"Slow-Burn" Spillover and "Fast and Furious" Contagion: A Study of International Stock Markets

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Abstract

“Fast and furious” contagion across capital markets is an important phenomenon in an increasingly integrated financial world. Different from “slow-burn spillover” or interdependence among these markets, “fast and furious” contagion can occur instantly. To investigate this kind of contagion from the U.S., Japan, and Hong Kong to other Asian economies, we design a research strategy to capture fundamental interdependence, or “slow-burn spillover”, among these stock markets as well as short-term departures from this interdependence. Based on these departures, we propose a new contagion measure which reveals how one market responds over time to a shock in another market. We also propose international portfolio analysis for contagion via variance decomposition from the portfolio manager’s perspective. Using this research strategy, we find that the U.S. stock market was cointegrated with the Asian stock markets during the four specific periods from July 3, 1997 to April 30, 2014. Beyond this fundamental interdependence, the shocks from both Japan and Hong Kong have significant “fast and furious” contagion effects on other Asian stock markets during the U.S. subprime crisis, but the shocks from the U.S. have no such effects.

JEL Codes: C5, F3, G1

Keywords: stock markets, contagion, interdependence, international portfolio analysis

1 Introduction

As globalization ushers us into the new millennium, international trade and capital markets connect the world more than ever, information flows almost instantly around the world (see Dooley and Hutchison (2009)), and investment strategies of investors tend to be more diversified across the global financial markets (see Ng (2000)). What are the features of the interconnection among stock markets? How could an international investment strategy be affected by this interconnection?

In this paper, we investigate interdependence and financial contagion among eleven stock markets based on daily data, focusing on the short term impact from the U.S., Japan, and Hong Kong to other Asian economies[1] during the period of July 3, 1997–April 30, 2014.[2] Following Kaminsky et al. (2003) and Reinhart and Rogoff (2009), we refer interdependence as "slow-burn" spillover across markets driven by common (external and internal) factors. We view contagion as "fast and furious" shock waves across markets driven by information cascade in the sense of Bikhchandani et al. (1992).

We are interested in investigating a number of interesting hypotheses. First, is it true that after we have taken the long-run interdependence among different markets into account, we still could not find any "fast and furious" contagion across these markets?[3] Second, were the U.S. stock market and the Asian stock markets segregated during the U.S. subprime crisis?[4] Third, is contagion from the U.S. stock market different from that from the Japanese and Hong Kong markets?

To identify the pattern and dynamics of "fast and furious" contagion across stock markets, we have made two innovations. First, we propose a new measure of contagion beyond the long-run interdependence. Second, we propose a new way of implementing international portfolio analysis for contagion via variance decomposition.

This study differs from the existing studies in a number of different ways. First, we study more updated data to find out how contagion channels from stock markets in some

[1]They are China, India, Indonesia, Korea, Malaysia, Singapore, and Taiwan. We also include the U.K. stock market as an important stock market in the world so that our selection of the stock markets represents the international stock markets well. In addition, we follow the sequence of the U.S. stock market—Asian mature (Japan and Hong Kong) and other Asian stock markets—the U.K. stock market in our study.

[2]This paper extends the study by Ng (2000), which covers the period of 1975-1996.

[3]Dooley and Hutchison (2009) and Baele and Inghelbrecht (2010) could not find any evidence for contagion.

[4]Reinhart and Rogoff (2009, p. 245) report that during the period of 2007–2008, the U.S., U.K., Japan experienced financial crisis but Hong Kong, China, India, Indonesia, Korea, Malaysia, Singapore, and Taiwan did not.

key developed economies (the U.S., U.K., Japan, and Hong Kong) to other Asian stock markets during the periods of major regional and global financial market events. This is of particular interest as many of the existing studies focus on how contagion occurred among mature stock markets (e.g., Hamao et al. (1990), King and Wadhwani (1990), Loretan and English (2000), Baele and Inghelbrecht (2010)) or from Asian stock markets to more mature stock markets prior to 2000 (Forbes and Rigobon (2002)). Witnessed the financial crisis in the U.S. in 2009, we wish to study how contagion transmits from more mature stock markets in the U.S., Japan, and Hong Kong to other Asian stock markets in Taiwan, Singapore, Korea, Indonesia, Malaysia, China, and India.[5]

Second, in this paper we distinguish long-run interdependence among asset prices from short-term departures around that long-run interdependence. The concept of contagion evolves over time. In earlier studies, the differentiation of contagion from the long-run interdependence is not distinct. For example, Dornbusch et al. (2000) define contagion as "the spread of market disturbances—mostly on the downside—from one (emerging market) country to the other." Kaminsky and Reinhart (2002) suggest that contagion is shown as "speculative attacks ... are bunched together across countries." Forbes and Rogobon (2002) define "contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries)." However, the concept of contagion has been more refined lately. For example, Kaminsky et al. (2003) also define contagion as "fast and furious" shock waves while the conventional interdependence as "slow-burn" spillover.[6] Bekaert et al. (2005) differentiate fundamental linkages and deviations from these linkages and consider contagion as "correlation over and above what one would expect from economic fundamentals." Dungey et al. (2010) refer to contagion as "distinct from crisis-driven changes in fundamental linkages."[7] We design an empirical framework for the more refined concept of contagion in this paper.

Third, in this paper we propose (1) a modeling framework, which is consistent with the common factor model, for capturing "slow-burn" spillover among asset prices, (2) a new measure for "fast and furious" contagion, and (3) a new approach for implementing international portfolio analysis for contagion via variance decomposition. As Baele and Inghelbrecht (2010) point out, the identification of contagion defined above depends critically

[5] Ng (2000) works on volatility spillover from the U.S. and Japan to other Asian countries.

[6] We use the spillover concept to refer to interdependence across different markets over different time zones.

[7] Please see an excellent survey on contagion by Pericoli and Sbracia (2003) and see a study on a domino effect by Markwat et al. (2009).

on the models used to capture fundamental dependence. Following Bekaert et al. (2005), Baele and Inghelbreht (2010) use a less restricted time-varying multi-factor model and do not find any evidence of contagion. Therefore, it is critical to consider the fundamental interdependence and comovements as well as any pattern and dynamics of contagion in these stock markets.

We have the following interesting findings. First, using cointegration models we find the time-varying "slow-burn" spillover effects among these stock markets. Although, during the U.S. subprime crisis, the U.S. stock market was highly cointegrated with the Asian stock markets, the shock from the U.S. stock market did not have any "fast and furious" contagion effect on the Asian stock markets. Second, there were significant "fast and furious" contagion effects from both the Japanese and Hong Kong stock markets to other Asian stock markets beyond the "slow-burn" spillover effects. Third, we find significant overreactions of other Asian stock markets to the shocks from the Japanese and Hong Kong stock markets but marked underreactions to the shock from the U.S. stock market during the subprime crisis. Fourth, our international portfolio analysis for contagion also confirms the role that the Japanese and Hong Kong stock markets play to other Asian stock markets. In addition to the above findings, we note that capital controls used in, and net equity investment flows across, these markets may offer some plausible explanations for the existence, or lack thereof, of "fast and furious" contagion.

The research work done in this paper is relevant to the real world need for risk measure and management in the context of global investment. The flexible approach for identifying cointegration relations can be used to evaluate the comovements in these markets during significant regional and global financial market events. Our contagion measure can be used to find the contagion effect of one market to another beyond long-run interdependence. We can use the portfolio approach to further evaluate the role of contagion in portfolio risk measure and management.

The remainder of this paper is organized as follows. Section 2 introduces our modeling framework, new contagion measure, and new international portfolio analysis. Section 3 describes the data used in this research, summary statistics and crash transition probabilities. Section 4 presents the empirical analysis, including the cointegration analysis, SVAR analysis of shocks across stock markets, contagion analysis and international portfolio analysis. Section 5 concludes.

2 Research Methodology

2.1 Characterization of data generating process

Bekaert et al. (2005) and Pukthuanthong and Roll (2009) show the stock market returns are influenced by a set of common factors. We further find that for any two stock market prices to be cointegrated, they must also be governed by the same stochastic trend and be perturbed by the common/correlated shocks.[8] Over the last few decades, the cointegration relations among markets are changing (see Bekaert and Harvey (1995) and Brada et al. (2005))[9] and becoming increasingly strong among close related stock markets during significant regional and global financial market events (de Jong and de Roon (2005)). Hence, we use the rolling cointegration technique developed by Hansen and Johansen (1999) to identify episodes of stable cointegration relations among stock markets. We use Fukuda's method (2011) to check the robustness of these episodes by finding out the change of the number of stable cointegration relations.[10] This strategy allows us to identify current market interdependence, often referred to as "slow-burn" spillover, even in the context of structural changes.[11]

To describe the data generating process, long-run dependence and contagion, let $\mathbf{p}_t = [p_{1,t}, p_{2,t}, \ldots, p_{n,t}]'$ denote an $n \times 1$ vector of n market portfolio prices (in log). Hence, returns on the n stock market portfolios, $\Delta\mathbf{p}_t$, can be cast in a vector autoregressive (VAR) model, which has a multivariate moving average (MA) or Wold representation:

$$\Delta\mathbf{p}_t = \mathbf{\Psi}(L)\mathbf{e}_t = \mathbf{e}_t + \mathbf{\Psi}_1\mathbf{e}_{t-1} + \mathbf{\Psi}_2\mathbf{e}_{t-2} + \cdots , \tag{1}$$

where $\mathbf{\Psi}(L) = \sum_{k=0}^{\infty} \mathbf{\Psi}_k L^k$ with $\mathbf{\Psi}_0 = \mathbf{I}$. $\mathbf{\Psi}(L)$ is an $n \times n$ polynomial matrix in lag operator L. The error terms in $\mathbf{e}_t$ are, in general, not orthogonal to each other, as there may be non-zero correlation between contemporaneous error terms. $\mathbf{\Psi}(L)$ maps historical error terms, $\mathbf{e}_t, \mathbf{e}_{t-1}, \mathbf{e}_{t-2} \ldots$, of the model into the current returns $\Delta\mathbf{p}_t$.

We are interested in structural innovations in $\mathbf{v}_t$, combinations of which appear as error

[8] For the theoretical work and simulation on this, see Appendix A.

[9] Chan et al. (1992) and DeFusco et al. (1996) find no cointegration relations in, and between, mature and emerging stock markets. Darrat and Zhong (2002) find cointegration between the U.S. (but not Japan) and other Asian countries. Bessler and Yang (2003) find the linkages among mature stock markets.

[10] Martins and Gabriel (2013) attempt to use the regime-switching model to deal with "interrupted" cointegration relations.

[11] Bekaert et al. (2005) use the correlations of lagged stock market returns as the market linkages for identifying current contagion whereas we employ the current cointegration relations among stock market indices for identifying current contagion.

terms in $\mathbf{e}_t$, as well as causal chains among structural innovations. We use $\mathbf{A}\mathbf{e}_t = \mathbf{B}\mathbf{v}_t$, where $\mathbf{A}$ and $\mathbf{B}$ are both $n \times n$ matrices, to link innovations to error terms. As the structural innovations in $\mathbf{v}_t$ are orthogonal to each other, $\mathbf{B}$ is a diagonal matrix with diagonal elements being the standard deviations of structural innovations. $\mathbf{A}$ characterizes contemporaneous correlations among the error terms. Therefore, we obtain

$$\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t. \tag{2}$$

Substituting equation (2) into equation (1) yields

$$\Delta\mathbf{p}_t = \mathbf{\Psi}(L)\mathbf{e}_t = \mathbf{\Psi}(L)\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t. \tag{3}$$

We use the structural VAR (SVAR) analysis to investigate the contemporaneous information transmission among multiple stock markets[12] based on the short-term departures from the long-run cointegration relations.[13] In this paper, we use the directed acyclic graph (DAG) method to identify the contemporaneous information transmission among these stock markets[14] and the pattern and dynamics of "fast and furious" contagion across stock markets.[15]

According to the Granger Representation Theorem (see Engle and Granger (1987)), the n market portfolio prices in $\mathbf{p}_t$ are said to be cointegrated with rank r if $\mathbf{\Psi}(1)$ is of rank $(n-r)$, and there exist two $n \times r$ matrices, α and β, both of rank r, such that $\beta'\mathbf{\Psi}(1) = \mathbf{0}$ and $\mathbf{\Psi}(1)\alpha = \mathbf{0}$. The columns of β are the cointegrating vectors and the columns of α contain the error correction coefficients.[16]

Now we explain the long-run pricing impact and related pricing error. Define $\mathbf{G} = \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix}$, where β' is a $r \times n$ matrix and $\alpha'_\perp$ is an $(n-r) \times n$ matrix satisfying $\alpha'_\perp \alpha = \mathbf{0}$.

[12]Most other studies concerning contagion are based on bivariate analyses, and do not investigate interdependence in a multivariate environment (see, for example, Forbes and Rigobon (2002), Boyer et al. (2006), Rodrigues (2007), and Fazio (2007)).

[13]Although the importance of contemporaneous information transmission among stock markets is well recognized, more studies focus on non-contemporaneous information transmission (see Eun and Shim (1989) Bessler and Yang (2003), and Dungey et al. (2010)).

[14]The DAG method is used by Swanson and Granger (1997) to analyze causal chains of VAR residuals. Chen and Hsiao (2007) show that time series causal models based on the DAG are consistent to structural VAR models.

[15]We also use (1) normalization (assigning 1 to the focal market) in matrix $\mathbf{A}$ and (2) the time-zone and end-of-business-day differences to identify the structural VAR (see Kleimeier et al. (2008)).

[16]Note that the cointegration relations under consideration in this study have no deterministic components, which lie outside the cointegrating space in the sense of Johansen (1991).

Using $\mathbf{G}$, we can rewrite $\Delta\mathbf{p}_t$ as

$$\begin{aligned}
\Delta\mathbf{p}_t &= \boldsymbol{\Psi}(L)\mathbf{G}^{-1}\mathbf{G}\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \qquad (4)\\
&= \begin{bmatrix} \mathbf{D}_1(L) & \mathbf{D}_2(L) \end{bmatrix} \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix} \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \\
&= \mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \\
&= \underbrace{\mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t}_{\text{long-run pricing impact denoted as } \boldsymbol{\Phi}\mathbf{v}_t} + \underbrace{[\mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}]\mathbf{v}_t}_{\text{pricing error denoted as } \boldsymbol{\Phi}^*(L)\mathbf{v}_t \text{ with } \boldsymbol{\Phi}^*(1)\mathbf{v}_t=\mathbf{0}},
\end{aligned}$$

where $\mathbf{D}_1(L)$ contains the first $(n-r)$ columns of $\boldsymbol{\Psi}(L)\mathbf{G}^{-1}$ and $\mathbf{D}_2(L)$ contains the last r columns. We decompose $\Delta\mathbf{p}_t$ into long-run pricing impact and pricing error. The total price impact of $\mathbf{v}_t$ on $\Delta\mathbf{p}_t$ is $\boldsymbol{\Phi}\mathbf{v}_t + \boldsymbol{\Phi}^*(0)\mathbf{v}_t$, in which the long-run pricing impact is $\boldsymbol{\Phi}\mathbf{v}_t$ and $\boldsymbol{\Phi}^*(0)\mathbf{v}_t$ is the pricing error given $\boldsymbol{\Phi}^*(1)\mathbf{v}_t = \mathbf{0}$, which will be corrected if given a long-enough period.[17]

2.2 Contagion measure

To discuss how to measure "fast and furious" contagion, we propose our contagion measure. Let $\boldsymbol{\Phi}_{i,j}$ ($\boldsymbol{\Phi}^*_{i,j}$) be the i,j-th element of $\boldsymbol{\Phi}$ ($\boldsymbol{\Phi}^*$). We can evaluate "fast and furious" contagion from market j to market i using $C_{i,j}$:

$$C_{i,j} = \left(\frac{\boldsymbol{\Phi}_{i,j} + \boldsymbol{\Phi}^*(0)_{i,j}}{\boldsymbol{\Phi}_{j,j} + \boldsymbol{\Phi}^*(0)_{j,j}}\right)^2 - \left(\frac{\boldsymbol{\Phi}_{i,j}}{\boldsymbol{\Phi}_{j,j}}\right)^2. \qquad (5)$$

The first term of the right-hand side of equation (5) measures the total cross-market pricing impact from market j to market i ($\boldsymbol{\Phi}_{i,j} + \boldsymbol{\Phi}^*(0)_{i,j}$) relative to the total within-market pricing impact from market j to itself ($\boldsymbol{\Phi}_{j,j} + \boldsymbol{\Phi}^*(0)_{j,j}$). The total pricing impact has two components as explained before: long-run pricing impact ($\boldsymbol{\Phi}_{i,j}$, $\boldsymbol{\Phi}_{j,j}$) and pricing error ($\boldsymbol{\Phi}^*(0)_{i,j}$,$\boldsymbol{\Phi}^*(0)_{j,j}$). The second term of the right-hand side of equation (5) measures the cross-market long-run pricing impact ($\boldsymbol{\Phi}_{i,j}$) relative to the within-market long-run pricing impact ($\boldsymbol{\Phi}_{j,j}$). If the

[17] The formal proof can be found in Appendix B. Please note that the decomposition method used here is different from the widely used permanent-transitory decomposition methods (such as Gonzalo and Granger (1995) and Gonzalo and Ng (2001)), which may identify permanent and transitory shocks differently. In the literature, an innovation having non-zero long-run effect on the level of $\mathbf{p}_t$ is defined as a permanent shock, otherwise it is defined as a transitory shock. However, a permanent shock combined with an arbitrary transitory shock is still a permanent shock which has non-zero long-run effects. Hence, it is difficult to identify a unique permanent shock.

cross-market pricing error ($\mathbf{\Phi}^*(0)_{i,j}$) is greater in proportion than the within-market pricing error ($\mathbf{\Phi}^*(0)_{j,j}$) in the context of the cross-market long-run pricing impact relative to the within-market long-run pricing impact, $C_{i,j}$ will be significantly greater than 0. In this case, shocks in market j lead to more volatility in market i. This is considered as the evidence for contagion. If the cross-market pricing error ($\mathbf{\Phi}^*(0)_{i,j}$) is smaller in proportion than the within-market pricing error ($\mathbf{\Phi}^*(0)_{j,j}$) in the context of the cross-market long-run pricing impact relative to the within-market long-run pricing impact, $C_{i,j}$ will be significantly less than 0. In this case, shocks in market j lead to little volatility in market i. This is considered as the evidence against contagion.

2.3 International portfolio analysis for contagion

To understand and manage the risk of contagion from the perspective of international portfolio investment, we propose international portfolio analysis for contagion via variance decomposition of the corresponding vector error-correction models (VECMs) (see equation (4)). Using this method, we can trace the portion of the international portfolio return variance to external shocks from some markets, assets of which are not included in this international portfolio. The variance decomposition proposed here can show whether the contemporaneous transmission of external shocks exacerbates or reduces the volatility of the international portfolio return. Therefore, this decomposition can shed more light on "fast and furious" contagion beyond the fundamental interdependence and on risk measurement and management via portfolio diversification across many markets.

To explain our variance decomposition, denote the 1-step ahead conditional forecast error variance as $\mathbf{V}_p$, the efficient price volatility as $\mathbf{V}_p^e$, and the difference between them as ε_p (that is, $\mathbf{V}_p^e + \varepsilon_p = \mathbf{V}_p$). To define $\mathbf{V}_p$ and $\mathbf{V}_p^e$, we need the vector of international market portfolio weights $\mathbf{w}$,[18] which can be determined in an ad hoc way or via an optimization procedure. Using the variance of $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ and the definition of $\mathbf{w}$, we obtain the total portfolio variance,

$$\mathbf{V}_p = \mathbf{w}'[\mathbf{A}^{-1}\mathbf{B}][\mathbf{A}^{-1}\mathbf{B}]'\mathbf{w}. \tag{6}$$

Using the variance of the long-run impact in equation (4)—$\mathbf{\Phi}\mathbf{v}_t$—and the definition of $\mathbf{w}$,

[18] In this study, if we study the external shock from a market portfolio A on a composite market portfolio which consists of market portfolios B, C, and E, we can assign the weight 0 to market portfolio A and equal weights (1/3) to market portfolios B, C, and E

we obtain the efficient portfolio variance,

$$\mathbf{V}_p^e = \mathbf{w}'[\mathbf{D}_1(1)\alpha'_\perp \mathbf{A}^{-1}\mathbf{B}][\mathbf{D}_1(1)\alpha'_\perp \mathbf{A}^{-1}\mathbf{B}]'\mathbf{w}. \tag{7}$$

When $\mathbf{V}_p$ departs from $\mathbf{V}_p^e$, we can interpret the departure ε_p as follows. An ε_p value greater than 0 implies a crisis deteriorating case for the international portfolio variance while a ε_p value less than 0 implies a crisis recuperating case for the international portfolio variance. A zero ε_p indicates a crisis neutral case for the international portfolio variance.

Our approach has the following interpretation. If the contemporaneous information transmission of external shocks is efficient in the sense that all the markets can fully reflect this information instantaneously, then the 1-step ahead conditional forecast error variance for the market portfolio return should approach the efficient portfolio variance given by the evolution of price processes.[19] In contrast, inefficient contemporaneous information transmission among markets can exacerbate or reduce the total variance of the market portfolio return causing departures from the efficient portfolio variance.[20]

3 Data, Summary Statistics, and Crash Transition Probabilities

3.1 Data

The data used in this study consist of the daily market index prices[21] of the eleven stock markets for the period from July 3, 1997 to April 30, 2014. During this period, a series of significant regional and global financial market events, such as southeast Asian financial crisis (1997), the tech bubble (2001), subprime crisis (2007), and American financial tsunami (2008), occurred. All of these events lead to the major crashes in the U.S. stock market and other stock markets. The data cover four major mature stock markets including the U.S., U.K., Japanese and Hong Kong markets and seven Asian stock markets including the Taiwanese, Singaporean, Korean, Indonesian, Malaysian, Chinese, and Indian markets. Their market indices are the U.S. S&P 500 (US), U.K. FT 30 (UK), Japan Nikkei 225 (JP), Hong Kong Hang Seng (HK), Taiwan Stock Exchange Weighted (TW), Singapore Strait Times

[19] Please see Frijns and Schotman (2009) for the definition of an efficient price volatility.

[20] The contemporaneous information transmission reflects the underlying institutional arrangement and regulatory coordination that manage external shocks.

[21] The prices are closing prices. All stock market indices are measured in home-country currencies.

(SG), Korea Stock Exchange Composite (KR), Indonesia Jakarta Stock Exchange Composite (IN), Malaysia Kuala Lumpur Composite (ML), China Shanghai Composite (CN), and India Bombay Stock Exchange 30 (ID).[22]

(Please place Table 1 about here)

3.2 Summary statistics

Panel A of Table 1 provides the summary statistics of daily stock returns for the full sample period including mean, volatility, minimum, maximum, and 10th quantiles. These summary statistics show that relative to the more mature stock markets (the U.S., U.K., Japanese, and Hong Kong stock markets), other Asian stock markets, in general, have higher volatility but have higher annualized average returns. Table 1 also reports, in the fifth row, the 10% quantile measures of the empirical return distributions of the market indices, which are used in calculating crash transition probabilities in Panels B and C of Table 1.[23]

3.3 Crash transition probabilities

Panel B of Table 1 shows the crash transition probabilities in some specific markets, given the occurrence of crashes in the U.S., Japan and Hong Kong, respectively, during the full sample period of July 3, 1997–April 30, 2014. More specifically, Panel B of Table 1 lists the crash transition probabilities in non-U.S. markets conditional on the U.S. crash, the Japan crash, Hong Kong crash, Japan and U.S. crashes, and Hong Kong and U.S. crashes, respectively. The last column of Panel B of Table 1 reports the average of crash transition probabilities of other Asian stock markets. Panel B of Table 1 shows that the average crash transition probability from the U.S. is 28.35%, while those from Japan and Hong Kong are 33.48% and 42.59%, respectively. Conditional on both the Japan and U.S. (Hong Kong and U.S.) crashes, the average crash transition probability is 45.58% (49.95%). To make sense

[22]In any study involving the analysis of daily stock market data across major continents in the world, it will inevitably encounter the problem of international trading nonsynchronism. That is, international stock markets operate in different time zones and the data for the same trading calendar day may occur at different point in time. In particular, as trading on a given calendar day starts in Asia and ends in the U.S., a piece of information occurring in the U.S. stock market on a calendar day is available to Asian markets on the next calendar day. To truly study the contagion from the U.S. market, we shall align the data from the U.S. as the starting point. That is, the data for the U.S. are aligned with the data next day in Asian stock markets.

[23]Bae et al. (2003) and Markwat (2009) suggest that a crash in a given market occurs when the daily return lies below a certain quantile of the empirical return distribution over the full sample period. Among the choices of theirs—1%, 5% and 10% quantiles, we use the 10% quantile as it is more restrictive as to what constitutes a crash.

of these average crash transition probabilities, we note that if all markets are independent, these probabilities would be 10%. Clearly, these markets are interdependent as all these probabilities are at least double and quadruple the 10% benchmark. In addition, crash transition probabilities in other Asian stock markets tend to be higher conditional on the crashes in Japan and Hong Kong.

Panel C of Table 1 is organized similarly as Panel B but for the U.S. subprime crisis during the period of June 4, 2007–January 25, 2008. During this period, the average crash transition probability in seven Asian stock markets conditional on the U.S. crash increases from 28.35% to 33.57%, while the average crash transition probabilities conditional on the Japan crash and Hong Kong crash increase substantially from 33.48% to 58.93% and from 42.59% to 59.40%, respectively. To find out why these dramatic changes occurred during the U.S. subprime crisis, we note that the crash transition probability in Singapore conditional on the U.S. crash is 40.00% but this probability increases to more than 75% following the consecutive crash in Japan or Hong Kong. The similar observations emerge for other Asian stock markets. It appears that there is a discernible secondary order effect of the Japan and Hong Kong stock market crashes after the U.S. stock market crash on other Asian stock markets during the U.S. subprime crisis.

In Table 1, the fourth column of Panels B and C reports the crash transition probabilities of the Japanese stock market conditional on the U.S., Hong Kong, and Hong Kong and U.S. stock market crashes, respectively. The fifth column lists the crash transition probabilities of the Hong Kong stock market conditional on the the U.S., Japan, Japan and U.S. crashes, respectively. During the full sample period (see Panel B), the crash transition probabilities of Japan and Hong Kong conditional on one another and on the U.S. range from 45.20% to 64.89%. However, during the U.S. subprime crisis (see Panel C), these crash transition probabilities are higher, ranging from 63.16% to 75.00%. These crash transition probabilities (in Panels B and C) demonstrate a domino effect, where the U.S. crash causes the crashes in Japan and Hong Kong, which in turn lead to widespread crashes in other Asian stock markets. This domino effect may reflect the contagion effect, or interdependence, or both. Therefore, it is desirable to further investigate the transmission mechanism behind this domino effect.

4 Empirical Results

4.1 Interdependence and cointegration analysis

To identify the time-varying interdependence, or "slow-burn" spillover, among these stock markets, we use our prior knowledge about significant regional and global financial market events[24] and the rolling cointegration analysis for stable cointegration relations developed by Hansen and Johansen (1999),[25] and Fukuda's (2011) method for a regime switching point in the number of cointegration rank.

Using the rolling cointegration analysis with different window widths (1, 2, 3 years), we can see that there are four prominent episodes of cointegration relations among the eleven stock markets. When we combine this finding with significant regional and global financial market events, we find that when significant regional and global financial market events occurred in episodes 1, 2, and 4, cointegration relations strengthened and could last for as long as about three years. In episode 3, however, cointegration relations strengthened before the subprime crisis occurred and these relations weakened after the subprime crisis occurred. In order to check the robustness of the findings, we use the significant events as the starting points for episodes 1, 2, and 4 but as the ending point for episode 3. Then we use Fukuda's (2011) method to find a regime switching point of the number of cointegration rank for the other end of each episode.

Based on the above approaches, we find that while the eleven stock market indices (or a subgroup of them) are not always cointegrated at all times, they do maintain long-run interdependence (cointegration relations) during the following four periods: (1) August 24, 1998–August 10, 1999, (2) September 6, 2001–August 26, 2002, (3) December 21, 2006–May 9, 2008 and (4) October 28, 2008–November 20, 2009.

To show four cointegration periods of the eleven stock markets, we normalize the eleven stock market indices to 1 on July 3, 1997. We note that the Thai baht's collapse in July 1997 triggered a sequence of events in the Asian financial crisis. At the end of 1998, the Asian crisis almost ended and Asian stock markets benefited directly from the robust intraregional

[24] As observed by Elyasiani and Kocagil (2001) about the currency markets, these are a number of cointegration periods in which some major events in the national or global financial markets occurred. As noted by Dooley and Hutchison (2009), the emerging markets were decoupled from the U.S. market before the subprime crisis, but their linkages dramatically reemerged/recoupled by early 2008, with a remarkably uniform timing across most of the emerging markets.

[25] We use trace tests over one, two, and three year windows to ensure flexibility of the search although Awokuse et al.(2009) use a two-year window for analysis of stock markets while Brada et al. (2005) use a five-year window for analysis of macroeconomic time series.

trade and increasing investments in Asia.

Period 1 (August 24, 1998–August 10, 1999) is characterized by increasing trends among eleven stock markets as shown in Figure 1. Among these stock market indices, those in Singapore, China and India demonstrated strong increasing trends but the U.S. S&P stock market index had a major crash, marked by the vertical bar, in August 31, 1998.

Period 2 (September 6, 2001–August 26, 2002) is characterized by a relatively stable trend as shown in Figure 2. This period also witnessed the Argentina crisis and the 9-11 terrorist attack in 2001, marked by the vertical bar. The 9-11 terrorist attack severely interrupted the financial markets and caused market closure until September 17, 2001. Among these stock markets indices, those in Japan, Singapore, and China experienced even more rapid falls.

Period 3 (December 21, 2006–May 9, 2008) is characterized by severe volatility and changing tides in the stock markets as shown in Figure 3. During this period, the U.S. subprime crisis occurred. Two vertical bars are used to highlight the huge crashes on August 16, 2007 and January 21, 2008, respectively. During this period, Asian stock markets such as those in Hong Kong, Korea, Indonesia, India, and China experienced a good run relative to other more mature stock markets. As the subprime crisis started, no markets, including the Asian stock markets, could be immune to such a crisis.

As shown in Figure 4, period 4 (October 28, 2008–November 20, 2009) is characterized by the comovement of the markets' bottoming, highlighted by a vertical bar, on March 9, 2009 and then reversing their bearish trends onwards although these upward moves after the bottom varied and were not smooth.

(Please place Figures 1–4 about here)

Although our data start from July 3, 1997 and end on April 30, 2014, we do not find any additional period of stable cointegration relations from the end of period 4 to April 30, 2014.

The subsequent cointegration analysis is conducted on the stock market indices during the four periods. Table 2 report the estimation results and test results of the vector error correction models without any constant, trend, or lagged dependent variables, which are chosen based on the Akaike information criterion. In the Panel C of Table 2, we report the Johansen trace tests, the log-likelihood function values, and the AIC values. The test statistic in the bold font indicates that the chosen number of cointegrating vectors cannot be rejected at the 5% signnificant level. The p-value of the test statistic is given in the brackets. According to these test results, we find one cointegration relation in periods 1 and 4 and two cointegration relations in periods 2 and 4. If there is only one cointegrating vector, it is normalized for the U.S. stock market; if there are two cointegrating vectors, they are normalized for the U.S. and Japanese stock markets, respectively.

(Please place Table 2 about here)

In Panel A of Table 2, the coefficient estimates of cointegrating vectors across the four periods confirm the existence of time-varying cointegrating relations among most stock markets, since some coefficient estimates in the cointegrating vectors are positive in some periods but some are negative in others. However, when the U.S. stock market is normalized to one, there are negative coefficients for the U.K. stock market during periods 1, 2, and 3, which implies that the U.S. and U.K. markets move in tandem. When the Japanese stock market is normalized in period 2, the U.K. and Japan markets move in tandem in period 2 but in the opposite directions in period 3. The coefficient estimates of cointegrating vectors show that the Hong Kong market and U.S. market move in tandem in period 1 but in the opposite directions in periods 2 and 3. Overall across the four periods, the eleven stock markets studied in this paper show some significant cointegration relations. These relations represent the stable interdependence within each of the four periods.

In Panel B of Table 2, the adjustment coefficient estimates also change over time, reflecting the fact that the long-run relations among these stock markets may change across periods. These adjustment coefficient estimates indicate the directions and magnitudes of adjustments in the relevant stock markets to maintain the cointegrating relations with other stock markets. For example, positive (or negative) adjustment estimates suggest that the corresponding markets must make positive (or negative) adjustments to keep pace with those cointegrated markets. Similarly, large (or small) adjustment estimates suggest that the corresponding markets must make large (or small) adjustments to keep pace with those cointegrated markets. Large adjustment coefficient estimates in period 2 for Hong Kong and Singapore suggest that these stock markets are hyper sensitive to the 9-11 terrorist attack in the U.S. to maintain the long-run interdependence. Large adjustment coefficient estimates in period 3 for Indonesia, China, and India suggest that these stock markets are hyper sensitive to the turbulent U.S. market during the subprime crisis to maintain the long-run interdependence. We will analyze this further in the following sections.

Panel D of Table 2 reports the linear restriction tests for the cointegrating vectors. The evidence indicates that our cointegrating vectors reported in Panel A of Table 2 are supported by the data. Panel D of Table 2 also report the LM test statistics for multivariate autocorrelation of order one in the residuals of the vector error correction models and for univariate autocorrelation of order one, two, and three in the residuals of the single cointegration relations. Further, Panel D reports the LM test statistics for ARCH effects of order one, two, and three in the residuals of the single cointegration relations. Although we find little evidence of autocorrelation in these residuals, we do find that the residuals have demonstrated some ARCH effect of order two and three in period 3 and the ARCH effect of order three in period 2. This is consistent with the findings based on ARCH/GARCH models in Bekaert et al. (2005) and Baele and Inghelbreht (2010). This is a clue of contagion in these two periods. Hence, we need to rely on useful prior information to identify structural shocks from these residuals.

4.2 SVAR analysis

In this section, we use the SVAR model to analyze the innovations of the multivariate cointegration model for the eleven stock markets with a set of suitable identification restrictions.[26]

To obtain suitable restrictions, we use normalization, prior knowledge, and causation implied by the data. Some restrictions are made based on normalization, for which we set the diagonal elements of $\mathbf{A}$ to 1. Some restrictions are made according to prior knowledge. First, matrix $\mathbf{B}$ is a diagonal matrix, we impose zero restrictions on all off-diagonal elements. Second, in this study, a trading day starts from the U.S. and ends in the U.K.[27] Hence, in the same trading day, the U.S. market cannot be affected by the markets which open later than the U.S. market does (in this case, Asian and U.K. markets). Because of such prior knowledge, we impose zero restrictions on $\mathbf{A}$ for such impossible interdependence.

In addition to normalization and prior knowledge, we use the directed acyclic graph (DAG) to identify the remaining suitable zero restrictions that may be imposed on $\mathbf{A}$.[28] DAGs are used to get the information about zero unconditional correlation or zero partial correlation (conditional correlation) between variables in a system. If, according to DAGs, innovations in one market have no statistical linkage with innovations in another market, we

[26] In our SVAR model, we need to estimate two $n \times n$ matrices $\mathbf{A}$ and $\mathbf{B}$ in $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$. Since $\mathbf{A\Sigma A}' = \mathbf{BB}'$, the expressions on both sides of this equation are symmetric, we need to impose $n(n+1)/2$ restrictions on the $2n^2$ unknown elements in $\mathbf{A}$ and $\mathbf{B}$. Therefore, in order to identify $\mathbf{A}$ and $\mathbf{B}$, we need to supply at least $2n^2 - n(n+1)/2 = n(3n-1)/2$ additional restrictions.

[27] We have also studied a trading day starts from the U.K. and ends in India. As the U.S. stock market is the largest one among all the eleven markets and had significant regional and global financial market events, we design the trading day as such to better isolate the U.S. as the significant source of contagion.

[28] The implementation of the DAG in this paper can be found in Appendix C. See Spirtes et al. (2000) and Pearl (2000) for more information on the directed acyclic graph.

can impose a zero restriction between the two markets in $\mathbf{A}$.[29]

Based on the estimated matrix $\mathbf{A}$, we then calculate the i, j-th element of the estimated matrix $\mathbf{A}^{-1}\mathbf{B}$, $(\mathbf{A}^{-1}\mathbf{B})_{ij}$, which shows how much market i instantaneously responds to a structural innovation from market j.[30] Table 3 shows how much different markets instantaneously respond to a structural innovation from the U.S., Japanese and Hong Kong markets. The U.K., Japan, Hong Kong, and Singapore show the largest mean responses to the U.S. shocks at the level of 0.0085, 0.0076, 0.0093, and 0.0076, respectively. The Hong Kong, Singapore and Korea show the largest mean responses to Japanese shocks at the level of 0.0102, 0.0081, and 0.0081, respectively. Singapore, Indonesia, India, and Korea show the largest mean responses to the Hong Kong shocks at the level of 0.0101, 0.0075, 0.0075, and 0.0074, respectively. China responds with relatively small magnitudes to the shocks from the U.S., Japanese, and Hong Kong shocks. Except in period 1, Malaysia behaves similarly as China does. In general, other Asian stock markets show greater responses to the shocks from Japan and Hong Kong during each of the four periods. Even during the U.S. subprime crisis (in Period 3), the contemporaneous mean effects of the shocks from Japan (0.0085) and Hong Kong (0.0065) on other Asian stock markets are still greater than those from the U.S. market (0.0061). In contrast to the findings that other markets are most sensitive to the innovations from the U.S. market (e.g. Yang and Bessler (2008)), we find that, as shown in Table 3, other Asian stock markets are quite responsive to the shocks from Japan and Hong Kong showing an instantaneous shock transmission among these Asian stock markets.

(Please place Table 3 about here)

To further evaluate the instantaneous shock transmission, we test the null hypothesis that the initial impact is equal to the long-run impact for each shock source in each period. This null hypothesis represented by the restriction $\beta' \mathbf{A}^{-1}\mathbf{B} = \mathbf{0}$ can be tested by a likelihood ratio test. This test statistic follows a χ^2-distribution with one degree of freedom for the case of one cointegrating vector or with two degrees of freedom for the case of two cointegrating vectors. These test results, given at the bottom of each panel of Table 3, show that the null hypothesis can be rejected for all shock sources in period 3. In period 4, the null hypothesis for shocks from the U.S. and Japan markets are also rejected. The departure of the initial impact from the long-run impact is a sign of possible contagion in periods 3 and 4.

[29] DAGs are used in the literature for a similar purpose in related but distinctive time series settings such as impulse response and forecast error variance decompositions. See, for example, Yang and Bessler (2008).

[30] We use one standard deviation as the unit of innovations.

4.3 Contagion analysis

To analyze "fast and furious" contagion, we use the contagion measure $C_{i,j}$ given by equation (5). We want to find out whether or not U.S. crashes cause crashes in the Japanese, Hong Kong and other Asian stock markets, and whether or not crashes in the Japan and Hong Kong stock markets further cause crashes in other Asian stock markets. We report the relevant results in Table 4.[31]

(Please place Table 4 about here)

Panel A of Table 4 shows that there is little or weak contagion effect from the U.S. to Japan and Hong Kong in the four periods. The mean contagion measure from the U.S. to other markets $C_{i,US}$ is negative for each of the four periods, suggesting that during these periods there is little contagion from the U.S. to other Asian stock markets after taking into account the long-run interdependence. This finding is similar to that of Baele and Inghelbrecht (2010) and Bekaert et al. (2011)—there is little evidence for the contagion from the U.S. to European countries during times of financial crisis. It is notable that the mean contagion measure from the U.S., $C_{i,US}$, for Period 3 (-1.4117; see Panel A of Table 4, Period 3) is significantly smaller than that for the other three periods indicating that these Asian markets maintain their recuperating capability during a crisis.

The contagion effect from the U.S. to Taiwan, $C_{TW,US}$, is 0.0324 in Period 1 (see Panel A of Table 4, Period 1) and 0.0886 in Period 4 (see Panel A of Table 4, Period 4). The contagion effect from the U.S. to Hong Kong, $C_{HK,US}$, is 0.1717 in Period 2 (see Panel A of Table 4, Period 2). However, these effects are relatively small compared to those from Japan and Hong Kong to other Asian stock markets.

There is no significant contagion effect from the U.S. to Japan, from Japan to Hong Kong, and from Hong Kong to Japan, respectively in all periods. Even during the U.S. subprime crisis (in Period 3), we cannot find any "fast and furious" contagion effect among the U.S., Japan, and Hong Kong. As we can recall, however, during the U.S. subprime crisis (Period 3), the fundamental interdependence, or "slow-burn" spillover, exists among the U.S. and Japan and Hong Kong as illustrated by the crash transition probabilities conditional on the U.S. crash (Panels B and C of Table 1). The fundamental interdependence among these markets is also shown by the cointegrating vectors (see Panel A of Table 2 for Period 3).

[31] Nevertheless, we find that almost no contagion effect is found between other Asian stock markets for all integration periods. This fact renders it unnecessary to report the contagion measures between any pairs of other Asian stock markets. These estimation results can be found in Appendix D.

More specifically, we find that the Hong Kong stock market is cointegrated with the U.S. stock market and that the Hong Kong stock market is cointegrated with the Japanese stock market. These findings reveal the complexity of the linkages during crises.

In contrast to the findings given above, we note some evidence for the contagion effect from the Japanese and Hong Kong stock markets to other Asian stock markets during the U.S. subprime crisis and after-crisis markets' bottoming (see Panels B and C of Table 4, Periods 3 and 4). The contagion effects are positive and large in magnitude. The mean contagion measure from Japan to other Asian stock markets, $C_{i,JP}$, is valued at 0.2110 and 0.0428 in Periods 3 and 4, respectively, while that from Hong Kong to other Asian stock markets, $C_{i,HK}$, is valued at 0.0961 in period 3. In Period 4, only Singapore and Korea, but not other Asian markets, are affected by the contagion effect from Hong Kong. The Chinese stock market is relatively closed to the outside world and hence is not significantly affected by the contagion effects from the U.S., Japan, and Hong Kong. The Indian stock market, however, is affected most by the contagion effect from Japan (0.4112; see Panel B of Table 4, Period 3) in Period 3 and by the contagion effect from Hong Kong (0.2315; see Panel C of Table 4, Period 3).

In summary, in addition to the fundamental interdependence across these stock markets (from the U.S. stock market to other Asian stock markets), contagion does occur immediately across some of these markets in a domino fashion triggered by the fundamental interdependence (from the U.S. to Hong Kong and from Japan to Hong Kong). However, the structural innovations from the Japanese and Hong Kong stock markets do not directly feedback to the U.S. stock market on the same day in Period 3.

Kaminsky et al. (2003) and Reinhart and Rogoff (2009) note that the trade integration and trade patterns do not necessarily lead to contagion from one country to another. Because we study contagion across stock markets, it seems to be natural to examine the capital flows among, and capital controls by, the markets we study. According to the Chinn-Ito Financial Openness Index in Table 5 (see Chinn and Ito (2008)) for the period of 1997–2009,[32] the U.S., U.K., Japan, Hong Kong, and Singapore are ranked highest in financial openness. Indonesia, Malaysia and Korea are ranked moderate. The lowest ranked are China and India.

(Please place Table 5 about here)

[32]This index combines various pieces of information about the capital account openness. The higher (lower) the index value, the more (less) open an economy is. Chinn and Ito (2008) do not rank Taiwan.

If we examine the net equity investments into each market during the period of 1997–2010 using the International Monetary Fund's data,[33] we find from Figure 5 that, during the period of 2006-2009, the net equity investments into Japan fell substantially. During the period of 2008-2009, the net equity investments into the U.S., U.K, and Korea also fell substantially. However, during the entire period of 1997-2010, the net equity investments into China, India, Indonesia, Malaysia, and Singapore did not change much. Against this trend, the net equity investments into Hong Kong increased during the period of 2008–2010.

4.4 International portfolio analysis

To further evaluate the impact of contagion from the U.S., Japanese, and Hong Kong stock markets on other Asian markets as a whole, we first form a portfolio that weights other Asian stock markets equally. We then track the impact of the shocks from the U.S., Japan and Hong Kong on the return volatility of this portfolio. Therefore, $\mathbf{w}$ in equations (6) and (7) is an 11×1 vector of portfolio weights, in which we set 0 for the U.K., the U.S., Japan and Hong Kong, and 1/7 for each of other Asian stock markets. This international portfolio can be used to analyze the volatility of the international portfolio induced by shocks from the U.S., Japanese and Hong Kong stock markets. This is an effective way to examine the contagion risk in targeted portfolios.

Table 6 reports the results of variance decomposition. Panel A of Table 6 provides the estimated efficient price volatility, $\mathbf{V}_p^e$, and the estimated departure of the 1-step ahead conditional forecast error variance $\mathbf{V}_p$ from $\mathbf{V}_p^e$, ε_p, for the entire portfolio. The third rows ($\mathbf{V}_{p,US}$,$\mathbf{V}_{p,JP}$, and $\mathbf{V}_{p,HK}$) of Panels B, C and D of Table 6 show the forecast error variance decomposition for portfolio returns affected by the U.S., Japanese and Hong Kong shocks, respectively. In addition, the last rows ($\mathbf{V}_{p,US}/\mathbf{V}_p$,$\mathbf{V}_{p,JP}/\mathbf{V}_p$, and $\mathbf{V}_{p,HK}/\mathbf{V}_p$) of Panels B, C and D show the percentages of the forecast error variance decomposition of portfolio returns that are due to shocks from the U.S., Japan and Hong Kong, respectively. The first two rows ($\mathbf{V}_{p,j}^e$ and $\varepsilon_{p,j}$) in Panels B, C and D of Table 6 provide the estimated efficient portfolio variance and departure from it, respectively.

(Please place Table 6 about here)

According to the results in Table 6, we find that the shocks from the U.S., Japan, and Hong Kong account for a significant and increasing proportion of the forecast error variance

[33] The data for Taiwan are not available.

of portfolio returns over time. Compared to the U.S. shock, the shock from Hong Kong (Panel D of Table 6) has a greater impact on the variance of portfolio returns in all four periods. Similarly, compared to the U.S. shock, the shock from Japan (Panel C of Table 6) also has a greater impact in periods 2, 3, and 4. In particular, in Period 3, the shock from Japan contributes close to 35% of the variance of portfolio returns. In addition, from Period 1 to Period 4, the shocks from the U.S., Japan and Hong Kong account for an increasing proportion of the variance of portfolio returns over time. That is, from Period 1 to Period 4, the proportion of the variance due to the U.S., Japanese, and Hong Kong shocks ranges from 12.88% to 19.43%, from 2.12% to 25.59%, and from 19.80% to 32.85%, respectively. This evidence appears to confirm that, over time, other Asian stock markets were gradually integrated into the more mature stock markets. Our study further confirms the finding of Ng (2000) and shows that Asian stock markets are further integrated into the global stock markets.

In Panels C and D of Table 6, we highlight some numbers in the bold font in Period 3, which indicate that the shocks from the Japanese and Hong Kong stock markets increase the variance of portfolio returns by 0.000050 and 0.000027, respectively. However, the shock from the U.S. stock market decreases the variance of portfolio returns by 0.000069. Combining these with the findings in our SVAR analysis, we conclude that during the U.S. subprime crisis, other Asian stock markets appear to be less affected by contagion from the U.S. but more influenced by their long-run interdependence on the U.S. while they are more subject to the contagion effects from Japan and Hong Kong.

5 Concluding Remarks

In this paper, we attempt to study the interdependence and contagion among the eleven stock markets, examining whether there are contagion effects from the more matured markets such as the U.S., Japanese, and Hong Kong stock markets to other Asian stock markets. To do so we must differentiate contagion from long-run interdependence and view contagion as a departure from long-run interdependence. We adopt a research strategy in which the long-run interdependence among these stock markets is captured by cointegration relations. We find that there are four periods in which major regional and global financial market events occurred and the eleven stock markets shared systematic comovements. This captures the "slow-burn" spillover across the stock markets. Based on this framework, we propose a new contagion measure to capture "fast and furious" shock waves across the stock markets. In addition, we also propose international portfolio analysis for contagion via variance decomposition. We use this approach to evaluate and manage contagion risk from the portfolio management perspective.

We show that during the U.S. subprime crisis, the U.S. stock market was cointegrated with the Hong Kong and other Asian stock markets (except Japan) while the Japanese stock market was cointegrated with other Asian stock markets. These “slow-burn” spillover effects are as expected. However, the U.S. stock market had no “fast and furious” contagion effect on other Asian stock markets. This results partly from the capital controls in some Asian markets (such as China, India, Indonesia, Malaysia, and Korea) and partly from favorable net investment positions in some markets that were more open (such as Hong Kong). We also show that there were significant “fast and furious” contagion effects from both the Japanese and Hong Kong stock markets to other Asian stock markets. More specifically, we find significant overreactions of other Asian stock markets to the instantaneous shocks from the Japanese and Hong Kong stock markets but marked underreactions to the shock from the U.S. stock market. Our international portfolio analysis for contagion also confirms this conclusion. Perhaps from Asian market participants' point of view, the markets located in the same region and similar time zones do accommodate “fast and furious” shock waves, in addition to “slow-burn” spillover effects across these markets, while other markets in other regions and different time zones seem to generate more “slow-burn” spillover effects as the world becomes a more integrated place.

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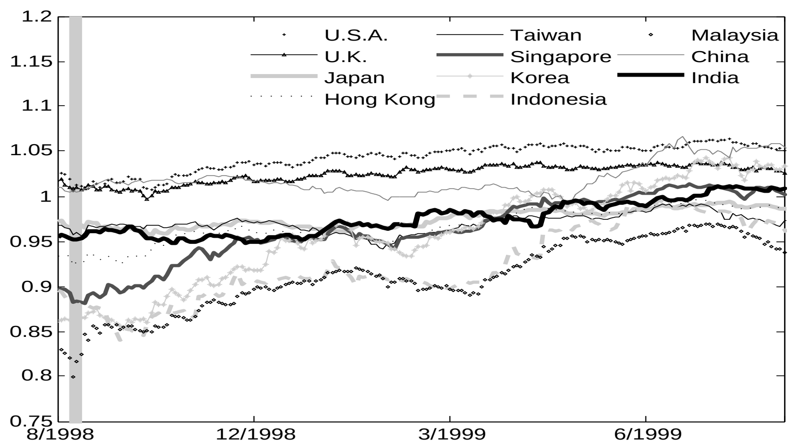
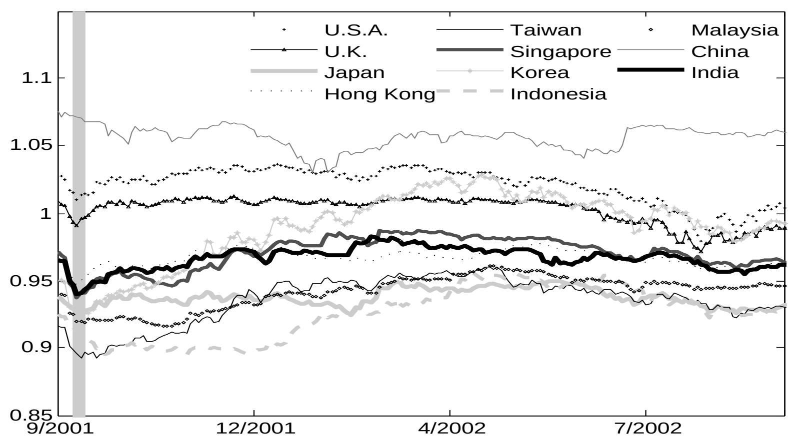
Figure 1: Eleven stock market trends in cointegration period 1



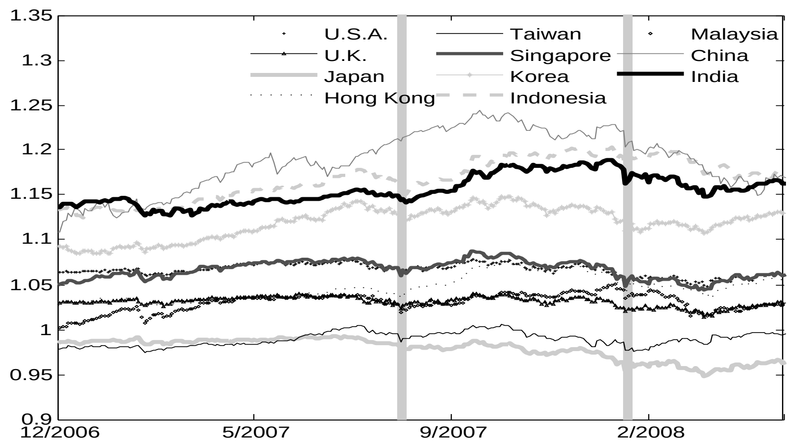
Note: During cointegration period 1 (August 24,1998-August 10, 1999), the eleven stock market indices demonstrate similar increasing trends while the market indices in Korea, Indonesia, Malaysia and Singapore demonstrate more rapid increasing trends. The vertical bar is used to highlight the huge market crash on August 31, 1998. All market indices are normalized to 1 on July 3, 1997.

Figure 2: Eleven stock market trends in cointegration period 2



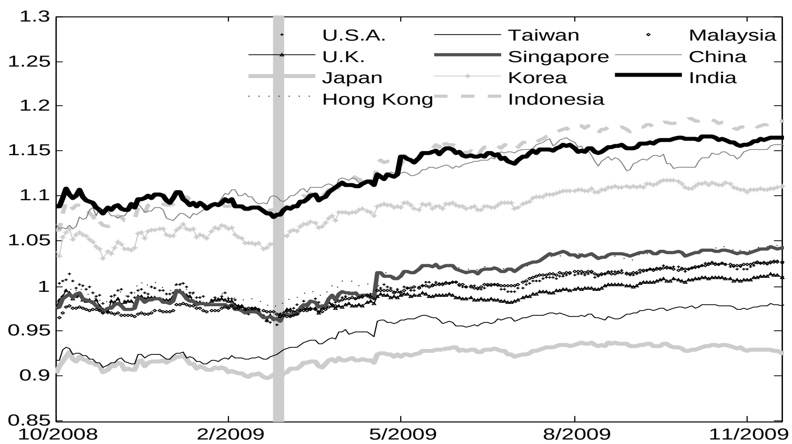
Note: During cointegration period 2 (September 6, 2001-August 26, 2002), the eleven stock market indices demonstrate similar stable trends while the market indices in Korea, the U.K. and the U.S. demonstrate more rapid decreasing trends at the end of the period. The vertical bar is used to highlight September 17, 2001 after the 9-11 terrorist attack. All market indices are normalized to 1 on July 3, 1997.

Figure 3: Eleven stock market trends in cointegration period 3



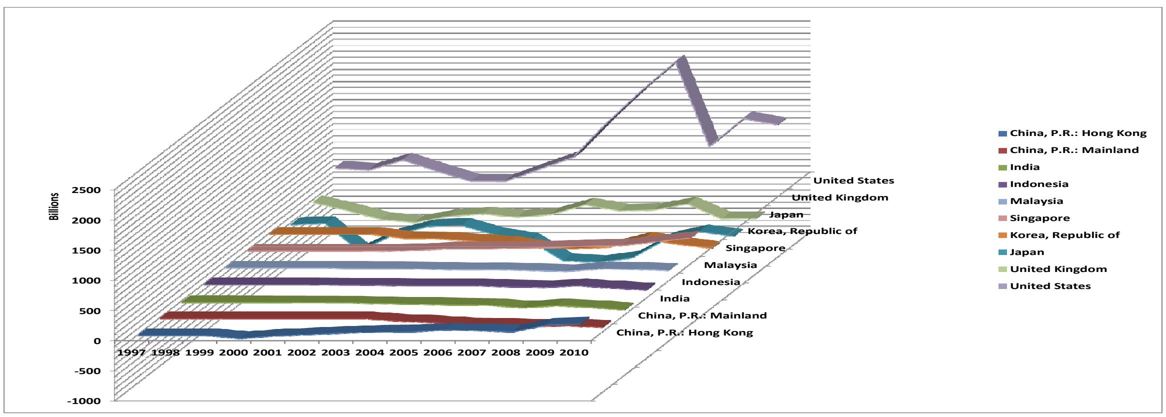
Note: During cointegration period 3 (December 21, 2006–May 9, 2008), the eleven stock market indices demonstrate severe volatility and changing tides. In particular, the Asian stock markets had a good run but became more integrated into the world stock markets than ever before. The U.S. subprime crisis occurred during the period. This period witnessed contagion from one market to another. Two vertical bars are used to highlight the huge market crashes on August 16, 2007 and January 21, 2008, respectively. All market indices are normalized to 1 on July 3, 1997.

Figure 4: Eleven stock market trends in cointegration period 4



Note: During cointegration period 4 (October 28, 2008–November 20, 2009), the eleven stock market indices demonstrate similar bottoming and reversing comovements although these upward moves after the bottom varied and were not smooth. The vertical bar is used to highlight the bottom time around March 9, 2009. All market indices are normalized to 1 on July 3, 1997.

Figure 5: Net Equity Investments into Ten Countries: 1997-2009



Note: The time series on International Investment Position Assets and Liabilities (Portfolio Investment, Equity Securities) for the ten countries (except Taiwan) are retrieved from International Monetary Fund eLibrary on March 12, 2012. During the period of 2006-2009, the net equity investments into Japan fell substantially. During the period of 2008-2009 the net equity investments into the U.S., U.K, and Korea also fell substantially. But during the entire period of 1997-2010, the net equity investments into China, India, Indonesia, Malaysia, and Singapore did not change much. Against this trend, the net equity investment into Hong Kong increased during the period of 2008–2010.

Table 1: Descriptive statistics of daily returns of eleven stock market indices and crash transition probabilities

	US	UK	JP	HK	TW	SG	KR	IN	ML	CN	ID	Mean
Panel A: Descriptive statistics, July 3,1997-April 30, 2014												
Mean	0.048	0.038	-0.033	0.088	0.032	0.083	0.159	0.206	0.060	0.131	0.198	0.124
Volatility	0.239	0.237	0.285	0.329	0.307	0.288	0.387	0.351	0.276	0.307	0.327	0.320
Min	-0.129	-0.098	-0.121	-0.148	-0.118	-0.139	-0.155	-0.146	-0.133	-0.132	-0.175	-0.142
Max	0.099	0.103	0.105	0.224	0.174	0.240	0.149	0.207	0.265	0.099	0.173	0.187
10th quantile	-0.023	-0.023	-0.028	-0.032	-0.032	-0.026	-0.038	-0.031	-0.024	-0.030	-0.032	-0.030
Panel B: Crash transition probabilities, July 3,1997-April 30, 2014												
Conditional on US crash			40.56%	40.56%	31.27%	34.06%	31.89%	27.86%	28.48%	18.89%	26.01%	28.35%
Conditional on JP crash				45.20%	37.15%	41.49%	40.56%	30.96%	34.37%	20.74%	29.10%	33.48%
Conditional on HK crash			45.20%		43.03%	59.44%	43.96%	41.49%	45.51%	26.32%	38.39%	42.59%
Conditional on JP and US crashes				64.89%	51.15%	54.96%	53.44%	45.80%	41.98%	28.24%	43.51%	45.58%
Conditional on HK and US crashes			64.89%		49.62%	66.41%	51.91%	51.15%	48.85%	32.06%	49.62%	49.95%
Panel C: Crash transition probabilities, June 4, 2007-January 25, 2008												
Conditional on US crash			40.00%	45.00%	40.00%	40.00%	35.00%	30.00%	35.00%	30.00%	25.00%	33.57%
Conditional on JP crash				75.00%	75.00%	75.00%	68.75%	50.00%	43.75%	56.25%	43.75%	58.93%
Conditional on HK crash			63.16%		63.16%	73.68%	63.16%	63.16%	47.37%	57.89%	47.37%	59.40%
Conditional on JP and US crashes				75.00%	87.50%	75.00%	75.00%	50.00%	50.00%	62.50%	37.50%	62.50%
Conditional on HK and US crashes			66.67%		66.67%	77.78%	66.67%	66.67%	66.67%	55.56%	44.44%	63.49%

Note: Panel A of the table shows summary statistics of the daily returns of eleven stock market indices, including the annualized mean (250 times the average daily return), annualized volatility (the average daily standard deviation of returns multiplied by the square root of 250), minimum, maximum and the 10th quantile, which is used to identify the occurrence of crashes. Panel B and C show the conditional probabilities of observing a crash in a given Asian stock market conditional on the occurrence of the US (one-day ahead), Japan and Hong Kong crashes. The average of crash transition probabilities of seven Asian emerging stock markets is also reported in the last column of the table. The sample covers the period of July 3, 1997 - April 30, 2014 with missing observations removed, leaving the daily data for 3235 days. The US subprime crisis period is from June 4, 2007 to January 25,2008 (127 observations).

Table 2: Parameter estimate results from cointegration analysis

	Period 1 (Aug 24,1998-Aug 10,1999)	Period 2 (Sep 6,2001-Aug 26,2002)		Period 3 (Dec 21,2006-May 9,2008)		Period 4 (Oct 28,2008-Nov 20,2009)
Panel A: coefficients in the cointegrating vector						
β_{US}	1	1	-	1	-	1
β_{UK}	-1.218 (0.191)	-1.059 (0.060)	-1.695 (0.600)	-0.535 (0.055)	11.290 (1.958)	
β_{JP}		-	1	-	1	0.348 (0.082)
β_{HK}	-0.685 (0.155)	0.200 (0.080)	1.087 (0.805)	0.413 (0.048)	6.993 (1.684)	
β_{TW}	0.481 (0.113)	-0.456 (0.083)	4.295 (0.831)	-0.195 (0.039)	-5.401 (1.360)	0.269 (0.083)
β_{SG}	0.389 (0.164)			-0.453 (0.066)	-13.109 (2.318)	-0.618 (0.159)
β_{KR}	0.265 (0.078)		-1.834 (0.620)	0.089 (0.044)	5.384 (1.545)	-0.950 (0.141)
β_{IN}	0.173 (0.055)		2.983 (0.670)			1.000 (0.156)
β_{ML}	-0.456 (0.086)	0.341 (0.174)	-7.276 (1.746)	0.289 (0.049)		-0.468 (0.201)
β_{CN}	-0.133 (0.065)	-0.222 (0.057)	2.501 (0.571)	-0.062 (0.012)		0.167 (0.062)
β_{ID}	-0.144 (0.074)	0.242 (0.090)	-3.485 (0.899)	-0.352 (0.045)	-9.212 (1.607)	-0.374 (0.108)
Panel B: adjustment coefficients						
α_{US}		-0.284 (0.060)	-0.022 (0.006)	-0.256 (0.067)	0.009 (0.002)	-0.101 (0.042)
α_{UK}	0.062 (0.036)			0.204 (0.087)		
α_{JP}		-0.136 (0.076)	-0.024 (0.008)			
α_{HK}		-0.276 (0.063)	-0.012 (0.006)			
α_{TW}	-0.170 (0.047)	-0.166 (0.092)	-0.039 (0.009)		0.014 (0.004)	
α_{SG}	-0.103 (0.053)	-0.251 (0.073)	-0.016 (0.008)		0.009 (0.004)	0.086 (0.055)
α_{KR}		-0.245 (0.099)	-0.029 (0.010)	0.188 (0.101)		0.168 (0.050)
α_{IN}		-0.141 (0.056)	-0.030 (0.006)	0.314 (0.132)		-0.087 (0.053)
α_{ML}	0.138 (0.068)	-0.174 (0.046)				
α_{CN}	-0.115 (0.044)	0.184 (0.078)		0.551 (0.181)		
α_{ID}		-0.174 (0.074)		0.284 (0.130)	0.014 (0.005)	
Panel C: Johansen trace test						
Trace statistic [Prob.]						
r=0	265.990 [0.038]	274.088 [0.016]		296.799[0.001]		273.171 [0.018]
r=1	**213.406** [0.092]	219.712 [0.048]		220.806[0.043]		**194.767** [0.378]
r=2	163.838 [0.236]	**169.888**[0.139]		**170.279**[0.134]		151.750 [0.516]
LogL	5236.126	5855.103		8619.453		6573.383
AIC	-54.647	-61.184		-65.285		-60.951
Panel D: tests for linear restrictions on β and residuals autocorrelation and ARCH tests						
Linear restriction test	$\chi^2(1)$: 0.232[0.630]	$\chi^2(4)$: 0.558[0.968]		$\chi^2(4)$: 3.708[0.447]		$\chi^2(2)$: 2.143[0.343]
Autocorrelation test						
LM test-VAR(1)	123.400 [0.422]	112.558 [0.696]		123.085[0.430]		141.201 [0.101]
LM test-AR(1)	0.318 [0.573]	0.041 [0.839]	0.009 [0.926]	0.231 [0.631]	0.055 [0.815]	0.482 [0.488]
LM test-AR(2)	0.419 [0.811]	1.813 [0.404]	2.597 [0.273]	0.609 [0.738]	1.871 [0.392]	1.623 [0.444]
LM test-AR(3)	0.782 [0.854]	2.057 [0.561]	3.384 [0.336]	1.115 [0.773]	2.170 [0.538]	1.166 [0.761]
ARCH effect test						
LM test-ARCH(1)	0.362 [0.547]	2.524 [0.112]	0.578 [0.447]	3.790 [0.052]	0.192 [0.662]	0.561 [0.454]
LM test-ARCH(2)	0.438 [0.803]	3.072 [0.215]	1.273 [0.529]	**7.671** [0.022]	**6.597** [0.037]	1.195 [0.550]
LM test-ARCH(3)	0.517 [0.915]	**12.027** [0.007]	1.275 [0.735]	**11.104** [0.011]	7.471 [0.058]	1.179 [0.758]

Note: The table reports parameter estimates and related test statistics for the vector error correction models without any constant, trend, or lagged dependent variables, which are chosen based on the Akaike information criterion. Panel A reports the parameter estimates in the cointegrating vectors (given by β_i). In Panel A, if there is one cointegration vector, it is normalized for the U.S. stock market. If there are two cointegration vectors, they are normalized for the U.S. and Japan stock markets, respectively. Panel B reports the adjustment coefficients (given by α_i) of cointegration. In Panel C, the Johansen trace test statistics are presented. The test statistics in bold font correspond to the chosen numbers of cointegrating vectors at the 5% significance level. Standard errors are given in parentheses, while p-values are reported in brackets. In Panel D, the linear restriction tests indicate that the identified cointegrating vectors are supported by the data. In panel D, the multivariate LM test statistics for residual autocorrelation up to order one, the univariate LM test statistics for residual autocorrelation up to order three, and the ARCH test statistics for residual conditional variance up to order three are reported. The test statistics in bond font indicate that the null hypothesis of no ARCH effect can be rejected at the 5% significant level.

Table 3: Results from SVAR analysis

	Period 1 (Aug 24,1998-Aug 10,1999)	Period 2 (Sep 6, 2001-Aug 26, 2002)	Period 3 (Dec 21, 2006-May 9, 2008)	Period 4 (Oct 28, 2008-Nov 20, 2009)	Mean
Panel A: shocks from the US market					
$\mathbf{A^{-1}B}_{UK,US}$	0.0070 (0.0010)	0.0095 (0.0013)	0.0064 (0.0008)	0.0109 (0.0013)	0.0085
$\mathbf{A^{-1}B}_{JP,US}$		0.0066 (0.0013)	0.0091 (0.0009)	0.0147 (0.0014)	0.0076
$\mathbf{A^{-1}B}_{HK,US}$	0.0095 (0.0016)	0.0062 (0.0011)	0.0090 (0.0011)	0.0127 (0.0016)	0.0093
$\mathbf{A^{-1}B}_{TW,US}$	0.0027 (0.0007)	0.0019 (0.0005)	0.0039 (0.0006)	0.0081 (0.0012)	0.0042
$\mathbf{A^{-1}B}_{SG,US}$	0.0089 (0.0016)	0.0046 (0.0008)	0.0071 (0.0008)	0.0099 (0.0014)	0.0076
$\mathbf{A^{-1}B}_{KR,US}$	0.0055 (0.0012)	0.0055 (0.0010)	0.0061 (0.0007)	0.0098 (0.0013)	0.0067
$\mathbf{A^{-1}B}_{IN,US}$	0.0054 (0.0013)	0.0003 (0.0001)	0.0067 (0.0009)	0.0087 (0.0012)	0.0053
$\mathbf{A^{-1}B}_{ML,US}$	0.0116 (0.0020)	0.0020 (0.0004)	0.0036 (0.0005)	0.0040 (0.0006)	0.0053
$\mathbf{A^{-1}B}_{CN,US}$	-0.0023(0.0013)	0.0015 (0.0006)	0.0021 (0.0005)	0.0049 (0.0009)	0.0015
$\mathbf{A^{-1}B}_{ID,US}$	0.0009 (0.0003)	0.0039 (0.0008)	0.0073 (0.0009)	0.0083 (0.0013)	0.0051
Mean	0.0049	0.0042	0.0061	0.0092	
LR test for binding restrictions:					
$\chi^2(1)$	0.0973[0.7551]			**19.3183**[0.0000]	
$\chi^2(2)$		4.0978[0.1289]	**32.7557**[0.0000]		
Panel B: shocks from the Japan market					
$\mathbf{A^{-1}B}_{UK,JP}$	0.0041 (0.0010)	0.0025 (0.0006)	0.0027 (0.0005)	0.0031 (0.0006)	0.0031
$\mathbf{A^{-1}B}_{HK,JP}$	0.0066 (0.0015)	0.0063 (0.0010)	0.0135 (0.0010)	0.0145 (0.0014)	0.0102
$\mathbf{A^{-1}B}_{TW,JP}$	0.0019 (0.0006)	0.0020 (0.0005)	0.0059 (0.0007)	0.0094 (0.0011)	0.0048
$\mathbf{A^{-1}B}_{SG,JP}$	0.0041 (0.0010)	0.0063 (0.0010)	0.0107 (0.0008)	0.0113 (0.0013)	0.0081
$\mathbf{A^{-1}B}_{KR,JP}$	0.0033 (0.0010)	0.0088 (0.0014)	0.0092 (0.0007)	0.0112 (0.0011)	0.0081
$\mathbf{A^{-1}B}_{IN,JP}$	0.0025 (0.0007)	0.0004 (0.0001)	0.0100 (0.0010)	0.0100 (0.0012)	0.0057
$\mathbf{A^{-1}B}_{ML,JP}$	0.0009 (0.0004)	0.0027 (0.0005)	0.0054 (0.0006)	0.0046 (0.0005)	0.0034
$\mathbf{A^{-1}B}_{CN,JP}$	0.0003 (0.0002)	0.0015 (0.0006)	0.0032 (0.0008)	0.0056 (0.0010)	0.0026
$\mathbf{A^{-1}B}_{ID,JP}$	0.0004 (0.0002)	0.0042 (0.0008)	0.0109 (0.0010)	0.0096 (0.0013)	0.0063
Mean	0.0041	0.0051	0.0085	0.0096	
LR test for binding restrictions:					
$\chi^2(1)$	1.6989[0.1924]			**8.7610**[0.0031]	
$\chi^2(2)$		0.3334[0.8464]	**11.5941**[0.0030]		
Panel C: shocks from the Hong Kong market					
$\mathbf{A^{-1}B}_{UK,HK}$	0.0042 (0.0009)	0.0048 (0.0010)	0.0022 (0.0004)	0.0040 (0.0007)	0.0038
$\mathbf{A^{-1}B}_{JP,HK}$					
$\mathbf{A^{-1}B}_{TW,HK}$	0.0057 (0.0013)	0.0036 (0.0009)	0.0064 (0.0006)	0.0120 (0.0011)	0.0069
$\mathbf{A^{-1}B}_{SG,HK}$	0.0124 (0.0013)	0.0071 (0.0010)	0.0065 (0.0006)	0.0145 (0.0011)	0.0101
$\mathbf{A^{-1}B}_{KR,HK}$	0.0100 (0.0019)	0.0069 (0.0013)	0.0039 (0.0005)	0.0088 (0.0014)	0.0074
$\mathbf{A^{-1}B}_{IN,HK}$	0.0075 (0.0014)	0.0006 (0.0002)	0.0096 (0.0010)	0.0121 (0.0012)	0.0075
$\mathbf{A^{-1}B}_{ML,HK}$	0.0026 (0.0011)	0.0032 (0.0005)	0.0041 (0.0006)	0.0036 (0.0005)	0.0034
$\mathbf{A^{-1}B}_{CN,HK}$	0.0009 (0.0004)	0.0031 (0.0011)	0.0024 (0.0006)	0.0065 (0.0012)	0.0032
$\mathbf{A^{-1}B}_{ID,HK}$	0.0013 (0.0004)	0.0075 (0.0010)	0.0090 (0.0009)	0.0123 (0.0013)	0.0075
Mean	0.0065	0.0055	0.0065	0.0092	
LR test for binding restrictions:					
$\chi^2(1)$	2.1770[0.1401]			5.0761[0.0790]	
$\chi^2(2)$		0.3996[0.8189]	**14.7719**[0.0001]		

Note: The table reports parameter estimates for the model $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}_t\mathbf{v}_t$, where $\mathbf{e}_t$ is a vector of the observed residuals of VECM and $\mathbf{v}_t$ is a vector of the unobserved structural innovations. The element (i, j) of matrix $\mathbf{A}^{-1}\mathbf{B}$, $(\mathbf{A}^{-1}\mathbf{B})_{ij}$, gives how market i instantaneously responds to one unit structural innovation from market j. Estimation is by SVAR analysis over daily index prices of eleven stock markets for four partitioned periods of cointegration. The LR test for binding restriction $\beta'\mathbf{A}^{-1}\mathbf{B} = \mathbf{0}$ is conducted for each shock source and each period to test for the deviation of initial impacts from long-run impacts. The values in bold font denote that the binding restriction can be rejected at the 5% significance level. Standard errors are given in parentheses, while p-values are reported in brackets. The means are also reported for all markets and periods. Some cells do not have any value because they correspond to zero restrictions identified by the analysis using the directed acyclic graph.

Table 4: Results of contagion tests

	Period 1 (Aug 24,1998-Aug 10,1999)	Period 2 (Sep 6, 2001-Aug 26, 2002)	Period 3 (Dec 21, 2006-May 9, 2008)	Period 4 (Oct 28, 2008-Nov 20, 2009)
Panel A: shocks from the US market				
$C_{JP,US}$	-0.0029	0.0654	-1.4624	-0.2843
	(-0.0102, 0.0000)	(-0.1064, 0.0950)	(-1.4689, -0.6628)	(-0.4005, -0.1679)
$C_{HK,US}$	0.0380	**0.1717**	-1.0913	-0.1981
	(-0.0247, 0.2080)	(0.1346, 0.5995)	(-1.2733, -0.2827)	(-0.3184, -0.0446)
$C_{TW,US}$	**0.0324**	0.0111	-0.2348	**0.0886**
	(0.0022, 0.0361)	(-0.2722, 0.0312)	(-0.2594, 0.0134)	(0.0447, 0.1231)
$C_{SG,US}$	0.1080	0.0958	-0.9672	-0.2200
	(-0.0719, 0.2199)	(-0.0329, 0.3399)	(-1.1618, -0.5317)	(-0.3140, -0.1025)
$C_{KR,US}$	-0.1151	0.1335	-1.4103	-0.4203
	(-0.2880, 0.0542)	(-0.0024, 0.2960)	(-2.6222, -1.4075)	(-0.5398, -0.2997)
$C_{IN,US}$	0.0939	-0.0967	-2.3230	0.0451
	(-0.0965, 0.2081)	(-0.8860, -0.0166)	(-5.5051, -2.0090)	(-0.0238, 0.1030)
$C_{ML,US}$	-0.0813	-0.0033	-0.6915	-0.0223
	(-0.1212, 0.1965)	(-0.1618, 0.1122)	(-1.1361, -0.4363)	(-0.0460, 0.0012)
$C_{CN,US}$	-0.0811	-0.2650	-1.8602	0.0371
	(-0.1061, -0.0003)	(-0.6893, -0.0759)	(-6.8849, -0.9916)	(-0.0072, 0.0543)
$C_{ID,US}$	-0.0209	0.0688	-2.3949	-0.2630
	(-0.0678, 0.0005)	(-0.0264, 0.2354)	(-3.9775, -2.3342)	(-0.3600, -0.1297)
Mean	-0.0092	-0.0080	-1.4117	-0.1078
Panel B: shocks from the Japan market				
$C_{HK,JP}$	-0.0068	0.0186	0.1773	0.0111
	(-0.0694, 0.1074)	(-0.0110, 0.0214)	(-0.0281, 0.3590)	(-0.0894, 0.1506)
$C_{TW,JP}$	-0.0871	-0.0948	**0.1461**	-0.0127
	(-0.1000, -0.0059)	(-0.1999, -0.0146)	(0.0272, 0.1719)	(-0.1002, 0.1020)
$C_{SG,JP}$	-0.1074	-0.0942	**0.3093**	**0.1475**
	(-0.4962, -0.0374)	(-0.1090, 0.0289)	(0.2290, 0.4280)	(0.0558, 0.2026)
$C_{KR,JP}$	0.0281	-0.1787	**0.2240**	**0.1489**
	(-0.0105, 0.0723)	(-0.3044, -0.0277)	(0.1522, 0.3762)	(0.0676, 0.2354)
$C_{IN,JP}$	-0.0223	0.0003	**0.3475**	-0.1105
	(-0.7643, -0.0196)	(-0.0182, 0.0006)	(0.2981, 0.6593)	(-0.1988, 0.0534)
$C_{ML,JP}$	-0.0014	-0.0099	0.0252	-0.0603
	(-0.2589, -0.0009)	(-0.0247, 0.0224)	(-0.0901, 0.0915)	(-0.0777, -0.0187)
$C_{CN,JP}$	-0.0148	-0.0388	**0.0137**	0.0410
	(-0.0843, -0.0014)	(-0.0550, 0.0214)	(0.0053, 0.4318)	(-0.0095, 0.0822)
$C_{ID,JP}$	0.0002	-0.0353	**0.4112**	**0.1458**
	(-0.0684, 0.0003)	(-0.0532, 0.0304)	(0.3156, 0.6788)	(0.0527, 0.1823)
Mean	-0.0293	-0.0645	0.2110	0.0428
Panel C: shocks from the Hong Kong market				
$C_{JP,HK}$	-0.0002	-0.0610	-0.0659	0.0000
	(-0.0060, 0.0000)	(-0.1816, -0.0569)	(-0.1231, -0.0082)	(-0.0227, 0.0071)
$C_{TW,HK}$	-0.1415	-0.2107	0.0081	-0.2993
	(-0.1949, 0.0081)	(-0.7484, -0.1558)	(-0.1447, 0.0463)	(-0.4769, -0.1663)
$C_{SG,HK}$	-0.3160	-0.1219	**0.1693**	**0.2276**
	(-0.4281, -0.1121)	(-0.2618, -0.0347)	(0.1158, 0.2080)	(0.1587, 0.2993)
$C_{KR,HK}$	-0.3673	-0.1025	**0.0668**	**0.1068**
	(-0.5240, -0.1584)	(-0.5124, -0.0588)	(0.0494, 0.1080)	(0.0716, 0.2324)
$C_{IN,HK}$	-0.1103	-0.0071	**0.2140**	-0.3209
	(-0.3758, 0.0043)	(-0.1428, 0.0026)	(0.0978, 0.3587)	(-0.5039, -0.1999)
$C_{ML,HK}$	0.0117	0.0290	0.0155	-0.0480
	(-0.0323, 0.0134)	(-0.0677, 0.1383)	(-0.0732, 0.0391)	(-0.0806, -0.0258)
$C_{CN,HK}$	-0.0508	-0.0306	-0.0325	-0.1421
	(-0.0669, 0.0018)	(-0.1395, 0.2331)	(-0.3075, 0.0865)	(-0.3020, -0.0292)
$C_{ID,HK}$	-0.0017	-0.0571	**0.2315**	0.0562
	(-0.0350, 0.0040)	(-0.1995, -0.0108)	(0.1073, 0.3513)	(-0.0475, 0.1513)
Mean	-0.1394	-0.0715	0.0961	-0.0599

Note: The contagion measure $C_{i,j}$ from market j to market i $\left(C_{i,j} = \left(\frac{\mathbf{\Phi}_{i,j}+\mathbf{\Phi}^*(0)_{i,j}}{\mathbf{\Phi}_{j,j}+\mathbf{\Phi}^*(0)_{j,j}}\right)^2 - \left(\frac{\mathbf{\Phi}_{i,j}}{\mathbf{\Phi}_{j,j}}\right)^2\right)$ is reported for different cointegration periods. A $C_{i,j}$ value that is significantly greater than 0 suggests the contagion effect from market j to market i. In every case, the Monte Carlo simulation method with 1000 replications is used to evaluate statistical significance. The values in parentheses are the 5th and 95th quantiles of the simulated distribution. The 5% quantile of $C_{i,j}$ that is greater than 0 (in bold font) indicates a significant contagion effect. The means for seven Asian emerging stock markets are also reported for all shock sources and periods.

Table 5: The Chinn-Ito Financial Openness Index: 1997—2009

Year	China	India	South Korea	Malaysia	Indonesia	Singapore	Hong Kong	Japan	United Kingdom	United States
1997	-1.148165	-1.148165	-1.148165	0.7003022	1.945758	1.426941	2.477618	2.211688	2.477618	2.477618
1998	-1.148165	-1.148165	-1.148165	0.4343722	0.9842288	1.426941	2.477618	2.211688	2.477618	2.477618
1999	-1.148165	-1.148165	-1.148165	0.1684423	1.413898	2.477618	2.477618	2.211688	2.477618	2.477618
2000	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2001	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2002	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2003	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2004	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2005	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2006	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2007	-1.148165	-1.148165	-0.0974876	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2008	-1.148165	-1.148165	0.1684423	1.147968	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618
2009	-1.148165	-1.148165	0.4343722	-0.0974876	1.147968	2.477618	2.477618	2.477618	2.477618	2.477618

Note: The values indicate the financial openness of the economies over time compiled by Chinn and Ito (2008). This index of capital account openness, called KAOPEN, measures the intensity of capital account openness for an economy in each year. The data is retrieved from `http://web.pdx.edu/~ito/Chinn-Ito_website.htm` on March 12, 2012. In this table, the highest value of the index is 2.477618 while the lowest value of it is -1.14817. The higher (lower) the index is, the more (less) open the capital account is, and less (more) restrictions the capital account faces. This table shows that China and India have the least open capital accounts and impose more capital controls while the U.S., U.K., Japan, Hong Kong, and Singapore have the most open capital accounts and impose little capital controls.

Table 6: Results of variance decomposition

	Period 1 (Aug 24,1998-Aug 10,1999)	Period 2 (Sep 6,2001-Aug 26,2002)	Period 3 (Dec 21,2006-May 9,2008)	Period 4 (Oct 28,2008-Nov 20,2009)
Panel A: portfolio variance				
$\mathbf{V}_p^e$	0.000272	0.000324	0.000181	0.000368
	(0.000270, 0.000413)	(0.000235, 0.000533)	(0.000151, 0.000354)	(0.000349, 0.000521)
ε_p	-0.000103	-0.000211	-0.000003	-0.000066
	(-0.000206, -0.000075)	(-0.000387, -0.000186)	(-0.000006, 0.000109)	(-0.000148, -0.000005)
$\mathbf{V}_p$	0.000169	0.000113	0.000178	0.000303
	(0.000152, 0.000222)	(0.000105, 0.000159)	(0.000128, 0.000390)	(0.000220, 0.000396)
Panel B: shocks from the US market				
$\mathbf{V}_{p,US}^e$	0.000015	0.000000	0.000096	.000094
	(0.000013, 0.000051)	(0.000000, 0.000004)	(0.000095, 0.000171)	(0.000063, 0.000190)
$\varepsilon_{p,US}$	0.000007	0.000008	-0.000069	-0.000035
	(-0.000010, 0.000022)	(-0.000006, 0.000030)	(-0.000157, -0.000055)	(-0.000102, 0.000012)
$\mathbf{V}_{p,US}$	0.000022	0.000008	0.000028	0.000059
	(0.000018, 0.000048)	(0.000001, 0.000031)	(0.000007, 0.000039)	(0.000053, 0.000105)
$\mathbf{V}_{p,US}/\mathbf{V}_p$	12.88%	7.04%	15.51%	19.43%
Panel C: shocks from the Japan market				
$\mathbf{V}_{p,JP}^e$	0.000007	0.000029	0.000012	0.000051
	(0.000006, 0.000030)	(0.000007, 0.000039)	(0.000006, 0.000068)	(0.000025, 0.000062)
$\varepsilon_{p,JP}$	-0.000003	-0.000015	**0.000050**	**0.000026**
	(-0.000024, -0.000001)	(-0.000030, -0.000001)	(0.000034, 0.000140)	(0.000012, 0.000046)
$\mathbf{V}_{p,JP}$	0.000004	0.000014	0.000062	0.000077
	(0.000003, 0.000008)	(0.000005, 0.000018)	(0.000032, 0.000181)	(0.000057, 0.000088)
$\mathbf{V}_{p,JP}/\mathbf{V}_p$	2.12%	12.14%	34.83%	25.59%
Panel D: shocks from the Hong Kong market				
$\mathbf{V}_{p,HK}^e$	0.000060	0.000047	0.000008	0.000116
	(0.000044, 0.000100)	(0.000039, 0.000126)	(0.000001, 0.000030)	(0.000093, 0.000188)
$\varepsilon_{p,HK}$	-0.000027	-0.000026	**0.000027**	-0.000016
	(-0.000059, -0.000009)	(-0.000095,-0.000020)	(0.000022, 0.000047)	(-0.000050, 0.000033)
$\mathbf{V}_{p,HK}$	0.000033	0.000021	0.000036	0.000099
	(0.000029, 0.000043)	(0.000020, 0.000036)	(0.000023, 0.000064)	(0.00088, 0.000152)
$\mathbf{V}_{p,HK}/\mathbf{V}_p$	19.80%	18.63%	20.00%	32.85%

Note: The table reports the results of 1-step ahead conditional forecast error variance decomposition for the market portfolio returns. $\mathbf{V}_p^e$ represents the variance driven by the efficient contemporaneous information transmission, and $\mathbf{V}_p$ represents the empirical variance. ε_p indicates a departure from the efficient contemporaneous information transmission and is calculated as $\varepsilon_p = \mathbf{V}_p - \mathbf{V}_p^e$. For a specific shock from market j, the measures are indicated by the second subscript j. In every case, the Monte Carlo simulation method with 1000 replications is used to evaluate statistical significance. The values in parentheses are the 5th and 95th quantiles of the simulated distribution. The $\varepsilon_{p,j}$ value with 5% quantile larger than 0 (in bold font) indicates the significant contagion effect. The table also reports the percentage of the variance of the market portfolio returns that is due to a specific shock source.

Appendices
for
"Slow-burn" Spillover and "Fast and Furious" Contagion: A Study of International Stock Markets

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Appendix A

In order to establish the theoretical basis for our analysis, we attempt to propose a theoretical setup for two stock markets. This setup gives us some insight as to how we can study contagion when two market portfolio indices are cointegrated. Then we implement a simple simulation to reinforce this insight.

In our theoretical setup, we attempt to characterize the cointegration relation between two stock markets 1 and 2, whose prices at time t, p_{1t} and p_{2t}, can be modelled, respectively, as:

$$d\ln p_{1t} = \alpha_1 d\ln p_{2t} + \beta_1 \left(a + \ln p_{1t} - b\ln p_{2t}\right) dt + dB_{1t} \tag{A-1}$$

and

$$d\ln p_{2t} = \alpha_2 d\ln p_{1t} + \beta_2 \left(c + \ln p_{2t} - d\ln p_{1t}\right) dt + dB_{2t}, \tag{A-2}$$

where α_1, α_2, β_1, β_2, a, b, c, and d are constant parameters and B_{1t} and B_{2t} are composite Wiener processes given by

$$B_{1t} = \sigma_{11}W_{1t} + \sigma_{12}W_{2t} \tag{A-3}$$

and

$$B_{2t} = \sigma_{21}W_{1t} + \sigma_{22}W_{2t}. \tag{A-4}$$

Let $\ln p_t = [\ln p_{1t}, \ln p_{2t}]^T$. Equations (A-1) and (A-2) can be presented in the matrix form as the multivariate:

$$Ad\ln p_t = \mu dt + C\ln p_t dt + \Sigma dW_t, \tag{A-5}$$

where $A = \begin{bmatrix} 1 & -\alpha_1 \\ -\alpha_2 & 1 \end{bmatrix}$, $dW_t = [dW_{1t}, dW_{2t}]^T$, $\mu = [\beta_1 a, \beta_2 c]^T$, $C = \begin{bmatrix} \beta_1 & -\beta_1 b \\ -\beta_2 d & \beta_2 \end{bmatrix}$, and $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$. From equation (A-5), we have

$$d\ln p_t = A^{-1}\mu dt + A^{-1}C\ln p_t dt + A^{-1}\Sigma dW_t, \tag{A-6}$$

which can be further simplified into

$$d\ln p_t = (\tilde{\mu} - \tilde{C}\ln p_t)dt + \tilde{\Sigma} dW_t. \tag{A-7}$$

This expression implies that for the two stock market prices to be cointegrated their prices must be governed by the same stochastic trend (e.g., the growth of the global capital markets) and be perturbed by shocks from same sources (e.g., common/correlated shocks to the global capital markets). This is the basis for us to study contagion.

To see the above point clearer, we derive $\ln p_t$. Given that the matrix exponential, $e^{-\tilde{C}t}$, exists, from equation (A-7) we obtain the following expression:

$$e^{-\tilde{C}t} d\ln p_t + e^{-\tilde{C}t}\tilde{C}\ln p_t dt = e^{-\tilde{C}t}\tilde{\mu}dt + e^{-\tilde{C}t}\tilde{\Sigma}dW_t. \tag{A-8}$$

Rewriting the left-hand side of equation (A-8), we have

$$de^{-\tilde{C}t}\ln p_t = e^{-\tilde{C}t}\tilde{\mu}dt + e^{-\tilde{C}t}\tilde{\Sigma}dW_t. \tag{A-9}$$

Now we integrate equation (A-9) from 0 to t resulting:

$$e^{-\tilde{C}t}\ln p_t - \ln p_0 = \int_0^t e^{-\tilde{C}s}\tilde{\mu}ds + \int_0^t e^{-\tilde{C}s}\tilde{\Sigma}dW_s, \tag{A-10}$$

where x_0 is the initial value of $\{x_t, t \geq 0\}$. We simplify the first term on the right-hand side of equation (A-10) to get

$$e^{-\tilde{C}t}\ln p_t - \ln p_0 = -\frac{\tilde{\mu}}{\tilde{C}}(e^{-\tilde{C}t} - \mathbf{1}) + \int_0^t e^{-\tilde{C}s}\tilde{\Sigma}dW_s, \tag{A-11}$$

where $\mathbf{1}$ is a square matrix with elements being unity. Further simplifying equation (A-11) yields

$$\ln p_t = e^{\tilde{C}t}\ln p_0 - \frac{\tilde{\mu}}{\tilde{C}}(\mathbf{1} - e^{\tilde{C}t}) + \int_0^t e^{-\tilde{C}(s-t)}\tilde{\Sigma}dW_s. \tag{A-12}$$

This expression further implies that for the two stock market prices to be cointegrated their prices must be governed by the same stochastic trend and be perturbed by the common/correlated shocks. As we note, the two market prices are not cointegrated either because they are not governed by the same stochastic trend, or are perturbed by uncommon/uncorrelated shocks, or both. In this case, we could not study contagion which is defined as the transmission of some shocks beyond their long-term interdependence.

In the following simulation, we propose a simple framework in which two stock markets, market 1 and 2, are affected by common factors (without the deterministic trend) but, sometimes, are affected by market-specific factors of their own. p_{it} is the market portfolio index (in log) for market i in period t. As can be seen later, this discussion can be easily extended to the case of n markets.

We assume that the market portfolio prices for these two markets are determined by two k-factor models.[1] That is, the market portfolio price for market i $(i = 1, 2)$ has the following data generate process: for $t = 1, 2, \ldots, T$,

$$p_{it} = \sum_{j=1}^{k} \mathtt{b}_{ij} f_{jt} + v_{it}, \tag{A-13}$$

where f_{jt}, $j = 1, 2, \ldots, k$, are the k common factors and v_{it} is the innovation unique to market i $(i = 1, 2)$. Here, $p_{it} \sim I(1)$, $f_{jt} \sim I(1)$, and $v_{it} \sim I(0)$. The first difference of the k-factor model for the stock market portfolio price leads to the k-factor model of the stock market portfolio return. That is, let $r_{it} = \Delta p_{it} = p_{i,t} - p_{i,t-1}$ is the market portfolio return for stock market i in period t. Then the k-factor model of the stock market portfolio price is $r_{it} = \sum_{j=1}^{k} \mathtt{b}_{ij} \Delta f_{jt} + \Delta v_{it}$.

The k-factor model in equation (A-13) assumes that, other than market specific risk factor v_{it}, there is no factor that is unique to a specific market and that the common factors jointly affect the two stock markets. If there exists such a market specific factor x_{1t} that systematically influences market 1 but not market 2,[2] the price equation for market 1 must be changed to

$$p_{1t} = \sum_{j=1}^{k} \mathtt{b}_{1j} f_{jt} + \mathtt{b}_{1,k+1} x_{1t} + v_{1t}. \tag{A-14}$$

The price equation for market 2 remains to be

$$p_{2t} = \sum_{j=1}^{k} \mathtt{b}_{2j} f_{jt} + v_{2t}. \tag{A-15}$$

The data generating processes for p_{1t} and p_{2t} are quite different when x_{1t} is $I(1)$ but is also a near $I(2)$. This reflects that stock market 1 experiences a growth pattern that differs from that of stock market 2.[3]

If $\mathtt{b}_{1,k+1} = 0$ in equation (A-14), the two market portfolio prices (p_{1t} and p_{2t}) share the

[1] In our simulation exercise, for simplicity, we assume that two market portfolio prices are regulated by their k-factor models.

[2] For easy of communication, we let market 1 to be exposed to x_{1t} in addition to the common factors f_{jt}, where $j = 1, 2, \ldots, k$ and $t = 1, 2, \ldots, T$. Please note that this is a simplification. Logically, this is equivalent to let market i to be exposed to x_{it} but market 1 is exposed to $x'_{1t} = x_{1t} - x_{2t}$.

[3] Here, a $I(1)$ but near $I(2)$ process x_{1t} can be used to describe this growth pattern. Such a process can be generated from $z_t \sim I(0)$ using $(1 - L)(1 - \rho L)x_{1t} = z_t$, where $|\rho| + \epsilon = 1$ and ϵ is a very small number. This implies $x_{1t} = (1 + \rho)x_{1,t-1} - \rho x_{1,t-2} + z_t$.

common factors and are cointegrated. If $\mathtt{b}_{1,k+1} \neq 0$, although these prices share the common factors, they may not be cointegrated because of the presence of the factor that is unique to market 1, x_{1t}. Our simulation results show that when x_{1t} has more influence on p_{1t} than f_{1t} and f_{2t} do, the cointegration between p_{1t} and p_{2t} may be weakened substantially. In this case, we cannot establish the long-run equilibrium between the two stock markets and hence we cannot evaluate contagion which is viewed as a departure from this long-run equilibrium. We will report our simulation exercise and results at the latter part of the appendix.

In practice, because we cannot observe the common and market specific factors, we can only rely on the identification of a cointegration relation between the two market portfolio prices to establish the long-run equilibrium. The cointegration relation can take one of the following forms:

$$p_{1t} = \alpha_1 + \beta_1 p_{2t} + e_{1t} \tag{A-16}$$

and

$$p_{2t} = \alpha_2 + \beta_2 p_{1t} + e_{2t}, \tag{A-17}$$

where α_k and β_k are cointegrating parameters and e_{kt} is the error term in period t in cointegration relation k for $k = 1, 2$. These error terms reflect deviations from these cointegration relations.[4]

Now we study e_{kt} for $k = 1, 2$ in period t. Substituting equation (A-13) into equations (A-16) and (A-17), we obtain

$$\sum_{j=1}^{k} \mathtt{b}_{1j} f_{jt} + v_{1t} = \alpha_1 + \beta_1 \left(\sum_{j=1}^{k} \mathtt{b}_{2j} f_{jt} + v_{2t} \right) + e_{1t}, \tag{A-18}$$

and

$$\sum_{j=1}^{k} \mathtt{b}_{2j} f_{jt} + v_{2t} = \alpha_2 + \beta_2 \left(\sum_{j=1}^{k} \mathtt{b}_{1j} f_{jt} + v_{1t} \right) + e_{2t}. \tag{A-19}$$

Now we express e_{kt}, $k = 1, 2$, as functions of v_{1t} and v_{2t}:

$$e_{1t} = \delta_{1t} + (v_{1t} - \beta_1 v_{2t}) \tag{A-20}$$

and

$$e_{2t} = \delta_{2t} + (v_{2t} - \beta_2 v_{1t}), \tag{A-21}$$

[4]One may note that $\alpha_2 = -\frac{\alpha_1}{\beta_1}$, $\beta_2 = \frac{1}{\beta_1}$, and $e_{2t} = -\frac{e_{1t}}{\beta_1}$.

where

$$\delta_{1t} = -\alpha_1 + \sum_{j=1}^{k} (\mathtt{b}_{1j} - \beta_1 \mathtt{b}_{2j}) f_{jt} \tag{A-22}$$

and

$$\delta_{2t} = -\alpha_2 + \sum_{j=1}^{k} (\mathtt{b}_{2j} - \beta_2 \mathtt{b}_{1j}) f_{jt}. \tag{A-23}$$

Equations (A-20) and (A-21) represent the deviations from the cointegration relations given in equations (A-16) and (A-17). In addition, the error terms of cointegration regressions, e_{1t} and e_{2t}, are $I(0)$. Because, for $i = 1, 2$, $E(v_{it}) = 0$ and $E(e_{it}) = 0$, then $E(\delta_{it}) = 0$. That is, the error terms of the k-factor models are expected to be zero and the residuals of the cointegration regressions are expected to be zero. These facts also imply that the two stock market portfolio prices are cointegrated if no other market specific factors to disturb specific markets.

Although the k-factor models give us some traction on the underlying data generating processes for the market portfolio prices, we cannot observe the common and market specific factors. However, we can use the factor models to make sense the cointegration relations shown by equations (A-16) and (A-17) and identify α_k, β_k, and e_{kt}, $k = 1, 2$. In addition, we also want to make sense of how the residuals from the cointegration relations, e_{1t} and e_{2t}, are related to the unobservable market specific factors embedded in the underlying factor models, v_{1t} and v_{2t}.

Please note that the general setup for n stock markets can be explained by the case of two stock markets which are affected by a set of common and market specific factors. Following our theoretical discussion, we can stack the error terms of cointegration regressions for two stock markets, e_{1t} and e_{2t}, into

$$\mathbf{e}_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}. \tag{A-24}$$

Now we can identify how $\mathbf{e}_t$ is related to v_{it} $(i = 1, 2)$, the orthogonal structural innovations to markets 1 and 2, v_{1t} and v_{2t}, respectively. Now we stack them into

$$\mathbf{v}_t = \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix}. \tag{A-25}$$

We can relate $\mathbf{v}_t$ to $\mathbf{e}_t$ using the following structure:

$$\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t. \tag{A-26}$$

where

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{A-27}$$

and

$$\mathbf{B} = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}. \tag{A-28}$$

Let $\gamma = \frac{1}{|\mathbf{A}|}$. Because

$$\mathbf{A}^{-1} = \begin{bmatrix} \gamma a_{22} & -\gamma a_{12} \\ -\gamma a_{21} & \gamma a_{11} \end{bmatrix}, \tag{A-29}$$

$$\begin{aligned} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} &= \begin{bmatrix} \gamma a_{22} & -\gamma a_{12} \\ -\gamma a_{21} & \gamma a_{11} \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix} \\ &= \begin{bmatrix} \gamma a_{22} b_{11} v_{1t} - \gamma a_{12} b_{22} v_{2t} \\ -\gamma a_{21} b_{11} v_{1t} + \gamma a_{11} b_{22} v_{2t} \end{bmatrix}. \end{aligned} \tag{A-30}$$

Expanding the above expression as two separate equations, we obtain

$$e_{1t} = \gamma a_{22} b_{11} v_{1t} - \gamma a_{12} b_{22} v_{2t} \tag{A-31}$$

and

$$e_{2t} = \gamma a_{11} b_{22} v_{2t} - \gamma a_{21} b_{11} v_{1t} \tag{A-32}$$

We see that equations (A-31) and (A-32) share the similar structures of equations (A-20) and (A-21) if $\delta_i = 0$, $i = 1, 2$. In addition to $\delta_i = 0$, $i = 1, 2$, if we further impose the restrictions $\gamma a_{22} b_{11} = \gamma a_{11} b_{22} = 1$, $\gamma a_{12} b_{22} = \beta_1$, and $\gamma a_{21} b_{11} = \beta_2$, then equations (A-31) and (A-32) share the identical structures of equations (A-20) and (A-21).

A simulation exercise can be used to illustrate the validity of using the cointegration analysis to identify equilibrium relations among stock market prices when they are influenced by a set of common factors. When some stock market prices are driven more by their market specific factors, the identification of such equilibrium relations could be difficult.

To specify the parameters in the simulation exercise for the data generating processes given in equations (A-14) and (A-15), we assume that the number of the factors is $k = 2$. The sample size is $T = 1000$. The bi-factor models have the following parameters: $\mathtt{b}_{11} = 0.2$, $\mathtt{b}_{12} = 0.2$, $\mathtt{b}_{13} = 0.4$, $\mathtt{b}_{21} = 0.1$, and $\mathtt{b}_{22} = 0.3$. The factor 1, f_{1t}, is generated by $(1 - L)f_{1t} = w_{1t} \sim N(2, 4)$. The factor 2, f_{2t}, is generated by $(1 - L)f_{2t} = w_{2t} \sim N(1, 1)$. The error terms of the bi-factor models are $u_{1t} \sim N(0, 1)$ and $u_{2t} \sim N(0, 1)$, respectively, and they are statistically independent. In addition, we let x_{1t} be a $I(1)$ but near $I(2)$ process. Such a process can be generated from $z_t \sim I(0)$ using $(1-L)(1-\rho L)x_{1t} = z_t$, where $|\rho|+\epsilon = 1$ and ϵ is a very small number. This implies $x_{1t} = (1 + \rho)x_{1,t-1} - \rho x_{1,t-2} + z_t$. In our simulation exercise, we let $\rho = 0.97$.

Figures A1 and A2 show the changes in two common factors, f_{1t} and f_{2t}. These two factors jointly influence two stock market portfolio returns and, therefore, their prices p_{1t} and p_{2t}. Figure A3 shows x_{1t}, which is $I(1)$ but near $I(2)$ with $\rho = 0.97$. This factor enters the data generating process of p_{1t} when $\mathtt{b}_{13} = 0.4$ (see Figure A4). When $\mathtt{b}_{13} = 0$, this factor does not enter the data generating process of p_{1t} (see Figure A5). In this simulation exercise, we do not allow p_{2t} to be affected by another market specific factor beyond the two common factors f_{1t} and f_{2t}. As can be seen in Figures A4 and A5, the return for stock market 1 portfolio can be affected by the factor that is specific to market 1.

Now we examine the plausible cointegration relation between the two stock market portfolio prices. As shown in Figure A7, the two prices appear to be not cointegrated when the stock market 1 portfolio price is influenced by x_{1t}. As shown in Figure A8, the two prices appear to be cointegrated when the stock market 1 portfolio price is not influenced by x_{1t}.

The examination of the residuals of this cointegration regression based on the graphical analysis (see Figure A9) and the cointegration test further confirms that the two prices under this condition are not cointegrated. If we eliminate the impact of x_{1t} on the stock market 1 portfolio price, we can find a cointegration relation between the two prices based on the graphical analysis (see Figure A10) and the cointegration test. Of course, the latter is completely expected as the two prices are influenced jointly by the two common factors.

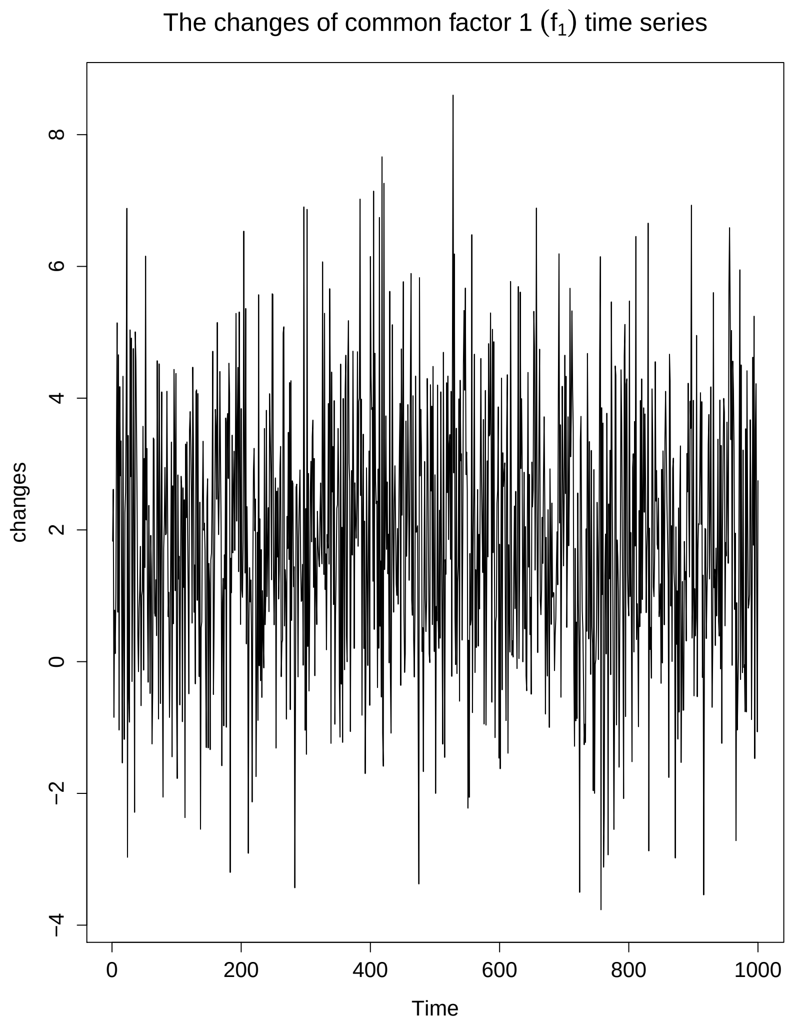

Figure A1: Changes of common factor f_1

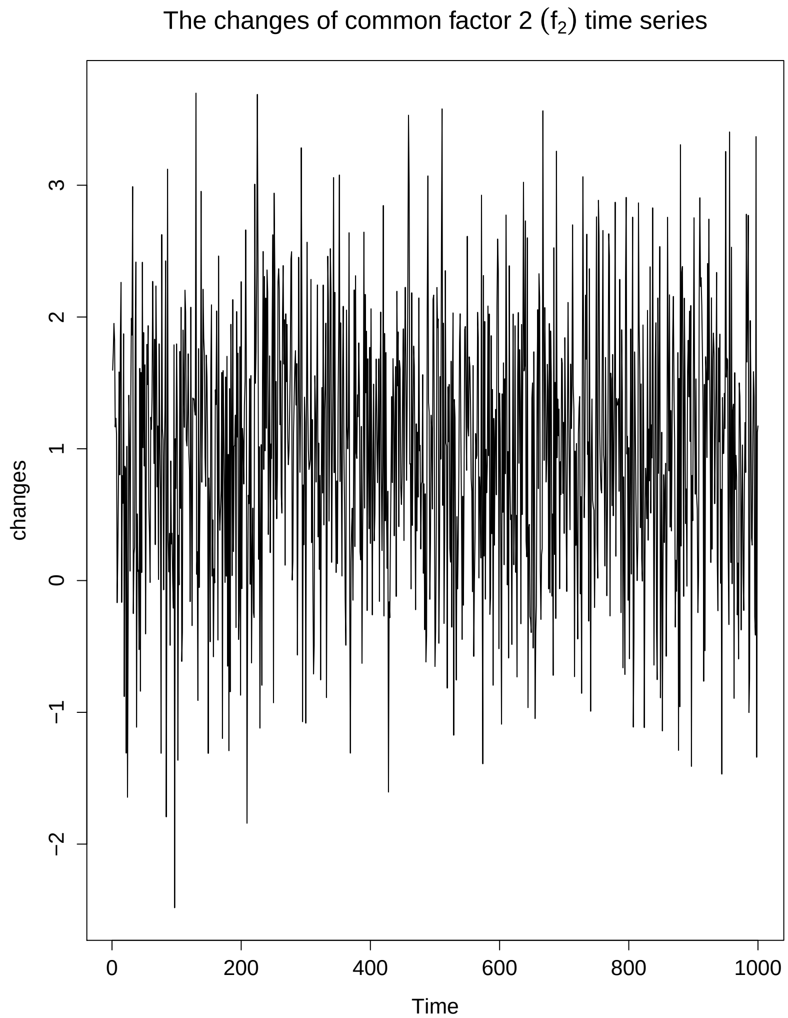

Figure A2: Changes of common factor f_2

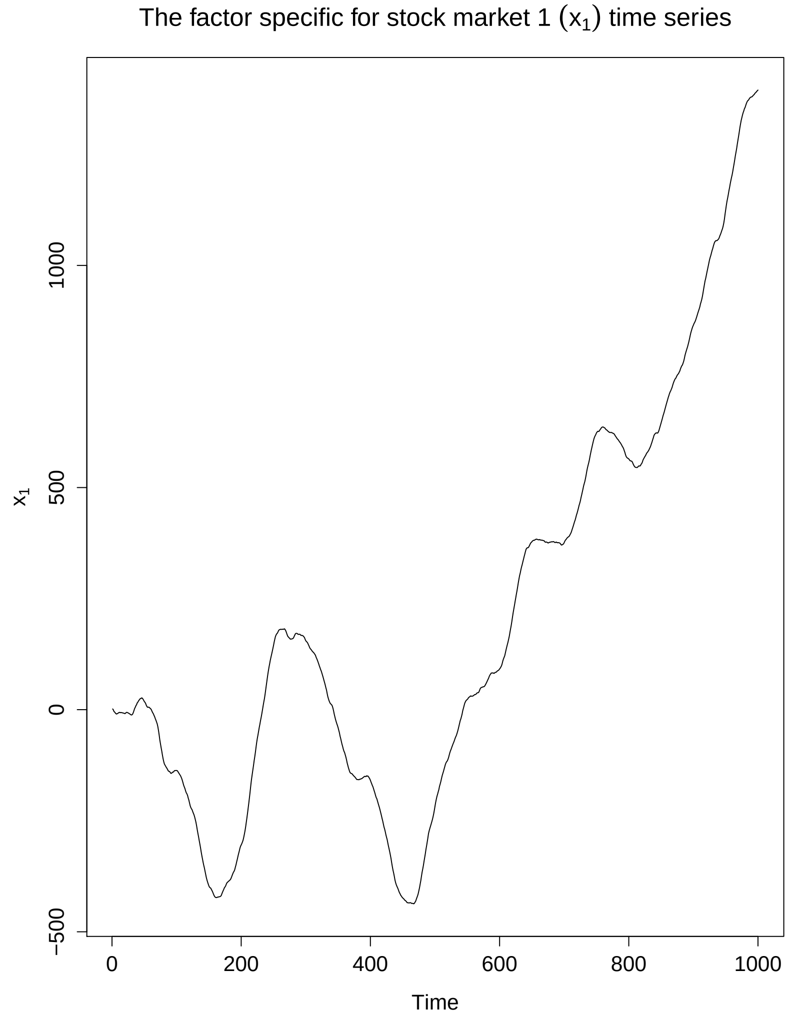

Figure A3: Factor specific for market 1, x_1

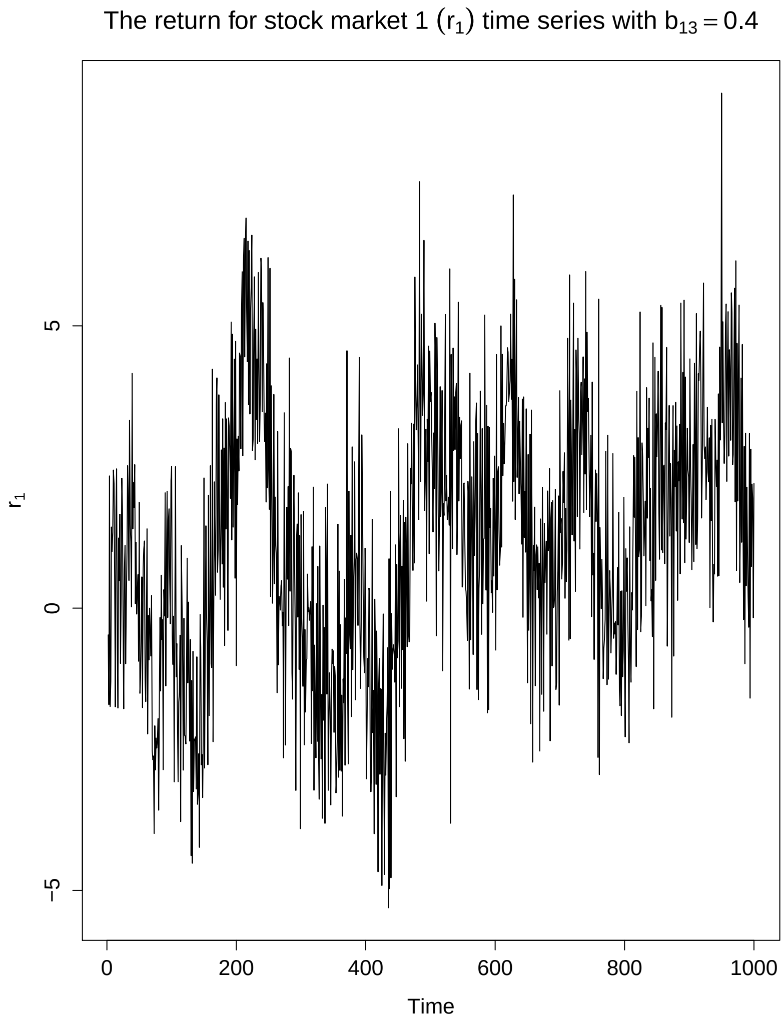

Figure A4: Market 1 portfolio return influenced by x_1

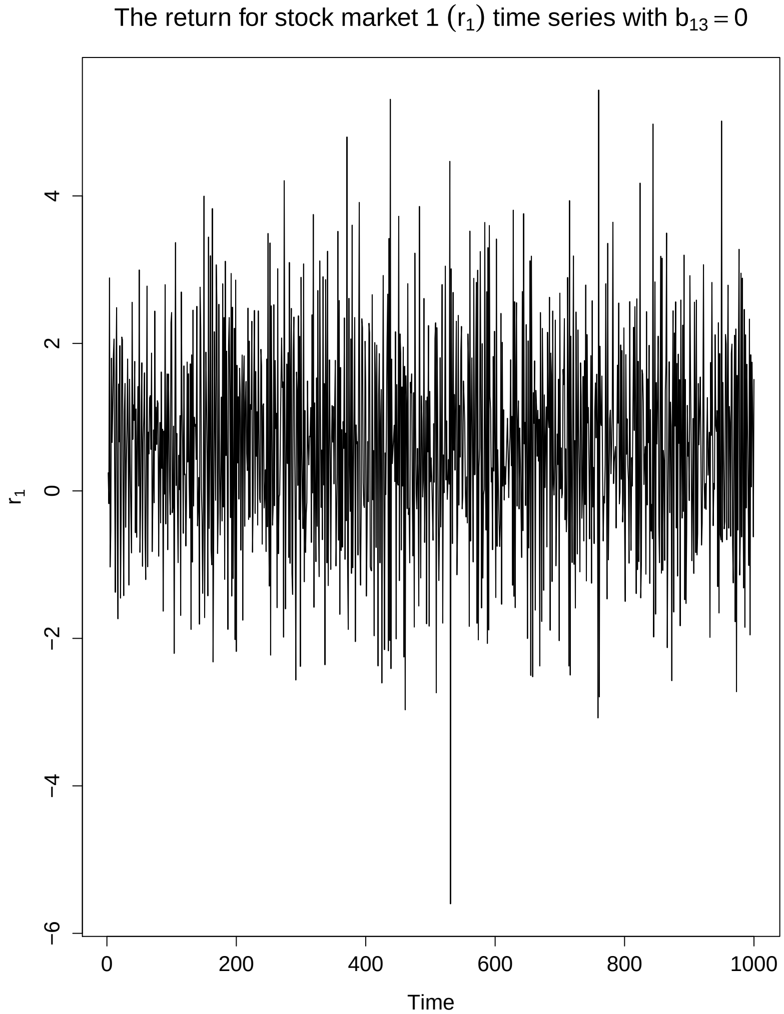

Figure A5: Market 1 portfolio return not influenced by x_1

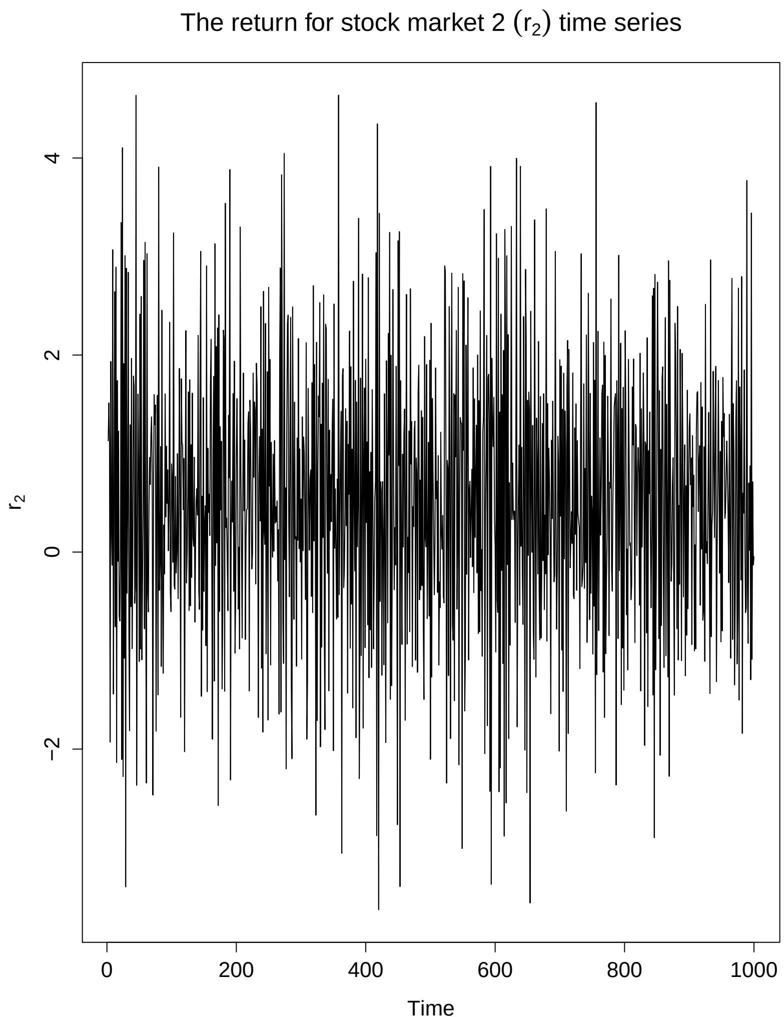

Figure A6: Market 2 portfolio return

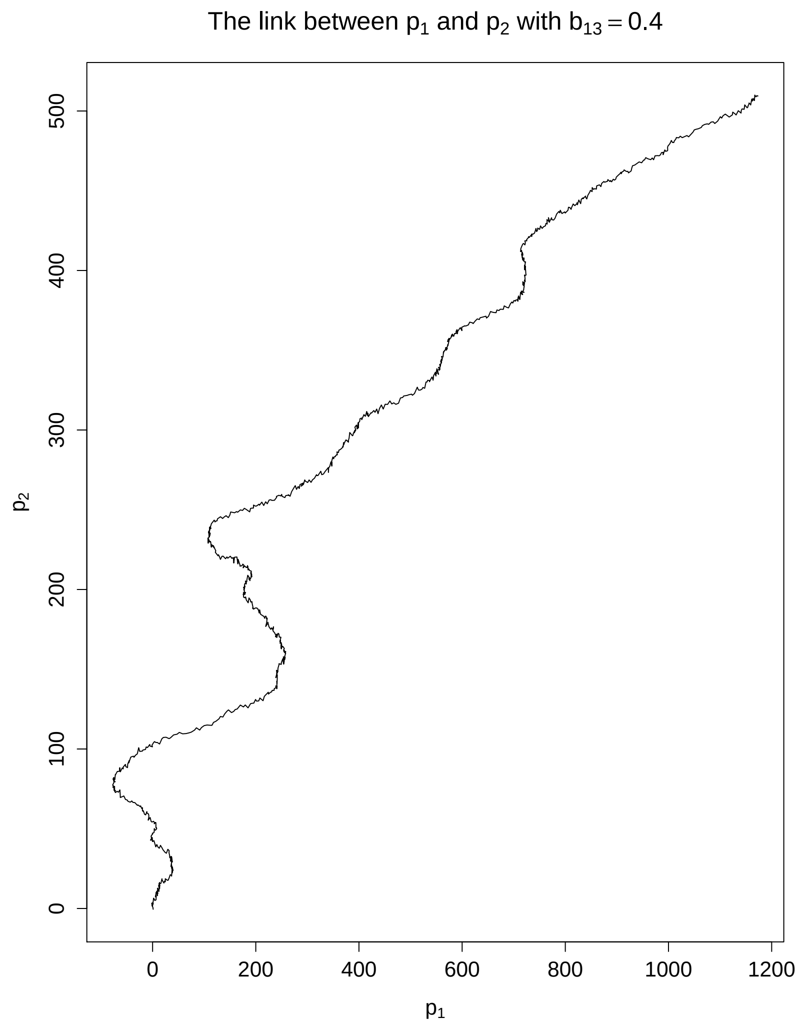

Figure A7: The link between two market portfolio prices with market 1 influenced by x_1

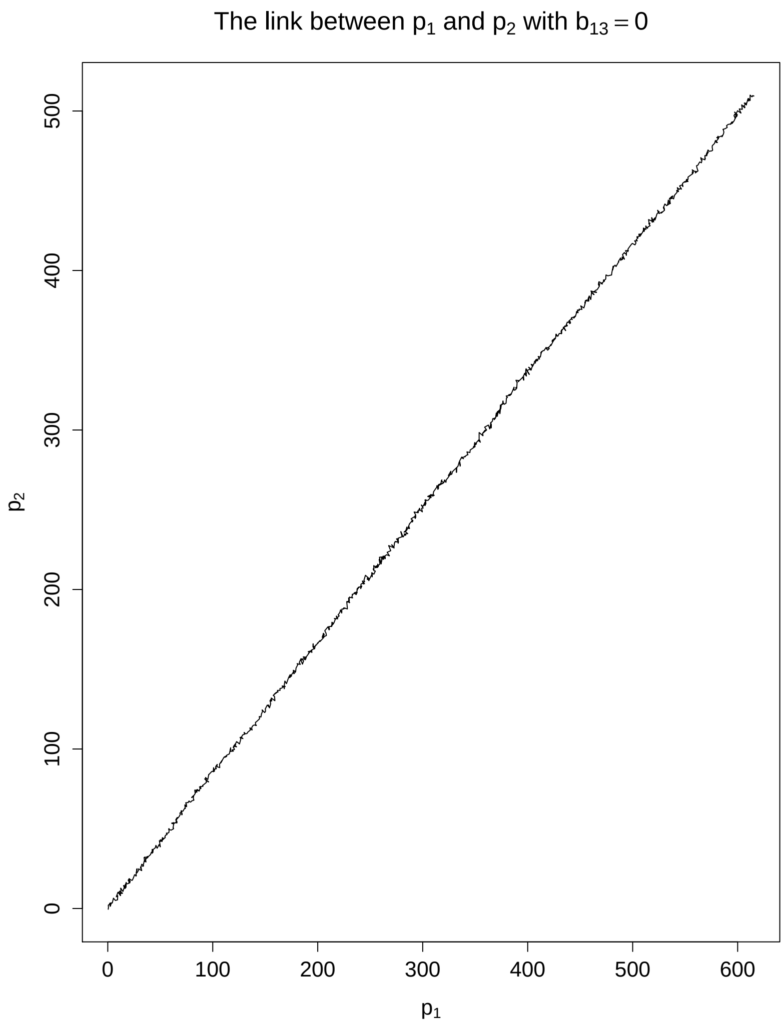

Figure A8: The link between two market portfolio prices with market 1 not influenced by x_1

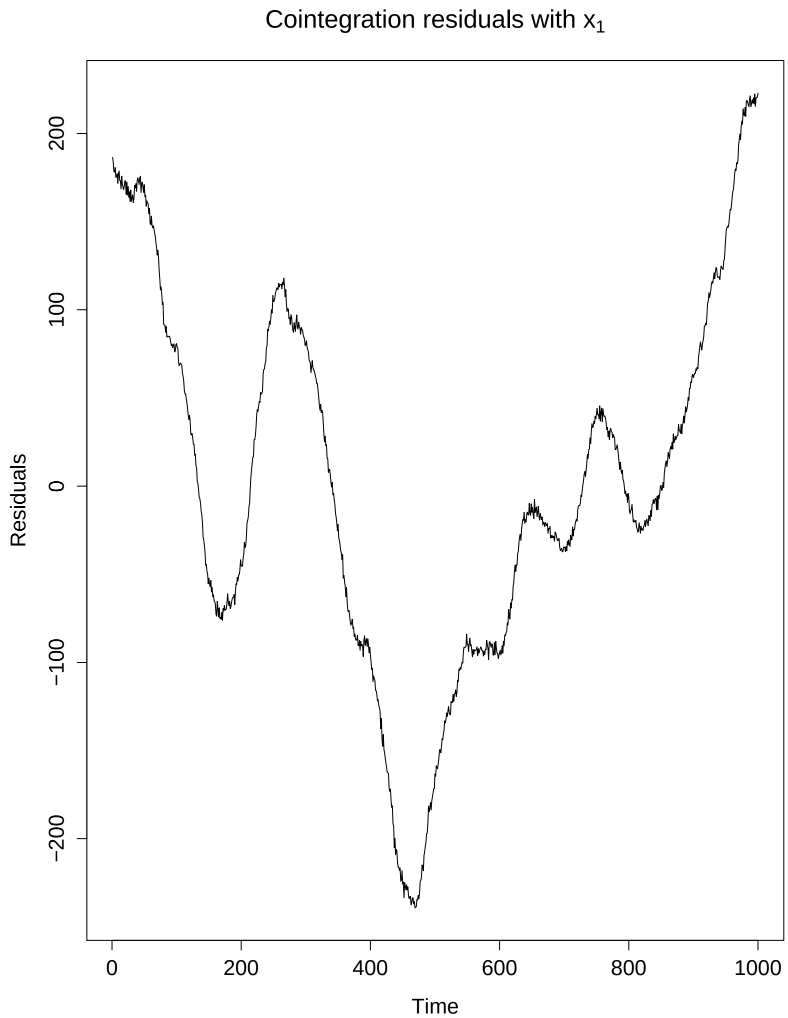

Figure A9: Non-stationary residuals in the cointegration regression with market 1 influenced by x_1

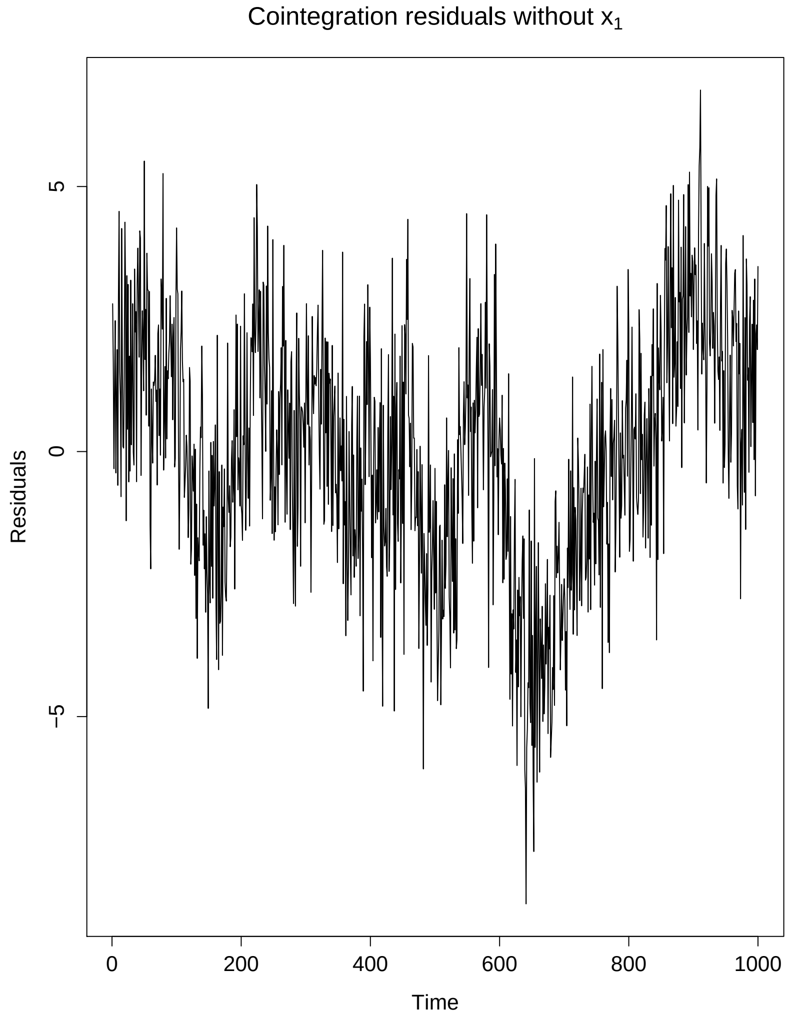

Figure A10: Stationary residuals in the cointegration regression with market 1 not influenced by x_1

Appendix B

Without loss of generality, we assume that stock market portfolio returns follow the data generating process of $\Delta\mathbf{p}_t = \mathbf{\Pi}\mathbf{p}_{t-1} + \mathbf{\Gamma}\Delta\mathbf{p}_{t-1} + \mathbf{e}_t$. This data generating process permits dynamics and comovements within and across stock markets. The VECM has a VAR representation

$$\mathbf{A}(L)\mathbf{p}_t = \mathbf{e}_t \tag{B-1}$$

where $\mathbf{A}(L) = \mathbf{I}_n - \mathbf{A}_1 L - \mathbf{A}_2 L^2$ with $\mathbf{A}_1 = \mathbf{\Pi} + \mathbf{I}_n + \mathbf{\Gamma} = \alpha\beta' + \mathbf{I}_n + \mathbf{\Gamma}$ and $\mathbf{A}_2 = -\mathbf{\Gamma}$. Here α is an $n \times r$ matrix and β an $n \times r$ matrix capturing the r cointegration relations among n elements in $\mathbf{p}_t$.

Gonzalo and Granger (1995) define $\Delta\mathbf{P}_t$ and $\Delta\mathbf{T}_t$ as the innovations associated with the permanent (P) and transitory (T) components of $\Delta\mathbf{p}_t$, respectively. Their P-T decomposition is as follows:

$$\Delta\mathbf{p}_t = \Delta\mathbf{P}_t + \Delta\mathbf{T}_t = \theta_1\Delta\mathbf{f}_t + \theta_2\Delta\mathbf{z}_t, \tag{B-2}$$

where $\theta_1 = \beta_\perp(\alpha'_\perp\beta_\perp)^{-1}$ and $\theta_2 = \alpha(\beta'\alpha)^{-1}$ so that θ_1 is an $n \times (n-r)$ matrix and θ_2 is an $n \times r$ matrix. $\mathbf{f}_t = \alpha'_\perp\mathbf{p}_t$ and $\mathbf{z}_t = \beta'\mathbf{p}_t$.

Let $\mathbf{G} = \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix}$, then $\mathbf{G}\mathbf{p}_t = \begin{bmatrix} \mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix}$. Thus, we have

$$\mathbf{G}\mathbf{A}(L)\mathbf{G}^{-1}\begin{bmatrix} (1-L)\mathbf{I}_{n-r} & 0 \\ 0 & \mathbf{I}_r \end{bmatrix}^{-1}\begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \mathbf{G}\mathbf{A}(L)\mathbf{G}^{-1}\begin{bmatrix} \mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \mathbf{G}\mathbf{A}(L)\mathbf{p}_t = \mathbf{G}\mathbf{e}_t. \tag{B-3}$$

Equation (B-3) is the AR representation of $\begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix}$. To write it in an extensive form, define the first $n-r$ columns of $\mathbf{G}^{-1}$ as $\mathbf{G}^{-1}_{n-r}$ and the last r columns of $\mathbf{G}^{-1}$ as $\mathbf{G}^{-1}_r$. Then we have

$$\begin{bmatrix} \mathbf{I}_{n-r} - (\alpha'_\perp\mathbf{\Gamma}\mathbf{G}^{-1}_{n-r})L & (-\alpha'_\perp\mathbf{\Gamma}\mathbf{G}^{-1}_r)L(1-L) \\ (-\beta'\mathbf{\Gamma}\mathbf{G}^{-1}_{n-r})L & \mathbf{I}_r - (\beta'\alpha + \mathbf{I}_r + \beta'\mathbf{\Gamma}\mathbf{G}^{-1}_r)L + (\beta'\mathbf{\Gamma}\mathbf{G}^{-1}_r)L^2 \end{bmatrix}\begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \mathbf{G}\mathbf{e}_t. \tag{B-4}$$

We can write equation (B-4) compactly as

$$\begin{bmatrix} \mathbf{F}_{11}(L) & \mathbf{F}_{12}(L) \\ \mathbf{F}_{21}(L) & \mathbf{F}_{22}(L) \end{bmatrix}\begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \mathbf{G}\mathbf{e}_t \tag{B-5}$$

$\mathbf{F}_{ij}(L)$ can be derived according to equation (B-3). For example, $\mathbf{F}_{11}(L)$ is an $(n-r)\times(n-r)$

matrix which is from "(the first $n-r$ rows of $\mathbf{G}$) $\times\mathbf{A}(L)\times$ (the first $n-r$ columns of $\mathbf{G}^{-1}$)$/(1-L)$". We can obtain $\mathbf{F}_{12}(L)$, $\mathbf{F}_{21}(L)$ and $\mathbf{F}_{22}(L)$ similarly. Let $L=0,1$, we have

$$\begin{aligned}
\mathbf{F}_{11}(0) &= \mathbf{I}_{n-r}, \quad \mathbf{F}_{11}(1) = \mathbf{I}_{n-r} - \alpha'_{\perp}\mathbf{\Gamma}\mathbf{G}_{n-r}^{-1}. \\
\mathbf{F}_{12}(0) &= \mathbf{0}, \quad \mathbf{F}_{12}(1) = \mathbf{0}, \\
\mathbf{F}_{21}(0) &= \mathbf{0}, \quad \mathbf{F}_{21}(1) = -\beta'\mathbf{\Gamma}\mathbf{G}_{n-r}^{-1}, \\
\mathbf{F}_{22}(0) &= \mathbf{I}_{r}, \quad \mathbf{F}_{22}(1) = -\beta'\alpha.
\end{aligned} \tag{B-6}$$

Let $\mathbf{u}_t^P = \alpha'_{\perp}\mathbf{e}_t$ and $\mathbf{u}_t^T = \beta'\mathbf{e}_t$. We can write equation (B-5) as

$$\begin{bmatrix} \mathbf{F}_{11}(L) & \mathbf{F}_{12}(L) \\ \mathbf{F}_{21}(L) & \mathbf{F}_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix}. \tag{B-7}$$

Inverting equation (B-7) we obtain

$$\begin{bmatrix} \Delta\mathbf{f}_t \\ \mathbf{z}_t \end{bmatrix} = \begin{bmatrix} \mathbf{F}^{11}(L) & \mathbf{F}^{12}(L) \\ \mathbf{F}^{21}(L) & \mathbf{F}^{22}(L) \end{bmatrix} \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix}, \tag{B-8}$$

where $\begin{bmatrix} \mathbf{F}^{11}(L) & \mathbf{F}^{12}(L) \\ \mathbf{F}^{21}(L) & \mathbf{F}^{22}(L) \end{bmatrix} = \begin{bmatrix} \mathbf{F}_{11}(L) & \mathbf{F}_{12}(L) \\ \mathbf{F}_{21}(L) & \mathbf{F}_{22}(L) \end{bmatrix}^{-1}$. We assume that $\mathbf{F}^{ij}(L)$'s exist and can be determined by inverting the partitioned matrix. Therefore, we have

$$\begin{aligned}
\mathbf{F}^{11}(L) &= (\mathbf{F}_{11}(L) - \mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L))^{-1}, \qquad \text{(B-9)} \\
\mathbf{F}^{12}(L) &= -(\mathbf{F}_{11}(L) - \mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L))^{-1}\mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}, \\
\mathbf{F}^{21}(L) &= -\mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L)(\mathbf{F}_{11}(L) - \mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L))^{-1}, \\
\mathbf{F}^{22}(L) &= \mathbf{F}_{22}(L)^{-1} + \mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L)(\mathbf{F}_{11}(L) - \mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}\mathbf{F}_{21}(L))^{-1}\mathbf{F}_{12}(L)\mathbf{F}_{22}(L)^{-1}.
\end{aligned}$$

Let $L=0,1$, we have

$$\begin{aligned}
\mathbf{F}^{11}(0) &= \mathbf{I}_{n-k}, \quad \mathbf{F}^{11}(1) = \mathbf{F}_{11}(1)^{-1}, \qquad \text{(B-10)} \\
\mathbf{F}^{12}(0) &= \mathbf{0}, \quad \mathbf{F}^{12}(1) = \mathbf{0}, \\
\mathbf{F}^{21}(0) &= \mathbf{0}, \quad \mathbf{F}^{21}(1) = -\mathbf{F}_{22}(1)^{-1}\mathbf{F}_{21}(1)\mathbf{F}_{11}(1)^{-1} \\
\mathbf{F}^{22}(0) &= \mathbf{I}_{r}, \quad \mathbf{F}^{22}(1) = \mathbf{F}_{22}(1)^{-1}.
\end{aligned}$$

Furthermore, we can express $\Delta\mathbf{P}_t$ and $\Delta\mathbf{T}_t$ equation by equation compactly as

$$\begin{aligned}
\begin{bmatrix} \Delta\mathbf{P}_t \\ \Delta\mathbf{T}_t \end{bmatrix} &= \begin{bmatrix} \theta_1 & 0 \\ 0 & \theta_2 \end{bmatrix} \begin{bmatrix} \Delta\mathbf{f}_t \\ \Delta\mathbf{z}_t \end{bmatrix} \qquad \text{(B-11)} \\
&= \begin{bmatrix} \theta_1 & 0 \\ 0 & \theta_2 \end{bmatrix} \begin{bmatrix} \mathbf{I}_{n-r} & 0 \\ 0 & (1-L)\mathbf{I}_r \end{bmatrix} \begin{bmatrix} \mathbf{F}^{11}(L) & \mathbf{F}^{12}(L) \\ \mathbf{F}^{21}(L) & \mathbf{F}^{22}(L) \end{bmatrix} \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix} \\
&= \begin{bmatrix} \theta_1\mathbf{F}^{11}(L) & \theta_1\mathbf{F}^{12}(L) \\ \theta_2(1-L)\mathbf{F}^{21}(L) & \theta_2(1-L)\mathbf{F}^{22}(L) \end{bmatrix} \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\Delta\mathbf{P}_t &= \theta_1\mathbf{F}^{11}(L)\mathbf{u}_t^P + \theta_1\mathbf{F}^{12}(L)\mathbf{u}_t^T, \qquad \text{(B-12)} \\
\Delta\mathbf{T}_t &= \theta_2(1-L)\mathbf{F}^{21}(L)\mathbf{u}_t^P + \theta_2(1-L)\mathbf{F}^{22}(L)\mathbf{u}_t^T.
\end{aligned}$$

It is worth noting that $\mathbf{F}^{12}(1) = \mathbf{0}$ in equation (B-10), which implies that the permanent shock $\Delta\mathbf{P}_t$ still has the transitory component $\theta_1\mathbf{F}^{12}(L)\mathbf{u}_t^T$.

Substituting equations (B-12) into equation (B-2), we have

$$\begin{aligned}
\Delta\mathbf{p}_t &= \Delta\mathbf{P}_t + \Delta\mathbf{T}_t \qquad \text{(B-13)} \\
&= \begin{bmatrix} \theta_1\mathbf{F}^{11}(L) + \theta_2(1-L)\mathbf{F}^{21}(L) & \theta_1\mathbf{F}^{12}(L) + \theta_2(1-L)\mathbf{F}^{22}(L) \end{bmatrix} \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix} \\
&= \begin{bmatrix} \mathbf{D}_1(L) & \mathbf{D}_2(L) \end{bmatrix} \begin{bmatrix} \mathbf{u}_t^P \\ \mathbf{u}_t^T \end{bmatrix}.
\end{aligned}$$

Here we define

$$\begin{aligned}
\mathbf{D}_1(L) &= \theta_1\mathbf{F}^{11}(L) + \theta_2(1-L)\mathbf{F}^{21}(L). \qquad \text{(B-14)} \\
\mathbf{D}_2(L) &= \theta_1\mathbf{F}^{12}(L) + \theta_2(1-L)\mathbf{F}^{22}(L).
\end{aligned}$$

Because $\mathbf{F}^{12}(1) = \mathbf{0}$, $\mathbf{D}_2(1) = \mathbf{0}$, which means that $\mathbf{u}_t^T$ only has transitory effect on the level of $\mathbf{p}_t$. Hence, $\mathbf{u}_t^P$ and $\mathbf{u}_t^T$ are named the permanent and transitory shocks, respectively, by Gonzalo and Ng (2001). This P-T decomposition differs from that of Gonzalo and Granger (1995).

However, if we focus on the components of $\mathbf{D}_1(L)$, we find that the permanent shock still has transitory component. Let $L = 0, 1$. We have

$$\begin{aligned}
\mathbf{D}_1(0) &= \theta_1\mathbf{F}^{11}(0) + \theta_2\mathbf{F}^{21}(0) = \theta_1\mathbf{I}_{n-r}, \qquad \text{(B-15)}\\
\mathbf{D}_2(0) &= \theta_1\mathbf{F}^{12}(0) + \theta_2\mathbf{F}^{22}(0) = \theta_2\mathbf{I}_r,\\
\mathbf{D}_1(1) &= \theta_1\mathbf{F}^{11}(1) = \theta_1\mathbf{F}_{11}(1)^{-1},\\
\mathbf{D}_2(1) &= \theta_1\mathbf{F}^{12}(1) = \mathbf{0}.
\end{aligned}$$

Here, $\mathbf{D}_1(0) = \theta_1\mathbf{I}_{n-r}$ is the initial impact of a permanent shock, $\mathbf{u}_t^P$. $\mathbf{D}_1(1) = \theta_1\mathbf{F}_{11}(1)^{-1}$ is the long-run pricing impact. Only when $\mathbf{F}_{11}(1)^{-1} = \mathbf{I}_{n-r}$, i.e., $\mathbf{\Gamma} = \mathbf{0}$, the initial impact of $\mathbf{u}_t^P$ is equal to its long-run pricing impact.

As we can see, different P-T decomposition methods always provide different identifications for permanent and transitory shocks. In fact, all the information can be fully reflected in the level of $\mathbf{p}_t$ if given long-enough period. What we focus on, especially in contagion analysis, should be the deviation of the initial impact of innovations on stock markets from the long-run pricing impact and why this deviation exists. Therefore, we only consider the deviation of the initial impact from the long-run pricing impact and avoid using the terms "permanent shocks" and "transitory shocks," which could be ambiguous in our context.

The $n \times 1$ vector of error terms, $\mathbf{e}_t$, can be expressed in a structural relation with the $n \times 1$ vector of unobservable structural innovations $\mathbf{v}_t$: $\mathbf{A}\mathbf{e}_t = \mathbf{B}\mathbf{v}_t$, where $\mathbf{v}_t \sim (\mathbf{0}, \mathbf{I}_n)$ and $\mathbf{A}$ and $\mathbf{B}$ are $n \times n$ matrices of structural parameters. Some parameters are restricted to 0 or 1 for identification while others are to be estimated. $\mathbf{A}$ contains the contemporaneous correlation coefficients among error terms while $\mathbf{B}$ is a diagonal matrix containing the standard deviations of structural innovations. Substituting $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ into equation (B-13), we obtain

$$\begin{aligned}
\Delta\mathbf{p}_t &= \begin{bmatrix} \mathbf{D}_1(L) & \mathbf{D}_2(L) \end{bmatrix} \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix} \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t\\
&= \mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t. \qquad \text{(B-16)}
\end{aligned}$$

According to equation (B-15), the initial impact of the structural innovation $\mathbf{v}_t$ on the level of $\mathbf{p}_t$ is $\mathbf{D}_1(0)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{D}_2(0)\beta'\mathbf{A}^{-1}\mathbf{B} = \theta_1\mathbf{I}_{n-r}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \theta_2\mathbf{I}_r\beta'\mathbf{A}^{-1}\mathbf{B}$. The long-run pricing impact is $\mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} = \theta_1\mathbf{F}_{11}(1)^{-1}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}$. Therefore, equation (B-16) can be further decomposed into

$$
\begin{aligned}
\Delta\mathbf{p}_t &= \begin{bmatrix} \mathbf{D}_1(L) & \mathbf{D}_2(L) \end{bmatrix} \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix} \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \\
&= \mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \qquad \text{(B-17)} \\
&= \underbrace{\mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t}_{\left(\substack{\text{Long-run Pricing Impact} \\ \text{Denoted } \mathbf{\Phi}\mathbf{v}_t}\right)} + \underbrace{\Big(\mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}\Big)\mathbf{v}_t}_{\left(\substack{\text{Pricing Error} \\ \text{Denoted}\mathbf{\Phi}^*(L)\mathbf{v}_t, \text{ and } \mathbf{\Phi}^*(1)\mathbf{v}_t = \mathbf{0}}\right)}
\end{aligned}
$$

where the long-run pricing impact of innovations $\mathbf{v}_t$ is measured by a matrix of scalars, $\mathbf{\Phi}$, and the pricing error induced by the innovations has a dynamic effect, $\mathbf{\Phi}^*(L)$, which satisfies $\mathbf{\Phi}^*(0) = \theta_1 I_{n-r}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \theta_1\mathbf{F}_{11}(1)^{-1}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \theta_2\mathbf{I}_r\beta'\mathbf{A}^{-1}\mathbf{B}$ and $\mathbf{\Phi}^*(1) = \mathbf{0}$.

Finally, when $\mathbf{\Gamma} = \mathbf{0}$ and $\beta'\mathbf{A}^{-1}\mathbf{B} = \mathbf{0}$,

$$
\begin{aligned}
\mathbf{\Phi}^*(0) &= \mathbf{D}_1(0)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{D}_2(0)\beta'\mathbf{A}^{-1}\mathbf{B} \\
&= \theta_1\mathbf{I}_{n-r}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \theta_1\mathbf{I}_{n-r}\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{0} \\
&= \mathbf{0} \qquad \text{(B-18)}
\end{aligned}
$$

When $\mathbf{\Gamma} = \mathbf{0}$, then no long-run auto-correlations exist among the elements in $\mathbf{p}_t$. This implies high efficiency of stock markets. When $\beta'\mathbf{A}^{-1}\mathbf{B} = \mathbf{0}$, then the contemporaneous innovations maintain their cointegration relations. This implies high efficiency of contemporaneous information transmission across stock markets. Only when these two conditions are satisfied, stock markets are said to fully reflect new information in their own locations and across locations.

Appendix C

Figure C1 contains DAG results based on the innovations from our error correction model for all eleven stock markets for the four periods. A DAG shows the causal flow among a set of variables such that there are no directed cycles.[5] The nodes of these graphs represent variables on which data have been obtained while line segments connecting nodes (directed edges) are generated by calculations of conditional statistical dependence among pairs of variables (ceteris paribus). Under the assumption that variables $v_1, v_2, v_3, \ldots, v_n$ under study follow Markov processes, one can simplify the empirical joint distribution of these variables based on conditional statistical dependence.

Now we use X, Y, and Z to describe conditional statistical dependence among variables $v_1, v_2, v_3, \ldots, v_n$. For example, if there is a directed edge between variables X and Y like $X \rightarrow Y$, X is described as the parent of Y. In addition, a graph represented by $Y \leftarrow X \rightarrow Z$ implies that the three variable, X, Y and Z have a relation such that X causes Y and Z. This causal relationship implies that the unconditional association between Y and Z is nonzero but the conditional association between Y and Z , given the knowledge of the common cause X, is zero. Alternatively, a graph represented by $Y \rightarrow X \leftarrow Z$ implies that the unconditional association between Y and Z is zero but the conditional association between them, given the common effect X, is nonzero.

Following Pearl (2000), DAGs can be used to represent conditional independence as implied by the recursive product decomposition:

$$\Pr(v_1, v_2, \ldots, v_n) = \prod_{i=1}^{n} \Pr(v_i | \text{pa}_i), \tag{C-1}$$

where Pr is the probability of variables $v_1, v_2, \ldots, v_n$ and pa_i (also called parents) represents a set of variables that immediately causes v_i.

In Spirtes et al. (2000), a causal search algorithm, called the PC algorithm, is provided for making inference on directed acyclic graphs from observational data. It begins with a complete undirected graph, where every variable is connected to every other variable. Edges between variable are then removed based on vanishing correlation or partial correlation, at a predetermined level of significance. The significance level is a threshold for independence. The higher it is set, the less discerning the PC algorithm is when determining the indepen-

[5]This means that it is not possible to start at a variable and follow a directed path back to the same variable.

dence between two variables. Spirtes et al. (2000, p. 116) recommend that one drop the level of significance used as the number of observation increases. For small samples less than 100 observations, a significance level of 20% is recommended. For larger samples greater than 100 and less than 300 observations, they suggest a 10% significance level. In our research, because we have over two hundred observations for each period, we set the significance level at 10%. Therefore, if estimated correlations and partial correlations linking some variables that form edges are not statistically significantly different from zero at the 10% significance level, the causal search algorithm will remove those edges. The software TETRAD IV is employed to conduct the DAG analysis.

We apply the DAG to identify the dependence among the stock markets so that we can place zero restrictions on matrix $\mathbf{A}$ in our SVAR model. This strategy permits that restrictions imposed on matrix $\mathbf{A}$ can accurately reflect the data generating process. The PC algorithm sometimes generate graphs with cycles and bidirected edges, as shown in Panel B ($CN \leftrightarrow HK$) and Panel D ($CN \leftrightarrow HK$) of Figure C1. Since ignoring undirected edges might distort our SVAR analysis, both directions are considered for the undirected edge in the SVAR analysis with the level of significance set to 5%.

In $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ of our SVAR model, two 11×11 matrices $\mathbf{A}$ and $\mathbf{B}$ have to be estimated. Since $\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}' = \mathbf{B}\mathbf{B}'$, the expressions on both sides are symmetric. This fact imposes $11(11+1)/2$ restrictions on the 2×11^2 unknown elements in $\mathbf{A}$ and $\mathbf{B}$. Therefore, in order to identify $\mathbf{A}$ and $\mathbf{B}$, we need to supply at least $2 \times 11^2 - 11(11+1)/2 = 176$ additional restrictions. The parameter estimation of matrix $\mathbf{A}$ for the four periods are reported in Table C1. LR tests for over-identification are also reported in Table C1.

Figure C1: DAG-recovered patterns of contemporaneous shock transmission among eleven stock markets during four cointegration periods

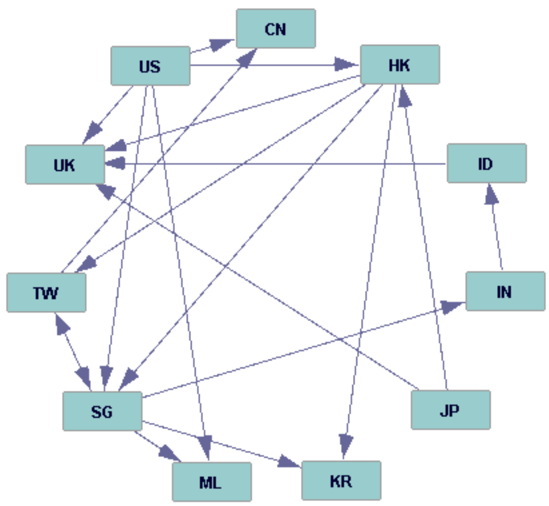

Figure C1: Panel A (Period 1)

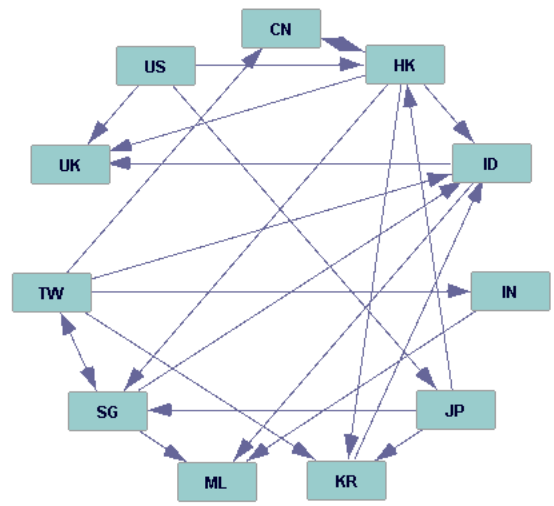

Figure C1: Panel B (Period 2)

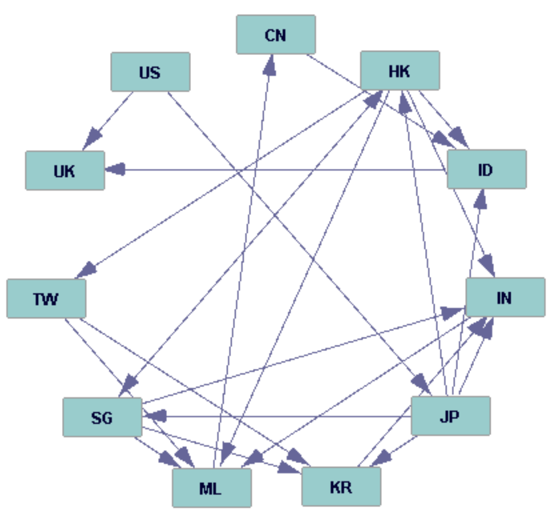

Figure C1: Panel C (Period 3)

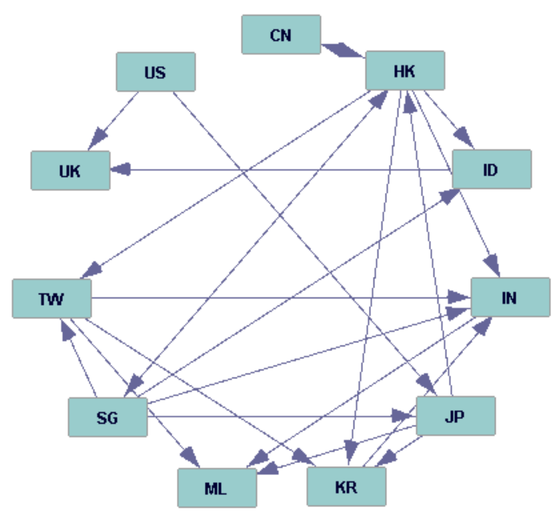

Figure C1: Panel D (Period 4)

Table C1: Parameter estimation of matrix **A** for four periods

$\mathbf{A}_{i,j}$	US	UK	JP	HK	TW	SG	KR	IN	ML	CN	ID
Panel A: Period 1 (Aug 24,1998-Aug 10,1999)											
US	1.0000										
UK	-0.3452 (0.0669)	1.0000	-0.1553 (0.0538)	-0.2149 (0.0443)							0.0928 (0.0422)
JP			1.0000								
HK	-0.6415 (0.1003)		-0.3784 (0.0847)	1.0000							
TW				-0.2831 (0.0603)	1.0000						
SG	-0.2093 (0.0872)			-0.5681 (0.0580)	-0.1692 (0.0615)	1.0000					
KR				-0.3308 (0.1197)		-0.2691 (0.1224)	1.0000				
IN						-0.6019 (0.0946)		1.0000			
ML	-0.6573 (0.1362)					-0.2125 (0.0883)			1.0000		
CN	0.1878 (0.0893)				-0.1610 (0.0652)					1.0000	
ID								-0.1724 (0.0464)			1.0000
Log likelihood:			5166.19								
LR test for over-identification:											
$\chi^2(37)$			41.907	[0.2664]							
Panel B: Period 2 (Sep 6,2001-Aug 26,2002)											
US	1.0000										
UK	-0.4777 (0.0820)	1.0000		-0.2812 (0.0919)							-0.1661 (0.0747)
JP	-0.4482 (0.0828)		1.0000								
HK	-0.2480 (0.0665)		-0.3743 (0.0547)	1.0000							
TW					1.0000						-0.4810 (0.0887)
SG			-0.1590 (0.0580)	-0.4293 (0.0772)	-0.1886 (0.0445)	1.0000					-0.1381 (0.0644)
KR			-0.3096 (0.0808)	-0.4383 (0.0968)	-0.4104 (0.0599)		1.0000				
IN					-0.1766 (0.0425)			1.0000			
ML						-0.3627 (0.0414)		-0.1055 (0.0454)	1.0000		-0.0797 (0.0396)
CN				-0.3021 (0.0890)	0.1787 (0.0618)					1.0000	
ID				-0.5489 (0.0832)			-0.0926 (0.0603)				1.0000
Log likelihood:											
LR test for over-identification:			5782.21								
$\chi^2(33)$			26.8752	[0.6298]							

Note: Parameter estimates of matrix **A** in the model $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ are reported in Panels A–D for different cointegration periods, respectively. The elements of **A** show contemporaneous correlations among observed residuals. The element (i, j) of matrix **A**, $\mathbf{A}_{i,j}$, gives how the observed residual of market i instantaneously responds to that of market j. Th table also reports the LR test results for over-identification. Standard errors are given in parentheses, while p-values are reported in brackets.

Table C1: Parameter estimation of matrix **A** for four periods—continued

$\mathbf{A}_{i,j}$	US	UK	JP	HK	TW	SG	KR	IN	ML	CN	ID
Panel C: Period 3 (Dec 21,2006-May 9,2008)											
US	1.0000										
UK	-0.4145 (0.0671)	1.0000									-0.2479 (0.0353)
JP	-0.8227 (0.0766)		1.0000								
HK			-0.9892 (0.0557)	1.0000							
TW				-0.4324 (0.0383)	1.0000						
SG			-0.3443 (0.0518)	-0.4411 (0.0388)		1.0000					
KR			-0.2945 (0.0521)		-0.2565 (0.0387)	-0.3409 (0.0513)	1.0000				
IN			0.2061 (0.0803)	-0.3599 (0.0656)		-0.4978 (0.0894)	-0.2833 (0.0810)	1.0000			
ML				0.1046 (0.0507)	-0.2112 (0.0426)	-0.3049 (0.0626)		-0.2364 (0.0445)	1.0000		
CN									-0.5800 (0.1244)	1.0000	
ID			-0.1975 (0.0775)	-0.6186 (0.0582)						0.0623 (0.0309)	1.0000
Log likelihood:											
LR test for over-identification:			8526.734								
$\chi^2(27)$			30.8331	[0.4500]							
Panel D: Period 4 (Oct 28,2008-Nov 20,2009)											
US	1.0000										
UK	-0.3606 (0.0526)	1.0000									-0.3222 (0.0442)
JP	-0.6522 (0.0634)		1.0000			0.0148 (0.0857)					
HK			-0.8587 (0.0741)	1.0000							
TW				-0.6434 (0.0400)	1.0000						
SG				-0.6194 (0.0453)	-0.2471 (0.0504)	1.0000					
KR			-0.2569 (0.0622)	-0.1803 (0.0662)	-0.4533 (0.0636)		1.0000				
IN				-0.2295 (0.0809)	-0.1994 (0.0745)	-0.2899 (0.0881)	-0.1373 (0.0671)	1.0000			
ML			-0.0964 (0.0265)		-0.1124 (0.0303)			-0.1870 (0.0297)	1.0000		
CN				-0.2890 (0.0710)					-0.3098 (0.1787)	1.0000	
ID				-0.2683 (0.1023)		-0.5011 (0.1145)					1.0000
Log likelihood:											
LR test for over-identification:			6472.153								
$\chi^2(33)$			32.6746	[0.3600]							

Note: Parameter estimates of matrix **A** in the model $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ are reported in Panels A–D for different cointegration periods, respectively. The entry A examines the contemporaneous correlation among observed residuals. The element (i, j) of matrix **A**, $\mathbf{A}_{i,j}$, gives how the observed residual of market i instantaneously responds to that of market j. The table also reports the LR test results for over-identification. Standard errors are given in parentheses, while p-values are reported in brackets.

Appendix D

In this appendix, we report the contagion measures for the four periods across all stock markets studied in this paper in Table D1. More specifically, the estimate contagion measures are reported in an 11×11 matrix for each cointegration period in Table D1. The element of the matrix, $C_{i,j}$, measures the contagion effect from a given market j (column) to another market i (row). In every case, the significance of the statistics is based on the Monte Carlo simulation method with 1000 replications.

Note that in Table D1 the elements in the first row, the second column and the diagonal are empty. As we define a trading day that starts from the U.S. and ends in the U.K., the markets that open after the U.S. market closes cannot affect the U.S. market. Hence, the contagion measures in the first row do not exist. By the same token, the U.K. market cannot affect other stock markets in the same trading day based on our trading day definition. Hence, the contagion measures in the second column do not exist either. Diagonal elements are empty as there are no contagion measures from a market to its own ($C_{j,j}$ is always equal to zero).

As shown in Table D1, little contagion effect is found between some Asian stock markets (Indonesia, Malaysia, China and India) for all cointegrated periods. Therefore, we focus on the $C_{i,j}$ values that are relevant to shocks from the U.S., Japan and Hong Kong markets.

To conduct a robustness test, we also use a different trading day definition, assuming that a trading day starts from the U.K. market and ends in the Asian markets. We find that this alternative trading day definition changes little to our analysis and conclusions, which are quite robust.

To provide a context, we also report the correlations among each and every pair of market portfolio index portfolio returns in Table D2.

Table D1: Estimates of contagion measures $C_{i,j}$ between stock markets for four periods

$\mathbf{C}_{i,j}$	US	UK	JP	HK	TW	SG	KR	IN	ML	CN	ID
Panel A: Period 1 (Aug 24,1998-Aug 10,1999)											
US											
UK	-0.0074		0.0373	0.0112	-0.0464	-0.0194	-0.0044	-0.0003	-0.0179	-0.0010	0.0079
JP	-0.0029			-0.0002	-0.0074	-0.0001	-0.0005	-0.0001	-0.0031	-0.0008	-0.0026
HK	0.0380		-0.0068		-0.0895	-0.0120	-0.0168	-0.0025	-0.0026	-0.0005	-0.0030
TW	**0.0324**		-0.0871	-0.1415		-0.1202	-0.0011	0.0000	-0.1436	-0.0002	-0.0009
SG	0.1080		-0.1074	-0.3160	-0.0245		-0.0003	0.0000	-0.0575	-0.0012	-0.0085
KR	-0.1151		0.0281	-0.3673	-0.0068	-0.1783		-0.0002	-0.0141	-0.0001	-0.0012
IN	0.0939		-0.0223	-0.1103	-0.0520	-0.1306	-0.0398		-0.0261	-0.0009	-0.0004
ML	-0.0813		-0.0014	0.0117	-0.1890	-0.2623	-0.0424	-0.0170		-0.0004	-0.0043
CN	-0.0811		-0.0148	-0.0508	0.0255	-0.0747	-0.0014	-0.0012	-0.0342		-0.0005
ID	-0.0209		0.0002	-0.0017	0.0002	-0.0127	-0.0001	-0.0238	-0.0040	-0.0005	
Mean	-0.0036		-0.0235	-0.0970	-0.0392	-0.0812	-0.0107	-0.0045	-0.0304	-0.0013	-0.0015
Panel B: Period 2 (Sep 6,2001-Aug 26,2002)											
US											
UK	-0.2302		0.0026	-0.0441	-0.0085	0.0000	-0.0008	-0.0960	-0.0135	-0.0035	0.0081
JP	0.0654			-0.0610	-0.0058	0.0000	-0.0045	-0.2966	-0.0549	-0.0101	-0.0890
HK	**0.1717**		0.0186		-0.1027	-0.0045	-0.0082	-0.1968	-0.0106	-0.0658	-0.0021
TW	0.0111		-0.0948	-0.2107		-0.1043	-0.0827	-0.7979	-0.7915	-0.0353	-0.5955
SG	0.0958		-0.0942	-0.1219	-0.1337		-0.0064	-0.2762	0.0000	-0.0202	-0.1381
KR	0.1335		-0.1787	-0.1025	-0.1100	-0.0050		-0.5587	-0.2201	-0.0009	-0.3151
IN	-0.0967		0.0003	-0.0071	**0.0307**	-0.0077	-0.0286		-0.5484	-0.0524	-0.1764
ML	-0.0033		-0.0099	0.0290	-0.0761	-0.0407	-0.0004	0.0111		-0.0158	-0.0298
CN	-0.2650		-0.0388	-0.0306	-0.2050	-0.0130	0.0000	-0.0570	-0.3055		-0.0304
ID	0.0688		-0.0353	-0.0571	-0.0401	0.0000	0.0048	-0.1374	-0.0136	-0.0141	
Mean	-0.0049		-0.0478	-0.0673	-0.0724	-0.0195	-0.0141	-0.2673	-0.2176	-0.0242	-0.1520
Panel C: Period 3 (Dec 21,2006-May 9,2008)											
US											
UK	-0.7976		0.0139	0.0222	-0.0289	-0.0123	0.0000	-0.0199	-0.0119	-0.0029	-0.0711
JP	-1.4624			-0.0659	-0.1562	-0.0617	-0.0085	-0.0118	-0.0166	-0.0010	-0.0361
HK	-1.0913		0.1773		-0.2358	-0.0571	-0.0142	-0.0548	-0.0288	-0.0025	-0.0960
TW	-0.2348		**0.1461**	0.0081		-0.1415	-0.1006	-0.0025	-0.0016	-0.0018	-0.6866
SG	-0.9672		**0.3093**	**0.1693**	-0.2432		-0.0239	-0.0428	-0.0385	-0.0001	-0.2930
KR	-1.4103		**0.2240**	**0.0668**	0.0642	-0.0531		-0.0273	-0.0455	-0.0001	-0.1700
IN	-2.3230		**0.3475**	**0.2140**	-0.2148	0.2020	-0.1403		-0.1195	-0.0057	-0.4823
ML	-0.6915		0.0252	0.0155	0.0449	-0.1018	-0.0136	**0.0540**		-0.0006	0.0000
CN	-1.8602		**0.0137**	-0.0325	-0.0892	0.0336	-0.0082	0.0001	-0.3973		-2.0686
ID	-2.3949		**0.4112**	**0.2315**	-0.4013	-0.2429	-0.1405	-0.0001	-0.1231	-0.0058	
Mean	-1.3233		0.1854	0.0699	-0.1400	-0.0483	-0.0500	-0.0117	-0.0870	-0.0023	-0.4337
Panel D: Period 4 (Oct 28,2008-Nov 20,2009)											
US											
UK	-0.1536		0.0048	0.0156	0.0011	-0.0079	-0.1217	-0.0008	-0.7890	-0.0062	0.0211
JP	-0.2843			0.0000	-0.0175	-0.0283	-0.0606	-0.0360	-1.0541	-0.0164	-0.0171
HK	-0.1981		0.0111		-0.0002	-0.1124	-0.1717	-0.0193	-0.9435	-0.0101	-0.0302
TW	0.0886		-0.0127	-0.2993		-0.1080	-0.0145	-0.0281	-0.6821	-0.0081	-0.0213
SG	-0.2200		**0.1475**	**0.2276**	0.0371		-0.1913	-0.0621	-0.7941	-0.0005	-0.0107
KR	-0.4203		**0.1489**	**0.1068**	0.0704	-0.0090		-0.2749	-1.4680	-0.0058	-0.0184
IN	0.0451		-0.1105	-0.3209	-0.0602	-0.3447	-0.1452		-0.3279	-0.0138	-0.1075
ML	-0.0223		-0.0603	-0.0480	-0.0044	-0.0145	0.0006	-0.0903		-0.0011	-0.0056
CN	0.0371		0.0410	-0.1421	-0.0120	-0.0112	0.0001	-0.0041	-0.2706		-0.0077
ID	-0.2630		**0.1458**	0.0562	-0.0143	**0.1128**	-0.1244	-0.0005	-0.3131	-0.0128	
Mean	-0.1391		0.0351	-0.0449	0.0000	-0.0581	-0.0921	-0.0573	-0.7381	-0.0083	-0.0219

Note: The contagion measure $C_{i,j}$ from market j (column) to market i (row) $\left(C_{i,j} = \left(\frac{\mathbf{\Phi}_{i,j} + \mathbf{\Phi}^*(0)_{i,j}}{\mathbf{\Phi}_{j,j} + \mathbf{\Phi}^*(0)_{j,j}} \right)^2 - \left(\frac{\mathbf{\Phi}_{i,j}}{\mathbf{\Phi}_{j,j}} \right)^2 \right)$ is reported for different cointegration periods. In every case, the significance of a contagion measure is based on the Monte Carlo simulation method with 1000 replications. The 5% quantile of $C_{i,j}$ that is greater than 0 (in bold font) indicates a significant contagion effect. The mean contagion measures are also reported for all markets and periods.

Table D2: Correlations among the eleven stock market portfolio daily returns

	US	UK	JP	HK	TW	SG	KR	IN	ML	CN	ID
Panel A: Correlation matrix, July 3,1997-April 30,2014											
US	1.0000										
UK	0.3977	1.0000									
JP	0.5096	0.4036	1.0000								
HK	0.4919	0.4717	0.5551	1.0000							
TW	0.3864	0.3088	0.4497	0.4996	1.0000						
SG	0.4195	0.4490	0.5099	0.7240	0.5077	1.0000					
KR	0.3727	0.3440	0.4888	0.5369	0.4854	0.4997	1.0000				
IN	0.2906	0.2741	0.3586	0.5043	0.3576	0.5191	0.3914	1.0000			
ML	0.2824	0.2277	0.2817	0.4403	0.2927	0.4631	0.3224	0.4250	1.0000		
CN	0.1496	0.1039	0.1904	0.2750	0.1757	0.1997	0.1343	0.1673	0.1329	1.0000	
ID	0.2666	0.3341	0.3392	0.4610	0.3261	0.4470	0.3543	0.3713	0.2435	0.1767	1.0000
Mean	0.3567	0.3241	0.3967	0.4916	0.3575	0.4257	0.3006	0.3212	0.1882	0.1767	
Panel B: Correlations, December 21,2006-May 9,2008											
US	1.0000										
UK	0.3567	1.0000									
JP	0.4361	0.5147	1.0000								
HK	0.4952	0.5631	0.8195	1.0000							
TW	0.5683	0.4505	0.6258	0.6825	1.0000						
SG	0.5021	0.6265	0.7489	0.8764	0.6721	1.0000					
KR	0.4465	0.6188	0.7805	0.8025	0.7031	0.8005	1.0000				
IN	0.4798	0.5945	0.6850	0.8406	0.6410	0.8674	0.7781	1.0000			
ML	0.5912	0.4881	0.6119	0.7521	0.7511	0.7736	0.7011	0.8290	1.0000		
CN	0.2681	0.2270	0.3478	0.4762	0.4116	0.3587	0.2818	0.3671	0.3898	1.0000	
ID	0.4012	0.5382	0.6479	0.7686	0.5955	0.7154	0.6668	0.7550	0.6913	0.4592	1.0000
Mean	0.4545	0.5135	0.6584	0.7427	0.6291	0.7031	0.6070	0.6504	0.5405	0.4592	

Note: The correlations are calculated based on the daily market portfolio return data for the U.S. (US), U.K. (UK), Japan (JP), Hong Kong (HK), Taiwan (TW), Singapore (SG), Korea (KR), Indonesia (ID), Malaysia (ML), China (CN), and India (ID). The U.S. data at $t-1$ are aligned with the data of other countries at t due to the selected time zone order from the U.S. stock market, to the Asian stock markets, and, then, to the U.K. stock market.