Is There a Contagion? A Frequency-Domain Analysis of Stock Market Comovements During the Subprime Crisis

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Abstract

Comovements of international stock markets before and during the subprime mortgage crisis are examined using cross-spectral methodology. The paper performs a simple frequency-domain-based test for contagion that avoids biases of the correlation breakdown tests used in the extant literature. The most recent financial crisis is found to be manifest in greater comovements along high-frequency components. Calculated changes in the high-frequency portion of the covariance indicate a contagion for the majority of the pairs of countries in the sample.

Keywords: Stock Market Comovements, Subprime Mortgage Crisis, Cospectral Analysis.

JEL classification: G15, F36, C14

1 Introduction

Default problems in the US subprime mortgage market has precipitated the largest global financial crisis since 1930s. The most recent financial crisis has heightened a debate surrounding the ever expanding interdependencies in the international stock markets. A very important part in this debate is played by the notion of contagion. If there is a silver lining associated with the mortgage crisis, it is that this crisis gave rise to an environment conducive to examining issues related to interdependencies and contagions. Indeed, the mortgage crisis provides a very convenient natural experiment for studying international spillovers in stock markets (Cheung, Fung and Tsai, 2010).

In the past two decades the world has witnessed how financial crises in one country precipitated crises in other countries, sometimes geographically distant, characterized by diverse economic environments, and often featuring little trade or investment interdependence with the country of origin of the crisis. Such developments left many researchers and policymakers puzzled: When and how do the country-specific crises spread to other regions? Could the shock-propagation mechanism

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during a crisis be different from that during a relatively calm period? It is this latter query that prompted many researchers to treat "tranquil periods" and "crises" as potentially different regimes when investigating international transmission of financial shocks (Pericoli and Sbracia, 2003).

The objective of this paper is two-fold. First, the paper uses frequency domain techniques to examine the comovements of stock markets before and during the most recent financial crisis. We believe that the cross-spectral analysis employed in this paper offers insights regarding financial crises that are not apparent from a conventional time-domain framework. Second, the paper implements a simple frequency-domain-based test for contagion. We argue that the proposed test avoids biases associated with the correlation breakdown and other tests used in the extant literature.

One of the focal points of debate in the international finance literature is whether contagion, defined as an increase in market comovement following a shock to one country, occurred during recent financial crises. Crises that originated in Mexico in 1994–95, Thailand in 1997, Russia in 1998, and US in 2007 have spread to other countries and regions. Here we investigate the subprime mortgage crisis by comparing cross-spectra of stock markets in tranquil and crisis periods. Future research can apply our methodology to other economic cataclysms.

In the extant literature, the study of comovements in financial markets does not go beyond the analyses of second moments. These conventional analyses can produce spurious results if the relative importance of high-frequency volatility is changed after the onset of a crisis. On the other hand, higher correlation *per se* should not necessarily indicate a contagion, as one might expect higher correlations during periods of high volatility (Bekaert, Harvey and Ng, 2005). Since correlation coefficients are conditional on market volatility, simple correlation coefficients may be biased (Forbes and Rigobon, 2002). This paper overcomes the biases that heteroskedasticity brings to the tests for contagion based on simple correlations.

To see why the conventional time-domain approach can be misleading, suppose that the stock market covolatility is higher for the tranquil period than the crisis period. In this case the researcher would be tempted to conclude that the change in the macroeconomic environment does not affect the stock market interdependencies. However, this conclusion should be deemed spurious if during the crisis most of the covolatility can be accounted for by the high-period components. Cospectral density estimation offers a valuable perspective on stock market comovements — a perspective which helps to refine results of the conventional time-domain analyses.

This paper uses cospectral analysis to determine the relative importance of cycles of different frequencies in accounting for stock market covariance in a cross-section of countries during two periods: before and during a financial crisis. We investigate whether, and to what extent, stock market comovements are influenced by financial crises. Thus, the paper re-examines the link between financial crises and stock market comovements in a frequency-domain framework, thereby taking a new step toward resolving the "contagion debate" empirically.

To further see why the results of the conventional time-domain approach may be misleading, suppose that the correlation coefficient does not change from one period to the next. If during a crisis the weight is shifted away from the trend component of covariance and toward irregular components, one should report the presence of contagion. Needless to say, in this scenario a second-moment study would conclude that the interdependence of financial markets is immune to changes in the economic environment.

The issue of contagion has received very close attention since the Asian financial crisis of 1997–98, and this attention magnified during the subprime mortgage crisis. Correspondingly, the methodology outlined above (and delineated in Section 4) is applied to the daily stock market returns for 27 American, Asian, and European stock market indices for the period from 2005 to 2009. This paper examines how the proportion of covariance due to high-frequency fluctuations changes between crisis and pre-crisis periods. The paper, therefore, goes beyond the simple comparison of correlations.

The contagion research in general, and this paper in particular, also have implications for the theory and practice of international portfolio management. The benefits that international investors expect to reap from international diversification may wildly differ between a relatively tranquil period and a period with more pronounced (high-frequency) comovements. Changes in financial comovements require additional care in risk management, portfolio selection and derivative pricing, as portfolio returns are directly affected by the changes in comovements (Calvet, Fisher and Thompson, 2006). International investors holding global market portfolios thus may have to alter their diversification and hedging strategies. Future research could provide deeper insights into these points, thereby advancing the fields of economics and finance.

The next section reviews the literature that is most closely related to the analysis undertaken in this paper. Description of our data and a brief motivation behind our choice of a starting date of the mortgage crisis appear in Section 3. Section 4 outlines our methodology. Empirical results on the existence of contagion, as well as the comparison of time- and frequency-domain results, are discussed in Section 5. Section 6 provides conclusions and suggests fruitful avenues for future research.

2 Related Literature

The literature offers no agreed-upon definition of contagion (e.g., Forbes and Rigobon, 2001, Bekaert, Harvey and Ng, 2005). Pericoli and Sbracia (2003) survey the various definitions of contagion used in the extant literature and note that, indeed, there is no consensus regarding a single theoretical or empirical procedure to identify a contagion. Whereas many early works view "contagion" and "financial interdependence" as synonymous (Fratzscher, 2003), several recent studies acknowledge that contagion should be characterized by "abnormally" high comovements.

Of all the definitions of contagion that are entertained by the literature, this paper focuses on two. The first definition describes contagion through "volatility spillovers" from one country to another. The other identifies a contagion with a significant increase in comovements after the beginning of a crisis.[1]

Bekaert, Harvey and Ng (2005) test for contagion in the equity markets, loosely defining contagion as a finding of greater comovements during periods of crisis. They believe that a correlation higher than what can be accounted for by economic fundamentals should be an indication of contagion. Bekaert et al. note that there is no consensus on the definition of economic fundamentals, and that fundamentals are likely to be country-specific. Fundamentals-based models of contagion usually have low explanatory power because it is rather difficult to find a single set of fundamentals that would account for the crises in all affected economies (Fratzscher, 2003). Thus, to explain and predict the spread of a crisis, a more fruitful research avenue, it seems, can be found in a pragmatic approach of looking at how the financial interdependence among the affected countries changes over time. This point is reinforced by recent findings of Calvet, Fisher and Thompson (2006), among others, who argue that there is at best a weak link between financial volatility and the standard macroeconomic variables.

Bekaert et al. (2005) point out that increased correlations *per se* cannot serve as a reliable signal of contagion, as, statistically, correlations should be higher during high volatility periods. In the stock market context, they define contagion as the correlation of residuals from a CAPM factor model. Unfortunately, such a test for contagion depends heavily on the researcher's choice of global and country-specific fundamentals, as well as model specification.

Dungey, Fry, González-Hermosillo and Martin (2005) discuss four widely used tests of contagion: the latent factor model (Dungey, Fry, González-Hermosillo and Martin, 2002), in which parameters

[1] These are Definitions 2 and 4 surveyed by Pericoli and Sbracia (2003).

depend on the change in volatility between noncrisis and crisis periods; the correlation test (Forbes and Rigobon, 2002), which compares (unconditional) correlations of asset returns between the two periods; the dummy variable approach (Favero and Giavazzi, 2002), which studies how outliers in the data for one country affects return equations for other countries, and the probability-based measure (Bae, Karolyi and Stulz, 2003), which extends the dummy variable approach to several countries. Dungey et al. (2005) point out that all of these tests are designed to test the significance of changes in the returns volatility between non-crisis and crisis periods. Theses tests, clearly, have their merits, but none of them go outside the time-domain representation of the question.

Dungey and Tambakis (2005) survey the issues associated with identifying crisis periods, gathering empirical evidence on contagion, investor behavior during a crisis, as well as policymaking in preventing and coping with a crisis. The frequency-domain approached pursued by our paper allows us to circumvent many of the empirical problems prevalent in the time-series analyses (e.g., modeling the data generating processes, finding breaks in the data generating processes, deciding on the frequency of the data, etc.).

Recently, two novel test for contagion were put forward in the literature. Baur and Fry (2009) propose a contagion test that focuses on fixed time effects and controls for interdependencies and systematic risks. The test is applied to the Asian financial crisis of 1997–98. Fry, Martin and Tang (2010) propose coskewness-based tests of contagion. They argue that those tests are able to capture contagion channels that are not identified by the correlation-based tests. While having their important merits, these test are inherently based on time-series consideration, which makes us believe that cospectral-based test can offer an alternative view on interdependencies and contagion.

Several works have employed cross-spectral methodology to study movements of the international equity markets. The first attempt was probably by Granger and Morgenstern (1970), who calculated coherences among eight world markets for the early 1960s period. Hilliard (1979) did a comparable study for the period surrounding the 1973 oil shock, concluding that there is comovement among European markets but not across continents. Fischer and Palasvirta (1990) use the cross-spectral methodology to study market comovements around the 1970s and 1980s, and report an increasing interdependence among the world markets over time. Smith (1999) uses the cross-spectral methodology to test whether the six largest international equity markets exhibit higher comovements following the 1987 stock market crash. He compares the pre- and post-crash coherences, as well as phases, and reports tighter comovements in the post-crash period. A sequel paper by Smith (2001) studies the comovement of the Pacific Rim countries around the 1987 crash and also finds a greater comovement in the post-crash period for seven out of eight pairwise country comparisons.

The papers cited in the preceding paragraph notwithstanding, the extant literature's empirical work on stock market interdependence during crises does not usually go beyond tests for correlation breakdown between calm periods and financial turmoils (e.g., Boyer, Gibson and Loretan, 1999), modelling regime switching (e.g., Fratzscher, 2003, Calvet, Fisher and Thompson, 2006), or studies of external shocks in a context of GARCH models (e.g., Engle, Ito and Lin, 1990). Some of the recent body of work (e.g., Forbes and Rigobon, 2002) may not find contagion because in the wake of a crisis there are important linkages only at high frequencies, while during a calm period most comovement is in the trend component (*cf.* cointegration). This paper addresses this concern by calculating the exact percent change in cospectral density due to high frequencies after an onset of a financial crisis.

Studying exchange rate fluctuations, Black and McMillan (2004) adopt a Component-GARCH model to decompose volatility into a permanent component and a transitory component. They then study the volatility spillovers by calculating correlations among permanent components for six dollar-denominated exchange rates. The temporary component correlations for the major European currencies (in the pre-Euro era) are found to be much lower than trend correlations. Black and McMillan make an important step in the right direction by pointing out that there exist multiple volatility components. Cospectral analysis undertaken in this paper allows for a more refined decomposition of fluctuations and a more rigorous treatment of all volatility components. Like Black and McMillan's work, this paper is able to quantify the potential convergence of financial markets.

In this paper the interdependencies in the stock markets before and during financial crises are compared using frequency domain techniques. Conventional analyses of second moments can produce spurious results if, for example, the high-frequency comovements are reduced (increased) while the overall covariance is increased (reduced) after the onset of a crisis. The paper uses cospectral analysis to determine relative importance of cycles of different frequencies in accounting for stock market covariance in a cross-section of countries during two periods — before and during the most recent financial meltdown.

3 Stock Market Data and the Subprime Crisis

The issue of stock market comovements has received even greater attention during the recent financial crisis. This paper uses frequency-domain methodology (described in the next section) to study the effects of the subprime mortgage crisis on stock market comovements in 27 international stock market indices listed in Table 1. We examine daily stock quotes for major indicators for Argentina, Austria, Belgium, Brazil, Canada, China, France, Germany, Hong Kong, India, Indonesia, Israel, Italy, Japan, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Singapore, S. Korea, Spain, Sweden, Switzerland, Taiwan, the UK, and the US

Table 1 here

Our choice of countries was motivated by two main considerations. First, our sample is representative in that it includes (i) both developed economies and emerging markets, and (ii) representative economies from virtually all continents (except Africa due to unreliable data).[2] Second, our sample includes only countries with no significant financial distress within two years prior to the onset of the subprime financial crisis. This latter consideration allows us to cleanly separate crisis and non-crisis periods and focus solely on the effects of the subprime meltdown on the stock market comovements.

Since stock market quotes are nonstationary processes, we transform our data by defining stock market returns as $r = 100 \ln \left(\frac{p_t}{p_{t-1}} \right)$, where p_t is stock market closing quote at date t, and p_{t-1} is date $t-1$ quote. Thus, we study daily log-differences of stock market closing prices.[3]

Table 1 also lists basic descriptive statistics for daily stock market returns for the 27 economies between January 2005 and December 2009. As delineated in the preceding paragraph, the returns are expressed in percentage terms. All average daily returns are less than 0.08% in absolute value and, with the exception of Belgium, Italy and Japa, all average returns are positive. The most volatile data have been observed for IBOVESPA of Brazil (with the standard deviation of 2.12%), the least volatile — for NZ-50 Gross Index of New Zealand (standard deviation of 0.86%). The biggest one-day loss has been reported for Hang Seng (−13.58%), while the highest daily return of 13.68% was enjoyed by the traders on the Sao Paolo exchange. In fact, the majority of extreme daily returns in the sample — both on the winning and losing sides — are in the double digits.

The subprime mortgage literature identifies several possible starting dates of the crisis. Sub-

[2] This exception is due to the underdevelopment of financial markets in the region and, correspondingly, lack of reliable data.

[3] Applying the first difference filter to the stock quotes produces results that are nearly identical to those for the returns.

prime mortgage defaults started to increase in February 2007. This was evident in the fall of the ABX price index ,which reflects the price of credit default swaps (Brunnermeier, 2009). However, the financial crisis did not fully break until summer of 2007. Cheung, Fung and Tsai (2010) choose July 2007 based on the TED spread, a commonly used measure of liquidity or credit risk. Fry, Martin and Tang (2010) agree that the subprime financial crisis started in July 2007. Another plausible cut-off date would be October 2007 when the US stock market was at its peak. We pick July 1, 2007, as the demarcation date for our sample for several reasons. First, many researchers seem to agree on this date. Second, this date is in the middle of the distribution of plausible dates (February through October 2007). Third, by July 2007 Moody's, Standard & Poor's and Fitch downgraded most of mortgage-related products and the credit markets started to feel the ramifications. Fourth, in July 2007 the market for mortgage-backed securities started its sharp decline (Brunnermeier, 2009). Finally, by July 2007 the liquidity crisis, as reflected in the TED spread, has become evident, as most market participants were no longer willing to lend. We therefore split our data set into two subsamples — January 2005 through June 2007 and July 2007 through December 2009.[4]

Figure 1 plots daily closing prices (first 27 graphs), as well as log-differences, or returns, of the daily quotes (last 27 graphs), for the 27 international stock market indices in the sample between January 2005 and December 2009. For convenience, the dotted vertical line in each panel corresponds to July 1, 2007 — the date that we chose as the beginning of the subprime crisis for our benchmark analysis. Tables 2, 3 and 4 present correlation matrices for the pre-crisis period (2005–2007), crisis period (2007–2009) and the entire sample, respectively.

Figure 1 here

Tables 2, 3, and 4 here

4 Methodology

4.1 Cospectral Analysis

This paper conducts a cross-spectral analysis of the stock market data between January 2005 and December 2009. Specifically, we use frequency-domain techniques to determine the relative importance of cycles of different frequencies in accounting for stock market comovement among 27 countries during two periods — before and during the subprime mortgage crisis. The goal of the spectral analysis is to determine how important cycles of different frequencies are in accounting for volatility and comovement of the time series (Hamilton, 1994). According to Granger (1966), one

[4] In our robustness exercises we check if our results are dependent on the choice of this date. We find that the results are unchanged if the sample is divided anywhere between February and October 2007.

of the advantages of the spectral methods is that they do not require specification of a model and so the results are not based on any rigid modeling assumptions.

To perform the cospectral analysis, we first use the finite Fourier transform to decompose the data into a sum of sine and cosine waves of different amplitudes and wave lengths to obtain periodograms. According to the spectral representation theorem (Hamilton, 1994), any covariance-stationary process x_t can be expressed as the finite Fourier transform decomposition of x_t:

$$x_t = \bar{x} + \sum_{k=1}^{m} \left[a_k \cos(\omega_k t) + b_k \sin(\omega_k t)\right], \tag{1}$$

where t is the time subscript ($t = 1, 2, \ldots, n$), n is the number of observations in the time series, $\bar{x}$ is the mean value of x, m is the number of frequencies in the Fourier decomposition,[5] a_k are the cosine coefficients, b_k are the sine coefficients, and ω_k are the Fourier frequencies ($\omega_k = \frac{2\pi k}{n}$). Such an approach allows one to describe the value of x_t as a sum of periodic functions of different amplitudes and wavelengths. Each time series is thus decomposed into a number of orthogonal components associated with various frequencies.[6] We then calculate the amplitude cross-periodograms for each pair of countries as

$$J_k^{xy} = \frac{n}{2}\left(a_k^x a_k^y + b_k^x b_k^y\right) + i\frac{n}{2}\left(a_k^x b_k^y - b_k^x a_k^y\right), \tag{2}$$

where i represents the imaginary unit $\sqrt{-1}$. A cross-periodogram is a sample analog of the population cross-spectrum and it shows the contribution of the kth harmonic to the total covariance between two data series.

The cross-periodogram is, admittedly, a volatile and inconsistent estimator of the cross-spectrum. Besides, it does not become more accurate with an increase in sample size. To overcome this deficiency, cospectral density estimates are produced by smoothing the real part of cross-periodogram ordinates.[7] The idea behind such nonparametric (or kernel) estimation is to use frequencies $\{\omega_k, \omega_{k\pm1}, \omega_{k\pm2}, \ldots, \omega_{k\pm h}\}$ in estimating the cospectrum at ω_k. So the bandwidth parameter h and the relative weights (that must sum to unity) given to each frequency fully characterize the kernel. Because the kernel estimate is an average over a number of frequencies, and because estimates of the cospectrum at ω_k and ω_l are approximately independent for large n and $k \neq l$ (Hamilton, 1994), kernel estimates are less volatile and provide more consistent estimates of the cross-spectrum than

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[5] $m = \frac{n}{2}$ if n is even, and $m = \frac{n-1}{2}$ if n is odd.

[6] Since the value of $\cos(\omega t)$ repeats itself every $\frac{2\pi}{\omega}$ periods, a frequency ω corresponds to a period of $\frac{2\pi}{\omega}$.

[7] There is an obvious trade-off: smoothing reduces the variance of the estimator but introduces a bias.

the cross-periodogram. We use a triangular weight function (with $h = 31$) in the moving average applied to the cross-periodogram to form smoothed cospectral density estimates.[8]

Finally, we compare the cospectra for all pairs of countries for pre- and post-crisis periods. The cross-spectrum $s_{xy}(\omega)$ integrates to the unconditional covariance, and the quadrature spectrum $q_{xy}(\omega)$ (the imaginary part of the cross-spectrum) integrates to zero since $q_{xy}(-\omega) = -q_{xy}(\omega)$ (Hamilton, 1994). Therefore, the area under the cospectrum (or the real component of the cross-spectrum) is equal to the covariance between x and y. Note that the cospectrum may be positive over some frequencies and negative over others.[9]

4.2 Changes in Covariance due to High Frequencies

To obtain accurate results, we calculate the exact percent change in cospectral density due to high frequencies after the onset of a financial crisis. One would expect the irregular components of stock market covariance to become relatively more important during a crisis. Cospectral analysis reveals that covariances between the stock market returns are positive at some frequencies and negative at others. To make meaningful comparisons between the tranquil and crisis periods, we need to deal appropriately with potentially negative (frequency components of) covariances. The following modified formula for percent change in high-frequency covariance, ΔCOV^{high}, allows us to properly record changes even when one or both subsamples are characterized by negative portions of covariance:

$$\Delta COV^{high} = \frac{COV_{crisis}^{high} - COV_{tranquil}^{high}}{COV_{tranquil}^{high}} sign\left(COV_{tranquil}^{high}\right) \cdot 100, \tag{3}$$

where $COV_{crisis}^{high} = 2\int\limits_{\omega_1}^{\pi} \hat{c}_{xy}(\omega)\, d\omega$ is the portion of the covariance of stock market returns that is attributed to cycles with frequencies greater than or equal to ω_1.

Thus, to calculate the contribution of various frequencies, we multiply the cospectral density $\hat{c}_{xy}(\omega_k)$ by $\frac{4\pi}{n}$, where n is the number of observations in a time series, and sum over the relevant frequencies. We compare the contributions of frequencies $\omega \geq 0.45$ before and after the beginning of

[8] The main conclusions of this paper are immune to using other relative weights (or kernels) applied to the periodogram ordinates to form the cospectral density estimates.

[9] Additionally, we can compute the coherence for all pairs of stock market time series as $h_{xy}(\omega) = \frac{[c_{xy}(\omega)]^2 + [q_{xy}(\omega)]^2}{s_x(\omega)s_y(\omega)}$, where $s_x(\omega)$ and $s_y(\omega)$ are the spectra, $c_{xy}(\omega)$ is the cospectrum, and $q_{xy}(\omega)$ is the quadrature spectrum. The coherence measures the degree to which x and y are jointly influenced by cycles of frequency ω, therefore, estimating the coherence during the crisis can uncover the frequencies at which the propagation of adverse shocks occurs.

the subprime mortgage crisis.[10] An increase in the contribution of high-frequency components with cycles less than or equal to 2 weeks in duration in excess of 10 percent will indicate the presence of contagion.

To see that formula (3), indeed, reports the true percent changes in covariances due to the higher frequencies, consider two simple numerical examples: (i) $COV^{high}_{tranquil} = -1$, $COV^{high}_{crisis} = -2$ $\Rightarrow \Delta COV^{high} = -100\%$; (ii) $COV^{high}_{tranquil} = -1$, $COV^{high}_{crisis} = 1 \Rightarrow \Delta COV^{high} = 200\%$. In the first example the comovement becomes weaker during the crises (i.e., the stock markets become more negatively correlated), which is captured by the negative sign of the percent change. Further, the doubling of the absolute value of the covariance produces the correct 100% change in absolute value. Note that in this scenario the ordinary percent change formula would have registered a positive increase in covariance. In the second example the covariance changes signs from negative to positive but remains the same in absolute value. Our formula gives us a 200% percent change, which conforms to both the numerics and the fact that the covariance has indeed gone up. The ordinary percent change formula would have registered a spurious -200% change. Thus, the $sign\left(COV^{high}_{tranquil}\right)$ term allows one to draw accurate conclusions about the true changes in the components of covariance between the two periods.

5 Empirical Results[11]

5.1 Cospectral Densities

We apply the methodology summarized in the previous section to a subset of the 27 time series described in Section 3. Interdependencies of stock markets for the following 12 countries that were potentially affected by the contagion are considered: Brazil, China, Germany, India, Indonesia, Japan, Malaysia, Mexico, the Philippines, Singapore, South Korea and Thailand. Figures 2 through 4 plot spectral and cospectral densities of stock market log-differences against frequency. Together, these figures span all possible pairs of the 12 countries. The diagonal graphs show the spectral densities, while all other graphs are cospectral densities of column and row countries. Dashed and solid lines represent tranquil (i.e., prior to July 1, 2007) and crisis periods, respectively.[12]

Figures 2, 3, and 4 here

Several patterns emerge from Figures 2 through 4. First, the estimated spectral densities for

[10] Frequencies $\omega \geq \frac{2\pi}{14} \approx 0.45$ correspond to the periodicity of 2 weeks or less.

[11] Note: the numerical results that appear in this section need to be recalculated.

[12] In addition to a brief summary of the results in the ensuing paragraphs, the reader is invited to take a self-guided tour of all graphs in Figures 2 through 4.

most countries are larger during the crisis relative to the tranquil period. This is an expected result, as the overall volatility should be higher during the turmoil. The notable exception is China, which is characterized by *lower* volatility after the onset of the subprime mortgage crisis. This seemingly counterintuitive result can be accounted for by the fact that China maintained a de facto crawling band around the US dollar (Reinhart and Rogoff, 2004), as well as by the Chinese strict capital control policies that were established in an attempt to cope with possible financial crises.

Second, cospectral densities are several orders of magnitudes smaller during the crisis for geographically distant countries (e.g., Brazil and India, Brazil and Japan, or China and Mexico) compared with countries that are geographically proximate (e.g., India and Indonesia, Japan and Thailand, or Indonesia and Singapore). This suggest that geographical proximity plays a role in crisis propagation. However, this finding should be interpreted carefully: geographically proximate countries may be characterized by similar sets of fundamentals to a greater extent than geographically distant countries. The results may also stem from the fact that geographical proximity bodes well for trade and investment interdependence.

Third, the crisis period is characterized by much more volatile spectra and cospectra at both high and low frequencies. This observation should compel a researcher to take care in disentangling the most unpredictable and destabilizing, high frequency components of comovements prior to making statements about the spread of contagion. We believe we make several additional steps in that direction in the following subsections.

Fourth, for many pairs of countries the crisis manifested itself in greater comovements particularly along the high-frequency components. Examples include Brazil and Germany (Figure 2), Malaysia and Mexico (Figure 3), and Germany and India (Figure 4). This result confirms the expectation that covariance during a crisis is likely to be accounted for in no trivial way by high-frequency comovements.

Finally, the low-frequency (or trend) components are relatively more important during the calm period for several pairs of countries, e.g, Brazil and Indonesia (Figure 3), Mexico and the Philippines (Figure 3), and Japan and Mexico (Figure 4). This finding is in accord with our expectation that important comovements can shift from low- to high-frequency components after the onset of a crisis. However, we also observe that for some pairs of countries the low-frequency comovement becomes more pronounced during the crises. Examples in this category include India and Indonesia (Figure 2), Singapore and South Korea (Figure 3), and Japan and Singapore (Figure 4).

5.2 Is There a Contagion?

To produce accurate conclusions and to further quantify the results for the entire sample, we compute the exact percent changes in stock market covariance due to frequencies higher than a certain cut-off level. We calculate the contribution of various frequencies by multiplying the cospectral densities $\hat{c}_{xy}(\omega)$ from Figures 2 through 4 by $\frac{4\pi}{n}$, where n is the number of observations in a time series, and summing over the relevant frequencies. As explained in Section 4, we compare the contributions of frequencies $\omega \geq 0.45$ before and after the beginning of the crisis.

We use our methodology described in Subsection 4.2 to summarize how the linkages among the countries under consideration changed after the onset of the most recent financial crisis.[13] Table 5 reports the results using formula (3) for the change in the high-frequency component of the covariance. The table compares variances and covariances due to frequencies $\omega \geq 0.45$ or, equivalently, periodicities of fourteen days or less, before and after the beginning of the subprime meltdown.[14] Looking along the diagonal of the matrix, we note that the variance due to high frequencies is higher during the crisis for 10 of the 12 currencies under consideration: Brazil, Germany, Indonesia, Japan, Malaysia, Mexico, the Philippines, Singapore, South Korea and Thailand. Further, for eight countries this increase in high-frequency volatility is well above 100%. China and India were the only two countries that enjoyed a reduction in high-frequency volatility of their national currency, −85 and −2 percent, respectively. Although this reduction is not (economically) significant, the explanation likely lies in the fact that both China and India were enforcing restrictions on capital mobility since late 1990s, with Chinese capital control policies being much more stringent than those in India.

Table 5 here

Table 5 reports an increase in the high-frequency covariance for 48 out of the possible 66 pairs of countries. This suggests that, indeed, there is an indication of contagion for most countries in the sample. Seventeen of the 18 instances of negative changes in high-frequency comovement occur when a pair of countries includes China, Germany or India. This should not be surprising in light of the capital control policies established by China and India in an attempt to prevent the spread of the contagion to their economies. Also, relatively strong European economies like Germany probably had a better chance of avoiding the devastating effects of the global financial meltdown.

[13] We effectively perform an exercise that speaks to Hypothesis 3 of Dungey (2005) — contagion between two individual countries. Since they find mixed evidence for this hypothesis, we are poised to make a contribution to the current literature.

[14] The results are largely invariant to choosing alternative cut-off frequencies.

A superscript "C" next to a percent change in the high-frequency component of the covariance denotes a contagion. A "C" on the diagonal indicates that the high-frequency volatility was more than 10 percent higher during the crisis relative to the tranquil period, suggesting that the corresponding country was affected by the crisis. The off-diagonal elements report whether the links between the pairs of counties change by more than 10 percent, which we record as the presence of contagion. Thus, a pair of countries is said to experience a contagion if the percent change in covariance due to high frequencies is greater than 10 percent. Note that we do not make any claims regarding the causality, although one could certainly speculate with regards to the direction of the spread of contagion.[15]

Due to capital controls and, possibly, geographical distance and economic diversity, there is no evidence of the spread of contagion between Brazil and Germany, Brazil and Japan, China and Indonesia, China and Malaysia, China and Mexico, China and the Philippines, China and Singapore, China and Thailand, Germany and India, Germany and Indonesia, Germany and Malaysia, Germany and Mexico, Germany and South Korea, India and Japan, India and Malaysia, India and Mexico, India and Singapore, and India and Thailand.

5.3 Comparison of Time- and Frequency-Domain Results

This subsection compares the conclusions that can be drawn from the standard time-domain analyses with the results obtained by studying the comovement of stock markets in the frequency domain. First, for all pairs of countries in our sample we calculate the percent change in *overall* covariance similar to the calculations in Table 5 and formula (3). We then divide the results by those obtained using (3) and record the ratios in Table 6. Thus, each cell in Table 6 represents the percent change in covariance due to high frequencies ($\omega \geq 0.45$) as a fraction of the percent change in the overall covariance for a given pair of countries. **Table 6 here**

Table 3 further compares time-series and frequency-domain results by adopting the following convention: If the change in overall covariance and the change in the high-frequency component of the covariance are within 10 percent of one another, i.e., if the ratio in any given cell is between 0.9 and 1.1, we conclude that time-series results are fairly *accurate* (subscript "A") If the ratio is outside the $[0.9, 1.1]$ range and still positive, we report that time-series results are *inaccurate* (subscript "A"). Finally, if the high-frequency comovement changes in the opposite direction of

[15] Since this paper is silent with respect to the direction of the spread of contagion, future research can take a thorough look into this important question by coupling anecdotal evidence with the standard causality tests.

the change of the overall volatility, i.e., the entry in Table 3 is negative, we deem the time-series results *spurious* (subscript "S").

Careful examination of Table 6 reveals seven instances where a simple analysis of the covariance would lead a researcher to an erroneous conclusion. In the cases of Brazil and Indonesia, Brazil and Japan, Brazil and Thailand, Germany and Malaysia, India and Indonesia, India and Japan, and India and Thailand the high-frequency comovement and the overall covariance changed in the opposite direction following the onset of the crisis. Further, for 51 out of 66 pairs of countries frequency domain analysis is found to have increased the accuracy of results, and only for eight pairs of countries were we able to conclude that consideration of all frequency components does not dramatically improve the conventional analysis of second moments. We interpret these findings as further support for our claim that the frequency-domain analysis conducted in this paper can refine, and sometimes refute, the results obtained using standard time-domain methodology.

5.4 Sensitivity Analysis

Edward Leamer (1985) famously noted that "[a] fragile inference is not worth taking seriously" (p. 308). Understanding of the importance of sensitivity analysis, this subsection checks the robustness of the results reported above with respect to (i) the starting date of the financial crisis, (ii) the choice of the cut-off frequency, and (iii) the cut-off for the percent change in the high-frequency covariance. This is, once again, in line with Leamer's (1985) suggestion that a "sensitivity study should be carried out with respect to all dimensions of the model in one grand exercise" (p.311). Recall that in the benchmark exercise conducted above the starting date of the crisis is July 1, 2007; the cut-off frequency is 0.45, which corresponds to a period of 14 days; and the threshold percent change in the high-frequency covariance is 10%.

The results reported in this paper are immune to changing the starting date of the crisis by as much as three month in either direction. This is can probably be accounted by the fact that we have four years of daily data (or at least a year and a half before and a year and a half after the onset of the crisis).

The results are slightly more sensitive to varying the cut-off frequencies, but the contagion is still found for the majority of the pairwise comparisons for the cut-off frequencies between one week and one month. Finally, The number of pairs of countries for which we find contagion doesn't change if the threshold percentage is increased to 20%. Even when this threshold is set at 50%, the contagion is found of two thirds of the pairs of countries. Thus our results are fairly robust to varying (i) the starting date of the crisis (July 1, 2007 in the benchmark), (ii) the choice of the cut-off frequency, and (iii) the cut-off for the percent change in the high-frequency covariance.

6 Conclusions and Future Research

Financial crises in Asia, Latin America, Russia, and, most recently, the US have reshaped the way researchers in economics and finance think about the world economy. Researchers and policymakers need to be able to identify financial contagions and to understand the propagation mechanisms so that governments and international organizations, such as IMF, can design proper policies to insulate individual economies from the spread of contagions. The extant literature has made several important attempts to test for contagion and to study the propagation of a crisis (e.g., Forbes and Rigobon, 2002, Bekaert, Harvey and Ng, 2005).

The frequency domain analysis conducted in this paper adds to the understanding of stock market comovements. We use cospectral methodology to examine whether the 2007–2009 financial crisis caused a contagion in the stock markets by comparing cross-spectra in tranquil and crisis periods. The paper implemented a cospectrum-based test for contagion. We find that cospectral densities are several orders of magnitudes smaller during the crisis for geographically distant countries relative to countries that are geographically proximate. This result may suggest that geographically proximate economies are likely characterized by similar sets of fundamentals, and that there are more trade and investment interdependencies among such countries.

We find that for many countries the recent global financial crisis that was precipitated by subprime mortgage troubles in the US manifested itself in greater comovements particularly along the high-frequency components, thereby confirming our expectation that important portions of covariance can shift from low- to high-frequency components after the onset of a crisis. Based on the change in the high-frequency portion of the covariance, this paper reports a contagion for the vast majority of the possible pairs of countries in our sample. Thus our results are consistent with, for example, Cheung, Fung and Tsai (2010), who find stronger interdependence among global stock markets during the most recent financial crisis.

This paper also shows that even if the frequency-domain conclusions are generally consistent with the time-domain results, cospectral analysis offers a deeper understanding of the effects of a finanical crisis on stock market comovements. Cospectral densities of stock market quotes estimated in this paper greatly reduce the potential for erroneous results and misleading policy implications.

Additionally, the goal of this paper is to compare two alternative policy regimes. In such a context, conventional parametric models are always subject to the Lucas' (1976) critique, so nonparametric and semiparametric methods, such as the one used in this paper, should yield more reasonable results.[16]

We acknowledge that market volatility covolatility *per se* is not destabilizing and only reflects preferences, stochastic properties of the fundamentals, as well as the ways in which beliefs are formed. However, financial volatility is particularly problematic in the presence of incomplete markets. In an economy where some states of the world are noninsurable, speculative attacks can pose serious problems. With higher financial volatility, lending to firms and banks might be reduced in an attempt to cope with additional risks and prevent bankruptcies and failures. Also, the costs of portfolio adjustments (usually modelled as quadratic) can be substantial under high volatility. Finally, high volatility increases the probability of extremes, such as a depletion of foreign reserves and, thus, inability of the monetary authorities to conduct desired currency interventions.

In closing, we would like to offer several avenues for future research. First, as suggested in the introductory section, our methodology can be applied to other recent economic and financial disturbances, including the current crisis. Second, another interesting question that can be answered in the context of this paper (and using our methodology) is the following: Can the restrictions on the mobility of financial capital reduce high-frequency interdependencies among international currency markets data during a crisis, thereby lowering the probability of contagions? It would also be useful to investigate real and financial links among countries that facilitate the transmission of a crisis. For example, Dungey and Tambakis (2005) list several such links: international trade, exchange rate changes and the ensuing competitiveness effects, capital flows, liquidity effects, and common creditors.

Finally, as was stressed in the introductory section, the contagion research in general, and this paper in particular, have implications for international portfolio management. The benefits of international diversification may be significantly reduced if cross-country comovements of asset prices are higher during crises (Pericoli and Sbracia, 2003). Such changes in financial comovements call for additional care in risk management and portfolio selection since portfolio returns depend upon the changes in comovements (Calvet, Fisher and Thompson, 2006). We leave deeper insights into these points to future research.

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[16] In much the same sprit, Leamer (1985) notes that "[a]n epidemic of overparameterization debilitates our data analyses" (p. 312).

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Table 1: Data Summary

Country	Stock Market Index[a]	Stock Returns[b]						
		Mean	Median	Min	Max	St. Dev.	Skewness	Kurtosis
Argentina	Merval Buenos Aires (MERV)	0.04	0.14	−12.95	10.43	1.99	−0.62	8.39
Austria	Viena ATX	0.01	0.13	−10.25	12.02	1.93	−0.30	8.43
Belgium	Bel-20 Brussels (BFX)	−0.02	0.02	−8.32	12.08	1.47	0.18	12.84
Brazil	IBOVESPA Sao Paolo (BVSP)	0.08	0.16	−12.10	13.68	2.12	−0.03	8.18
Canada	TSX Composite index (Toronto)	0.02	0.11	−9.79	9.37	1.49	−0.66	10.96
China	Shanghai Composite (SSE)	0.07	0.12	−9.26	9.03	2.00	−0.34	5.65
France	CAC 40 Paris	0.00	0.04	−9.47	10.59	1.53	0.08	11.51
Germany	DAX	0.03	0.11	−7.43	10.80	1.50	0.16	11.67
Hong Kong	Hang Seng index	0.04	0.08	−13.58	13.41	1.92	0.09	11.05
India	BSE SENSEX Bombay (BSE 30)	0.08	0.15	−11.60	15.99	1.96	0.08	8.76
Indonesia	Jakarta Composite (JKSE)	0.08	0.17	−10.95	7.62	1.66	−0.66	8.94
Israel	Tel Aviv TV-100 IND	0.05	0.02	−10.54	9.71	1.59	−0.46	7.90
Italy	Milan MIBTEL	−0.04	0.06	−8.60	10.37	1.39	−0.06	12.15
Japan	Nikkei 225	−0.01	0.05	−12.11	13.23	1.75	−0.45	11.75
Malaysia	Kuala Lumpur (KLSE)	0.03	0.05	−12.97	12.79	1.05	−0.96	46.25
Mexico	IPC (MXX)	0.07	0.17	−7.27	10.44	1.62	0.16	7.42
Netherlands	Amsterdam AEX General	0.00	0.08	−9.59	10.03	1.57	−0.21	12.26
New Zealand	NZ-50 Gross Index (NZ50)	0.01	0.04	−4.94	5.81	0.86	−0.29	7.16
Norway	Oslo Exchange	0.05	0.20	−9.71	9.19	1.92	−0.63	7.40
Singapore	Straits Times Index (STI)	0.03	0.07	−9.22	7.53	1.45	−0.34	8.67
S. Korea	Seoul Composite (KS11)	0.05	0.16	−11.17	11.28	1.62	−0.59	10.04
Spain	Madrid IGBM (SMSI)	0.02	0.10	−9.68	9.87	1.45	−0.16	11.36
Sweden	Stockholm General	0.02	0.09	−7.38	8.63	1.54	0.03	7.69
Switzerland	Swiss SMI	0.01	0.07	−8.11	10.79	1.30	0.08	11.59
Taiwan	Taiwan Weighted (TWII)	0.05	0.16	−11.17	11.28	1.62	−0.59	10.04
UK	TSE 100	0.01	0.06	−9.26	9.38	1.41	−0.13	11.52
US	S&P 500	0.00	0.08	−9.47	10.96	1.51	−0.24	13.13

[a]The indexes are daily adjusted closing prices between January 2005 and December 2009.

[b]Daily log-differences.

Table 2: Correlation Matrix: 2005–2007

Country	Argentina	Austria	Belgium	Brazil	Canada	China	France	Germany	Hong Kong	India	Indonesia	Israel	Italy	Japan	Malaysia	Mexico	Netherlands	New Zealand	Norway	Singapore	S. Korea	Spain	Sweden	Switzerland	Taiwan	UK	US
Argentina	1	0.33	0.36	0.58	0.53	0.12	0.36	0.34	0.22	0.18	0.07	0.17	0.39	0.09	0.13	0.51	0.34	0.01	0.30	0.19	0.17	0.37	0.36	0.34	0.17	0.39	0.55
Austria	0.33	1	0.65	0.35	0.36	0.08	0.65	0.61	0.43	0.42	0.38	0.30	0.68	0.40	0.26	0.40	0.64	0.19	0.63	0.45	0.39	0.65	0.67	0.63	0.39	0.67	0.29
Belgium	0.36	0.65	1	0.38	0.34	0.06	0.87	0.82	0.39	0.37	0.27	0.38	0.83	0.36	0.27	0.49	0.84	0.14	0.52	0.43	0.33	0.79	0.75	0.79	0.33	0.80	0.41
Brazil	0.58	0.35	0.38	1	0.57	0.14	0.39	0.36	0.20	0.20	0.13	0.13	0.40	0.16	0.12	0.66	0.35	0.00	0.29	0.21	0.20	0.38	0.32	0.33	0.20	0.40	0.65
Canada	0.53	0.36	0.34	0.57	1	0.14	0.37	0.34	0.23	0.26	0.16	0.08	0.40	0.18	0.18	0.54	0.35	0.07	0.41	0.24	0.25	0.37	0.36	0.33	0.25	0.43	0.61
China	0.12	0.08	0.06	0.14	0.14	1	0.03	0.03	0.20	0.03	0.10	0.05	0.07	0.12	0.17	0.11	0.01	0.10	0.04	0.15	0.11	0.03	0.05	0.05	0.11	0.03	0.09
France	0.36	0.65	0.87	0.39	0.37	0.03	1	0.94	0.35	0.37	0.25	0.36	0.89	0.36	0.23	0.48	0.92	0.09	0.54	0.40	0.32	0.86	0.79	0.84	0.32	0.88	0.46
Germany	0.34	0.61	0.82	0.36	0.34	0.03	0.94	1	0.33	0.34	0.23	0.36	0.87	0.33	0.22	0.45	0.91	0.10	0.49	0.37	0.30	0.85	0.77	0.81	0.30	0.84	0.47
Hong Kong	0.22	0.43	0.39	0.20	0.23	0.20	0.35	0.33	1	0.49	0.52	0.29	0.37	0.59	0.44	0.27	0.37	0.24	0.39	0.67	0.60	0.33	0.39	0.38	0.60	0.34	0.13
India	0.18	0.42	0.37	0.20	0.26	0.03	0.37	0.34	0.49	1	0.47	0.26	0.38	0.41	0.28	0.20	0.35	0.17	0.43	0.49	0.42	0.35	0.36	0.39	0.42	0.36	0.11
Indonesia	0.07	0.38	0.27	0.13	0.16	0.10	0.25	0.23	0.52	0.47	1	0.27	0.27	0.42	0.37	0.15	0.24	0.24	0.36	0.57	0.42	0.26	0.30	0.27	0.42	0.26	0.01
Israel	0.17	0.30	0.38	0.13	0.08	0.05	0.36	0.36	0.29	0.26	0.27	1	0.39	0.21	0.17	0.23	0.34	0.11	0.32	0.31	0.21	0.34	0.35	0.37	0.21	0.33	0.15
Italy	0.39	0.68	0.83	0.40	0.40	0.07	0.89	0.87	0.37	0.38	0.27	0.39	1	0.30	0.25	0.46	0.86	0.15	0.58	0.40	0.31	0.84	0.78	0.79	0.31	0.84	0.43
Japan	0.09	0.40	0.36	0.16	0.18	0.12	0.36	0.33	0.59	0.41	0.42	0.21	0.30	1	0.37	0.19	0.36	0.27	0.33	0.59	0.64	0.32	0.34	0.37	0.64	0.32	0.09
Malaysia	0.13	0.26	0.27	0.12	0.18	0.17	0.23	0.22	0.44	0.28	0.37	0.17	0.25	0.37	1	0.15	0.22	0.26	0.22	0.55	0.32	0.26	0.24	0.25	0.32	0.26	0.09
Mexico	0.51	0.40	0.49	0.66	0.54	0.11	0.48	0.45	0.27	0.20	0.15	0.23	0.46	0.19	0.15	1	0.45	0.03	0.30	0.27	0.22	0.43	0.39	0.42	0.22	0.46	0.64
Netherlands	0.34	0.64	0.84	0.35	0.35	0.01	0.92	0.91	0.37	0.35	0.24	0.34	0.86	0.36	0.22	0.45	1	0.09	0.52	0.39	0.32	0.82	0.77	0.82	0.32	0.86	0.45
New Zealand	0.01	0.19	0.14	0.00	0.07	0.10	0.09	0.10	0.24	0.17	0.24	0.11	0.15	0.27	0.26	0.03	0.09	1	0.17	0.29	0.26	0.13	0.12	0.14	0.26	0.10	−0.05
Norway	0.30	0.63	0.52	0.29	0.41	0.04	0.54	0.49	0.39	0.43	0.36	0.32	0.58	0.33	0.22	0.30	0.52	0.17	1	0.41	0.33	0.53	0.60	0.47	0.33	0.59	0.20
Singapore	0.19	0.45	0.43	0.21	0.24	0.15	0.40	0.37	0.67	0.49	0.57	0.31	0.40	0.59	0.55	0.27	0.39	0.29	0.41	1	0.55	0.40	0.44	0.41	0.55	0.39	0.11
S. Korea	0.17	0.39	0.33	0.20	0.25	0.11	0.32	0.30	0.60	0.42	0.42	0.21	0.31	0.64	0.32	0.22	0.32	0.26	0.33	0.55	1	0.30	0.34	0.34	1.00	0.29	0.12
Spain	0.37	0.65	0.79	0.38	0.37	0.03	0.86	0.85	0.33	0.35	0.26	0.34	0.84	0.32	0.26	0.43	0.82	0.13	0.53	0.40	0.30	1	0.78	0.77	0.30	0.82	0.44
Sweden	0.36	0.67	0.75	0.32	0.36	0.05	0.79	0.77	0.39	0.36	0.30	0.35	0.78	0.34	0.24	0.39	0.77	0.12	0.60	0.44	0.34	0.78	1	0.75	0.34	0.76	0.36
Switzerland	0.34	0.63	0.79	0.33	0.33	0.05	0.84	0.81	0.38	0.39	0.27	0.37	0.79	0.37	0.25	0.42	0.82	0.14	0.47	0.41	0.34	0.77	0.75	1	0.34	0.81	0.39
Taiwan	0.17	0.39	0.33	0.20	0.25	0.11	0.32	0.30	0.60	0.42	0.42	0.21	0.31	0.64	0.32	0.22	0.32	0.26	0.33	0.55	1.00	0.30	0.34	0.34	1	0.29	0.12
UK	0.39	0.67	0.80	0.40	0.43	0.03	0.88	0.84	0.34	0.36	0.26	0.33	0.84	0.32	0.26	0.46	0.86	0.10	0.59	0.39	0.29	0.82	0.76	0.81	0.29	1	0.44
US	0.55	0.29	0.41	0.65	0.61	0.09	0.46	0.47	0.13	0.11	0.01	0.15	0.43	0.09	0.09	0.64	0.45	−0.05	0.20	0.11	0.12	0.44	0.36	0.39	0.12	0.44	1

Table 3: Correlation Matrix: 2007–2009

Country	Argentina	Austria	Belgium	Brazil	Canada	China	France	Germany	Hong Kong	India	Indonesia	Israel	Italy	Japan	Malaysia	Mexico	Netherlands	New Zealand	Norway	Singapore	S. Korea	Spain	Sweden	Switzerland	Taiwan	UK	US
Argentina	1	0.57	0.55	0.77	0.73	0.15	0.64	0.64	0.34	0.37	0.38	0.34	0.63	0.26	0.19	0.69	0.64	0.21	0.63	0.39	0.30	0.61	0.59	0.58	0.30	0.63	0.65
Austria	0.57	1	0.73	0.56	0.52	0.20	0.81	0.77	0.49	0.48	0.48	0.49	0.79	0.47	0.33	0.53	0.81	0.33	0.75	0.50	0.44	0.78	0.80	0.75	0.44	0.78	0.47
Belgium	0.55	0.73	1	0.60	0.54	0.20	0.84	0.77	0.43	0.47	0.37	0.44	0.83	0.38	0.39	0.59	0.85	0.29	0.67	0.44	0.38	0.79	0.79	0.78	0.38	0.85	0.54
Brazil	0.77	0.56	0.60	1	0.75	0.19	0.66	0.65	0.41	0.39	0.31	0.33	0.62	0.24	0.19	0.81	0.65	0.11	0.60	0.39	0.32	0.60	0.63	0.59	0.32	0.64	0.77
Canada	0.73	0.52	0.54	0.75	1	0.11	0.60	0.59	0.33	0.34	0.24	0.39	0.58	0.29	0.17	0.70	0.60	0.16	0.61	0.32	0.29	0.57	0.56	0.56	0.29	0.60	0.77
China	0.15	0.20	0.20	0.19	0.11	1	0.17	0.17	0.51	0.32	0.31	0.25	0.19	0.32	0.28	0.15	0.17	0.23	0.21	0.34	0.37	0.16	0.16	0.15	0.37	0.16	0.04
France	0.64	0.81	0.84	0.66	0.60	0.17	1	0.92	0.42	0.46	0.36	0.50	0.94	0.40	0.30	0.65	0.95	0.29	0.78	0.45	0.38	0.91	0.89	0.89	0.38	0.95	0.59
Germany	0.64	0.77	0.77	0.65	0.59	0.17	0.92	1	0.42	0.47	0.32	0.44	0.86	0.37	0.27	0.67	0.88	0.23	0.75	0.44	0.42	0.85	0.85	0.82	0.42	0.88	0.64
Hong Kong	0.34	0.49	0.43	0.41	0.33	0.51	0.42	0.42	1	0.63	0.63	0.45	0.44	0.69	0.45	0.38	0.42	0.38	0.48	0.78	0.70	0.42	0.44	0.41	0.70	0.43	0.27
India	0.37	0.48	0.47	0.39	0.34	0.32	0.46	0.47	0.63	1	0.52	0.44	0.49	0.42	0.36	0.38	0.48	0.30	0.50	0.66	0.50	0.47	0.47	0.46	0.50	0.47	0.35
Indonesia	0.38	0.48	0.37	0.31	0.24	0.31	0.36	0.32	0.63	0.52	1	0.41	0.39	0.52	0.61	0.28	0.39	0.38	0.49	0.64	0.57	0.38	0.37	0.36	0.57	0.37	0.16
Israel	0.34	0.49	0.44	0.33	0.39	0.25	0.50	0.44	0.45	0.44	0.41	1	0.50	0.40	0.34	0.30	0.50	0.30	0.51	0.46	0.42	0.48	0.47	0.48	0.42	0.48	0.25
Italy	0.63	0.79	0.83	0.62	0.58	0.19	0.94	0.86	0.44	0.49	0.39	0.50	1	0.45	0.41	0.61	0.91	0.33	0.77	0.48	0.41	0.89	0.87	0.85	0.41	0.89	0.53
Japan	0.26	0.47	0.38	0.24	0.29	0.32	0.40	0.37	0.69	0.42	0.52	0.40	0.45	1	0.51	0.23	0.38	0.55	0.43	0.61	0.73	0.41	0.40	0.41	0.73	0.40	0.11
Malaysia	0.19	0.33	0.39	0.19	0.17	0.28	0.30	0.27	0.45	0.36	0.61	0.34	0.41	0.51	1	0.18	0.32	0.33	0.35	0.47	0.45	0.33	0.31	0.28	0.45	0.30	0.09
Mexico	0.69	0.53	0.59	0.81	0.70	0.15	0.65	0.67	0.38	0.38	0.28	0.30	0.61	0.23	0.18	1	0.64	0.13	0.55	0.41	0.33	0.61	0.62	0.58	0.33	0.63	0.79
Netherlands	0.64	0.81	0.85	0.65	0.60	0.17	0.95	0.88	0.42	0.48	0.39	0.50	0.91	0.38	0.32	0.64	1	0.29	0.81	0.45	0.38	0.88	0.87	0.85	0.38	0.93	0.60
New Zealand	0.21	0.33	0.29	0.11	0.16	0.23	0.29	0.23	0.38	0.30	0.38	0.30	0.33	0.55	0.33	0.13	0.29	1	0.31	0.38	0.42	0.29	0.26	0.34	0.42	0.30	−0.02
Norway	0.63	0.75	0.67	0.60	0.61	0.21	0.78	0.75	0.48	0.50	0.49	0.51	0.77	0.43	0.35	0.55	0.81	0.31	1	0.50	0.46	0.74	0.78	0.71	0.46	0.79	0.48
Singapore	0.39	0.50	0.44	0.39	0.32	0.34	0.45	0.44	0.78	0.66	0.64	0.46	0.48	0.61	0.47	0.41	0.45	0.38	0.50	1	0.67	0.46	0.48	0.43	0.67	0.47	0.28
S. Korea	0.30	0.44	0.38	0.32	0.29	0.37	0.38	0.42	0.70	0.50	0.57	0.42	0.41	0.73	0.45	0.33	0.38	0.42	0.46	0.67	1	0.39	0.41	0.37	1.00	0.39	0.23
Spain	0.61	0.78	0.79	0.60	0.57	0.16	0.91	0.85	0.42	0.47	0.38	0.48	0.89	0.41	0.33	0.61	0.88	0.29	0.74	0.46	0.39	1	0.84	0.84	0.39	0.87	0.55
Sweden	0.59	0.80	0.79	0.63	0.56	0.16	0.89	0.85	0.44	0.47	0.37	0.47	0.87	0.40	0.31	0.62	0.87	0.26	0.78	0.48	0.41	0.84	1	0.80	0.41	0.86	0.54
Switzerland	0.58	0.75	0.78	0.59	0.56	0.15	0.89	0.82	0.41	0.46	0.36	0.48	0.85	0.41	0.28	0.58	0.85	0.34	0.71	0.43	0.37	0.84	0.80	1	0.37	0.88	0.55
Taiwan	0.30	0.44	0.38	0.32	0.29	0.37	0.38	0.42	0.70	0.50	0.57	0.42	0.41	0.73	0.45	0.33	0.38	0.42	0.46	0.67	1.00	0.39	0.41	0.37	1	0.39	0.23
UK	0.63	0.78	0.85	0.64	0.60	0.16	0.95	0.88	0.43	0.47	0.37	0.48	0.89	0.40	0.30	0.63	0.93	0.30	0.79	0.47	0.39	0.87	0.86	0.88	0.39	1	0.57
US	0.65	0.47	0.54	0.77	0.77	0.04	0.59	0.64	0.27	0.35	0.16	0.25	0.53	0.11	0.09	0.79	0.60	−0.02	0.48	0.28	0.23	0.55	0.54	0.55	0.23	0.57	1

Table 4: Correlation Matrix: 2005–2009

Country	Argentina	Austria	Belgium	Brazil	Canada	China	France	Germany	Hong Kong	India	Indonesia	Israel	Italy	Japan	Malaysia	Mexico	Netherlands	New Zealand	Norway	Singapore	S. Korea	Spain	Sweden	Switzerland	Taiwan	UK	US
Argentina	1	0.52	0.51	0.72	0.68	0.14	0.57	0.57	0.32	0.32	0.29	0.30	0.57	0.22	0.18	0.64	0.57	0.16	0.55	0.34	0.27	0.55	0.54	0.53	0.27	0.57	0.62
Austria	0.52	1	0.72	0.52	0.50	0.17	0.78	0.75	0.48	0.46	0.46	0.45	0.78	0.46	0.32	0.50	0.78	0.31	0.73	0.50	0.43	0.76	0.78	0.73	0.43	0.76	0.44
Belgium	0.51	0.72	1	0.55	0.51	0.17	0.85	0.78	0.43	0.44	0.34	0.43	0.83	0.38	0.36	0.56	0.85	0.26	0.64	0.44	0.37	0.79	0.78	0.78	0.37	0.84	0.52
Brazil	0.72	0.52	0.55	1	0.71	0.18	0.60	0.59	0.36	0.34	0.26	0.28	0.57	0.22	0.18	0.77	0.59	0.09	0.53	0.35	0.29	0.55	0.56	0.54	0.29	0.58	0.73
Canada	0.68	0.50	0.51	0.71	1	0.11	0.57	0.55	0.32	0.32	0.23	0.34	0.56	0.27	0.18	0.66	0.57	0.15	0.57	0.31	0.28	0.54	0.53	0.53	0.28	0.58	0.75
China	0.14	0.17	0.17	0.18	0.11	1	0.14	0.13	0.44	0.24	0.25	0.19	0.16	0.27	0.25	0.14	0.14	0.20	0.16	0.29	0.30	0.13	0.13	0.13	0.30	0.13	0.05
France	0.57	0.78	0.85	0.60	0.57	0.14	1	0.92	0.41	0.44	0.34	0.48	0.93	0.40	0.29	0.60	0.95	0.26	0.73	0.44	0.37	0.90	0.87	0.88	0.37	0.94	0.58
Germany	0.57	0.75	0.78	0.59	0.55	0.13	0.92	1	0.41	0.44	0.30	0.42	0.86	0.37	0.26	0.61	0.89	0.21	0.70	0.43	0.40	0.85	0.83	0.82	0.40	0.87	0.62
Hong Kong	0.32	0.48	0.43	0.36	0.32	0.44	0.41	0.41	1	0.60	0.60	0.42	0.43	0.67	0.45	0.35	0.41	0.35	0.46	0.76	0.68	0.41	0.43	0.40	0.68	0.42	0.25
India	0.32	0.46	0.44	0.34	0.32	0.24	0.44	0.44	0.60	1	0.51	0.40	0.46	0.41	0.34	0.33	0.45	0.27	0.49	0.62	0.48	0.44	0.44	0.45	0.48	0.44	0.30
Indonesia	0.29	0.46	0.34	0.26	0.23	0.25	0.34	0.30	0.60	0.51	1	0.37	0.36	0.50	0.55	0.25	0.36	0.35	0.46	0.62	0.54	0.35	0.35	0.34	0.54	0.35	0.13
Israel	0.30	0.45	0.43	0.28	0.34	0.19	0.48	0.42	0.42	0.40	0.37	1	0.48	0.36	0.31	0.28	0.47	0.26	0.47	0.43	0.37	0.45	0.45	0.46	0.37	0.45	0.23
Italy	0.57	0.78	0.83	0.57	0.56	0.16	0.93	0.86	0.43	0.46	0.36	0.48	1	0.42	0.38	0.57	0.90	0.29	0.73	0.47	0.40	0.89	0.85	0.84	0.40	0.88	0.52
Japan	0.22	0.46	0.38	0.22	0.27	0.27	0.40	0.37	0.67	0.41	0.50	0.36	0.42	1	0.48	0.22	0.37	0.49	0.41	0.60	0.71	0.40	0.39	0.41	0.71	0.39	0.11
Malaysia	0.18	0.32	0.36	0.18	0.18	0.25	0.29	0.26	0.45	0.34	0.55	0.31	0.38	0.48	1	0.18	0.30	0.31	0.32	0.48	0.43	0.32	0.30	0.28	0.43	0.29	0.09
Mexico	0.64	0.50	0.56	0.77	0.66	0.14	0.60	0.61	0.35	0.33	0.25	0.28	0.57	0.22	0.18	1	0.59	0.10	0.49	0.37	0.30	0.56	0.56	0.54	0.30	0.58	0.73
Netherlands	0.57	0.78	0.85	0.59	0.57	0.14	0.95	0.89	0.41	0.45	0.36	0.47	0.90	0.37	0.30	0.59	1	0.26	0.75	0.44	0.37	0.87	0.85	0.85	0.37	0.92	0.59
New Zealand	0.16	0.31	0.26	0.09	0.15	0.20	0.26	0.21	0.35	0.27	0.35	0.26	0.29	0.49	0.31	0.10	0.26	1	0.28	0.36	0.38	0.26	0.23	0.30	0.38	0.26	−0.02
Norway	0.55	0.73	0.64	0.53	0.57	0.16	0.73	0.70	0.46	0.49	0.46	0.47	0.73	0.41	0.32	0.49	0.75	0.28	1	0.48	0.44	0.70	0.75	0.66	0.44	0.75	0.44
Singapore	0.34	0.50	0.44	0.35	0.31	0.29	0.44	0.43	0.76	0.62	0.62	0.43	0.47	0.60	0.48	0.37	0.44	0.36	0.48	1	0.64	0.45	0.48	0.42	0.64	0.46	0.26
S. Korea	0.27	0.43	0.37	0.29	0.28	0.30	0.37	0.40	0.68	0.48	0.54	0.37	0.40	0.71	0.43	0.30	0.37	0.38	0.44	0.64	1	0.37	0.40	0.37	1.00	0.37	0.21
Spain	0.55	0.76	0.79	0.55	0.54	0.13	0.90	0.85	0.41	0.44	0.35	0.45	0.89	0.40	0.32	0.56	0.87	0.26	0.70	0.45	0.37	1	0.83	0.83	0.37	0.86	0.54
Sweden	0.54	0.78	0.78	0.56	0.53	0.13	0.87	0.83	0.43	0.44	0.35	0.45	0.85	0.39	0.30	0.56	0.85	0.23	0.75	0.48	0.40	0.83	1	0.79	0.40	0.84	0.51
Switzerland	0.53	0.73	0.78	0.54	0.53	0.13	0.88	0.82	0.40	0.45	0.34	0.46	0.84	0.41	0.28	0.54	0.85	0.30	0.66	0.42	0.37	0.83	0.79	1	0.37	0.87	0.53
Taiwan	0.27	0.43	0.37	0.29	0.28	0.30	0.37	0.40	0.68	0.48	0.54	0.37	0.40	0.71	0.43	0.30	0.37	0.38	0.44	0.64	1.00	0.37	0.40	0.37	1	0.37	0.21
UK	0.57	0.76	0.84	0.58	0.58	0.13	0.94	0.87	0.42	0.44	0.35	0.45	0.88	0.39	0.29	0.58	0.92	0.26	0.75	0.46	0.37	0.86	0.84	0.87	0.37	1	0.56
US	0.62	0.44	0.52	0.73	0.75	0.05	0.58	0.62	0.25	0.30	0.13	0.23	0.52	0.11	0.09	0.73	0.59	−0.02	0.44	0.26	0.21	0.54	0.51	0.53	0.21	0.56	1

Table 5: Percent Change in Variance and Covariance due to Frequencies $\omega \geq 0.45$ Between Tranquil and Crisis Periods, (frequencies $\omega \geq \frac{2\pi}{14} \approx 0.45$ correspond to the periodicity of 2 weeks or less.)

Country	Brazil	China	Germany	India	Indonesia	Japan	Malaysia	Mexico	Philippines	Singapore	S. Korea	Thailand
Brazil	38^C											
China	53^C	-85										
Germany	-116	358^C	63^C									
India	86^C	42^C	-3017	-2								
Indonesia	293^C	-1082	-2220	1000^C	121215^C							
Japan	-13	134^C	35^C	-233	11417^C	198^C						
Malaysia	808^C	-395	-122	-1063	291770^C	1025^C	7364^C					
Mexico	909^C	-39	-424	-1804	17053^C	313^C	17623^C	272^C				
Philippines	1698^C	-98	579^C	908^C	77172^C	608260^C	75667^C	3468^C	20172^C			
Singapore	423^C	-80	70^C	-270	112899^C	558^C	14119^C	2864^C	87000^C	1910^C		
S. Korea	543^C	649^C	-685	5357^C	270456^C	219^C	9853^C	1662^C	10713^C	3579^C	10703^C	
Thailand	23^C	-137	200^C	-8597	74082^C	222^C	22522^C	74^C	18690^C	6495^C	7743^C	478^C

Superscript "C" denotes a contagion (i.e., percent change in covariance due to high frequencies greater than 10%).

Table 6: Comparison of Time-Series and Frequency-Domain Results: Percent Change in Covariance due to High Frequencies Relative to Percent Change in Overall Covariance

Country	Brazil	China	Germany	India	Indonesia	Japan	Malaysia	Mexico	Philippines	Singapore	S. Korea	Thailand
Brazil	1.24^{I}											
China	1.53^{I}	0.99^{A}										
Germany	5.52^{I}	1.10^{A}	1.05^{A}									
India	0.66^{I}	0.36^{I}	44.86^{I}	0.45^{I}								
Indonesia	-0.88^{S}	1.51^{I}	1.24^{I}	-1.58^{S}	0.92^{A}							
Japan	-0.22^{S}	0.74^{I}	0.75^{I}	-4.64^{S}	0.87^{I}	0.95^{A}						
Malaysia	1.16^{I}	2.06^{I}	-1.40^{S}	0.55^{I}	0.78^{I}	0.80^{I}	0.88^{I}					
Mexico	1.01^{A}	4.98^{I}	1.14^{I}	4.27^{I}	0.79^{I}	1.00^{A}	3.27^{I}	1.00^{A}				
Philippines	1.28^{I}	1.23^{I}	0.59^{I}	0.98^{A}	0.64^{I}	0.03^{I}	0.66^{I}	0.89^{I}	0.87^{I}			
Singapore	1.18^{I}	1.54^{I}	0.54^{I}	3.04^{I}	0.94^{A}	0.87^{I}	0.69^{I}	1.37^{I}	0.91^{A}	0.92^{A}		
S. Korea	0.28^{I}	0.72^{I}	0.99^{A}	0.63^{I}	0.03^{I}	0.49^{I}	0.62^{I}	0.66^{I}	0.51^{I}	0.65^{I}	1.03^{A}	
Thailand	-3.78^{S}	1.47^{I}	0.64^{I}	-3.02^{S}	1.01^{A}	0.88^{I}	0.84^{I}	0.14^{I}	0.70^{I}	0.84^{I}	0.78^{I}	0.85^{I}

The superscript are: “A” for “Accurate” (if entry is between 0.9 and 1.1); “I” for “Inaccurate” (if entry is between 0 and 0.9 or greater than 1.1); “S”for “Spurious” (if entry is less than zero, i.e., the changes are of opposite signs)

Figure 1: Daily Stock Market Quotes (first 27 graphs) and Log-Returns (last 27 graphs), 2005–2009

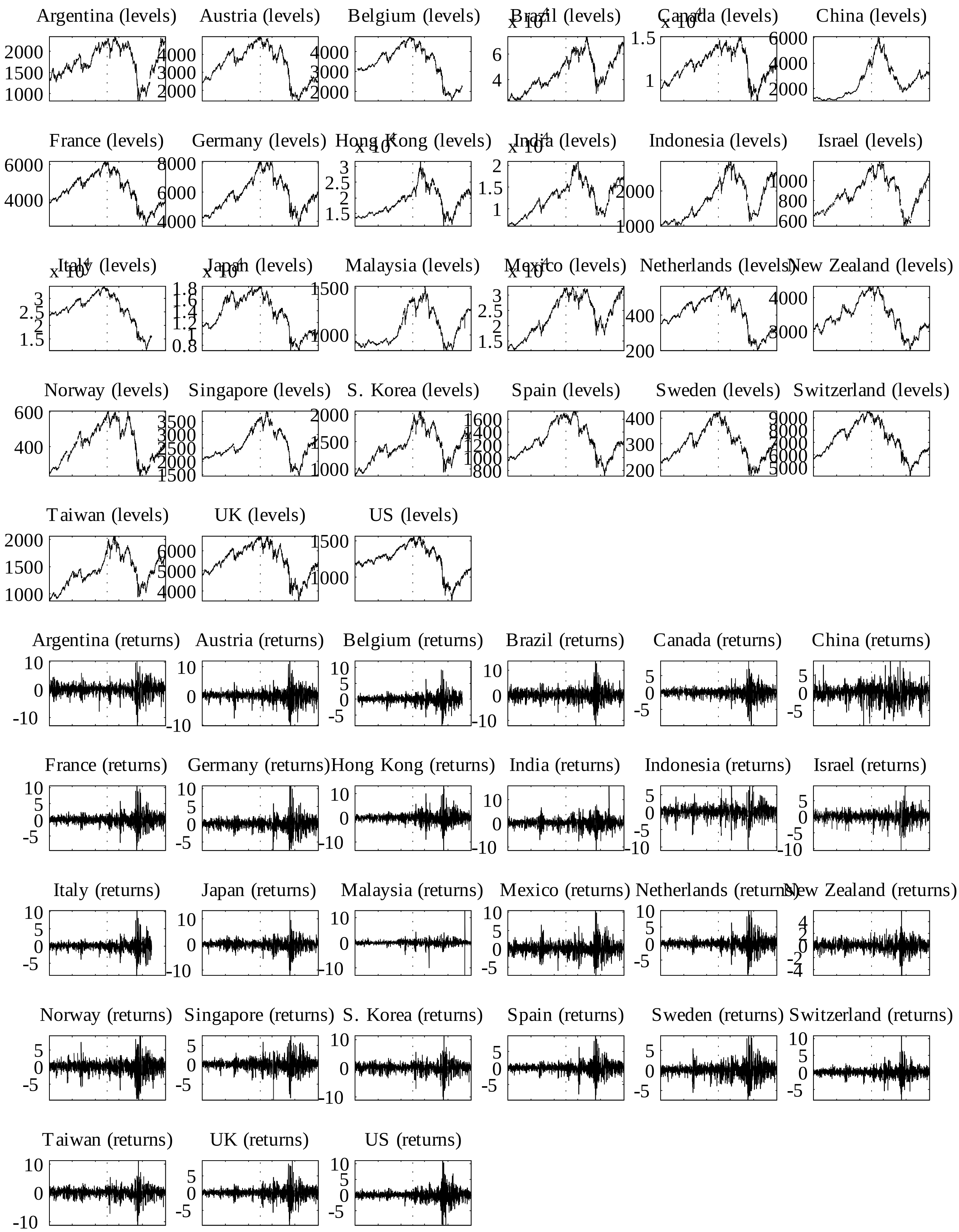

Figure 2: Spectral and Cospectral Densities of Stock Market Returns Before (Dashed Lines) and During (Solid Lines) the Subprime Crisis

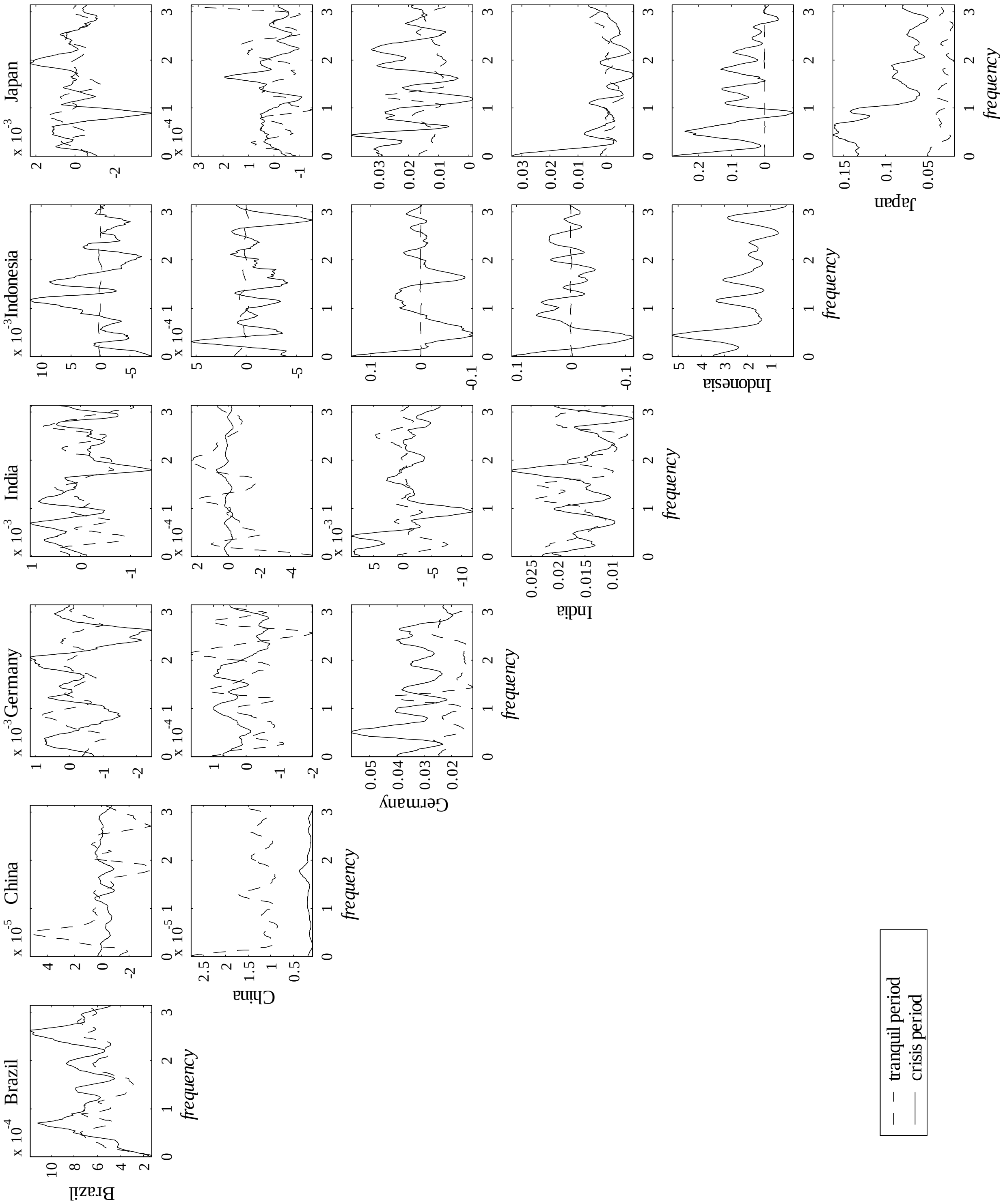

Figure 3: Spectral and Cospectral Densities of Stock Market Returns Before (Dashed Lines) and During (Solid Lines) the Subprime Crisis

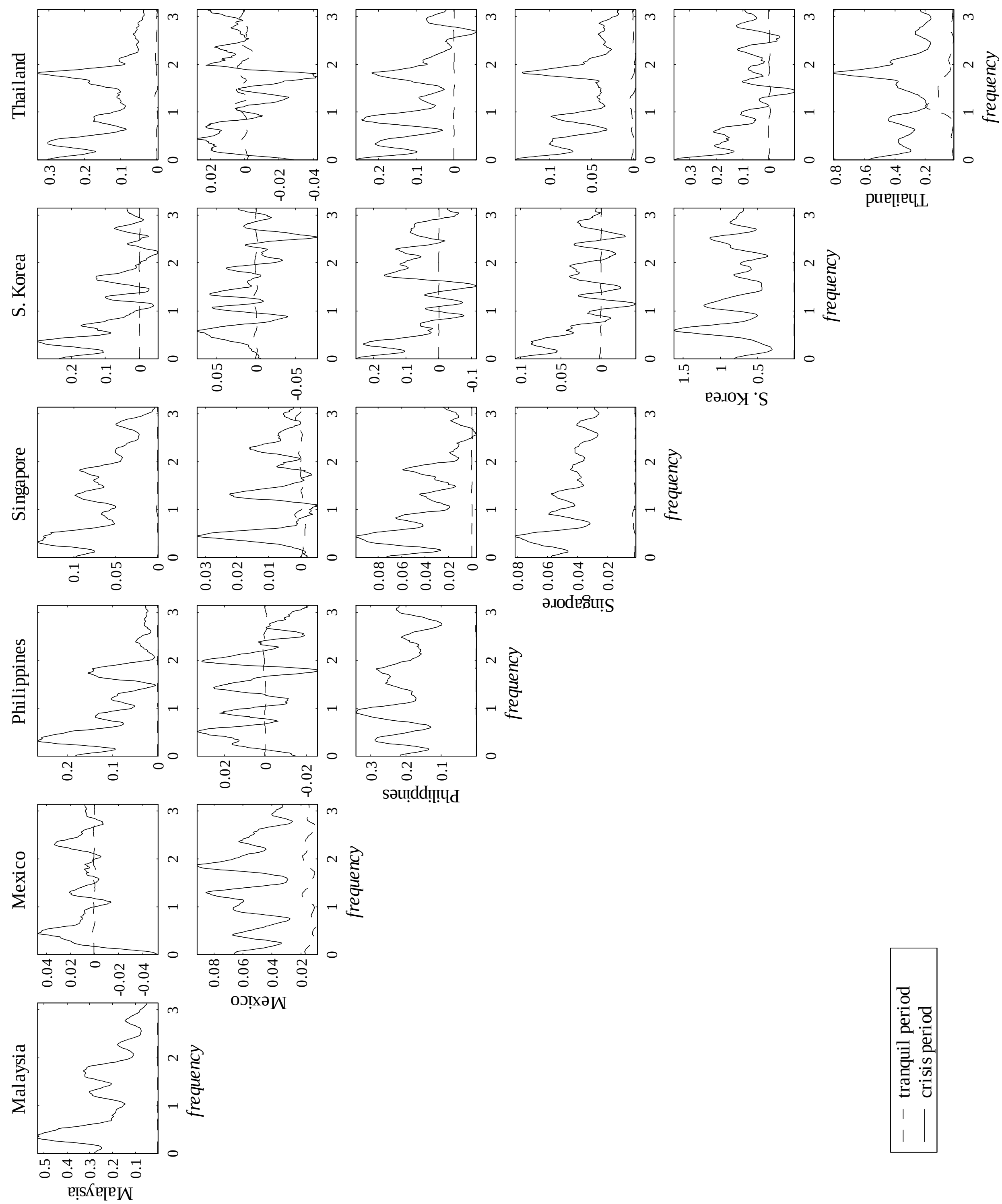

Figure 4: Spectral and Cospectral Densities of Stock Market Returns Before (Dashed Lines) and During (Solid Lines) the Subprime Crisis