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. Eraker et al. (2003) find that the jumps command larger risk premiums than continuous returns. Das and Uppal (2004) examine the portfolio choice problem of an international investor when returns are categorized by jumps, leading to systemic risks. Using monthly return data for a few developed markets, they measure diversification benefits and the home bias. They do not consider a large number of markets and do not apply the jump technology in this paper. Asgharian and Bengtsson (2006) find significant jumps in large markets that lead to jumps in other markets. They conclude that markets in the same region and with similar industry structures tend to experience jump contagion. Jumps might be more prominent in emerging market returns where skewness and kurtosis are widely documented (Bekaert, et al. (1998a, b).

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

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

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.

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 is 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.

With discretely sampled returns, tests for jumps are effectively tests for the presence of unusually large returns (in absolute value). It remains to be seen whether jump tests have adequate power when the smooth variation in returns follows a leptokurtic distribution.

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,…,K between $G_{i,k}$ and $G_{j,k}$.

In previous papers, Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007) adopt the BNS method and develop a Z statistic for jumps using tri-power quarticity. The latter paper also develops a "staggered" version of bi-power variation to tackle microstructure noise that induces autocorrelation in the high-frequency returns. Zhang, Zhou, and Zhu (2009) use the BNS method to identify jump risk of individual firms from high-frequency equity prices in order to explain credit default swap premiums.

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

[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.

with data preceding a particular return observation being tested for a jump and the resulting test statistic is $L = R_{i,t+1,k}/\sqrt{B_{i,k}}$. 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.

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

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

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

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 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 attenuate outliers.

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 common 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

[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.

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. The problem of non-synchronicity is inconsequential in this study because we aggregate daily returns to longer periods of at least a month and sometimes a half-year.

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 overlapping day.

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

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 both 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

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

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 $[K/\lambda]$. 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

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

JT derive asymptotic properties for both statistics. When there are joint jumps, $\Phi^{(J)}$ converges to a Gaussian with mean 1.0 and variance given by their equation 4.1, (p. 1800.) When there are only joint jumps, $\Phi^{(D)}$ also converges to 1.0, and it generally converges to a positive value when there are both joint and disjoint jumps. When there are uniquely disjoint jumps, $\Phi^{(D)}$ converges to zero and $\Phi^{(J)}$ converges to 2.0. If there are no jumps at all, $\Phi^{(D)}$ should also converge to zero, so a test of $\Phi^{(D)}$ against a null hypothesis of zero (and perhaps $\Phi^{(J)}$ against a null hypothesis of 2.0) should be rejected when jumps are joint and thus not idiosyncratic.

2.5. Other tests we do not employ.

While JT tests for cojumps in a pair of returns based on higher order power variation, Gobbi and Mancini (2006, 2008) propose a strategy to separate the covariation between the diffusive and jump components in a pair of returns. Using a related method, Bollerslev, Law, and Tauchen (2008) do not test for cojumps between a particular pair of returns, but rather in the cojumps embodied in a large ensemble of returns.

Aït-Sahalia and Jacod (2009) and Tauchen and Zhou (2010) propose nonparametric tests for presence of price jumps based on high-frequency data. Also, more recently, Aït-Sahalia, Cacho-Diaz, and Laeven (2010) model asset return dynamics with a drift component, a volatility component and mutually exciting jumps known as Hawkes processes. They use this approach to capture adverse mutual shocks to stock markets, with a jump in one region of the world propagating a different jump in another region of the world.

Of course, this paper would be unacceptably lengthy if every existing jump test were thoroughly examined. Hence, we simply selected four tests that seem promising and are relatively easy to implement. We also develop and implement a set of simulations that help assess the relative merits of these tests and could be used in the same way to examine any of the tests just mentioned above. All of the above tests above probably deserve to be studied further in future research.

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). The appendix 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 1, 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 2 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 2 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. The results are available upon request.

Recall from section 2.1 that the BNS measures are asymptotically unit normal under the null hypothesis of no jumps. Our results reveal 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 3 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

[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.

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 4 provides summary statistics from these four different estimates of international jump correlations.

The international correlations of jump measure reported in Table 4 stand in stark contrast with the return correlations reported earlier in Table 1. 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 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 1 reports have *T*'s exceeding 2.0 in 60% to 80% of the cases.

This conclusion is further supported by Table 5, which gives influential months and semesters for the correlations among jump measures. Unlike the influential periods for returns (Table 2), 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 5 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 5.

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 6 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 randomness 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 6.

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

[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.

jumps seem unlikely, we focus now on the second and higher order moments of the resulting *L* statistic.

Due to limited space, these results for each of our 82 countries are not reported but are available upon request. 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, 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 for most countries and sometimes is truly enormous, such as 22.18 for Denmark or 200.1 for Ghana. 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. 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.

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

	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 7 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 (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 7 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 8 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 8 should be compared with Table 6, 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 8 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 8 seem more intuitively plausible than some of those in Table 6. 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 9 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

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

in Table 4 display *T*-statistics in excess of 2.0 in around 6% of the cases, while Table 9 reports *T*-statistics that exceed 2.0 in more than 39% of the cases. The correlations base on the JO measure are also quite a bit larger on average, 0.134, and 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 10, which lists the most influential months according to JO. Table 10 can be compared to Table 2 for returns and Table 5 for the BNS jump measure. The JO measure picks out a few of the same months as the BNS measure as being most influential: 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 return 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 not sure why these 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 11 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 measure *T*-statistics of at least 9.0. A striking feature of Table 11 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 11 are European, as they were for the LM measure of extreme jump co-movements. But Australia, Hong Kong, Japan and Singapore also appear.

4.4. 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. When there are joint jumps, $\Phi^{(J)}$ converges asymptotically to 1.0 in large samples. When there are only disjoint jumps, $\Phi^{(D)}$ converges to zero and $\Phi^{(J)}$ converges to 2.0. Critical levels for the two JT statistics are quite complex and depend on the sample size; for our sample size of approximately

21 trading days per month, $\Phi^{(D)} > 0.5$ rejects the null hypothesis of uniquely disjoint jumps while $\Phi^{(J)} > 1.5$ rejects the null hypothesis of joint jumps.[11]

One difficulty in applying the JT test involves its assumption that there are indeed jumps, either joint or disjoint. JT (2009) recommend using one of the other statistics such as BNS to first purge periods when no jumps occur; then the JT tests can be applied to the remaining periods. We did not follow this recommendation here for the simple reason that jumps seem so ubiquitous according to the other statistics.

Averaged over all months and country pairs, the mean value of $\Phi^{(J)}$ is 2.324 and the t-statistic is 207 relative to its asymptotic value of 1.0 (assuming independence across pairs.) Hence, on average, the JT $\Phi^{(J)}$ statistic is a long and significant distance away from its asymptotic value of 1.0 when there are joint jumps. However, only 56.9 percent of the country pairs reject the null hypothesis of joint jumps, which means that 43.1 percent do not.

The mean value of $\Phi^{(D)}$ is 0.352 with a t-statistic of 235, which rejects, on average, the hypothesis of uniquely disjoint jumps; but only 23.6 percent of the country pairs reject the proposition that there are uniquely disjoint jumps, which means that 72.4 percent do not.

These results suggest that more than half of all country pairs have disjoint jumps and are thus strictly idiosyncratic. In fewer than half of the country pairs, jumps are both joint and disjoint. In other words, jumps are often disjoint but there is a non-negligible chance that joint jumps occur at least occasionally for some country pairs.

In agreement with the other statistics, the JT tests suggest that international jumps are frequent. They are strictly idiosyncratic in more than half the country pairs but they do occur jointly on occasion. According to the JT tests, jumps are unique to a majority but not to all individual national markets. This is essentially in agreement with the earlier results.

There is also essential agreement with respect to both the most influential months in the sample on the JT statistics and on the pairs of countries that exhibit the largest average values. No month stands out as being overwhelmingly influential in terms of contributing to the largest values of $\Phi^{(D)}$. The single most prominent month is September 2008, but it was largest for only 197 out of 3281 pairs of countries. This was followed in order of prominence by October 1997, February 2007, and August 1991.

[11] These critical values are supposed to be for a 5% significance level. They are admittedly somewhat questionable so we shall subject them to simulation tests in section 5 below.

There are 45 pairs of countries whose average $\Phi^{(D)}$ exceeds 0.6 and the majority (28) are European. Greece alone figures in 18 pairs.

5. The Efficacy of Jump Measures for Detecting Correlated Jumps.

In the preceding section, the four jump measures display some conflicting results. Among other issues, JO seems to detect more correlated jumps than BNS and LM while JT exhibits some rather non-intuitive behavior. None of the four jump measures were designed originally for the purpose they are employed in this paper, to detect the extent of correlated jumps; consequently, they need not be equally adept in our application.

To gain some insight about the underlying reasons for the empirical differences uncovered in section 4, we undertake in this section a set of simulations for which the true nature of correlated jumps are known between two hypothetical countries. We generate artificial return data that has both a smooth Gaussian variation, including non-zero smooth correlation between the two bivariate return series, appended by artificial jumps of various sizes, frequencies, and co-movement across the two hypothetical countries. Using these artificial data, we study the efficacy of the four jump measures in detecting correlated jumps.[12]

Without loss of generality, the bivariate smooth Gaussian process has mean zero and unit variance for both series plus a pre-specified correlation. Since the average correlation in the monthly international return data is 0.314 (see Table 1, Panel A), we take this as an upper bound because it is also influenced by jumps and not just by smooth variation. In the simulations, we use a value in this general neighborhood, 0.3, and also two smaller values, 0.15 and zero.

The simulated jumps are also Gaussian with mean zero but their intensity is modeled by specifying their standard deviation as a multiple (such as 5 or 15) of the underlying smooth series, whose standard deviations are both 1.0. Also, jumps arrive randomly with particular but rather small frequencies. For example, with a daily frequency probability of .02 and 21 trading days per month, the probability of a jump occurring on some day during the month is .42. The jump frequencies are studied over a range from very unlikely to very likely during each month. These frequencies are applied independently to both simulated return series.

Conditional on a jump arriving in either series on a given day, there is also a specified co-probability that the same jump will be transmitted to the other series. This co-probability is a

[12] We use the G variant of the BNS test and the $\Phi^{(D)}$ for "disjoint" jumps variant of the JT test.

key parameter, because it specifies jump co-movement, the object of our study. In the simulations, we allow it to vary from zero (no common jumps) to .999 (almost completely common jumps.) Note that the two simulated series can also have common jumps during the same month simply because of random arrivals, even though the jumps are not really common. The co-probability simply increases their natural commonality.

In summary, there are four parameters that vary across simulations: (1) smooth correlation, (2) jump intensity, (3) jump frequency, and (4) jump co-probability. Other parameters are held constant: the mean and volatility of the bivariate smooth returns, the type I error (5%), and the number of replications for each parameter combination (1,000). The 5% type I error implies a different critical level for each of the jump measures, as was explained in sections 3 and 4. We experimented with different replication numbers but they all deliver essentially the same results.

Each simulation produces an entire probability distribution of the test statistic for correlated jumps, but these numbers are too voluminous to report in their entirety. Instead, we report only a single indication of effectiveness, the test power. When the jump co-probability is positive in the simulated returns, (and hence there are genuinely correlated jumps), the test power is the fraction of replications that reject the false null hypothesis of no jump co-movement. In the special case when the co-probability is actually zero, and hence jumps are only randomly common in the two simulated return series, the test power is the fraction of replications that falsely reject the true null hypothesis of no jump co-movement.

As a base case, we first look at the computed test power when the jump frequency is zero for both simulated return series. Since jumps cannot occur, they cannot be common across the two series. Nonetheless, we compute test power in this case, which is essentially the probability of falsely rejecting the true null hypothesis that there are no correlated jumps. The results are plotted in Figure 1. When the smooth variation correlation is zero, the BNS, LM, and JO tests provide appropriate results: i.e., at a 5% type I rejection level, they reject (wrongly) in the vicinity of five percent of the time. The JT test never rejects wrongly; (it is plotted in Figure 1 but has a value of zero and thus does not appear as a bar.)

As the smooth correlation increases, going from zero in the left panel to .15 in the center panel and then to .30 in the right panel, the BNS and LM tests increase the incorrect rejection frequency slightly; they are behaving relatively well. However, the JO test does not share this desirable attribute; it incorrectly rejects about 40% of the time for the mid-range correlation of 0.15 and almost 90% of the time at the high end, a correlation of 0.3. Jiang and Oomen (JO) assert in their paper that their test is very sensitive to even small jumps. Evidently, it is detecting "jumps" in even smooth Gaussian variation, at least in our application of their test where we first estimate the JO measure and then correlate the measures over time between the two simulated countries. Even a seemingly small amount of smooth correlation seems to compromise the JO test, leading to an incorrect inference that there are common jumps. There is correlation here, but not jump co-movement. To retain the originality of the JO test, we do not use the simulation results to alter the critical values in the earlier empirical part of the paper. This could have been done and probably should be done if the JO test is used in for a similar purpose in the future.

The JT test never rejects wrongly, even five percent of the time; hence, it actually has too few rejections.

With true co-movements in jumps, Table 12 reports some representative simulation results. The table covers all four jump measures, BNS, LM, JO, and JT, and two values of the smooth variation correlation (zero and .15), two values of jump intensity, (5 and 15), two values of jump frequency (.01 and .03), and three values of the co-probability of jumps, (.3, .6, and .9.) We actually produced simulation results for a variety of other parameter values, but those in Table 12 provide a reasonable picture of the overall results.[13]

First notice that BNS seems to provide reasonably reliable results overall. Its test power is higher with more intense jumps and with a higher level of jump co-movement between the two simulated series. This is what one would hope to obtain in a test procedure. It is interesting though, that test power seems to be lower when jumps are more frequent. At first, this might seem surprising but on further reflection, it seems sensible for the following reason: really frequent jumps are more or less akin to smooth variation but simply with a higher volatility. The daily jump frequencies in Table 12 are .01 and .03, which imply monthly jump probabilities of at least .21 and .63, respectively. With a monthly probability of around .6, it is highly likely that at least one of the two simulated return series will have a jump in a given month and this is transferred to the other series with the specified co-probability. Evidently, the commonality that is easiest to detect, at least by the BNS method, involves rather rare jumps.

[13] The complete set of results for all parameter values will be provided to interested readers.

In comparison to BNS, the LM test provides relatively weak power. Indeed, for jump intensity five times the smooth variation volatility, the power is virtually negligible. It improves for a jump intensity of 15, but mainly when the co-probability is quite high. Even then, the best power rarely exceeds 50%. To be fair though, we applied the LM test after having first utilized a non-parametric contingency table of its values; (see section 4.) This non-parametric approach was adopted to avoid contamination by the smooth correlation, but it seems to have weakened power quite a bit. Nonetheless, the LM approach seems to have the appropriate pattern; it simply requires highly intense and highly correlated jumps to have much power.

The JO test has more power than the LM test at all levels of intensity, frequency, and co-probability. However, it seems to have less power than BNS throughout. Moreover, unlike BNS and LM, it tends to detect jumps that do not exist (Figure 1.)

The last panel of Table 12 reports the results for the JT test. For the higher jump intensity of 15 and the highest co-probability of jump transmission (.9), the JT measure achieves 100% power, the best of any of the four jump measures we examine in this paper. However, for a lower intensity of 5, its power is negligible unless the co-probability is very high. Also, unlike the other tests, JT does better when the jump frequency is higher, ceteris paribus. The power of the JT test is zero for lower co-probability, which may be worrying as the power should be at least equal to the size of the test. We examined this curiosity by perturbing the critical values, thinking that they might be sensitive to small sample sizes, but the JT test statistic values in the simulations were so small that even much lower critical values failed to produce any differences.

These results and comparisons are further illustrated in Figures 2-4. Figure 2 shows test power for the four jump measures and high jump intensity across three levels of smooth correlation. BNS has the highest power overall. The test powers of BNS, LM and JO do not change much when the smooth correlation goes from zero to 0.3; (the latter value is in the same general vicinity as the average smooth correlation in the international index returns.) However, JT's power increases dramatically, from around 10% to over 70%. In simulations, Jacod and Todorov (2009, section 6) also find that power is affected by the level of smooth correlation, though the effect appears to be less dramatic than in our application here.

Figure 3 depicts the influence of jump intensity. Again, BNS has good power throughout. Its power exceeds 60% even at low levels of intensity (5) and it grows to 80% at an intensity of 10. Both LM and JO exhibit strongly increasing power with growing intensity and

JO has the higher of these two at all levels but neither reaches the power of BNS. JT's power is outstanding and the best of all measures at higher jump intensities (10 and 15) but has only about 10% power at an intensity of 5.

Finally, Figure 4 plots the power for each of the four jump measures against jump frequency and jump co-movement probability. BNS, LM and JO have the pattern one would expect, very low probability of incorrectly rejecting a true null hypothesis (when the co-movement probability is zero) and increasing power against a false null hypothesis as the co-movement probability increases from 0.3 through 0.999. However, when there is truly some jump co-movement, BNS has higher power than LM and JO throughout; (the latter are similar.) Notice too that power is generally better for rare jumps, when the frequency is lower, for BNS, LM and JO. The pattern for JT is quite different. It has virtually no power until the co-movement probability reaches 0.6 but it has the best power of all when this probability is .9 and above. Another contrast is that JT's power is (slightly) better for higher jump frequencies.

The bottom line from these simulations turns out to be fairly clear-cut. BNS, the Barndorff-Nielsen and Shephard jump measure, seems preferable overall for the explicit purpose we have here, estimating the co-movement of jumps across international markets. It performs well when there are no correlated jumps and it has acceptable power when there are many such jumps. Although the LM and JO measures display a similar pattern, they have weaker power when there are actually jumps. Moreover, JO (but not LM) incorrectly indicates the presence of correlated jumps when there are actually none. JT has outstanding power at very high levels of jump co-movement but performs poorly at lower levels.

6. A Simple Validity Check.

To this point, our basic inference from the empirical results is that jumps, though common in all countries, are mostly idiosyncratic and not very related across countries. This suggests that any well-diversified portfolio should exhibit fewer jumps than any single country considered alone.[14] This can be readily checked by constructing a globally diversified portfolio and estimating the prevalence of jumps by using one of the measures studied above. Previously, Bollerslev, Law, and Tauchen (2008), using the BNS measure, and Lee and Mykland (2008)

[14] We are grateful to Hanno Lustig for suggesting this idea.

document more frequent and larger sized jumps for the individual stocks as compared to an index.

We take the simplest possible approach by first constructing an equal-weighted global portfolio from the available daily returns of the 82 countries listed in Table 1. Thus, the constructed index is a simple average of the countries already investigated and covers the same time period. Since the previous section's simulations suggested that the BNS jump measure has relatively sound properties, we adopt it for this validity check.

Table 13 presents the results. The first panel is copied from Table 3 and simply provides summary statistics for individual countries. The second panel reports on the BNS G jump measure for the global equal-weighted portfolio. The difference is indeed striking and completely supports the notion that jumps are largely diversifiable. Notice that the mean value of individual country BNS G measures is -6.799 while the equal-weighted index' mean measure is only -0.276. (Recall that large negative values of the BNS G measure reject the null hypothesis of no jumps.)

Other comparisons in Table 13 also support the same inference. For example, the index has much smaller standard deviation across months, only 0.787 versus 15.19 for countries on average. The minimum monthly value for the index is -9.527 as compared to -102.1 for countries.

Although the index displays much smaller jump measures, the average jump measure is still significantly negative. The T-value for the sample mean is even larger than for individual countries, -8.127 versus -5.232. This can be attributed to the index having more available observations than countries have on average and also to the much smaller variance of the index' jump measure across months. The bottom line here is that jumps are largely diversified away but not completely. Evidently, country jumps are mostly, but not entirely, idiosyncratic.

7. Conclusions.

The extent of international correlation is very important for diversifying investors and government officials attempting to coordinate policies across borders. In this paper, we examine daily data for broad equity indexes from 82 countries and adopt several competing jump measures suggested in previous papers.

Returns are quite correlated internationally. Almost all the monthly return correlations are positive and almost 80% are statistically significant at the 1% level; this is for 3,321 individual correlation coefficients computed with returns from 82 countries. But jumps are less correlated. For some of the jump measures, the correlation is very weak and is statistically significant in only a few pairs of countries. This is true for the Barndorff-Nielsen and Shephard (BNS) (2006) jump statistic and the Lee and Mykland (LM) (2008) statistic. The Jiang and Oomen (JO) (2009) statistic, however, produces higher average international jump correlations and more pairs of countries with statistically significant jump co-movements.

Our simulations in section 5 partly explain this observed empirical pattern. BNS performs very well in the sense that it does not indicate the presence of correlated jumps when there are actually none and it has good power to reject a false null hypothesis of no correlated jumps. LM provides similar results, albeit with weaker power, perhaps because we employ a non-parametric variant of the statistic in this application. JO detects correlated jumps when there are none in the simulated data, so we think it may overstate the presence and significance of jump co-movements. JT performs well when jumps are quite highly correlated.

In the paper, we also 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 pairs involve the larger and more developed countries. Jump co-movement is uncommon among developing countries.

We suggest some possibilities that explain these observed patterns in jumps but cannot at this point provide a complete explanation. This would require the identification of the various underlying causes of jumps. At this point, the lack of international correlation among jumps suggests they are mostly caused by local influences such as political events and not by common global factors such as energy prices.

In term of asset allocation, jumps are more correlated among European neighbors, which suggests that international diversification is less effective in that region.

Lastly, our approach can be readily adapted to ascertain whether jumps are entirely contemporaneous or whether they have a lead/lag relation on occasion. This interesting issue is left for future research.

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.

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Table 1

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.[15] 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	0.006	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%

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

Table 2

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 3

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 4

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.[16] 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%

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

Table 5

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

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 6

Country pairs with large jump correlations according to the BNS measure

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 7

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 8

Country pairs with large jump co-dependence according to the LM measure

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 9

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.[17] 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

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

Table 10

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 11

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 12

Selected results from simulations to check the power of four different jump measures for detecting correlated jumps.

The jump measures are those derived by Barndorff-Nielsen and Shephard [2006] (BNS), Lee and Mykland [2008] (LM), Jiang and Oomen [2008] (JO), and Jacod and Todorov [2009] (JT). Simulated bivariate returns have two components, a smooth Gaussian variation with unit variance (for both bivariate returns) and a specified smooth correlation plus a Gaussian jump component with specified frequency, intensity, and co-movement probability, "Co-Prob." Jump intensity is in multiple units of the smooth variation volatility.

Smooth correlation = 0.				Smooth Correlation = 0.15			
Jump Intensity	Jump Frequency	Jump Co-Prob	Test Power	Jump Intensity	Jump Frequency	Jump Co-Prob	Test Power
BNS							
5	0.01	0.3	27.9	5	0.01	0.3	29.6
5	0.03	0.3	26.6	5	0.03	0.3	26.1
5	0.01	0.6	52.4	5	0.01	0.6	55.1
5	0.03	0.6	43.5	5	0.03	0.6	42.8
5	0.01	0.9	65.9	5	0.01	0.9	69.5
5	0.03	0.9	57.2	5	0.03	0.9	52.8
15	0.01	0.3	44.9	15	0.01	0.3	43.9
15	0.03	0.3	29.1	15	0.03	0.3	29.7
15	0.01	0.6	76.1	15	0.01	0.6	77.9
15	0.03	0.6	49.7	15	0.03	0.6	47.8
15	0.01	0.9	89.9	15	0.01	0.9	90.0
15	0.03	0.9	74.1	15	0.03	0.9	73.2
LM							
5	0.01	0.3	1.5	5	0.01	0.3	2.9
5	0.03	0.3	1.2	5	0.03	0.3	3.0
5	0.01	0.6	1.9	5	0.01	0.6	2.6
5	0.03	0.6	2.8	5	0.03	0.6	2.8
5	0.01	0.9	2.6	5	0.01	0.9	3.5
5	0.03	0.9	2.8	5	0.03	0.9	2.8
15	0.01	0.3	9.4	15	0.01	0.3	12.3
15	0.03	0.3	5.9	15	0.03	0.3	6.6
15	0.01	0.6	30.0	15	0.01	0.6	33.8
15	0.03	0.6	28.6	15	0.03	0.6	16.7
15	0.01	0.9	55.0	15	0.01	0.9	58.3
15	0.03	0.9	33.4	15	0.03	0.9	36.1
JO							
5	0.01	0.3	19.7	5	0.01	0.3	22.9
5	0.03	0.3	19.4	5	0.03	0.3	19.7
5	0.01	0.6	25.6	5	0.01	0.6	28.4

5	0.03	0.6	26.0	5	0.03	0.6	26.2
5	0.01	0.9	34.6	5	0.01	0.9	36.4
5	0.03	0.9	28.0	5	0.03	0.9	28.8
15	0.01	0.3	33.4	15	0.01	0.3	33.6
15	0.03	0.3	26.0	15	0.03	0.3	28.9
15	0.01	0.6	49.3	15	0.01	0.6	50.4
15	0.03	0.6	51.4	15	0.03	0.6	51.9
15	0.01	0.9	66.6	15	0.01	0.9	66.3
15	0.03	0.9	62.5	15	0.03	0.9	61.3
JT							
5	0.01	0.3	0.0	5	0.01	0.3	0.0
5	0.03	0.3	0.0	5	0.03	0.3	0.0
5	0.01	0.6	0.0	5	0.01	0.6	0.0
5	0.03	0.6	0.0	5	0.03	0.6	0.0
5	0.01	0.9	0.0	5	0.01	0.9	0.0
5	0.03	0.9	41.9	5	0.03	0.9	54.9
15	0.01	0.3	0.0	15	0.01	0.3	0.0
15	0.03	0.3	0.0	15	0.03	0.3	0.0
15	0.01	0.6	0.2	15	0.01	0.6	1.0
15	0.03	0.6	45.1	15	0.03	0.6	44.1
15	0.01	0.9	44.9	15	0.01	0.9	60.7
15	0.03	0.9	100.0	15	0.03	0.9	100.0

Table 13

Barndorff-Nielsen/Shephard (2006) G jump measures, Country Averages vs. Equal-Weighted Global Index

The jump measures described in Section 2.1 of the text are computed from daily observations within available calendar month for each of 82 countries and also for an equal-weighted index of all countries. Summary statistics are computed from the resulting time series of jump measures. N is the average sample size in months for individual countries and the number of months for the equal-weighted index. 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, Individual Countries (from Table 3)									
252.1	-6.799	-0.994	15.19	-5.232	8.781	-5.177	47.16	0.364	-102.1
G Measure (Difference), Monthly, Equal-Weighted Global Index									
538	-0.276	-0.0895	0.787	-8.127	0.416	-5.815	49.82	0.411	-9.527

Figure 1

The probability of rejecting a true null hypothesis that there are no jumps in either of two simulated return series. The two return series both have a smooth unit Gaussian variation and a specified level of correlation. The underlying jump measures are those derived by Barndorff-Nielsen and Shephard [2006] (BNS), Lee and Mykland [2008] (LM), Jiang and Oomen [2008] (JO), and Jacod and Todorov [2009] (JT). The type I rejection level is 5%. Simulations have 1,000 replications.

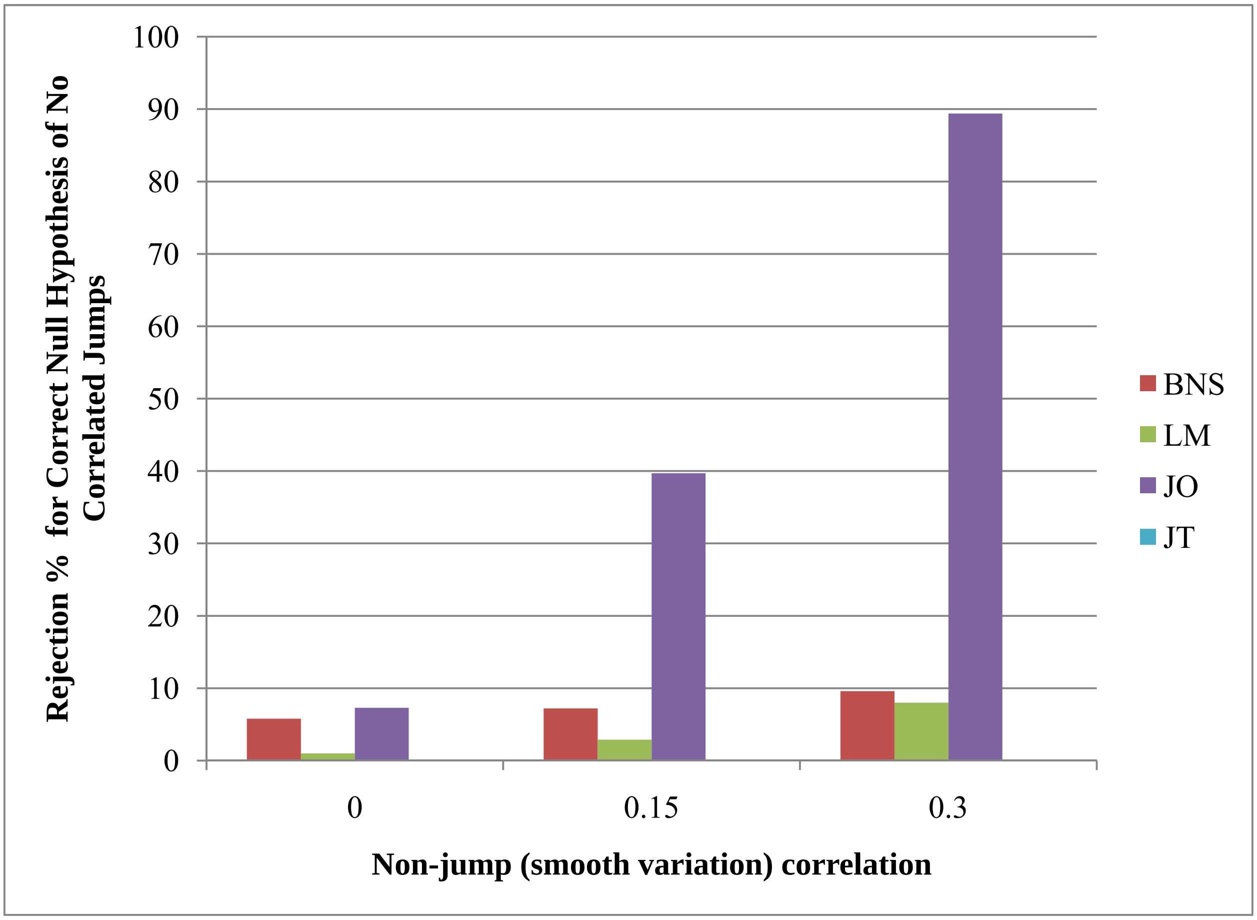


Figure 2

Smooth Correlation and Test Power Against a False Null Hypothesis of No Jump Co-Movement for Jump Intensity = 15, Jump Frequency = .02, and Jump Co-Probability = 0.9. The two return series both have a smooth unit Gaussian variation and a specified level of correlation. The underlying jump measures are those derived by Barndorff-Nielsen and Shephard [2006] (BNS), Lee and Mykland [2008] (LM), Jiang and Oomen [2008] (JO), and Jacod and Todorov [2009] (JT). The type I rejection level is 5%. Simulations have 1,000 replications.

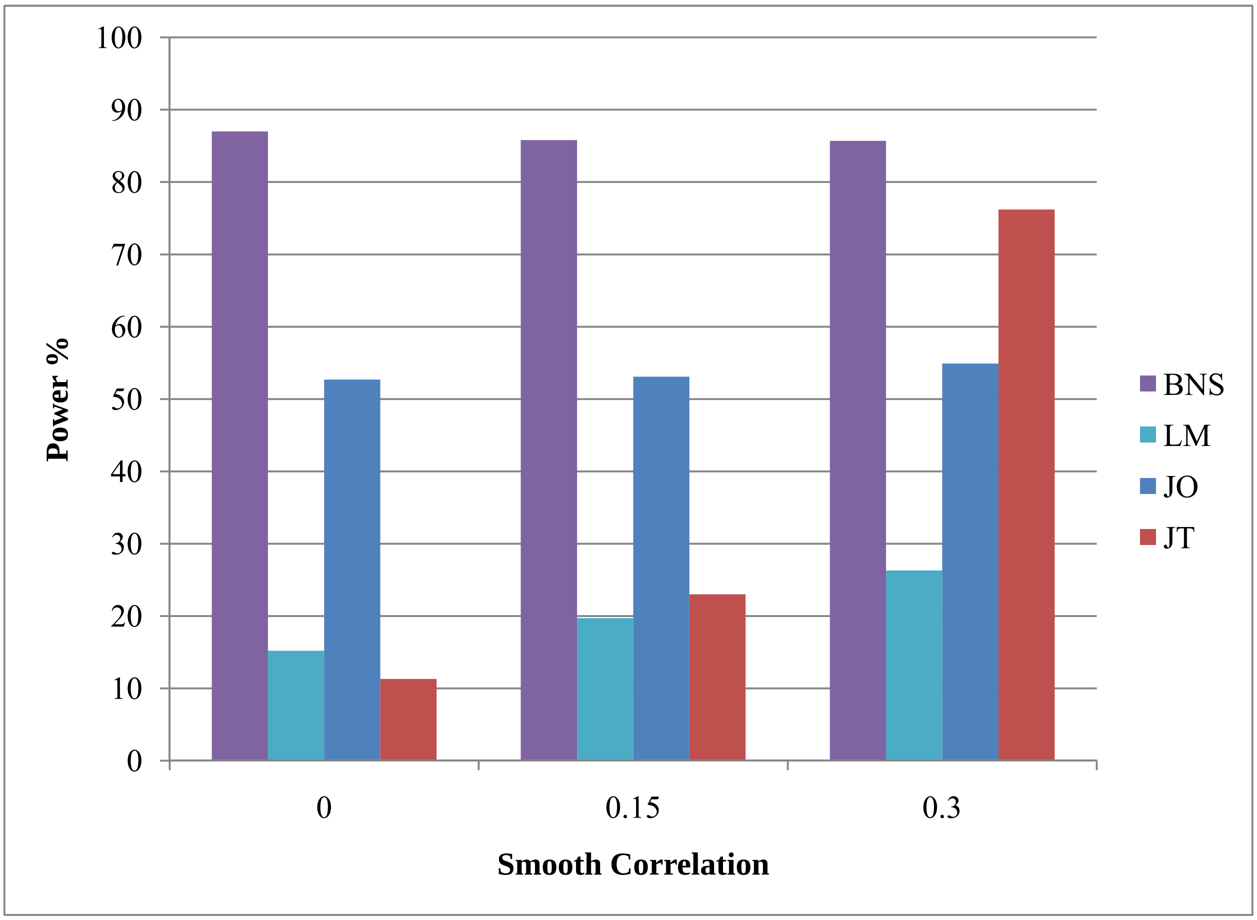


Figure 3

Jump Intensity and Test Power Against a False Null Hypothesis of No Jump Co-Movement for Smooth Correlation = 0.15, Jump Frequency = .02, and Jump Co-Probability = 0.9. The two return series both have a smooth unit Gaussian variation and the specified level of correlation (0.15). The underlying jump measures are those derived by Barndorff-Nielsen and Shephard [2006] (BNS), Lee and Mykland [2008] (LM), Jiang and Oomen [2008] (JO), and Jacod and Todorov [2009] (JT). The type I rejection level is 5%. Simulations have 1,000 replications.

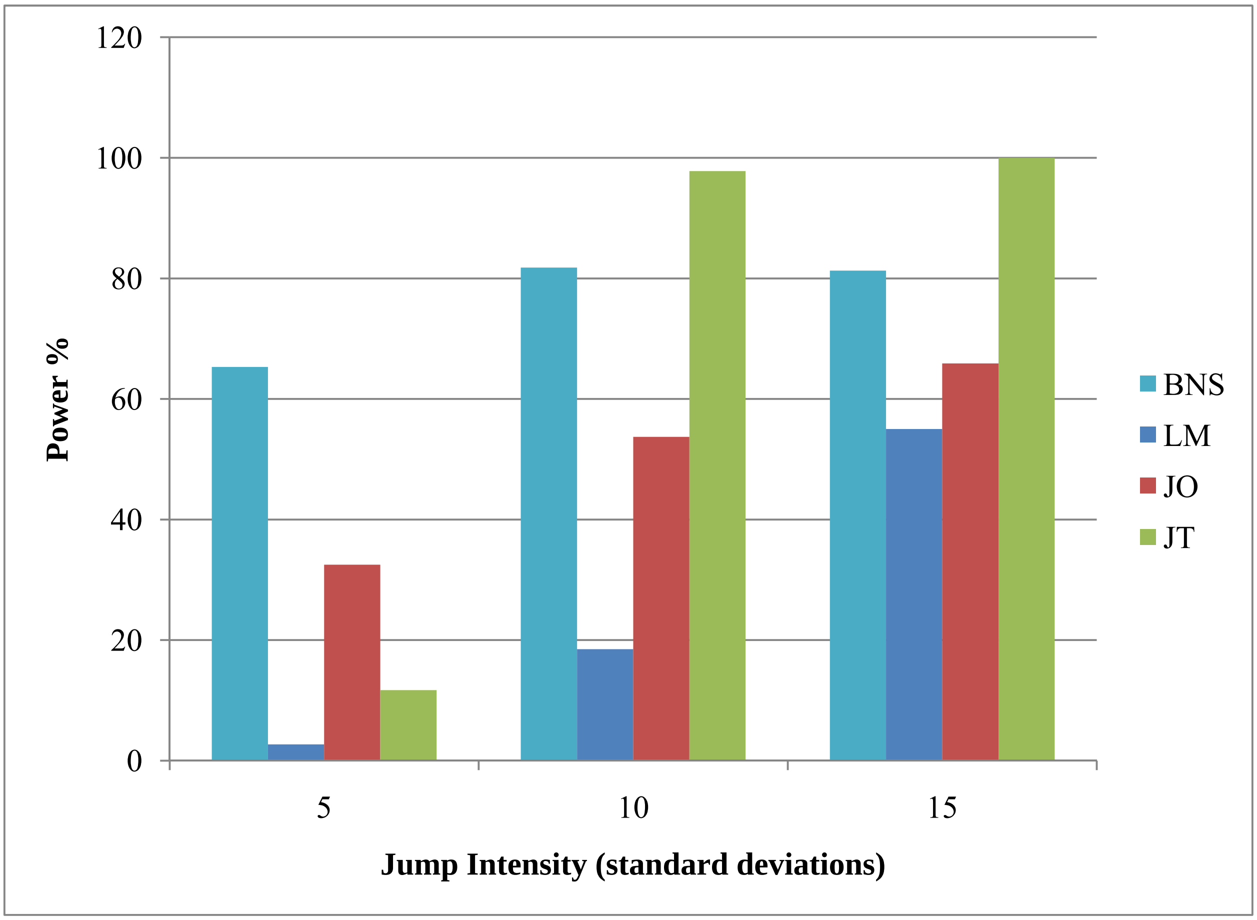
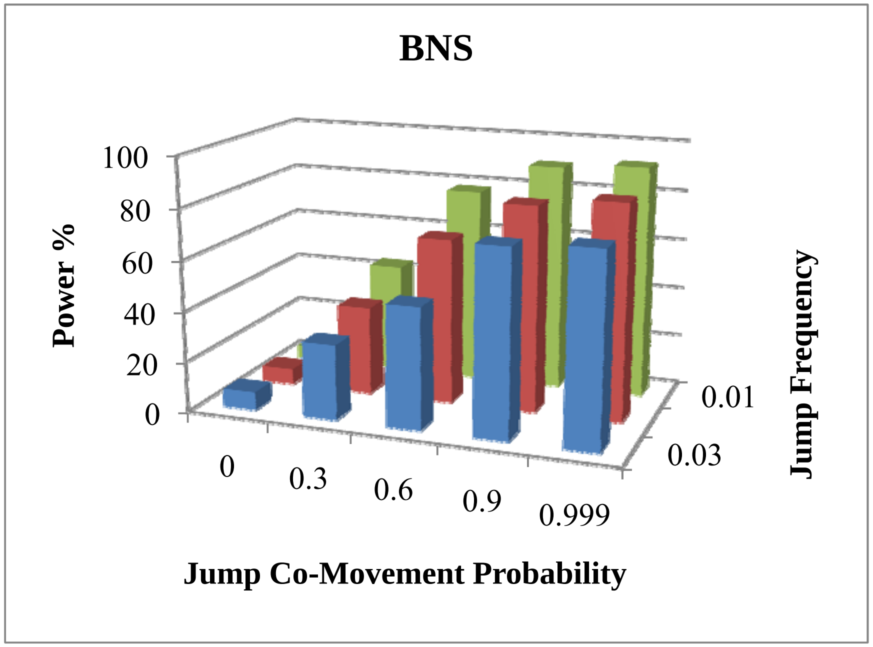
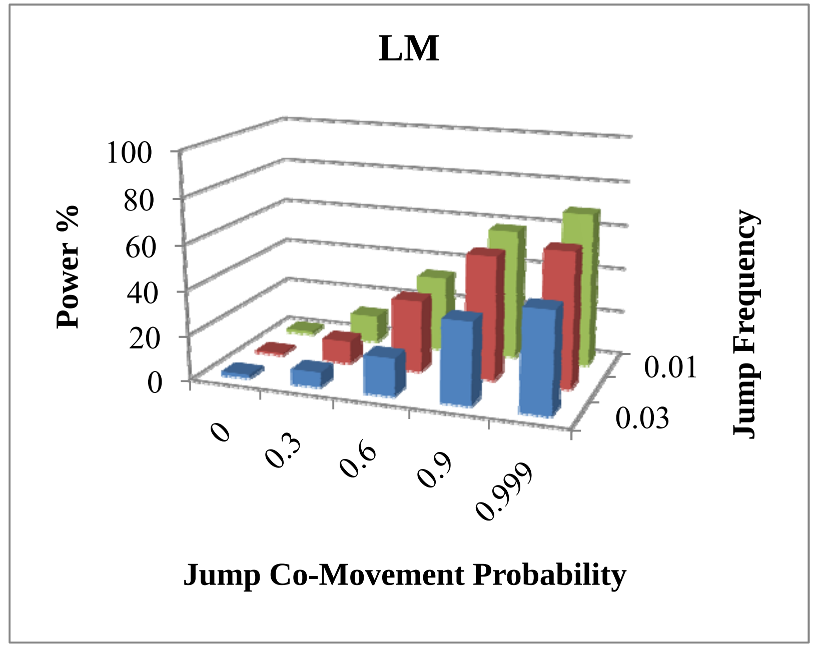
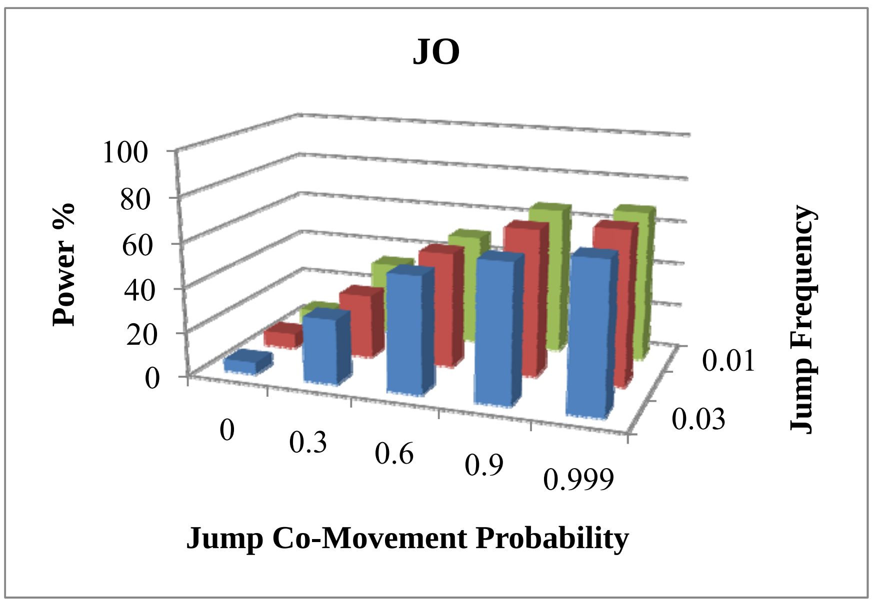


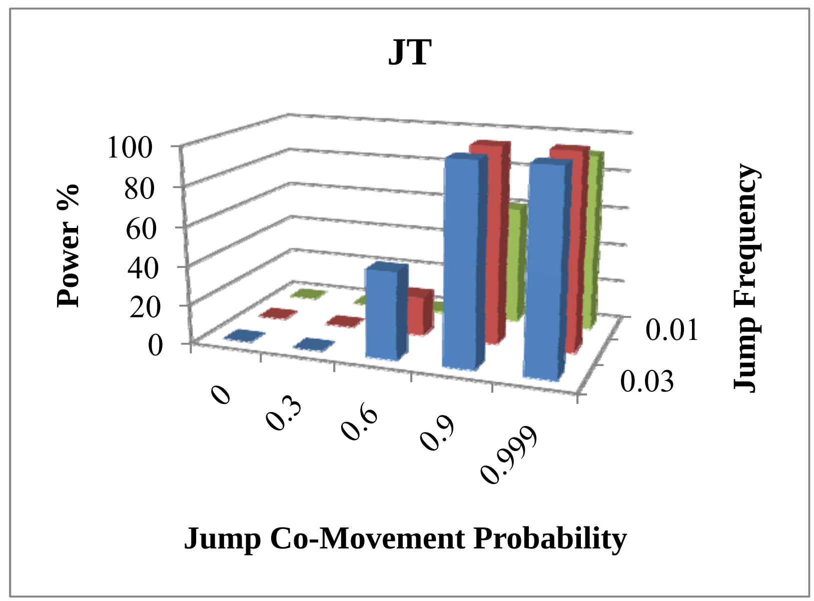
Figure 4

Jump Frequency, Co-Movement Probability and Test Power against a Null Hypothesis of No Jump Co-Movement for Smooth Correlation = 0.15 and Jump Intensity = 15. For a Co-Movement Probability of zero, the Null Hypothesis is true; otherwise, it is false. The two return series both have a smooth unit Gaussian variation and a specified level of correlation. The underlying jump measures are those derived by Barndorff-Nielsen and Shephard [2006] (BNS), Lee and Mykland [2008] (LM), Jiang and Oomen [2008] (JO), and Jacod and Todorov [2009] (JT). The type I rejection level is 5%. Simulations have 1,000 replications.


BNS
Power %
100
80
60
40
20
0
0
0.3
0.6
0.9
0.999
0.01
0.03
Jump Frequency
Jump Co-Movement Probability


LM
Power %
100
80
60
40
20
0
0
0.3
0.6
0.9
0.999
0.01
0.03
Jump Frequency
Jump Co-Movement Probability


JO
Power %
100
80
60
40
20
0
0
0.3
0.6
0.9
0.999
0.01
0.03
Jump Frequency
Jump Co-Movement Probability


JT
Power %
100
80
60
40
20
0
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0.3
0.6
0.9
0.999
0.01
0.03
Jump Frequency
Jump Co-Movement Probability

Appendix

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$(RI)
United States	4-Jan-68	26-Oct-09	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Venezuela	2-Jan-90	26-Oct-09	VENEZUELA-DS MARKET	TOTMVE$(RI)
Zimbabwe	6-Apr-88	6-Oct-06	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)