\frac{V(f_{i,j},1)}{\sqrt{V(g_i,1)V(g_j,1)}}.$$

We are mainly interested in testing the null hypothesis that jumps are simultaneous, for which the first of these statistics is pertinent. JT prove, under fairly general conditions, that $(\Phi_{i,j}^{(J)}-1)/\sqrt{K}$ converges to a Gaussian with mean zero and variance given by their equation 4.1, (p. 1800.) We shall also calculate and report the second statistic above, which JT proves converges to a positive variate and, when suitably scaled by expressions given in their equations 4.2, has an expectation of 1.0.

3. Data and Summary Statistics for Returns.

3.1. Data.

Daily data are extracted for 82 countries from DataStream, a division of Thomson Financial. The data consist of broad country indexes converted into a common currency (the US dollar). Table 1 lists the countries, identifies the indexes, reports the time span of daily data availability, and provides the DataStream mnemonic indicator (which could help in any replication.) If the mnemonic contains the symbol "RI", the index includes reinvested dividends; otherwise, the index an average daily price.

Daily data availability extends back to the 1960s for a few countries but most joined the database at a later time. The latest available date, when all the data were downloaded, is October 26, 2009 for all countries except Zimbabwe, (which closed its stock market after October 2006.)

Daily returns are calculated as log index relatives from valid index observations. An index observation is not used if it exactly matches the previous reported day's index. When an index is not available for a given trading day, DataStream inserts the previous day's value. This happens whenever a trading day is a holiday in a country and also, particularly for smaller countries, when the market is closed or the data are simply not available. Our daily returns are thus filtered to eliminate such invalid observations.

Using the daily data for valid observations, calendar month and semiannual returns are computed by adding together the (log) daily returns. The subsequent analysis uses these longer-term returns, which also helps alleviate the effect of invalid daily observations. In order to be included in the computations, a country must have at least ten valid monthly observation or 30 valid observations within a semester.

3.2. Summary statistics for return correlations.

Our focus is mainly on jumps, but we first report some results for raw returns; these will prove useful as a basis for comparison.

Simple product moment correlations are computed for each pair of countries. Summary statistics for the correlations are reported in Table 2, Panel A for monthly correlations and Panel B for semiannual. The number of observations depends on data availability. The maximum number of months is 538, (e.g., Germany and the United Kingdom), and the minimum is eight, (e.g., Greece and Zimbabwe.) Most pairs of countries have at least 100 concurrent monthly observations and quite a few have several hundred. For semiannual periods, the maximum number is 90 and the minimum is eight. Greece and Zimbabwe do not have enough concurrent semiannual observations to compute a correlation.

As the table reveals, correlations are somewhat higher with semiannual than with monthly returns; both the mean and median are higher by about 0.12. Cross-country-pair variation is only slightly higher for semiannual returns as indicated by the standard deviation and the mean absolute deviation while the number of highly significant correlations is lower; this is probably attributable to the lower sample sizes for semiannual data. There is no evidence of skewness or kurtosis.

Table 3 provides a list of the single most influential observation for the return correlation between each pair of countries. To obtain these results, we simply computed the de-meaned product of returns that was the algebraically largest over all the available observations. The table lists each influential period, the number of country pairs with data available for that period, and the fraction of country pairs for which that particular period was the most influential. Periods are omitted if their influential observations amounted to less than one percent of the available correlations.

Perhaps the most striking aspect of Table 3 is the pronounced dominance of October 2008 for monthly data and the second semester of 2008 for semiannual data. For 3,240 monthly correlation coefficients among the 82 countries, October 2008 was the single most influential observation in 2,457, more than 75% of the cases. The second semester of 2008 was the most influential in 87.1% of the 3,240 semiannual correlations. No other periods even come close. The next most influential monthly observation is October 1987, with 16.9% of the 378 correlations available then. The next most influential semester was the second half of 1993, a paltry 4.86% of the 1,378 available correlations.

4. International jump correlation results.

The basic approach of this section is to compute a jump statistic for each country and calendar period and then correlate the resulting jump statistics across countries.

4.1. The Barndorff-Nielsen and Shephard (2006) statistics.

The Barndorff-Nielsen and Shephard (BNS) $G_{i,k}$ and $H_{i,k}$ statistics for country i in period k, are described in section 2.1 above. For each period k, either a calendar month or a semester, $G_{i,k}$ and $H_{i,k}$ are computed from the daily return observations during the period. Table 4 presents summary statistics by country for the monthly $G_{i,k}$ measure.

Recall from section 2.1 that the BNS measures are asymptotically unit normal under the null hypothesis of no jumps. Table 4 reveals that every single estimate of G is negative on average and all of the computed *T*-statistics indicate significance, most being highly significant. If the underlying returns are independently distributed across time, Barndorff-Nielsen and

Shephard show that their jump statistics are also time-series independent, so the *T*-statistics should be fairly reliable.

An additional indication of jumps is that skewness and kurtosis are decidedly non-normal in almost all countries. Skewness is negative for every country, which shows that some months during the sample have dramatically smaller values of the jump measure than could be expected under the null; (recall that negative values of G indicate jumps within the month.) The uniformly large values of kurtosis reveal extreme value of G in some months, which is also shown by the very large minimum values of G in many cases. In contrast, the maximum values of G never exceed 1.0.

The semiannual G measure and the monthly and semiannual H measures yield similar though not identical results.[6] Table 5 provides averages for the two BNS jump measures computed over both monthly and semiannual periods.[7] The averages for the H measure, which is based on a ratio rather than a difference, are considerably smaller than the averages for the G measure. But the H measures also have much less variability, so the significance levels are similar. Measures based on semiannual observations are less significant because the sample sizes are smaller. Despite these distinctions, all measures agree that the null hypothesis of no jumps should be rejected for almost all countries. Only one jump statistic, the H measure for Romania with semiannual data, is positive out of the 4(82) = 328 measures computed.

Since Tables 4 and 5 show clearly that jumps are happening all over the globe, the next step is to ascertain how correlated they are across countries. To this end, using the calculated BNS measures G and H computed for both months and semesters within individual countries, we compute four international correlation matrices. Table 6 provides summary statistics from these four different estimates of international jump correlations.

The international correlations of jump measure reported in Table 6 stand in stark contrast with the return correlations reported earlier in Table 2. The jump measures are simply not that correlated. The mean correlation coefficients are only around 0.01 to 0.02. Although the means are supposedly statistically significant based on the *T*-statistic for the mean, only a modest

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[6]A full table for each measure will be provided to interested readers.

[7]In these averages, measures that exceed 1,000 in absolute value are expunged because they are probably due to data errors. For example, the January 1999 monthly G measure for Ghana is -202,343. In the original data, the Ghanian price index changed only in the seventh significant digit every day in January until the last (typical successive values are 426.8350, 426.8352, and so on, up and down.) Then, on the last day of January, the index shot up to 452.95. In February, the index remained around 452.95 until the last day as well. It seems likely that no trades occurred on most days in these months and the index changed only because of rounding error.

number of individual correlations have individual *T*'s greater than 2.0, between five and seven percent of them. This differs dramatically from individual correlations among returns, which Table 2 reports have *T*'s exceeding 2.0 in 60% to 80% of the cases.

This conclusion is further supported by Table 7, which gives influential months and semesters for the correlations among jump measures. Unlike the influential periods for returns (Table 3), there are no grossly dominant periods. The first semester of 1973 has the largest percentage of influential observations, but only 21.9%, in contrast with the 87.1% of influential observations exhibited by the second semester of 2008 for return correlations. Moreover, there were many more available pairs during the second semester of 2008, 3,240, versus only 105 in the first semester of 1973, so the dominance of 2008 is all the more impressive.

For monthly jump measures, Table 7 shows that only one month reaches even a ten percent level as being most influential; this is November 1978 with the H measure. Notice also that the two most dominant months for returns, October 2008 and October 1987, do not even appear in Table 7.

Combining the results in Tables 5, 6, and 7, one can only conclude that jumps are occurring in all countries but not usually at the same time. Perhaps this is good news for investors because is seems to suggest that diversification can be effective in protecting against extreme movements in prices even though the smooth component of return variation is quite correlated internationally. Evidently, jumps are much more idiosyncratic than normal variation.

Despite the weak international correlation among jumps, it could still be useful to examine special cases of countries that exhibit somewhat more jump co-movement. Table 8 presents a list of country pairs whose jump correlations have *T*-statistics exceeding 3.0 for <u>both</u> of the BNS measures. Many of these seem intuitively plausible since they are close neighbors and trading partners; indeed, quite a few pairs are countries within the European community.

There are some, however, that seem a bit odd, particularly for the jump measures computed with semiannual data. Examples are Argentina, partnered with both Bangladesh and Kuwait, or China partnered with Jordan, or Brazil with Lithuania. Perhaps some of these oddities are simply attributable to random happenstance that is the inevitable companion of large-scale data comparisons

Other cases might very well be worthy of a more in-depth investigation. For example, are semiannual jumps correlated between Indonesia and Morocco because their religious faith subjects them to occasional common shocks? Are Israel and Switzerland paired through technology? What is the relation between Kuwait and Romania, South Korea and Sweden, or Ecuador and the Philippines? It would be interesting to know the underlying reasons for such connections, if indeed there are any.

Most countries provide good diversification protection against extreme movements in prices. But there are a few exceptions such as those listed in Table 8

4.2. The Lee and Mykland (2008) statistic.

For each month having at least ten valid daily return observations, we first compute the average daily return over the available days, d, and also the bipower variation over the same days within the month.[8] To achieve the proper scale factor for the numerator of the L statistic, we multiply the average daily return by $\sqrt{2d/\pi}$ and then divide it by the bipower variation. LM show that this L statistic is distributed as a standard normal when there are no jumps within the month. When there are jumps, however, the L statistic has an amplified variance; the mean might be influenced as well but only if the jumps are biased above or below zero. Since biased jumps seem unlikely, we focus now on the second and higher order moments of the resulting L statistic.

Table 9 tabulates these results for each of our 82 countries. The standard deviations are almost all larger than 1.0, which should be their value under the null hypothesis of no jumps. The United States is the only exception. To get a perspective on the significance of their differences from 1.0, a p-value of at least .01 would result if the observed sample standard deviation were above 1.29, 1.20, and 1.14 for sample sizes of 100, 200, and 500, respectively. For the actual sample sizes shown in Table 9, 79% of the countries have computed standard deviations that exceed 1.0 with a p-value of .05 and 62% exceed 1.0 with a p-value of .01.

Statistics related to the third and fourth moments, skewness and kurtosis, are also often non-normal, again supporting a conclusion that jumps occur in many countries. Finally, the extrema are often very unlikely under a unit normal. The maximum observed value exceeds 3.0

[8] LM recommend that the bipower variation be computed from earlier data, we see no compelling reason to do so because bipower variation is not affected by jumps, at least asymptotically. Moreover, taking the return and the bipower estimator of instantaneous volatility from the same time period helps to alleviate serial dependence induced by persistence in the volatility process.

for most countries and sometimes is truly enormous, such as 22.18 for Denmark. The minimum observed value is not quite as striking, but it is generally well below 2.5.[9]

Overall, the Lee and Mykland statistic seems to indicate slightly fewer jumps than the Barndorff-Nielsen and Shephard statistic (Table 4). Both measures agree, nonetheless, that jumps are occurring all over.

We now turn to the correlation in the LM jump measure across countries. Since the LM measure's numerator is a return, it should not be used directly because the results would be contaminated by the non-jump component. Instead, we resort to a non-parametric approach. First, for each country separately, we classify months into those with likely jumps and those without. Since the L statistic is asymptotically unit normal, we rather arbitrarily adopt a ten percent criterion for each tail; i.e., when a monthly value of $|L|$ is above 1.65 relative to the mean, the month is classified as having a jump; all others are classified as non-jump months.

After classifying each sample month as jump or non-jump for a every country, we then construct a 2X2 contingency table for each pair of countries, depicted below for countries i and j $N_{i,j}$ is the number of months in column i and row j and their sum is N, the total number of months with concurrent observations for countries i and j.

	Jump in j	No jump in j
Jump in i	$N_{1,1}$	$N_{2,1}$
No jump in i	$N_{1,2}$	$N_{2,2}$

If there is no connection between the jumps that occur in countries i and j, then the "expected" number of months in the top left cell is $E_{1,1} = (N_{1,1}+N_{1,2})(N_{1,1}+N_{2,1})/N$, the product of the marginals, and so on for each of the other cells. The Chi-square statistic is

$$\chi^2 = \sum_{i,j} \frac{(N_{i,j} - E_{i,j})^2}{E_{i,j}},$$

which has two degrees of freedom. Critical values rejecting the null hypothesis of no common jumps at the .05, .01, and .001 levels are, respectively, 5.99, 9.21, and 13.82.

Table 10 reports summary statistics for the full matrix of Chi-square statistics. The mean Chi-square value of 2.676 exceeds modestly its expected value of 2.0 under the null hypothesis

[9] The difference in maxima and minima could also be influenced by a positive mean return which to this point we have not expunged.

(no international correlation of jumps.) However, this excess is statistically significant provided that one believes that the entire ensemble of Chi-square values are independent of each other. The *T*-statistic for the difference between the global mean and 2.0 is 6.977 for the mean Chi-square.

There is also an indication in the last two columns of Table 10 that at least <u>some</u> countries have correlated jumps. In 11.50% of the bi-country comparisons, the Chi-square statistic is significant with a p-value of .05. For a p-value of .01, 6.534% of them are significant. These percentages exceed, though only modestly, what one would expect under the null hypothesis of no dependence between <u>any</u> two countries.

Table 11 gives country pairs that the LM measure indicates have the most interdependent jumps. It lists all pairs for which the Chi-square statistic from the jump/non-jump contingency table exceeds the .0001 level, which is 18.42. The computed Chi-square value is also given in the Table.

Table 11 should be compared with Table 8, which has a list of significantly dependent jump countries based on the BNS statistics. There are some differences. Very few of the pairs in Table 11 involve less developed countries. A significant majority involve countries in Europe with each other and with the U.S. There only a few cases that feature non-geographic neighbors: Jamaica and Lebanon, Mexico and New Zealand, Nigeria and Taiwan.

We also looked at the sample months that had the largest absolute de-meaned L statistic for each country to ascertain whether such extreme events occurred simultaneously in a number of countries. Only two months, January 1994 and December 2003, had the largest L statistic for four countries each. Ten other months had two countries each with the largest L. This is a total of 28 countries; hence, 82-28 = 54 countries had their largest L alone in a month that was not shared by any other country. This suggests that the most extreme jumps are relatively isolated and idiosyncratic events.

Overall, the LM jump measure is more or less in agreement with the BNS measure. There seems to be a small amount of cross-country dependence in jumps, but jumps are mainly idiosyncratic. One is tempted to speculate on the minor differences between BNS and LM. The results in Table 11 seem more intuitively plausible than some of those in Table 8. Does this suggest that LM is more reliable? Perhaps, but we are reluctant to take a more definite stand.

4.3. The Jiang and Oomen (2008) Statistic.

The log version of the Jiang and Oomen (2008) (hereafter JO), statistic is

$$\sigma_i J_{i,k} = Ln\frac{1}{T_k}\sum_{t=1}^{T_k}(R_{i,t,k}^{ar} - R_{i,t,k}^{\ln}) - Ln\frac{1}{T_k}\sum_{t=1}^{T_k}(R_{i,t,k}^{\ln})^2,$$

where the superscripts "ar" and "ln" denote, respectively, the arithmetic return (P_t/P_{t-1}-1) and the log return $\ln(P_t/P_{t-1})$ with P_t as the country index value at time t[10] and σ_i is the standard deviation of the expression on the right-hand side, which we assume is a constant over all periods for country i. JO prove that $J_{i,k}$ is asymptotically unit normal under the null hypothesis of no jumps during period k.

After computing the right-side expression for all available periods (months) for every pair of countries i and j, the time series correlations over k are computed between $\sigma_i J_{i,k}$ and $\sigma_j J_{j,k}$. These correlations are clearly unaffected by the unknown parameters σ_i and σ_j provided that they are constants, so this enables us to avoid errors that might be introduced by their estimation.

Table 12 provides summary statistics for the resulting correlations. This is something of a surprise because it contrasts with the previously reported co-movement of jumps detected by the BNS and LM statistics; (compare Tables 6 and 10.) For example, the BNS correlations reported in Table 6 display *T*-statistics in excess of 2.0 in around 6% of the cases, while Table 12 reports *T*-statistics that exceed 2.0 in more than 39% of the cases. The correlations based on the JO measure are also quite a bit larger on average, 0.134, and are more statistically significant. They are not as significant as correlations between returns but they are closer to returns than the jump correlations for the previous two measures.

A further indication that the JO measure detects jumps differently is provided in Table 13, which lists the most influential months according to JO. Table 13 can be compared to Table 3 for returns and Table 7 for the BNS jump measure. The JO measure picks out a few of the same months as the BNS measure as being most influential: e.g., November 1978, and January 1991 and 1994. But it also identifies October 1987 as the most influential jump month of all and October 2008 as next most; these are months having the largest influence on <u>return</u> correlations. It thus seems that the JO measure of jumps portrays them as more systematic, though not to the same extent as returns, and less idiosyncratic as compared to the BNS and LM measures. We are

[10]The i and k subscripts on P are suppressed for ease of exposition.

not sure why the measures differ in this respect. Perhaps JO are correct in arguing that their measure is more sensitive to jumps, but further research is needed to reach a definite conclusion.

Finally for the JO measure, Table 14 lists pairs of countries that are deemed to have the largest degree of jump correlation. Since the JO correlations are large, for space we limited the list in this table to correlations with measured *T*-statistics of at least 9.0. A striking feature of Table 14 is that every single country is developed. According the JO measure of jumps, extreme international correlations do not happen for developing countries. Also, many country pairs in Table 14 are European, as they were for the LM measure of extreme jump co-movements. But Australia, Hong Kong, Japan and Singapore also appear.

4.d. The Jacod and Todorov (2009) Statistics.

The two JT statistics explained in section 2.1 above, $\Phi^{(J)}$ for "joint" jumps and the $\Phi^{(D)}$ for "disjoint" jumps are calculated for daily data within months when two countries have at least ten valid daily log returns. This is repeated for each of the 3,321 pairs of countries. Critical levels for the two JT statistics are quite complex, but a rule of thumb implied in JT is that $\Phi^{(J)} > 1.85$ rejects the null hypothesis of no joint jumps and $\Phi^{(D)} > 0.5$ rejects the null hypothesis of no disjoint jumps. Summary information about the results test statistic values are reported in Table 15.

Panels A and B of Table 15 report summary information about the monthly averages of the two JT statistics computed for each pair of countries. The grand mean is the average over all months and country pairs.

The grand mean of $\Phi^{(J)}$ is 2.324, which exceeds the critical value of 1.85. The mean test statistic is right-skewed but Panel C of Table 15 shows nonetheless that on average (over country pairs) 47.29% of the individual monthly $\Phi^{(J)}$'s exceed the critical value. The maximum percentage of 87.5% indicates that one country pair has "joint" jumps this frequently while at the other extreme, one country pair has "joint" jumps in only 5.696% of the months. The prevalence of joint jumps indicated by the JT statistic far exceeds that found above with the other three competing statistics.

The "disjoint" jump statistic $\Phi^{(D)}$ is less significant on average. It's grand mean is 0.352, which is less than the critical value of 0.5 and only 23.62% of the months on average experience significant disjoint jumps (although one pair of countries has disjoint jumps in 91.11% of the months.) But even though disjoint jumps are less prevalent than joint jumps, they are still rather common, particularly when compared to the co-movements displayed by the competing jump measures, BNS, LM, and JO.

The JT statistics vary across sample months, of course, and it should be enlightening to record when they are particularly large historically. Table 16 provides this information by listing all months when at least one of the two JT statistics was the monthly maximum for at least one percent of the country pairs. The percentages listed in Table 16 relate the number of maximal pairs to the number of available pairs in that calendar month.

As the table shows, there are very few really dominant months according to the JT statistics, a pattern for which, like the other jump statistics already discussed, contrasts sharply with the pattern for returns. Recall that return correlations are dominated by the Octobers in 2008 and 1987. Neither appears in the JT dominant months of Table 16. For the JT "joint" statistic $\Phi^{(J)}$, only a couple of months are largest in even two percent of the country pairs. The JT "disjoint" statistic $\Phi^{(J)}$ exhibits more concentration with one month, August 1991, exceeding the ten percent level and a few others exceeding four percent.

Comparing Tables 15 and 16, the JT statistics seem to be significant quite often but extreme values are spread out across calendar time. Perhaps future research should examine whether the critical values used in Table 15 are sound. If these critical values are too small, then the JT statistics would agree quite well with the other jump measures in that jumps are uncommon and idiosyncratic in most cases.

Finally, Table 17 reports country pairs with extreme values of both JT jump statistics. For reasons of space, country pairs are excluded unless the JT statistics satisfy the joint condition: $\Phi^{(J)} > 2$ and $\Phi^{(J)} > 0.55$. As the table reveals, Europe again plays a dominant role. The vast bulk of country pairs are located on that continent. Some notable exceptions are geographic neighbors in other regions: Canada with the United States, Hong Kong with both Malaysia and Singapore, Namibia with South Africa. The results in Table 17 are pretty much in agreement with the other measures of jumps.

5. Conclusions.

The international correlation of stock price jumps (extreme returns) is very important for diversifying investors and government officials attempting to coordinate policies across borders. Using daily data for broad equity indexes from 82 countries, we examine several competing jump measures suggested in previous papers.

Returns are quite correlated internationally. Almost all the monthly return correlations are positive and roughly 80% are statistically significant at the 1% level; this is for 3,321 individual correlation coefficients computed from returns over 82 countries.

Jumps occur regularly in most countries but they are less internationally correlated than returns. According to some measures, international jump correlation is very weak and is statistically significant for only a few pairs of countries. This is true for the Barndorff-Nielsen and Shephard (2006) jump statistic and the Lee and Mykland (2008) statistic. The Jiang and Oomen (2009) statistic produces higher average international jump correlations and more pairs of countries with statistically significant jump co-movements. The Jacod and Todorov (2009) statistics also indicate more prevalent joint jumps. All measures agree, however, that jumps are mostly idiosyncratic, unlike returns, which are dominated by global systematic influences.

We document two other interesting features of jumps: first, we display particular calendar periods that contribute the most to international jump correlations. Perhaps surprisingly, these are not usually the same months that are most influential for return correlations, though again, there are some differences among the jump measures. Second, we provide information on particular pairs of countries that are most influenced by extreme jumps. Another surprise is that most such pairs involve the larger and more developed countries, particularly in Europe. Jump co-movement is uncommon among developing countries and among most non-European developed countries.

The bottom line is a bit of good news for investors. Although jumps are frequent in all countries and are probably hard to predict, they are not as correlated internationally as returns themselves. Returns seem to be more driven by global systematic influences while jumps are somewhat more idiosyncratic. Europe is the only region where diversification does not protect well against jumps.

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Table 1

Country Index Sample Periods and Index Identification

Eighty-Two countries have index data availability from DataStream, a division of Thomson Financial. Some countries have several indexes and the index chosen has the longest period of data availability. All index values are converted into a common currency, the US dollar. An index with the designation “RI” is a total return index (with reinvested dividends.) The designation “PI” denotes a pure price index. When calculating log returns from the indexes, neither the beginning nor the ending index value can be identical to its immediately preceding index value; (this eliminates holidays, which vary across countries, and days with obviously stale prices.)

Country	DataStream Availability		Index Identification	DataStream Mnemonic
	Begins	Ends		
Argentina	2-Aug-93	26-Oct-09	ARGENTINA MERVAL	ARGMERV(PI)~U$
Australia	1-Jan-73	26-Oct-09	AUSTRALIA-DS MARKET	TOTMAU$(RI)
Austria	1-Jan-73	26-Oct-09	AUSTRIA-DS Market	TOTMKOE(RI)~U$
Bahrain	31-Dec-99	26-Oct-09	DOW JONES BAHRAIN	DJBAHR$(PI)
Bangladesh	1-Jan-90	26-Oct-09	BANGLADESH SE ALL SHARE	BDTALSH(PI)~U$
Belgium	1-Jan-73	26-Oct-09	BELGIUM-DS Market	TOTMKBG(RI)~U$
Botswana	29-Dec-95	26-Oct-09	S&P/IFCF M BOTSWA0.	IFFMBOL(PI)~U$
Brazil	7-Apr-83	26-Oct-09	BRAZIL BOVESPA	BRBOVES(PI)~U$
Bulgaria	20-Oct-00	26-Oct-09	BSE SOFIX	BSSOFIX(PI)~U$
Canada	31-Dec-64	26-Oct-09	S&P/TSX COMPOSITE INDEX	TTOCOMP(RI)~U$
Chile	2-Jan-87	26-Oct-09	CHILE GENERAL (IGPA)	IGPAGEN(PI)~U$
China	3-Apr-91	26-Oct-09	SHENZHEN SE COMPOSITE	CHZCOMP(PI)~U$
Colombia	10-Mar-92	26-Oct-09	COLOMBIA-DS Market	TOTMKCB(RI)~U$
Côte d'Ivoire	29-Dec-95	26-Oct-09	S&P/IFCF M COTE D'IVOIRE	IFFMCIL(RI)~U$
Croatia	2-Jan-97	26-Oct-09	CROATIA CROBEX	CTCROBE(PI)~U$
Cyprus	3-Sep-04	26-Oct-09	CYPRUS GENERAL	CYPMAPM(PI)~U$
Czech Republic	9-Nov-93	26-Oct-09	CZECH REP.-DS NON-FINCIAL	TOTLICZ(RI)~U$
Denmark	31-Dec-69	26-Oct-09	MSCI DENMARK	MSDNMKL(RI)~U$
Ecuador	2-Aug-93	26-Oct-09	ECUADOR ECU (U$)	ECUECUI(PI)
Egypt	2-Jan-95	26-Oct-09	EGYPT HERMES FINANCIAL	EGHFINC(PI)~U$
Estonia	3-Jun-96	26-Oct-09	OMX TALLINN (OMXT)	ESTALSE(PI)~U$
Finland	2-Jan-91	26-Oct-09	OMX HELSINKI (OMXH)	HEXINDX(RI)~U$
France	1-Jan-73	26-Oct-09	FRANCE-DS Market	TOTMKFR(RI)~U$

Germany	31-Dec-64	26-Oct-09	DAX 30 PERFORMANCE	DAXINDX(RI)~U$
Ghana	29-Dec-95	26-Oct-09	S&P/IFCF M GHA0.	IFFMGHL(PI)~U$
Greece	26-Jan-06	26-Oct-09	ATHEX COMPOSITE	GRAGENL(RI)~U$
Hong Kong	2-Jan-90	26-Oct-09	HANG SENG	HNGKNGI(RI)~U$
Hungary	2-Jan-91	26-Oct-09	BUDAPEST (BUX)	BUXINDX(PI)~U$
Iceland	31-Dec-92	26-Oct-09	OMX ICELAND ALLSHARE	ICEXALL(PI)~U$
India	2-Jan-87	26-Oct-09	INDIA BSE (100) NATIONAL	IBOMBSE(PI)~U$
Indonesia	2-Apr-90	26-Oct-09	INDONESIA-DS Market	TOTMKID(RI)~U$
Ireland	1-Jan-73	26-Oct-09	IRELAND-DS MARKET	TOTMIR$(RI)
Israel	23-Apr-87	26-Oct-09	ISRAEL TA 100	ISTA100(PI)~U$
Italy	1-Jan-73	26-Oct-09	ITALY-DS MARKET	TOTMIT$(RI)
Jamaica	29-Dec-95	26-Oct-09	S&P/IFCF M JAMAICA	IFFMJAL(PI)~U$
Japan	1-Jan-73	26-Oct-09	TOPIX	TOKYOSE(RI)~U$
Jordan	21-Nov-88	26-Oct-09	AMMAN SE FINANCIAL MARKET	AMMANFM(PI)~U$
Kenya	11-Jan-90	26-Oct-09	KENYA NAIROBI SE	NSEINDX(PI)~U$
Kuwait	28-Dec-94	26-Oct-09	KUWAIT KIC GENERAL	KWKICGN(PI)~U$
Latvia	3-Jan-00	26-Oct-09	OMX RIGA (OMXR)	RIGSEIN(RI)~U$
Lebanon	31-Jan-00	26-Oct-09	S&P/IFCF M LEBANON	IFFMLEL(PI)~U$
Lithuania	31-Dec-99	26-Oct-09	OMX VILNIUS (OMXV)	LNVILSE(RI)~U$
Luxembourg	2-Jan-92	26-Oct-09	LUXEMBURG-DS MARKET	LXTOTMK(RI)~U$
Malaysia	2-Jan-80	26-Oct-09	KLCI COMPOSITE	KLPCOMP(PI)~U$
Malta	27-Dec-95	26-Oct-09	MALTA SE MSE -	MALTAIX(PI)~U$
Mauritius	29-Dec-95	26-Oct-09	S&P/IFCF M MAURITIUS	IFFMMAL(PI)~U$
Mexico	4-Jan-88	26-Oct-09	MEXICO IPC (BOLSA)	MXIPC35(PI)~U$
Morocco	31-Dec-87	26-Oct-09	MOROCCO SE CFG25	MDCFG25(PI)~U$
Namibia	31-Jan-00	26-Oct-09	S&P/IFCF M NAMBIA	IFFMNAL(PI)~U$
Netherlands	1-Jan-73	26-Oct-09	NETHERLAND-DS Market	TOTMKNL(RI)~U$
New Zealand	4-Jan-88	26-Oct-09	NEW ZEALAND-DS MARKET	TOTMNZ$(RI)
Nigeria	30-June-95	26-Oct-09	S&P/IFCG D NIGERIA	IFGDNGL(PI)~U$
Norway	2-Jan-80	26-Oct-09	NORWAY-DS MARKET	TOTMNW$(RI)
Oman	22-Oct-96	26-Oct-09	OMAN MUSCAT SECURITIES MKT.	OMANMSM(PI)~U$
Pakistan	30-Dec-88	26-Oct-09	KARACHI SE 100	PKSE100(PI)~U$
Peru	2-Jan-91	26-Oct-09	LIMA SE GENERAL(IGBL)	PEGENRL(PI)~U$
Philippines	2-Jan-86	26-Oct-09	PHILIPPINE SE I(PSEi)	PSECOMP(PI)~U$
Poland	16-Apr-91	26-Oct-09	WARSAW GENERALINDEX	POLWIGI(PI)~U$
Portugal	5-Jan-88	26-Oct-09	PORTUGAL PSI GENERAL	POPSIGN(PI)~U$
Romania	19-Sep-97	26-Oct-09	ROMANIA BET (L)	RMBETRL(PI)~U$
Russia	1-Sep-95	26-Oct-09	RUSSIA RTS INDEX	RSRTSIN(PI)~U$

Saudi Arabia	31-Dec-97	26-Oct-09	S&P/IFCG D SAUDI ARABIA	IFGDSB$(RI)
Singapore	1-Jan-73	26-Oct-09	SINGAPORE-DS MARKET EX TMT	TOTXTSG(RI)~U$
Slovakia	14-Sep-93	26-Oct-09	SLOVAKIA SAX 16	SXSAX16(PI)~U$
Slovenia	31-Dec-93	26-Oct-09	SLOVENIAN EXCH. STOCK (SBI)	SLOESBI(PI)~U$
South Africa	1-Jan-73	26-Oct-09	SOUTH AFRICA-DS MARKET	TOTMSA$(RI)
South Korea	31-Dec-74	26-Oct-09	KOREA SE COMPOSITE (KOSPI)	KORCOMP(PI)~U$
Spain	2-Jan-74	26-Oct-09	MADRID SE GENERAL	MADRIDI(PI)~U$
Sri Lanka	2-Jan-85	26-Oct-09	COLOMBO SE ALLSHARE	SRALLSH(PI)~U$
Sweden	28-Dec-79	26-Oct-09	OMX STOCKHOLM (OMXS)	SWSEALI(PI)~U$
Switzerland	1-Jan-73	26-Oct-09	SWITZ-DS Market	TOTMKSW(RI)~U$
Taiwan	31-Dec-84	26-Oct-09	TAIWAN SE WEIGHTED	TAIWGHT(PI)~U$
Thailand	2-Jan-87	26-Oct-09	THAILAND-DS MARKET	TOTMTH$(RI)
Trinidad	29-Dec-95	26-Oct-09	S&P/IFCF M TRINIDAD & TOBAGO	IFFMTTL(PI)~U$
Tunisia	31-Dec-97	26-Oct-09	TUNISIA TUNINDEX	TUTUNIN(PI)~U$
Turkey	4-Jan-88	26-Oct-09	ISE TIOL 100	TRKISTB(PI)~U$
Ukraine	30-Jan-98	26-Oct-09	S&P/IFCF M UKRAINE	IFFMURL(PI)~U$
Utd. Arab Emirates	1-Jun-05	26-Oct-09	MSCI UAE	MSUAEI$
United Kingdom	1-Jan-65	26-Oct-09	UK-DS MARKET	TOTMUK$(RI)
United States	4-Jan-88	26-Oct-09	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Venezuela	2-Jan-90	26-Oct-09	VENEZUELA-DS MARKET	TOTMVE$(RI)
Zimbabwe	6-Apr-88	6-Oct-06	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)

Table 2

Cross-country return correlations

Product moment correlation coefficients are computed from dollar-denominated monthly and semiannual returns for all pairs of 82 countries. There are 3,321 pairs. For monthly observations, 3,321 coefficients are computed but the Greece/Zimbabwe correlation is missing from the semiannual calculations. The summary statistics below are computed across all the available coefficients. Sigma is the cross-coefficient standard deviation. *T* is the *T*-statistic assuming cross-coefficient independence (and hence may not be reliable.) MAD is the mean absolute deviation. The last two columns give the percentage of all correlation coefficients whose individual *T*-statistic exceeds 2.0 and 3.0, respectively.[11] The data are extracted from DataStream, a division of Thomson Financial.

Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum	$T > 2$	$T > 3$
Panel A. Monthly returns, 3,321 correlation coefficients										
0.314	0.313	0.191	94.7	0.153	0.302	0.00546	0.935	-0.238	78.0%	63.9%
Panel B. Semiannual returns, 3,320 correlation coefficients										
0.436	0.439	0.233	108.	0.188	-0.166	-0.157	0.989	-0.420	61.5%	27.8%

[11] The individual correlation coefficient is assumed to have a standard error equal to $1/(\text{Sample Size})^{1/2}$.

Table 3

The most influential periods for inter-country return correlations

An influential observation is defined here as the single calendar period that contributes the most to return correlations among each pair of countries. Periods with less than one percent of the most influential observations are omitted for reasons of space. The raw data are extracted from DataStream, a division of Thomson Financial.

	Number of Influential Observations	Number of Available Country Pairs	Percentage of Influential Observations
Month/Year	Monthly Returns		
January/1975	8	136	5.88%
October/1987	64	378	16.9%
December/1993	44	1431	3.07%
January/1994	33	1485	2.22%
August/1998	239	2628	9.09%
January/2006	40	3240	1.23%
September/2008	62	3240	1.91%
October/2008	2457	3240	75.8%
February/2009	34	3240	1.05%
Semester/Year	Semiannual Returns		
2/1985	3	253	1.19%
1/1986	3	276	1.08%
2/1993	67	1378	4.86%
1/1994	23	1485	1.55%
2/1997	76	2415	3.14%
1/1998	36	2628	1.37%
2/2006	38	3321	1.14%
2/2008	2822	3240	87.1%

Table 4

Summary statistics for the Barndorff-Nielsen/Shephard (2006) G jump measure, monthly

The jump measures described in Section 2.1 of the text are computed from daily observations within available calendar months for each of 82 countries. The summary statistics below are computed from the resulting time series of computed jump measures. N is the sample size in months. Sigma is the time-series standard deviation. *T* is the *T*-statistic assuming time-series independence. MAD is the mean absolute deviation. Daily stock index data are extracted from DataStream, a division of Thomson Financial.

Country	N	Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum
Argentina	195	-0.357	-0.097	0.917	-5.432	0.495	-5.413	42.48	0.335	-9.09
Australia	442	-0.128	-0.027	0.466	-5.771	0.284	-4.286	30.16	0.389	-4.71
Austria	442	-0.292	-0.061	0.900	-6.827	0.441	-8.117	99.77	0.350	-13.20
Bahrain	118	-0.562	-0.170	1.035	-5.897	0.707	-2.670	9.24	0.348	-6.11
Bangladesh	235	-8.539	-0.364	42.28	-3.096	14.36	-6.490	44.00	0.471	-385.5
Belgium	442	-0.139	-0.018	0.437	-6.695	0.299	-2.642	11.16	0.384	-3.21
Botswana	165	-4.883	-0.724	10.38	-6.042	6.309	-4.074	23.43	0.318	-86.57
Brazil	319	-2.115	-0.094	16.30	-2.317	3.556	-12.86	179.3	0.352	-250.0
Bulgaria	108	-0.251	-0.042	0.585	-4.464	0.413	-2.481	9.15	0.310	-3.59
Canada	458	-17.80	-0.265	72.73	-5.239	27.85	-7.662	68.97	0.335	-851.8
Chile	274	-0.168	0.006	0.852	-3.262	0.348	-9.095	103.2	0.345	-11.01
China	223	-0.303	-0.079	0.848	-5.328	0.471	-4.915	34.52	0.379	-8.09
Colombia	212	-0.342	-0.002	2.163	-2.301	0.586	-11.53	146.3	0.322	-29.08
Côte d'Ivoire	66	-6.829	-1.228	15.42	-5.705	8.538	-4.575	27.11	0.290	-130.4
Croatia	154	-0.267	-0.081	0.622	-5.317	0.409	-3.383	18.59	0.376	-4.83
Cyprus	62	-0.195	-0.069	0.414	-3.697	0.309	-1.441	2.07	0.330	-1.57
Czech Republic	192	-0.348	-0.022	1.574	-3.062	0.561	-9.203	98.04	0.382	-18.68
Denmark	458	-6.590	-0.920	33.04	-4.268	8.746	-15.87	289.8	0.303	-636.8
Ecuador	173	-1.534	-0.506	3.316	-6.085	1.848	-4.069	20.29	0.311	-25.41
Egypt	178	-0.241	-0.078	0.651	-4.933	0.386	-4.670	32.86	0.324	-5.90
Estonia	161	-0.228	-0.068	0.787	-3.679	0.355	-7.461	70.94	0.359	-8.39
Finland	226	-0.125	-0.012	0.419	-4.465	0.287	-2.519	9.62	0.386	-2.79
France	442	-0.130	-0.030	0.385	-7.108	0.274	-2.066	6.02	0.381	-2.51

Germany	538	-0.102	-0.007	0.413	-5.723	0.254	-4.448	37.22	0.342	-4.88
Ghana	164	-14.80	-1.635	40.05	-4.734	20.88	-4.160	18.71	0.275	-266.9
Greece	45	-0.230	-0.077	0.463	-3.326	0.374	-0.956	-0.19	0.337	-1.35
Hong Kong	238	-0.368	-0.184	0.681	-8.330	0.421	-3.845	21.88	0.311	-5.75
Hungary	226	-0.195	-0.013	0.697	-4.197	0.364	-7.038	71.29	0.376	-8.06
Iceland	202	-0.219	-0.100	0.519	-5.990	0.343	-2.584	9.25	0.366	-3.23
India	274	-0.356	-0.065	0.853	-6.919	0.531	-3.409	16.30	0.389	-6.75
Indonesia	235	-0.142	-0.035	0.408	-5.355	0.299	-2.260	9.57	0.382	-2.92
Ireland	442	-0.227	-0.077	0.500	-9.557	0.352	-2.237	6.82	0.395	-3.25
Israel	270	-0.198	-0.049	0.507	-6.430	0.324	-4.865	42.75	0.407	-5.47
Italy	442	-0.110	-0.014	0.355	-6.513	0.244	-2.941	15.75	0.352	-3.10
Jamaica	126	-97.98	-5.227	204.3	-5.382	130.3	-2.730	7.06	0.333	-987.1
Japan	442	-0.197	-0.091	0.427	-9.689	0.302	-2.199	7.29	0.337	-2.85
Jordan	251	-1.515	-0.445	3.717	-6.457	1.789	-5.690	40.95	0.389	-36.46
Kenya	238	-0.491	-0.099	1.584	-4.782	0.712	-5.447	33.34	0.380	-12.85
Kuwait	178	-0.851	-0.133	5.675	-2.000	1.255	-12.34	156.4	0.698	-74.39
Latvia	118	-0.178	-0.040	0.471	-4.097	0.333	-2.461	9.66	0.340	-2.97
Lebanon	41	-139.1	-38.920	202.8	-4.392	146.6	-1.713	1.82	0.270	-698.9
Lithuania	118	-0.215	-0.053	0.670	-3.487	0.371	-4.215	22.02	0.366	-4.61
Luxembourg	214	-0.237	-0.102	0.436	-7.959	0.325	-1.896	6.14	0.343	-2.89
Malaysia	358	-0.312	-0.050	2.150	-2.745	0.500	-16.15	281.6	0.375	-38.67
Malta	166	-0.301	-0.142	0.834	-4.654	0.423	-5.661	42.72	0.372	-7.85
Mauritius	160	-50.15	-5.770	122.1	-5.197	65.84	-4.174	19.12	0.226	-785.4
Mexico	262	-0.161	-0.061	0.393	-6.620	0.279	-2.212	8.26	0.336	-2.79
Morocco	262	-0.374	-0.055	1.587	-3.811	0.575	-11.13	149.5	0.379	-22.75
Namibia	117	-1.036	-0.274	2.519	-4.447	1.277	-5.061	29.25	0.377	-18.74
Netherlands	442	-0.112	-0.003	0.373	-6.307	0.265	-2.004	4.81	0.349	-1.83
New Zealand	262	-0.158	-0.044	0.404	-6.320	0.297	-2.032	6.61	0.332	-2.66
Nigeria	172	-0.260	0.056	1.345	-2.536	0.526	-9.065	97.63	0.367	-15.64
Norway	358	-0.137	-0.001	0.443	-5.861	0.290	-3.150	14.62	0.358	-3.27
Oman	156	-6.301	-0.748	19.60	-4.015	8.839	-6.370	48.14	0.873	-183.1
Pakistan	250	-0.293	-0.066	0.662	-6.998	0.446	-3.124	15.28	0.359	-5.05

Peru	226	-0.148	-0.017	0.448	-4.973	0.308	-3.059	16.80	0.314	-3.67
Philippines	286	-0.188	-0.038	0.551	-5.767	0.330	-4.275	28.26	0.343	-5.22
Poland	223	-0.520	-0.115	1.924	-4.035	0.727	-9.114	101.4	0.355	-24.05
Portugal	262	-0.132	0.000	0.497	-4.305	0.296	-4.650	32.17	0.339	-4.34
Romania	145	-0.081	0.042	0.486	-2.003	0.270	-4.764	30.32	0.344	-3.91
Russia	170	-0.094	-0.019	0.357	-3.447	0.251	-2.343	10.14	0.395	-2.41
Saudi Arabia	142	-2.830	-0.707	6.060	-5.565	3.402	-3.441	11.95	0.290	-34.27
Singapore	442	-0.137	-0.029	0.449	-6.425	0.283	-4.293	34.16	0.344	-4.97
Slovakia	194	-0.498	-0.192	1.014	-6.845	0.587	-3.876	18.99	0.378	-7.73
Slovenia	190	-0.101	0.031	0.397	-3.491	0.276	-2.487	9.15	0.441	-2.55
South Africa	442	-0.143	-0.043	0.460	-6.547	0.276	-6.076	68.70	0.332	-6.20
South Korea	418	-0.331	-0.139	0.713	-9.492	0.433	-3.836	21.10	0.341	-6.45
Spain	430	-0.259	-0.044	0.973	-5.524	0.423	-10.46	152.9	0.325	-15.81
Sri Lanka	298	-0.201	0.028	0.952	-3.654	0.428	-9.516	123.7	0.374	-13.42
Sweden	358	-2.152	-0.111	10.95	-3.719	3.460	-10.824	134.7	0.372	-156.9
Switzerland	442	-0.154	-0.033	0.516	-6.255	0.299	-5.146	40.26	0.361	-5.17
Taiwan	298	-0.315	-0.175	0.505	-10.75	0.367	-1.959	5.91	0.349	-3.47
Thailand	274	-0.272	-0.117	0.572	-7.871	0.386	-2.668	10.26	0.409	-3.97
Trinidad	133	-43.83	-2.512	115.0	-4.393	63.29	-3.835	16.18	0.501	-761.8
Tunisia	142	-0.146	-0.024	0.425	-4.096	0.291	-2.237	6.31	0.329	-2.26
Turkey	262	-0.164	-0.015	0.541	-4.895	0.336	-4.855	41.40	0.360	-5.71
Ukraine	129	-121.7	-17.03	221.7	-6.235	156.4	-2.243	4.31	0.373	-985.6
U. Arab Emirates	53	-0.790	-0.510	1.150	-5.003	0.649	-3.447	12.85	0.268	-6.12
United Kingdom	538	-11.05	-0.027	44.41	-5.770	19.99	-5.415	34.80	0.373	-448.8
United States	262	-0.254	-0.113	0.523	-7.860	0.335	-3.647	22.34	0.379	-4.71
Venezuela	238	-1.129	-0.133	8.217	-2.119	1.694	-12.05	153.7	0.306	-113.8
Zimbabwe	164	-0.197	0.040	1.152	-2.191	0.459	-8.975	95.74	0.361	-13.16

Table 5

Country averages of summary statistics for the Barndorff-Nielsen/Shephard (2006) jump measures

The jump measures described in Section 2.1 of the text are computed from daily observations within available calendar months and semiannual periods for each of 82 countries. Summary statistics are computed from the resulting country time series of jump measures and are then averaged over countries. N is the average sample size in months. Sigma is the average time-series standard deviation. *T* is the average *T*-statistic assuming time-series independence. MAD is the average mean absolute deviation. Observations with absolute values greater than 1,000 are deleted. Daily stock index data are extracted from DataStream, a division of Thomson Financial.

N	Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum
G Measure (Difference), Monthly									
252.1	-6.799	-0.994	15.19	-5.232	8.781	-5.177	47.16	0.364	-102.1
H Measure (Ratio), Monthly									
253.3	-0.718	-0.222	2.416	-5.418	0.981	-2.369	15.43	0.482	-23.39
G Measure (Difference), Semiannual									
42.9	-6.093	-2.518	10.976	-3.398	6.879	-2.261	7.512	0.110	-44.31
H Measure (Ratio), Semiannual									
42.9	-0.755	-0.368	1.432	-3.743	0.828	-1.450	3.676	0.127	-6.282

Table 6

Cross-country correlations of BNS jump measures

Product moment correlation coefficients are computed across countries for the Barndorff-Nielsen and Shephard (2006) (BNS) jump measures based on squared variation versus bipower variation differences and ratios, the G and H measures, respectively. G and H are calculated both monthly and semiannually. There are 3,321 pairs of countries. For monthly observations, 3,321 coefficients are computed but the Greece/Zimbabwe correlation is missing from the semiannual calculations. The summary statistics below are computed across all the available correlation coefficients. Sigma is the cross-coefficient standard deviation. *T* is the *T*-statistic assuming cross-coefficient independence (and hence may not be reliable.) MAD is the mean absolute deviation. The last column gives the percentage of all correlation coefficients whose individual *T*-statistic exceeds 2.0.[12] The data are extracted from DataStream, a division of Thomson Financial.

Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum	$T > 2$
G Measure (Difference), Monthly									
0.0126	0.0009	0.0926	7.85	0.0681	0.996	3.455	0.598	-0.358	6.38%
H Measure (Ratio), Monthly									
0.0164	0.0117	0.0924	10.21	0.0698	0.191	1.635	0.558	-0.413	6.17%
G Measure (Difference), Semiannual									
0.0258	0.0049	0.2211	6.73	0.1693	0.534	0.979	0.884	-0.843	6.72%
H Measure (Ratio), Semiannual									
0.0211	0.0131	0.2198	5.52	0.1702	0.212	0.708	0.847	-0.827	5.36%

[12] The individual correlation coefficient is assumed to have a standard error equal to $1/(\text{Sample Size})^{1/2}$.

Table 7

Influential periods for inter-country correlations of jumps

An influential observation is defined here as the single calendar period that contributes the most to the correlation of jumps between countries. The Barndorff-Nielsen and Shephard (2006) measures are calculated for each period and then correlated over time for all available pairs of countries. For each listed period, the table contains the percentage of country pairs for which that period was the single most influential contributor to the estimated jump correlation. To save space, periods are excluded if there are fewer than 100 available pairs of countries or have less than two percent of the most influential observations for both the G and H jump measures. The raw data are extracted from DataStream, a division of Thomson Financial.

	G Measure (Difference)	H Measure (Ratio)
Month/Year	Monthly Jumps	
October/1973	3.810%	3.810%
December/1974	2.500%	2.500%
April/1975	2.941%	2.206%
November/1978	8.824%	11.77%
May/1980	2.632%	3.684%
February/1983	4.211%	2.632%
November/1983	6.667%	4.286%
January/1991	6.554%	4.546%
January/1994	2.155%	2.492%
March/2009	2.161%	2.006%
Semester/Year	Semiannual Jumps	
1/1973	21.91%	21.91%
1/1974	7.500%	5.833%
1/1988	7.308%	6.417%
1/1991	11.11%	10.82%
1/1994	6.061%	5.724%
2/2000	6.524%	7.563%
1/2002	7.359%	6.760%
1/2006	7.377%	7.136%

Table 8

Country pairs with large jump correlations

The Barndorff-Nielsen and Shephard (2006) measures are calculated for each period and then correlated over time for all available pairs of countries. The pairs of countries listed here exhibit jump measure correlations with *T*-statistics of at least 3.0 for both the G and H measures. The raw data are extracted from DataStream, a division of Thomson Financial.

Monthly Jumps	
Belgium	France
Belgium	Ireland
Belgium	Netherlands
Belgium	Switzerland
Brazil	Lithuania
Canada	Sweden
Estonia	Israel
Finland	Romania
France	Germany
France	Hungary
France	Italy
France	Netherlands
France	United Kingdom
Germany	Hungary
Germany	Italy
Germany	Netherlands
Hong Kong	Norway
Hungary	Norway
Israel	Switzerland
Kenya	Oman
Netherlands	Poland
Netherlands	Switzerland
Netherlands	United Kingdom
Portugal	Switzerland
Romania	Sweden
Slovenia	Tunisia
South Korea	Sweden

Semiannual Jumps	
Argentina	Bangladesh
Argentina	Kuwait
Austria	Spain
Bangladesh	Kuwait
Belgium	Netherlands
Belgium	Switzerland
Canada	Sweden
Chile	India
China	Czech Republic
China	Jordan
Czech Republic	Jordan
Denmark	Nigeria
Denmark	Sweden
Ecuador	Philippines
Finland	Ukraine
France	Portugal
Germany	Netherlands
Germany	Switzerland
Ghana	Luxembourg
Ghana	Mauritius
Hungary	Poland
Hungary	Spain
Indonesia	Morocco
Kenya	Oman
Kuwait	Oman
Kuwait	Romania
Kuwait	Sweden
Malta	Nigeria
Netherlands	Switzerland

Table 9

Higher moment summary statistics for the Lee and Mykland (2008)
***L* statistic jump measure, monthly**

The LM jump measure described in Section 2.2 of the text is computed from daily observations within available calendar months for each of 82 countries. The summary statistics below are computed from the resulting monthly time series of computed *L* jump measures. N is the sample size in months. Sigma is the time-series standard deviation. MAD is the mean absolute deviation. Daily stock index data are extracted from DataStream, a division of Thomson Financial.

Country	N	Sigma	Skewness	Kurtosis	Maximum	Minimum
Argentina	195	1.208	0.030	-0.243	3.351	-3.077
Australia	442	1.206	-0.111	-0.108	4.191	-3.783
Austria	442	1.282	-0.187	-0.118	3.629	-4.178
Bahrain	118	1.503	0.200	-0.385	4.521	-2.603
Bangladesh	236	1.831	-1.082	5.344	6.098	-9.161
Belgium	442	1.151	-0.043	-0.361	3.232	-3.163
Botswana	166	2.194	3.615	29.11	19.13	-5.509
Brazil	319	1.612	-2.471	20.33	4.780	-14.52
Bulgaria	108	1.304	-0.178	-0.671	3.129	-2.429
Canada	458	2.566	-0.286	3.371	10.68	-10.88
Chile	274	1.352	-0.039	-0.581	3.339	-3.592
China	223	1.209	0.000	-0.562	3.598	-2.816
Colombia	212	1.506	-0.415	-0.369	3.240	-4.536
Côte d’Ivoire	66	2.020	0.324	0.368	6.383	-5.542
Croatia	154	1.183	-0.107	-0.691	2.630	-2.399
Cyprus	62	1.240	-0.098	-0.582	3.332	-2.408
Czech Republic	192	1.326	-0.115	-0.058	4.418	-3.259
Denmark	458	1.956	3.029	32.40	22.18	-4.874
Ecuador	174	1.562	0.449	1.337	5.825	-5.697
Egypt	178	1.453	-0.057	-0.644	3.607	-3.202
Estonia	161	1.324	-0.010	-0.762	3.033	-2.389
Finland	226	1.145	0.142	-0.153	3.438	-2.615
France	442	1.146	-0.102	-0.447	2.979	-2.915
Germany	538	1.107	-0.062	-0.405	3.123	-2.650
Ghana	166	15.72	12.31	153.0	200.1	-8.410
Greece	45	1.078	-0.328	-0.411	2.648	-2.204
Hong Kong	238	1.134	0.029	-0.726	3.072	-2.073
Hungary	226	1.170	-0.154	-0.540	2.938	-2.653
Iceland	202	1.326	-0.005	-0.767	3.359	-2.539
India	274	1.248	0.230	-0.731	3.394	-2.351
Indonesia	235	1.247	0.074	-0.683	3.345	-2.588
Ireland	442	1.270	-0.179	-0.295	3.732	-3.862

Israel	270	1.080	-0.030	-0.225	3.195	-2.741
Italy	442	1.151	0.194	-0.497	3.851	-2.392
Jamaica	159	23.45	-2.281	20.19	118.3	-148.8
Japan	442	1.176	0.100	-0.317	3.830	-2.930
Jordan	251	1.406	0.357	0.052	4.231	-3.259
Kenya	238	1.540	-0.036	-0.427	3.546	-4.108
Kuwait	178	1.477	-1.693	10.58	3.748	-9.709
Latvia	118	1.195	-0.135	-0.264	3.059	-2.455
Lebanon	49	9.590	0.214	0.802	27.77	-23.08
Lithuania	118	1.416	-0.014	-0.589	3.276	-3.108
Luxembourg	214	1.087	-0.099	0.203	3.211	-2.765
Malaysia	358	1.306	0.019	-0.908	3.094	-2.725
Malta	166	1.327	-0.067	-0.636	3.447	-3.062
Mauritius	165	8.164	2.056	15.03	47.01	-35.87
Mexico	262	1.161	-0.128	-0.638	2.935	-2.705
Morocco	262	1.211	-0.074	0.240	4.483	-3.411
Namibia	117	1.380	-0.017	0.162	3.869	-3.785
Netherlands	442	1.052	-0.136	-0.312	3.067	-2.357
New Zealand	262	1.140	0.047	-0.457	3.181	-2.806
Nigeria	172	1.559	-0.220	-0.440	3.727	-4.114
Norway	358	1.192	-0.032	-0.421	3.470	-3.346
Oman	156	1.935	-0.326	-0.464	3.948	-5.337
Pakistan	250	1.392	0.297	-0.002	4.300	-3.636
Peru	226	1.359	-0.096	-0.690	3.195	-2.854
Philippines	286	1.210	-0.026	-0.322	3.013	-3.097
Poland	223	1.362	0.191	-0.252	4.605	-3.270
Portugal	262	1.260	-0.096	-0.517	3.133	-2.915
Romania	145	1.228	-0.070	-0.431	3.216	-3.126
Russia	170	1.236	-0.130	-0.924	2.928	-2.343
Saudi Arabia	142	1.569	-0.030	-0.695	4.125	-3.047
Singapore	442	1.250	-0.092	-0.632	3.020	-3.162
Slovakia	194	1.268	-0.169	0.366	3.148	-4.361
Slovenia	190	1.237	-0.006	-0.461	3.040	-3.255
South Africa	442	1.181	-0.151	-0.494	3.031	-3.024
South Korea	418	1.113	0.186	-0.561	3.267	-2.777
Spain	430	1.287	-0.093	-0.232	3.468	-4.006
Sri Lanka	298	1.440	-0.154	-0.560	3.273	-3.732
Sweden	358	1.401	0.439	1.356	7.472	-3.150
Switzerland	442	1.129	-0.217	-0.216	2.938	-3.189
Taiwan	298	1.291	0.190	-0.615	3.733	-3.027
Thailand	274	1.267	0.040	-0.459	3.509	-2.881
Trinidad	166	34.79	5.375	40.60	323.1	-74.01
Tunisia	142	1.274	-0.022	-0.444	3.200	-3.226
Turkey	262	1.207	-0.065	-0.414	2.958	-3.654
Ukraine	141	10.62	-0.326	10.08	44.928	-60.20

U. Arab Emirates	53	1.482	0.571	-0.104	4.359	-2.504
United Kingdom	538	2.234	1.875	12.39	14.164	-10.65
United States	262	0.988	0.054	-0.481	2.741	-1.961
Venezuela	238	1.355	-0.106	0.117	4.024	-4.597
Zimbabwe	164	1.724	-0.374	-0.902	3.614	-3.043

Table 10

Cross-country dependence of LM jump measures

Chi-square statistics with two degrees of freedom are computed from two-by-two contingency tables tabulated for the Lee and Mykland (2008) (LM) jump measure, *L*. For each of 82 countries, the LM *L* statistic is computed from daily data for each calendar month and then the month is classified as a jump month if the absolute value of the *L* statistic exceeds the 10% level for a unit normal (1.65). Otherwise, the month is classified as a non-jump month. For each pair of countries, the contingency table is based on the jump/non-jump cross-classification. There are 3,321 pairs of countries. The summary statistics below are computed across all the available contingency table Chi-square statistics. Under the null hypothesis of no cross-country dependence in jumps, the Chi-square statistic has an expected value of 2.0. Sigma is the standard deviation. *T* is the *T*-statistic against the null expected mean of 2.0 assuming independence across the contingency tables. MAD is the mean absolute deviation. The last two columns give the percentage of all Chi-square values that are significant at the .05 and .01 levels respectively. The data are extracted from DataStream, a division of Thomson Financial.

Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum	p = .05	p = .01
2.676	0.852	5.585	6.977	2.967	5.551	45.53	87.78	0.000	11.50	6.534

Table 11
Country pairs with large jump co-dependence

Chi-square statistics with two degrees of freedom are computed from two-by-two contingency tables tabulated for the Lee and Mykland (2008) (LM) jump measure, *L*. For each of 82 countries, the LM *L* statistic is computed from daily data for each calendar month and then the month is classified as a jump month if the absolute value of the *L* statistic exceeds the 10% level for a unit normal (1.65). Otherwise, the month is classified as a non-jump month. For each pair of countries, the contingency table is based on the jump/non-jump cross-classification. There are 3,321 pairs of countries. The country pairs below have contingency table Chi-square values in excess of the .0001 significance level under the null hypothesis of no common jumps. The computed Chi-square value is in the right-most column. The raw data are extracted from DataStream, a division of Thomson Financial.

Australia	Canada	21.02
Australia	New Zealand	29.24
Australia	Singapore	18.66
Austria	Belgium	46.04
Austria	France	22.79
Austria	Luxembourg	22.17
Austria	Switzerland	41.28
Belgium	France	43.21
Belgium	Germany	27.23
Belgium	Ireland	48.33
Belgium	Italy	24.86
Belgium	Netherlands	48.81
Belgium	Norway	18.76
Belgium	Spain	24.07
Belgium	Switzerland	52.99
Canada	United Kingdom	19.28
Denmark	France	21.16
Denmark	Portugal	24.06
Denmark	United Kingdom	20.00
Finland	Ireland	22.70
Finland	Netherlands	18.89
Finland	Sweden	24.99
Finland	Switzerland	24.08
France	Germany	47.47
France	Ireland	47.84
France	Italy	23.11
France	Netherlands	39.91
France	Portugal	31.53
France	Spain	20.26
France	Switzerland	36.52
France	United Kingdom	29.17

Germany	Ireland	33.84
Germany	Israel	21.79
Germany	Italy	27.23
Germany	Netherlands	62.87
Germany	New Zealand	21.29
Germany	Sweden	18.63
Germany	Switzerland	37.18
Germany	United States	26.30
Greece	Netherlands	20.89
Greece	Singapore	20.35
Hungary	Poland	24.19
Ireland	Italy	25.21
Ireland	Netherlands	62.19
Ireland	Norway	39.87
Ireland	Spain	25.74
Ireland	Sweden	36.37
Ireland	Switzerland	24.19
Ireland	United Kingdom	87.78
Italy	Netherlands	33.87
Italy	Portugal	22.30
Italy	Sweden	22.58
Italy	United Kingdom	20.62
Jamaica	Lebanon	19.21
Malaysia	Singapore	51.06
Mexico	New Zealand	21.21
Netherlands	Norway	20.25
Netherlands	Spain	27.02
Netherlands	Sweden	23.54
Netherlands	Switzerland	50.73
Netherlands	United Kingdom	52.06
Netherlands	United States	44.44
New Zealand	Sweden	21.27
Nigeria	Taiwan	22.26
Norway	Spain	27.91
Norway	Sweden	22.79
Norway	United Kingdom	19.72
Portugal	Spain	24.88
Portugal	Switzerland	19.49
Spain	Switzerland	22.08
Sweden	Switzerland	38.63
Sweden	United Kingdom	21.07
Sweden	United States	24.42
Switzerland	United Kingdom	21.77
Switzerland	United States	26.30
United Kingdom	United States	44.61

Table 12

Cross-country correlations of JO jump measures

Product moment correlation coefficients are computed across countries for the Jiang and Oomen (2008) log version of the "swap variation" jump measure computed monthly from daily observations within the month. There are 3,321 pairs of countries. The summary statistics below are computed across all the correlation coefficients. Sigma is the cross-coefficient standard deviation. *T* is the *T*-statistic assuming cross-coefficient independence (and hence may not be reliable.) MAD is the mean absolute deviation. The last column gives the percentage of all correlation coefficients whose individual *T*-statistic exceeds 2.0.[13] The data are extracted from DataStream, a division of Thomson Financial.

Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum	$T > 2$
0.134	0.116	0.143	54.1	0.112	0.616	0.689	0.712	-0.491	39.14

[13] The individual correlation coefficient is assumed to have a standard error equal to $1/(\text{Sample Size})^{1/2}$.

Table 13

Influential periods for inter-country correlations of jumps using the JO measure

An influential observation is defined here as the single calendar period that contributes the most to the correlation of jumps between countries. The Jiang and Oomen (2008) measure is calculated for each month and then correlated over time for all pairs of countries. For each listed month, the table contains the percentage of country pairs for which that period was the single most influential contributor to the estimated jump correlation. To save space, periods are excluded if there are fewer than 100 available pairs of countries or have less than two percent of the most influential observations. The raw data are extracted from DataStream, a division of Thomson Financial.

November/1973	2.857
January/1975	2.206
November/1978	2.206
March/1980	3.158
October/1987	55.03
October/1988	4.100
October/1989	5.397
January/1991	2.643
August/1991	5.990
January/1994	3.838
October/1997	6.832
August/1998	8.562
September/2001	3.520
October/2008	13.89
November/2008	2.284
May/2009	2.191

Table 14

Country pairs with extremely large jump correlations according to the JO measure

The Jiang and Oomen (2008) measures are calculated for each month and then correlated over month for all pairs of countries. The pairs here exhibit JO jump measure correlations with *T*-statistics of at least 9.0. Computed jump correlations are in the right-most column. The raw data are extracted from DataStream, a division of Thomson Financial.

Australia	Ireland	0.473
Australia	New Zealand	0.586
Australia	Norway	0.565
Australia	Singapore	0.484
Australia	Switzerland	0.453
Australia	United Kingdom	0.525
Austria	Belgium	0.458
Austria	France	0.463
Austria	Germany	0.533
Austria	Netherlands	0.480
Austria	Switzerland	0.475
Belgium	France	0.507
Belgium	Germany	0.521
Belgium	Ireland	0.477
Belgium	Netherlands	0.630
Belgium	Norway	0.507
Belgium	Switzerland	0.585
Belgium	United Kingdom	0.481
France	Germany	0.624
France	Italy	0.478
France	Netherlands	0.582
France	Norway	0.485
France	Switzerland	0.563
France	United Kingdom	0.469
Germany	Italy	0.461
Germany	Netherlands	0.629
Germany	Norway	0.501
Germany	Switzerland	0.617
Hong Kong	Singapore	0.658
Ireland	Netherlands	0.458
Ireland	Singapore	0.437
Ireland	Switzerland	0.446
Ireland	United Kingdom	0.572
Japan	Netherlands	0.446
Netherlands	Norway	0.577
Netherlands	Switzerland	0.589
Netherlands	United Kingdom	0.498

Norway	Singapore	0.491
Norway	Switzerland	0.567
Norway	United Kingdom	0.567
Portugal	Spain	0.581
Singapore	Switzerland	0.455
Singapore	United Kingdom	0.502
Switzerland	United Kingdom	0.503

Table 15

Summary information for the JT jump test statistics computed for country pairs

The Jacod and Todorov (2009) (JT) jump statistics described in section 2.4 are computed monthly for all pairs of 82 countries. The two JT statistics are $\Phi^{(J)}$ for "joint" jumps, (which occur on the same day within the month) and $\Phi^{(D)}$ for "disjoint" jumps, (for jumps that occur in both countries within the same month but on different days.) There are 3,321 pairs of countries. Critical values rejecting the null hypotheses are approximately 1.85 for "joint" jumps and 0.5 for "disjoint" jumps. Panels A and B report summary statistics for the average values of $\Phi^{(J)}$ and $\Phi^{(D)}$ over all available months; i.e., the test statistics are first averaged across months and then the summary statistics are computed for the averages. Panels C and D report summary statistics over country pairs for the percentage of JT test statistics exceeding their critical values in the available months for each pair. Mean is the grand mean across all months and country pairs. Sigma is the cross-test statistic standard deviation. *T* is the *T*-statistic assuming cross-test statistic independence (and hence may not be reliable.) MAD is the mean absolute deviation. The data are extracted from DataStream, a division of Thomson Financial.

Mean	Median	Sigma	*T*	MAD	Skewness	Kurtosis	Maximum	Minimum
Panel A: $\Phi^{(J)}$ for "joint" jumps, averaged over months								
2.324	2.291	0.367	365.0	0.242	3.420	58.35	9.793	0.647
Panel B: $\Phi^{(D)}$ for "disjoint" jumps, averaged over months								
0.352	0.347	0.086	235.8	0.064	0.611	1.612	0.768	0.138
Panel C: Percentage of monthly $\Phi^{(J)}$'s exceeding the critical value of 1.85								
47.29	47.79	8.519	319.9	6.48	-0.538	1.834	87.5	5.696
Panel D: Percentage of monthly $\Phi^{(D)}$'s exceeding the critical value of 0.50								
23.62	20.76	12.25	111.1	9.06	1.548	3.248	91.11	2.041

Table 16

Influential periods for JT jump statistics

An influential observation is defined here as the single calendar period that had the largest value for one of the two Jacod and Todorov (2009) (JT) test statistics. For each listed period, the table contains the percentage of country pairs for which that period had the largest computed statistic. To save space, a period is excluded if neither JT statistic is largest for at least one percent of the country pairs. The raw data are extracted from DataStream, a division of Thomson Financial.

	$\Phi^{(j)}$ "joint" jumps	$\Phi^{(D)}$ "disjoint" jumps
October/1989	0.000%	8.889%
January/1991	1.480%	3.383%
August/1991	0.290%	10.92%
October/1997	1.781%	6.211%
January/1998	0.939%	1.174%
April/2000	0.410%	1.333%
February/2002	1.164%	0.377%
August/2002	1.034%	0.334%
January/2004	1.504%	0.535%
July/2004	1.365%	0.433%
May/2005	1.006%	0.162%
March/2006	1.356%	0.572%
June/2006	0.681%	1.795%
November/2006	1.734%	0.248%
February/2007	3.830%	4.382%
March/2007	0.402%	2.412%
July/2007	2.690%	2.120%
August/2007	0.316%	1.519%
September/2007	1.266%	2.025%
January/2008	0.158%	2.437%
February/2008	1.019%	0.741%
April/2008	1.203%	0.570%
September/2008	1.481%	6.080%
November/2008	0.216%	1.265%
August/2009	0.185%	2.623%

Table 17

Country pairs with extreme average values of the JT jump statistics

The Jacod and Todorov (2009) measures discussed in section 2.4 are calculated using daily data within each month and then averaged over months. The country pairs here exhibit large average values for both JT jump statistics, mean $\Phi^{(j)} > 2$ and mean $\Phi^{(D)} > 0.55$. The observed average values are in the rightmost two columns. The raw data are extracted from DataStream, a division of Thomson Financial.

Country Pair		Mean $\Phi^{(j)}$ "joint" jumps	Mean $\Phi^{(D)}$ "disjoint" jumps
Australia	Greece	2.207	0.552
Austria	Greece	2.001	0.677
Austria	Portugal	2.139	0.564
Belgium	Finland	2.155	0.551
Belgium	France	2.163	0.568
Belgium	Greece	2.414	0.641
Belgium	Portugal	2.053	0.578
Belgium	Switzerland	2.008	0.572
Canada	United States	2.048	0.593
Cyprus	Greece	2.297	0.679
Czech Republic	Greece	2.128	0.582
Denmark	Greece	2.087	0.614
Finland	France	2.064	0.622
Finland	Greece	2.170	0.616
Finland	Italy	2.074	0.556
Finland	Spain	2.091	0.570
Finland	Sweden	2.047	0.641
Finland	Switzerland	2.008	0.571
France	Greece	2.125	0.653
France	Italy	2.075	0.562
France	Spain	2.166	0.580
France	Sweden	2.020	0.560
France	Switzerland	2.064	0.592
France	United Kingdom	2.121	0.589
Germany	Greece	2.252	0.613
Germany	Italy	2.043	0.555
Germany	Spain	2.021	0.561
Greece	Hungary	2.148	0.595
Greece	Ireland	2.079	0.617
Greece	Italy	2.111	0.662
Greece	Netherlands	2.299	0.656
Greece	Norway	2.189	0.620
Greece	Russia	2.198	0.582
Greece	South Africa	2.130	0.610

Greece	Spain	2.196	0.641
Greece	Sweden	2.105	0.641
Greece	Switzerland	2.028	0.631
Greece	Turkey	2.093	0.572
Greece	United Kingdom	2.054	0.611
Hong Kong	Singapore	2.106	0.566
Italy	Spain	2.257	0.554
Luxembourg	Malta	2.060	0.581
Luxembourg	Tunisia	2.143	0.592
Malaysia	Singapore	2.380	0.564
Namibia	South Africa	2.015	0.553
Netherlands	United Kingdom	2.028	0.624
Portugal	Spain	2.097	0.568
Switzerland	United Kingdom	2.046	0.551