INTERNATIONAL FINANCIAL CONTAGION DURING THE SUBPRIME CREDIT CRISIS

Xuan Luo

A Thesis
In
The John Molson School of Business

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Administration (FINANCE) at
Concordia University
Montreal, Quebec, Canada

June 2009

Your file Votre référence
ISBN: 978-0-494-63093-8
Our file Notre référence
ISBN: 978-0-494-63093-8

ABSTRACT

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This study examines the financial contagion among G-7 countries during the subprime credit crisis from July 2007 through December 2008. Specifically, we investigate the excess comovements of stock indices of the banking sectors of G-7 countries. We examine innovations – the component which cannot be explained by the fundamental factors – of the banking sector indices of G-7 countries. Innovations are defined as the residuals from the regression of banking sector indices on a set of explanatory variables using GARCH. We use eight macroeconomic variables and the return of a global stock index to capture the fundamental effects. We identify the excess comovement evidenced by the fact that the estimated innovation of one country significantly affects the stock indices of the other countries. However, we find no evidence that the explanatory power of estimated innovation increases during the subprime crisis, which suggests that the subprime crisis does not trigger excess comovement. Furthermore, we employ correlation coefficient tests. We estimate the innovation using VAR models, controlling for the aforementioned fundamental variables. We then examine the correlation coefficients of estimated innovations among G-7 countries. We do not find any evidence that the excess comovements significantly increase during the subprime crisis. Hence, our study does not support the notion that the subprime crisis triggered financial contagion in the banking sectors of G-7 countries.

Acknowledgements

First, I would like to thank my supervisor, Dr. Qi, for her patient guidance and encouragement during the writing of this thesis. Whenever I suffer a setback, she is always there to provide me with her support.

I would also like to express my gratitude to the committee members: Dr.Lypny and Dr.Walker. Thanks to their time reviewing my work and the valuable advice they have provided, I have been able to finish my thesis smoothly.

My appreciation goes to Dr.Tirtiroglu as well. Without his help, I would not have come this far.

Finally, I sincerely thank the Institut de Mathématique de Montréal (IFM) for their most generous financial support, which made this work possible.

Dedications

I would like to dedicate this thesis to my husband, Tao Wang, for his endless love and support; to my parents, Chunlai Luo and Liqiu Guan, for their nurture and encouragement; and to my dear friends who are there for me during my most difficult times.

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1 Introduction

Starting in the summer of 2007, the subprime credit crisis, triggered by an unexpectedly large default rate of subprime mortgage loans in the U.S., caused a striking shrink in the capital of many banks and tightened credit around the world. A housing downturn turned into a crisis by an innovation called securitization. Financial firms bought up mortgages, bundled and securitized them into mortgage backed securities (MBS), which derive their value from mortgage payments and housing prices. This innovation, which enabled institutions and investors around the world to invest in the U.S. housing market, gave rise to housing and credit bubbles since it urged the mortgage industry to grant more loans to so-called subprime borrowers. In addition to mortgage and other asset-backed securities, financial firms created other derivatives, such as credit default swaps. This financial complexity made the entire system extremely fragile. As housing prices declined, the major global financial institutions that had borrowed and invested heavily in subprime MBS suffered significant losses. The heavy leverage of financial firms also played a critical role in making the housing downturn a crisis. The 'asset velocity' allowed banks to reuse capital multiple times as assets were originated and speedily moved off balance-sheets through securitisation. In addition, the compensation system of financial firms was criticized because it motivated everyone from mortgage brokers to Wall Street risk managers to tolerate short-term risk-taking behaviour, while ignoring long-term obligations. Consequently, the failure of risk management created the path to the crisis.

When the crisis unfolded, it spilled out of the credit markets and influenced other sectors of the economy. As has been documented by Longstaff (2008), the effects of the subprime credit crisis transmitted from lower-rated asset-based securities indices (ABX) of subprime mortgage-related asset-backed collateralized debt obligation (CDOs) to higher-rated ABX indices, and in turn traversed the boundary of subprime markets and spread into the Treasury bond and stock markets. Did the effect of the crisis also spread over the boundaries of countries? As shown in Dungey et al. (2008), the shock of the subprime crisis spread into Argentina via a link between its stock market and that of the U.S. It also influenced Russia through the bond market link. The International Monetary Fund (IMF), in its Global Financial Stability Report (2008), announces that 'the crisis is spreading beyond the U.S. subprime market'. It documents that the United States remains the center of the epidemic crisis and financial institutions in other countries are subject to the effects of the crisis.

As destructive as the subprime credit crisis is, it provides, from a research perspective, an excellent opportunity to study financial contagion across countries in response to the crisis. To this end, we conduct this work to examine financial contagion among G-7 countries during the subprime credit crisis. Our objective is to identify whether the subprime crisis is associated with financial contagion and to test the changes in strength of the international comovements due to the subprime crisis. Our study, however, does not mean to address the channels through which the effects of the subprime crisis have spread. Different from the studies focusing on the major stock index of each country, we concentrate on the comovements of stock indices of banking sectors among G-7 countries since the banking sector has suffered the most direct impact from the subprime mortgage crisis and credit contraction. In order to shed light on whether the crisis is associated with financial contagion, we collect data for both the pre-crisis and the crisis periods to compare the comovements of banking sector indices before and during the subprime crisis. The full sample period of our study is from January 2002 to January 2009.

Following previous literature (Pericoli and Sbracia 2003; Dungey and Tambakis 2005), we define contagion as the excess cross-country comovements which cannot be explained by macroeconomic fundamental factors. Such a definition is, however, different from Forbes and Rigobon (2002), who define that contagion exists when the cross-market correlation increases significantly. We use a two-stage threshold AR(1)-GARCH(1,1) -in-mean model [1] to test the existence of contagion and examine the marginal contagion[2] brought by the subprime crisis. We begin by using the threshold AR(1)-GARCH (1, 1)-in-mean model to estimate the response of the banking sector's indices of G-7 countries to fundamental factors of their own country economies, and to the shock of the global economy. We use eight country-level macroeconomic variables: the rate of growth of real gross domestic production (GDP); capital price index (CPI); unemployment rate; inflation rate; short-term interest rate; depreciation rate; current account; and capital account to control for the macroeconomic fundamentals. We also adopt the Morgan Stanley Composite Index (MSCI) world index as a global factor to

[1] The two-stage threshold AR(1)-GARCH(1,1) -in-mean model proposed by Hsin (2004) is operated in two steps with an asymmetric term (the threshold) in the volatility model to control for the asymmetric effect in response to the negative innovations; and with one lagged stock indices (AR(1) term) in the mean model.
[2] The marginal contagion denotes the additional financial contagion specifically due to the subprime credit crisis, after differentiating the crisis contagion from the non-crisis contagion.

approximate the shock of global economic conditions. The estimated residuals from the first stage GARCH model represent innovations that cannot be explained by the fundamental factors. We then use the residual of each country as an explanatory variable in the GARCH model to examine whether the innovation of country X has explanatory power on the index of country Y. The second stage GARCH model reveals whether contagion occurs; in other words, whether the innovation of banking index in country X affects the banking index of country Y. We find mutual contagion between the U.S. and four other countries: Canada, France, Germany, and the U.K., while there is no excess comovement between the U.S. and either Italy or Japan. The mutual contagion is especially pronounced between Canada and the U.S., suggesting that the banking sectors of the U.S. and Canada are highly related. We also observe regional contagion in Europe. We do not find evidence that the volatility of the U.S. banking sector increases the volatility of the banking sectors of the other countries. Furthermore, we extend the second stage GARCH model by adding an interaction term of a crisis dummy and the aforementioned innovations in order to test whether the crisis is associated with contagion. We find no evidence that the subprime crisis is related with contagion from the U.S. to other countries.

To further address the cross-country effects due to the macro-fundamental factors, we apply a vector autoregressive regression (VAR) model. We estimate the VAR model in which the explanatory variables are augmented with the cross-market macroeconomic variables. The estimated residuals from the VAR model are employed to study the financial contagion. Forbes and Rigobon (2002) document that the heteroscedasticity bias exists in the test of comovements and propose an adjusted correlation coefficient test.

We thus examine the comovements of the estimated residuals using both unadjusted and adjusted correlation coefficient tests.

To identify if there is any significant increase in banking sector comovements in response to the subprime crisis, we further decompose the sample period into the pre-crisis period, named the tranquil period, and the crisis period, named the turmoil period. We compare the correlation coefficients of the estimated residuals during both the tranquil period and the turmoil period to test whether the strength of the comovements increases significantly.

Using the unadjusted correlation coefficient test, we find that the crisis is associated with increases in the correlations of residuals between the U.S. and the other three countries: Canada, France and the U.K. Canada experiences the highest increase in correlation coefficient among these three countries. However, once the correlation coefficients are adjusted for heteroscedasticity, we find no evidence that the crisis increases the correlation coefficients. This result is consistent with our findings from the GARCH model. Overall, we conclude that the cross-country excess comovements exist among the banking sectors of G-7 countries. However, the subprime crisis is not associated with the unexplained comovements. Therefore, we cannot conclude that the subprime crisis caused financial contagion among the banking sectors of G-7 countries.

This paper is organized as follows: Section 2 provides the related literature reviews regarding the definition and possible causes of contagion. It also describes empirical methodologies to test the existence of contagion. Section 3 demonstrates the research design. Section 4 describes the sample and the selected variables and Section 5 provides the empirical results. Section 6 concludes the study.

2 Related Literature

2.1 Historical Definition of Financial Contagion

There is no consensus on the definition of contagion. Previous literature (Calvo and Reinhart 1996; Dornbusch et al. 2000; Dungey and Tambakis 2005) generally classifies two types of contagions based on the causes of contagion. One is fundamental-related contagion. This contagion occurs when the capital and/or trade markets across countries are highly integrated, and such integration facilitates the transmission of disturbances. That is, the disturbance in one market is transmitted to the other markets through fundamental-related links, such as international trade, dynamics in exchange rates, international capital flow and financial links created by the banking system, common lenders, and international portfolio diversification management. Such fundamental-related contagion includes liquidity effects, as classified by Dungey and Tambakis (2005). This type of contagion has also been termed as 'spillovers' (Masson 1998, 1999); 'fundamentals-based contagion' (Kaminsky and Reinhart 2000a); or 'interdependence' (Forbes and Rigobon 2002) which is associated with the macroeconomic fundamentals among market economies.

There are some excess comovements during an episode of crisis which cannot be explained by the correlation of economy fundamentals. These unexplained excess comovements occur even when the common shocks and all possible fundamental interconnections between countries are absent or controlled. Recent literature (Kaminsky and Reinhart 2000a; Edwards 2000; Forbes and Rigobon 2002; Moser 2003) tends to regard this category of contagion as 'pure contagion', 'true contagion', or as contagion itself differentiated from interdependence. This restrictive definition specifies contagion as a situation under which the magnitude of the transmission of shocks goes beyond the ex-ante expectation based on the knowledge of fundamentals. Instead of the links of macroeconomic fundamental factors, these excess comovements may be more closely related to an investor's rational or irrational behaviour. The proposed reasons to cause this excess transmission include information asymmetry and heterogeneity, multiple equilibriums and momentum trading. Different from the classification of Dungey and Tambakis (2005), Dornbusch et al. (2000) regard the liquidity effect as a non-fundamental-based cause of contagion.

In the discussion below, we regard the first category of contagion, the fundamental-related contagion, as interdependence, and the second category of contagion, the investor's behavior-related contagion, as contagion. Throughout this paper, contagion is defined as excess comovements, which cannot be explained by fundamental factors. We follow the classification criteria of Dornbusch et al. (2000) and include liquidity effects as one of the investor's behavior-related causes of contagion.

2.1.1 Interdependence

2.1.1.1 Common Shocks and Competitive Devaluation

A major economic shift, such as a change of commodity prices, a fluctuation of the exchange rate, or a change of the strength of the currency in one country, can lead to a global market adjustment which is represented by comovement in asset prices or capital flows. Masson and Mussa (1996) term the phenomena of a major economic shift in industrial countries resulting in a crisis in emerging markets as 'monsoonal effects'. The vulnerability of those emerging markets is attributed to the exposure to foreign currency borrowing and government debt. Furthermore, 'the vulnerability is greater when there is a large (floating rate) debt, when reserves are low, and when the trade balance is in deficit' (Masson 1998). Eichengreen and Rose (1999) document that the instability in foreign exchange markets may result in a speculative attack which has negative impacts on the international competitiveness of the countries and their current accounts. For instance, the depreciation of the Pound sterling in September 1992 impaired the export competitiveness of the U.K. Similarly, Finland's devaluation had a negative impact on Sweden since both Finland and Sweden compete for exports in the common third markets. The sharp devaluation of the Japanese Yen in 1995 increased the competitiveness of Japan. However, the devaluation reduced simultaneously foreign direct investment (FDI) from Japan to other countries (Diwan and Hoekman 1999). Goldstein (1998) indicates that 'one country after another in a region undergoes a depreciation of its currency, the countries that have not devalued experience deterioration in competitiveness, which in turn makes their currencies more susceptible to speculative attacks'. The changes in interest rate in one country will also influence other countries through international capital flows. Calvo and Reinhart (1996) examine the linkage between the changes in the U.S. interest rates and the capital flows to Latin America. They find that 'international capital movements are all significantly affected by swings in interest rates in the U.S.'.

2.1.1.2 Trade and Financial Links

Trade in goods and demands can give rise to a channel of international transmission of shocks via the terms of trade. Eichengreen et al. (1996) find that 'trade, rather than revisions of expectations based on macroeconomic factors, has been a dominant channel of transmission for contagious crises for the bulk of the sample period'. Kaminsky and Reinhart (2000b) distinguish several propagation patterns of shocks. One of them is that the transmission from one periphery country to another periphery country occurs if there is a direct linkage of bilateral trade or finance between the two countries. Pavlova and Rigobon (2007) explore the demand shocks which produce cross-market spillovers, and the trade of goods from an international perspective. They overturn previous beliefs that the productivity shock is the only source of uncertainty by applying the terms of trade to determine the dynamics in both stock and bond markets. In this way, not only can they study the dramatic dynamics and spillovers from an international perspective, but they can also keep tractability. Their results reveal that the demand shocks are twice as important as supply shocks in describing the dynamics of asset prices and it is likely that demand shocks reflect consumer confidence and represent differences in opinion. The globalization of economics involves not only trade links but also financial connections. One of these financial links is FDI. A shock in one country will lead to a reduction in FDI outflows into other countries. A small country may be more attractive for FDI, following a devaluation of main currencies, than the large countries (Diwan and Hoekman 1999).

2.1.2 Contagion

2.1.2.1 Liquidity

Liquidity concern can cause financial contagion because speculative investors may liquidate assets which are not directly affected by shocks. Kyle and Xiong (2001) develop a continuous-time framework to show that liquidity may cause financial contagion through a wealth effect. The changes of asset prices are determined endogenously as a function of endogenous wealth and exogenous noise. The phenomenon of contagion is explained with a theoretical model in which the level of risk aversion is subject to a wealth effect of a group of perfectly competitive convergence traders. When convergence traders encounter losses, the market liquidity decreases, while the price volatility and market correlation increase as the result of the reaction of convergence traders who liquidate positions in markets of risky assets. Kyle and Xiong (2001) contribute contagion to the liquidating effect of financial intermediaries on the markets. Their result confirms the finding of Kaminsky and Reinhart (2000b). Based on the 'event study' approach, Kaminsky and Reinhart (2000b) analyze the Russian-LTCM crisis by observing the daily behaviour of financial indicators over thirty-five countries around the crisis period. They unveil that there were dramatic liquidating activities which resulted in the reduced liquidity of markets and increased price volatilities.

International commercial banks are also subject to liquidity problems. One representative study in this field by Allen and Gale (2000) suggests that interregional claims of bank holding is one main channel of the international financial contagion when there is a small liquidity preference shock in one region. The interbank deposits are designed to deal with the regional liquidity demands. The region with liquidity surpluses can provide other regions with enough deposits so that when there is a liquidity shock in one region, it can be solved by exchanging deposits between banks. Such a mechanism, however, fails to work if there is an excess demand for liquidity since the healthy regions would rather shut the door to avoid a drainage of liquidity caused by the troubled region. Allen and Gale (2000) suggest that if the interbank market is complete, if the banks in the troubled region have direct claims on banks in any other regions and if the regions are fully connected to one another, the effect of a financial crisis can be absorbed within the banking system without escalating to financial contagion. Kaminsky and Reinhart (2000a) also stress the role of liquidity play in the propagation. They point out that when the banks of one country in turmoil have extensive exposure to other countries, the common lenders, in particular, foreign commercial banks, can act to not only exacerbate the crisis by calling loans and drying up credit lines in the troubled country, but also transmit the shocks by calling loans from other countries.

2.1.2.2 Information Asymmetries and Heterogeneity

As one of the common suggested causes of contagion, information asymmetry frequently receives attention among scholars. In this category, people claim that contagion occurs regardless of the underlying structure of the economy, as a result of the failure to distinguish between idiosyncratic and systematic shocks to the fundamentals. King and Wadhwani (1990) argue that it is information asymmetry that leads uninformed traders to incorrectly update their beliefs of payoffs from assets and markets in response to an idiosyncratic shock. King and Wadhwani (1990) examine the changes in cross-market correlations after a stock market crash with a framework in which the transmission of shocks occurs as a result of rational agents' attempts to infer information from price changes. Their model is based on the assumption that there are two types of information: idiosyncratic and systematic information. The former indicates that information is of a specific country, while the latter casts influence on all markets. When the information structure is complex and the dimensions of the signal space surpass the dimensions of the price space, to infer information from the change of market prices may not be effective since the stock prices no longer fully reveal agents' private information. The non-fully-revealing equilibrium may imply the possibility of contagion effects. With high-frequency data, King and Wadhwani (1990) find evidence that there is a cross-market transmission beyond the explanation of a fully-revealing fundamental model, which is in support of the observation of the contagion between the stock markets in New York, London and Tokyo in October 1987. Pasquariello (2007), in particular, sheds light on the new angle that the intensity of excess comovement may rise along with the increase of heterogeneity of investors' information endowments. He employs information heterogeneity, a more realistic view of a financial market, to explore the propagation of shocks across fundamentally unrelated assets. He defines information heterogeneity as significant and persistent differences in the endowment of private information among market participants. He claims that contagion may be an equilibrium outcome once the insiders obtain heterogeneous information and trade accordingly. In his framework, information asymmetry is a necessary but not sufficient condition for the occurrence of financial contagion across assets or markets. In addition, the strengthening of financial integration of the world equity market, as well as financial liberalization, have attracted more professional traders to participate in it, and hence the phenomenon of asymmetric sharing of information among insiders is likely to exist. On one hand, this trend may increase the rate of information sharing and, thus, reduce the strength of contagion resulting from information noise and uninformative trading shocks. On the other hand, this trend may increase the possibility that the financial shocks will spread into unrelated fundamentals. Kallberg and Pasquariello (2008) adopt market return volatility over a certain interval as a proxy for the level of information asymmetry among markets. They also use the dispersion in analysts' earning forecasts (EPS) to determine information heterogeneity unrelated to risk. Their result provides evidence that information heterogeneity among traders is the most relevant source of excess comovements, which is consistent with the notion introduced by Pasquariello (2007). This suggests that portfolio rebalancing activities motivated by rational consideration, rather than by risk, may play an important role in explaining contagion. Furthermore, Yuan (2005) addresses crises and contagion within a rational expectations equilibrium framework, in which downward price movements have been endogenously induced by the interaction of information asymmetry and borrowing constraints. Such a constrained information asymmetry explains why small fundamental shocks and asymmetric price distributions may result in large price movements and the contagion-vulnerability of markets with independent and fewer risk factor sharing assets.

2.1.2.3 Multiple Equilibria

Contagion occurs when a shock in one country triggers a switch of equilibrium in other countries (Pericoli and Sbracia 2003). Diamond and Dybvig (1983) show that there are two feasible equilibria in modeling bank runs. One equilibrium brings a good outcome as banks remain solvent to pay off high returns to all investors. The other equilibrium results in a panic where all participants withdraw funds from a bank since they believe that other participants' withdrawals are forcing the bank to cut high-profit investments. Upon the occurrence of an economic crisis, there will be a possible switch from the 'good' equilibrium to the 'bad' equilibrium. Similar to a bank run, when a switch takes place, the other countries will withdraw their funds or FDI from the troubled country in a panic that they will not be able to claim the foreign exchange reserves if they act too late. Masson (1998) also suggests that 'contagion would occur when the home country jumps to a "bad" equilibrium when there is a crisis in another emerging country'. The logic is that the increase of interest rate will result in the rise of debt service costs, which in turn places pressure on the reserves and spurs devaluation. Masson claims that the size of the stock of external debt is an important determinant to the occurrence of multiple equilibria. His later work (1999) further documents that macroeconomic fundamentals alone hardly justify contagion in response to Mexico's Tequila crisis, which affected Latin America in 1994, or contagion from Thailand to the other East Asian countries in 1997. Trade and competitiveness linkages are not convincing in explaining the spread of contagion. Masson adds that 'multiple equilibria can occur only in certain ranges for macroeconomic fundamentals, implying, in particular, conditions on reserves and the level of external debt'. Within these ranges, 'jumps between multiple equilibria, and hence contagion triggered by a crisis elsewhere, is possible'.

2.1.2.4 Momentum Trading

Active trading is made upon the reception of others' trading behaviour. Rational herding theory indicates that market participants are inclined to follow the herd even though they have their own information. Momentum trading, which is argued to be triggered by herding tendency, imitation, etc., may be one source of contagion by linking the prices among fundamentally unrelated assets or markets. Calvo and Mendoza (2000) argue that contagion may occur as an outcome of herding by imitating arbitrary international portfolios. When the marginal cost exceeds the marginal gain in gathering necessary decision-making information concerning market return, portfolio managers have an incentive to imitate arbitrary market portfolios. The range of optimal portfolios widens along with the growth of the market. The investors mimic one optimal portfolio according to market rumours. Hirshlerfer and Teoh (2008) examine theory and evidence about how the herding activities of individuals affect financial decisions and market prices. They point out that the financial decisions 'tend to converge quickly upon mistaken action choices'. In addition, they also take into consideration 'the readiness of investors to herd'. Although in perfect markets, investors tend to apply their own private information instead of imitating the others' investment behaviour, when uncertainty increases, investors may act opposite to the private information they have.

An influential early attempt by De Bondt and Thaler (1985) uses the behavioural principle to predict a new market anomaly and provides empirical evidence to support the overreaction hypothesis that most traders tend to 'overreact' to unforeseeable shocks. By testing two main hypotheses, that the extreme movements in stock prices result in the subsequent price movements in the opposite direction and that the subsequent adjustment will act in accordance with the initial price movement, they reveal an implied violation in the market efficiency. Wermers (1999) conducts a comprehensive empirical test to determine the existence of herding tendency in the investors' trading behaviour and the impact of herding on the stock prices based on a data set of mutual funds over a 20-year period. He examines a set of stocks traded by a number of mutual funds. He classifies that herding behaviour is present on a stock if there are large imbalances between the number of buyers and sellers of the specific stock. When focusing on the subgroups of stocks, he finds that there is a higher level of herding in small stocks and that such herds indicate the buy-side in the past winners and the sell-side in the past losers, implying that traders adopt 'rational' positive-feedback (momentum) trading strategies. Sias (2004) argues that an institutional investor either follows the past trading strategy of its peers (herding), or follows its own past trading strategy. The cross-sectional correlation between the trading over adjacent periods can be decomposed into two components: one part resulted from herding behaviour and the other part resulted from the tendency of following their own trading strategies.

2.2 Empirical Studies of Financial Contagion

2.2.1 Measures of Financial Contagion

To facilitate the measure of financial contagion, many efforts have been made to define contagion and interdependence. Previous literature (Sutton 2000; Forbes and Rigobon 2002; Corsetti el al. 2005) distinguishes contagion from interdependence from different perspectives.

Sutton (2000) studies the excess volatility and excess comovement of interest rates among five major bond markets: the U.S., Japan, Germany, the U.K. and Canada. By studying the behaviour of long-term interest rates, they explore the joint behaviour of bond yields between countries. In his paper, excess comovement exists when two conditions coincide. One is that two asset prices display excess volatility. The other is that the deviation of prices from predicted ones are positively correlated across assets.

Forbes and Rigobon (2002) identify contagion in a rather narrow and restricted spectrum as a significant increase in market-wide linkages after a shock to one country or a group of countries. Contagion occurs only when the comovement increases significantly after a shock. Otherwise, the pairwise linkage among countries, even strong, can be classified as interdependence only. Defining contagion in this way provides two important advantages. The first one is that it makes the method of testing whether contagion occurs straightforward. The second one is that it allows distinguishing possible explanations on how the shocks are spread across borders. This definition is also consistent with an earlier popular explanation made by King and Wadhwani (1990). They investigate the reason why almost all stock markets fell in October 1987 following the Wall Street crash, despite the widely different economic circumstances of each market. For the convenience of their test, they define contagion as a significant change in the correlation coefficient. Also, Pericoli and Sbracia (2003) discuss cross-country comovements from the aspect of both price and quantitative dimensions. Only a significant increase in comovements, 'excessive comovements', can account for contagion when a crisis occurs in one market or a group of markets. Such a definition stresses the difference between the interdependence-related normal comovements and the excessive comovements. Kallberg and Pasquariello (2008) define contagion as the covariation above the level resulting from 'common factors'. They determine the excess covariation as the correlation between two assets which cannot be explained by the fundamental factors.

Recent works by Corsetti el al. (2005) and Jokipii and Lucey (2007) define contagion as a structural break in the linear transmission mechanism of financial shocks, which mainly results in an intensification of relationships between different countries over the period of market turmoil. They also regard interdependence as a "divergent phenomenon" because it causes no change in the aforementioned relationships. Corsetti et al. (2005), furthermore, notice two important features based on their testing framework. One is that the shock of a common factor tends to trigger large comovements in prices during the turmoil episode. The other is that the test is symmetrical because it can be applied to structural breaks and contagion consisting of looser interdependence (neglected fundamental factor loading). They challenge the previous literature by Forbes and Rigobon (2002) by claiming that it is not reasonable to define contagion as a significant increase in correlations and that the tests of contagion based on this definition may be biased in favour of the null interdependence.

2.2.2 Methodologies and Evidence

2.2.2.1 Probit and Logit Models and Leading Indicators

To test whether a systematic effect on the probability of a speculative attack on one market is conditional on the occurrence of a crisis in other markets, Eichengreen et al. (1996) adopt an ad hoc exchange market pressure approach by constructing a weighted average index of exchange rate changes, reserve changes, and interest rate changes. In their framework, crisis, as a dependent dummy variable, is determined as a unit value when the extreme values are present in the index and as zero otherwise. Independent variables consist of a set of macroeconomic and political fundamental factors. Their Probit results indicate that a speculative attack on the foreign currencies increases the odds of an attack on the domestic currency by 8% without being conditional on the size or on any other relevant attacks. They also use this framework to determine the importance of transmission channels of trade and macroeconomic similarities. They find that the effect of contagion is much stronger through trades than through similarity of macroeconomic conditions. Van Rijckeghem and Weder (2001) develop some leading indicators of competition for bank funds to explain the pattern of international bank lending during three crises in Mexico, Asia, and Russia. Specifically, they examine disaggregated flows to test the hypothesis that the spread of a currency crisis is triggered by the banks' behaviour in response to losses in the troubled country. They study the link between a bank's capital flows and exposure to the crisis-originating country, after controlling for the other determinants of bank flows. Using multivariate OLS, they find that it is the common lender channel through which the shocks have been propagated. Forbes (2000) applies the event-study method to examine how the crises of the Asian Flu and Russian Virus had impacts on world-wide firms by calculating the abnormal returns of stocks in her sample. By constructing a unique data set of 10,000 companies from 45 countries, she finds that sales exposure to the countries in crisis plays a crucial role in influencing the returns of firms, while the higher debt ratios may shelter firms from suffering. Her findings confirm the idea that shocks are transmitted through trade channels. Gropp et al. (2006) apply a multinomial logit model to analyze contagion in a sample of European banks over the period of 1994 to 2003. They also adopt the distance to default, an indicator of bank soundness, to identify whether a bank suffers from a shock. They find strong evidence that the cross border contagion may be increased after the introduction of the Euro. Since their test is based on a non-crisis period, they conclude that the contagion identified should be regarded as a lower bound to the true existing contagion.

2.2.2.2 Correlation Coefficients Test

Forbes and Rigobon (2002) point out that the correlation coefficients are conditional on market volatility, which means that the traditional contagion tests based on the cross-market correlation coefficients may be subject to the heteroscedasticity bias. With proper adjustment, the comovement may highly depend on the fundamental factors instead of being classified as contagion. In their work, they apply a VAR framework in order to adjust the difference between stock market opening hours to control for serial correlation in stock returns and the exogenous global shocks. Specifically, they use five lags in the VAR model to deal with serial correlation and within-week variation in the trading patterns. Surprisingly, after applying cross-market correlation coefficient tests on the stock returns during the periods of the 1997 East Asian crisis, the 1994 Mexican peso devaluation, and the 1987 U.S. stock market crash,, their results show no evidence of contagion during three crises after correcting for the heteroscedasticity bias.

To deal with the biases of simultaneous equations, omitted variables and heteroscedasticity simultaneously, Rigobon (2003) applies a new approach, Determinant of the Change in the Covariance matrix test (DCC), based on the assumption that if the heteroscedasticity in a sub-sample can be captured by a shift in the variance of a sub-set of shocks, then a test of the stability of the coefficients will become possible. One advantage that makes the DCC approach stand out is that the null hypothesis of no contagion will be rejected when the assumption mentioned above is violated. The model is extended to account for trends, lags, and other additional controls. There is a trade-off when applying one control variable, interest rates, as a proxy for some of the omitted variables. This control variable captures common shocks such as monetary policy coordination across countries and changes in risk preferences which cannot be observed. However, the shortcoming is that the inclusion of interest rate may underestimate the transmission of shocks. Therefore, they conduct tests both with and without interest rate. Using the data of 36 daily stock market returns during 3 major international financial crises, Mexico 1994, Asia 1997 and Russia 1998, their test reveals that, except the Mexican crisis during which the transmission mechanism was relatively stable, during the periods of both the Russian and Asian crises, the contagion effects have been identified, and they are even pronounced in the case of the Asian crisis.

Specifically, Jokipii and Lucey (2007) research banking sectors of three main Central and Eastern European Countries, Czech Republic, Hungary and Poland, in order to find out whether there are comovements between these three countries over the period from July 1994 to December 2004 and whether the comovements, if any, are driven by contagion or interdependence. They first estimate the unadjusted correlation coefficients of the daily changes in the banking sector indices during the whole sample period and two sub-samples as turbulent and tranquil periods with the variance covariance generated by VAR. They then control the effects from the country's own fundamental factors by introducing a series of dummy variables of macroeconomic news such as unemployment, short term interest rates, consumer price index, terms of trade, real GDP, current account deficit. It shows that the lagged bank indices respond sensitively to the release of both positive and negative macroeconomic news by reflecting statistically significant rises and falls. They find that with the adjusted correlation coefficient test, the pair-wise comovement among countries can be driven by interdependence, except for the case between the Czech Republic and Hungary. After introducing the country's own macroeconomic factors, although the correlations between markets are high, the comovements are largely subject to the country's fundamental economic factors, except in the strong case of contagion from the Czech Republic to Hungary. The DCC test confirms the robustness of the previous outcome and the result of the granger-causality test shows that the causality runs from the Czech Republic to Hungary.

Since the prices of stock indices may not fully convey information to capture the phenomenon of contagion, Royen (2002) proposes to use quantities, investment flows, to replace prices since quantities will surely exhibit a pattern which distinguishes between tranquil times and contagious episodes. Royen (2002) tests the model using a unique database of cross-border equity flows. She constructs a daily index to measure the average likelihood of contagion between August 1996 and September 2000. Instead of testing for contagion at specific points of time before the occurrence of the crises, she determines the relevant periods endogenously. In addition, she introduces two extra aggregate indices in an attempt to measure the pervasiveness of excessive transmission. The uniqueness of these indices is that they can be decomposed according to the regions and groups and they take into account the likelihood of contagion and the magnitude and directions of net equity flows so that they can be used to distinguish positive from negative contagion. The results show that contagion appears to be regional and it seems that developed countries are sheltered from the influence of contagion.

2.2.2.3 ARCH and GARCH Models

A higher volatility of stock prices during a turmoil period may not necessarily be the result of some worldwide common factors. The importance of identifying the fundamental factors within a nation is key to exclude country-specific noise in testing for the contagion. In light of this consideration, Chiang et al. (2007) introduce a measure of interdependence from a standard factor model which needs no restriction on the variance of common factors. As has been proved by Chiang et al. (2007), the restrictions on country-specific noise can be the source of bias towards the acceptance of the null hypothesis of 'no contagion'. Although the simple-correlation analysis with a correction for heteroscedasticity proposed by Forbes and Rigobon (2002) has been widely used in the literature, this method fails to capture the time-varying characteristics of the market behaviour in response to the shocks on an ongoing basis. A cross-country, multivariate dynamic conditional correlation GARCH model first introduced by Engle (2002) is, thus, employed in the study of Chiang et al. (2007) to measure the time-varying conditional correlations after weighting the limitations of the methods from previous literature. The benefit of applying this model is that it will solve the heteroscedasticity problem addressed by Forbes and Rigobon (2002) without dividing the sample. It also helps deal with the omitted variable problem and to capture the global common factor, thus avoiding a simultaneous equation bias. Above all, it provides a sound mechanism to test time-varying correlation coefficients, which makes it possible to identify the dynamic investor behaviour when there is news or innovations. Chiang et al. (2007) apply the model on nine Asian daily stock-return data series from 1990 to 2003. In comparison with the effectiveness of the method used by Forbes and Rigobon (2002), this model appears to be more efficient in seperating the contagion from interdependence. In addition, by analyzing the correlation-coefficient series, they also identify two phases of the Asian crisis. One shows an increase in correlation and the other shows a continued high correlation that may be caused by herding.

Hsin (2004) focuses on the international comovement among 10 major developed countries, which includes G-7 countries and three major Asia-Pacific countries: Australia, Hong Kong and Singapore. Different from Chiang et al. (2007), in his research, Hsin extends the method of the two-stage GARCH framework proposed by Lin et al. (1994) to account for the international transmission in terms of conditional volatility, the possible asymmetry in volatility, and the prevailing risk-return relationships. The high-frequency data, daily price Morgan Stanley Capital International (MSCI) indices denominating in U.S. dollars are used in his study to keep track of the dynamics of international transmission. The advantages of using a threshold AR(1)-GARCH(1,1)-in-mean model is that it takes the dynamics in the stock returns into account and incorporates the mechanism of volatility transmissions simultaneously. Moreover, the multilateral impacts of different countries have been fully captured in the model, which helps avoid the problem of spurious observations of transmission effects as can be detected under the correlation tests and make the direct comparison about the impact strength possible. The results show the existence of significant international transmission effects in returns and volatility among ten major countries, and the U.S., Canada, and the U.K. are the three markets that still demonstrate contagion influence over countries outside their own region. The evidence also suggests that strong regional transmission effects exist. A further investigation using the extended model reveals that the linkages between the U.S.

and European markets are driven by positive global common forces and by negative international competitive effects. On the other hand, the U.S. and Asian markets are linked through positive global common forces and positive international contagion effects. The Asia-Pacific markets are more susceptible to contagion effects. Finally, they find that the performance of the Japanese market becomes more contagious toward other markets during the Asian financial crisis period.

2.2.2.4 Markov Switching Models

Jeanne and Masson (2000) propose to use a Markov-switching regimes approach in an empirical study on currency crises in line with the method suggested by Jeanne (1997). They illustrate the applicability of this model by studying the the French franc over the period of 1987 to 1993. They find that the model allowing for sunspot, an 'extrinsic' random variable, is superior in explaining the experience of the French frank and tracking the episodes of speculation. It improves the relationship between the economic fundamentals and the devaluation expectations compared to an ordinary fundamental based model.

To examine the nature of the currency crisis over the Mexican crisis episode in 1994, Mouratidis (2008) extends the empirical framework proposed by Jeanne and Masson (2000) by allowing transition probabilities to be time-varying. Uniquely, he makes comparisons among three models: a Markov regime switching model (MRS) with time-varying transition probabilities; a linear benchmark model; and an MRS model with constant transition probabilities based on an out-of sample forecasting exercise. In line with Jeanne and Masson (2000), he also attempts to explain the procedure by which currency crisis models with multiple equilibria can be estimated when employing the MRS model. Mouratidis's result implies that the explanation of the nature of a currency crisis is highly sensitive to the choice of proxy for the probability of devaluation.

3 Research design

3.1 Definition of Financial Contagion

In order to study the contagion effect that arises due to the subprime credit crisis, we define financial contagion as the cross-country excess comovements, i.e. the comovements of asset prices that exceed what can be explained by macroeconomic fundamental factors (see, e.g. Pericoli and Sbracia 2003; Dungey and Tambakis 2005). Accordingly, we use the GARCH and VAR model to filter the comovement effects due to fundamental factors, and then employ the estimated residuals from the first stage GARCH or VAR models to test the existence of excess comovements. Different from the studies focusing on the major stock index of each country, we concentrate on the comovements of stock indices of the banking sectors among G-7 countries, since the banking sector has suffered the most direct impact from the subprime mortgage crisis and credit contraction. In order to shed light on whether the crisis contributes to financial contagion, we collect data for both the pre-crisis period and the crisis period to compare the comovements of banking sector indices before and after the subprime crisis. The full sample period of our study is from January 2002 to January 2009.

3.2 Methodology

The empirical analysis in this paper focuses on assessing the comovements of the banking sector among G-7 countries during the subprime credit crisis. We employ two approaches to examine the question.

3.2.1 Two-stage Threshold AR(1)-GARCH(1,1)-in-Mean Framework

Following the method proposed by Lin et al. (1994) and extended by Hsin (2004), we adopt the two-stage threshold AR(1)-GARCH(1,1)-in-mean model. In the first stage, stock indices of each country are regressed on one-lagged stock indices, a set of selected macroeconomic variables, and estimated conditional variance estimated using the GARCH (1,1)-in-mean model. The estimated residuals from the first stage model approximate the innovations of the corresponding markets. In the second stage, the estimated residuals of innovative countries are added into the regression in order to test whether a transmission of innovations exists across markets. Meanwhile, the volatility of the estimated residuals is added into the GARCH model to test the potential volatility spillover, i.e. the transmission of volatility across markets. The specification of the framework is as below.

Stage 1:

$$r_{i,t} = \alpha_i + \beta_i r_{i,t-1} + \gamma_i h_{i,t} + \sum_{\pi=1}^{n} \kappa_{i,\pi} I_{i,\pi,t} + e_{i,t} \tag{1}$$

$$h_{i,t} = \omega_j + a_i e_{i,t-1}^2 + b_i h_{i,t-1} + f_i T_i e_{i,t-1}^2$$

where $e_{i,t}|\Omega_{t-1} \sim N(0, h_{i,t})$, $i \neq j$. $r_{i,t}$ is the log-transformed banking sector index of market i at time t. $h_{i,t}$ is the conditional variance of residuals estimated using the GARCH (1, 1) model. $I_{i,\pi,t}$ denotes macro-fundamental variables for market i at time t. n denotes the number of fundamental factors. We adopt eight country macroeconomic variables to capture the impact of fundamental factors. These variables are the growth rate of real GDP, growth rate of CPI, unemployment rate, inflation rate, short-term interest rate, depreciation rate of currency, growth rate of trading value in current account and growth rate of capital flows in capital accounts. In addition, we use the MSCI world index as a global factor to approximate the shock of global economic conditions. $e_{i,t}$ is the innovation, which is assumed to be serially uncorrelated, mutually independent and following the GARCH process. The distribution of $e_{i,t}$ conditional upon the historical information matrix Ω_{t-1} is normal with mean 0 and variance $h_{i,t}$. Zakoian (1994) points out that that positive and negative shock will influence the volatility asymmetrically. Therefore, in the GARCH model, we add one threshold dummy variable T_i. It is applied to measure the asymmetric effect of volatility. $T_i = 1$ when the innovation at time *t*-1 is negative and 0 otherwise. The asymmetric effect is reflected through f_i. If f_i is positive and significant, it indicates that the market reacts to bad news more strongly than to good news.

In the second stage, the index of market *j* is allowed to respond to the innovations from other markets simultaneously.

Stage 2

$$r_{j,t} = \alpha_j + \beta_j r_{j,t-1} + \gamma_j h_{j,t} + \sum_{\pi=1}^{n} \kappa_{j,\pi} I_{j,\pi,t} + \sum_{i=1}^{I} \delta_{i,j} \hat{e}_{i,t} + v_{j,t} \tag{2}$$

$$h_{j,t} = \omega_j + a_j v_{j,t-1}^2 + b_j h_{j,t-1} + \sum_{i=1}^{I} \lambda_{i,j} \hat{e}_{i,t}^2 + f_j T_j v_{j,t-1}^2$$

where $v_{j,t}|\Omega_{t-1} \sim N(0, h_{j,t})$, $i \neq j$. $r_{j,t}$ is the log-transformed banking sector index of market *j* at time *t*. $h_{j,t}$ is the conditional variance of residuals which are estimated using GARCH (1, 1) model. $I_{j,\pi,t}$ denotes macro-fundamental variables for market *j* at time *t*. n denotes the number of fundamental factors. We adopt eight country macroeconomic variables to capture the impact of the fundamental factors. These variables are the growth rate of real GDP, the growth rate of CPI, unemployment rate, inflation rate, short-term interest rate, depreciation rate of currency, growth rate of trading value in current account and growth rate of capital flows in capital accounts. In addition, we use the MSCI world index as a global factor to approximate the shock of global economic conditions. $v_{j,t}$ is the innovation, normal with mean 0 and variance $h_{j,t}$ conditional upon Ω_{t-1}, the information matrix at time *t*-1. T_j denotes the threshold dummy variable. $T_j = 1$ when the innovation at time *t*-1 is negative and 0 otherwise. The asymmetric effect is reflected through f_j. If f_j is positive and significant, it indicates that the market reacts to bad news more strongly than to good news.

$\hat{e}_{i,t}$ is the estimated residual of innovative country *i* in the first stage model. $\delta_{i,j}$ is the transmission coefficient of index *j* in response to the unexpected innovation from market *i*. It acts as an indicator of the presence of a contagion effect in the model. If $\delta_{i,j}$ is positive and significant, it shows that a contagion effect exists; if $\delta_{i,j}$ is negative and significant, it indicates a reduction in transmission effects. $\lambda_{i,j}$ is the volatility transmission coefficient, which captures the dynamics of the volatility of market *j* in response to the unexpected innovations from market *i*.

Our first null hypothesis is that there is no contagion effect, only interdependence, during our full sample period, which means the comovements among G-7 countries are triggered by the fundamental factors alone.

$$H_0: \delta_{i,j} \leq 0 \tag{3}$$

H_1: $\delta_{i,j} > 0$

A rejection of the null hypothesis, $\delta_{i,j} \leq 0$, suggests that excess comovement between market *i* and *j* exists.

To further identify the marginal transmission effect caused by the subprime credit crisis, we add one dummy variable 'D_t' into the model (2). The extended model in Stage 2 is shown below.

Stage 2a

$$r_{j,t} = \alpha_j + \beta_j r_{j,t-1} + \gamma_j h_{j,t} + \sum_{\pi=1}^{n} \kappa_{j,\pi} I_{j,\pi,t} + \sum_{i=1}^{I} (\delta_{i,j} + d\delta_{i,j} D_t) \hat{e}_{i,t} + v_{j,t} \tag{4}$$

$$h_{j,t} = \omega_j + a_j v_{j,t-1}^2 + b_j h_{j,t-1} + \sum_{i=1}^{I} \lambda_{i,j} \hat{e}_{i,t}^2 + f_j T_j v_{j,t-1}^2$$

where $v_{j,t}|\Omega_{t-1} \sim N(0, h_{j,t})$, $i \neq j$. $d\delta_{i,j}$ denotes the additional contagion effect from the subprime credit crisis. If $d\delta_{i,j}$ is positive and significant, the additional contagion effect brought on by the subprime credit crisis is present. $D_t = 1$ if the date is from July 27, 2007 to January 5, 2009; otherwise, $D_t = 0$. The other coefficients are identical to the coefficients in model (2). Our second null hypothesis is that there is no marginal contagion effect during the crisis.

$$H_0: d\delta_{i,j} \leq 0 \tag{5}$$

H_1: $d\delta_{i,j} > 0$

A rejection of the null hypothesis, $d\delta_{i,j} \leq 0$, indicates that the subprime crisis increases the contagion effects between markets *i* and *j*.

3.2.2 Correlation Coefficient Test

Although the two-stage threshold AR(1)-GARCH(1,1)-in-mean model is capable of addressing heteroscedasticity and of capturing the dynamics of the comovements of stock indices, it fails to consider the cross-market macro-fundamental effects. This means that the change of economic conditions in country i may affect the stock price of country j through fundamental factors such as international trade and capital flows. Therefore, we apply vector autoregressive regression (VAR), followed by the correlation coefficient tests.

3.2.2.1 Vector autoregressive regression

The correlation coefficient test usually works on the residuals of the VAR test. The advantage is that it can provide better control over the cross-market macro-fundamental effects, as well as serial correlation in indices. We treat the macro-fundamental factors as exogenous variables in the VAR framework so that we can generate fundamental-effect-free vectors of disturbances.

The general specification of the VAR framework takes the following form.

$$R_t = C + \sum_{L=1}^{m} \phi_L R_{L,t} + \sum_{\pi=1}^{n} \Phi_\pi I_{\pi,t} + \eta_t \quad (6)$$

$$R_t \equiv \{r_t^{CN}, r_t^{FR}, r_t^{GE}, r_t^{IT}, r_t^{JP}, r_t^{UK}, r_t^{US}\}'$$

$$R_{L,t} \equiv \{r_{L,t}^{CN}, r_{L,t}^{FR}, r_{L,t}^{GE}, r_{L,t}^{IT}, r_{L,t}^{JP}, r_{L,t}^{UK}, r_{L,t}^{US}\}'$$

$$I_{\pi,t} \equiv \{i_{\pi,t}^{CN}, i_{\pi,t}^{FR}, i_{\pi,t}^{GE}, i_{\pi,t}^{IT}, i_{\pi,t}^{JP}, i_{\pi,t}^{UK}, i_{\pi,t}^{US}\}'$$

with $E(\eta_t) = 0$, $E(\eta_t, \eta_t') = \sum$, $E(\eta_t, \eta_s') = 0$ if $t \neq s$. r_t is a vector of DataStream banking sector log index. R_t is a transposed vector of stock indices of G-7 countries. $R_{L,t}$ is a transposed vector of lagged stock indices. ϕ_L is the coefficient of lagged $R_{L,t}$. m denotes the autoregressive order. $I_{\pi,t}$ is a vector of exogenous macro-fundamental variables for G-7 countries. Φ_π is a vector of the coefficients of macro variables $I_{\pi,t}$. n denotes the number of macro-fundamental factors. η_t is a vector of error terms. We select m with the autoregressive order of two according to the Hannan-Quinn information criterion. We first apply the VAR model (6) to obtain the vectors of residuals. The variance-covariance matrices are then estimated for the full sample and two sub-samples based on VAR residuals. Subsequently, we use the estimated variance-covariance matrices to calculate the cross-market correlation coefficients for each pair of countries.

3.2.2.2 Unadjusted correlation coefficient test

We classify the full sample period into the tranquil period from January 7, 2002 to July 26, 2007 and the turmoil period from July 27, 2007 to January 5, 2009. We estimate the correlation coefficient for the two sub-periods separately. Following the standard test method of Forbes and Rigobon (2002), we apply a two-sample t-test to examine whether these correlation coefficients significantly increase in the turmoil period compared to the tranquil period. The third hypothesis we consider here is

$$H_0: \rho_{i,j}^l \geq \rho_{i,j}^h \tag{7}$$

$$H_1: \rho_{i,j}^l < \rho_{i,j}^h,$$

where $\rho_{i,j}^{l}$ and $\rho_{i,j}^{h}$ are the correlation of VAR residuals between markets *i* and *j* during the tranquil and turmoil periods, respectively. A rejection of the null hypothesis suggests that correlation increases during the crisis. This indicates that the crisis increases excess comovements.

3.2.2.3 Adjusted correlation coefficient test

Previous studies (Loretan and English 2000; Forbes and Rigobon 2002) point out that the potential heteroscedasticity in the stock indices may severely bias the correlation coefficient tests. Without any adjustment, the tests for a significant increase can be inaccurate since there is a possibility that the increases in correlations result from an increase in market volatility. Actually, the heteroscedasticity correction they recommended is specifically needed when one estimates the residuals of VAR based on the data set of both crisis and non-crisis periods because the volatility of the crisis period is much larger than that of the non-crisis period (Dungey and Zhumabekova 2001).[3] Therefore, we apply a correction adjustment on the correlation coefficients following the method proposed by Forbes and Rigobon (2002). The adjustment takes the following form.

$$\rho_{i,j}^{h*} = \frac{\rho_{i,j}^{h}}{\sqrt{1+\delta\left[1-\left(\rho_{i,j}^{h}\right)^{2}\right]}} \tag{8}$$

$$\delta = \frac{\sigma_{xx}^{h}}{\sigma_{xx}^{l}} - 1$$

[3] Dungey and Zhumabekova (2001) suggest that an alternative method to control for the heteroscedasticity is to estimate the VAR model for crisis and non-crisis periods separately. Given the limited number of observation during the subprime crisis period, and the large loss of degrees of freedom in a VAR model, a separate estimation is not feasible. We therefore adopt the adjusted correlation coefficient method.

where $\rho^h_{i,j}$ denotes the correlation between the VAR residuals of country i and country j during the turmoil period. σ^h_{xx} and σ^l_{xx} are the variances of the crisis country x , which is either country i or j during the turmoil and tranquil periods, respectively. Similar to the third hypothesis, the fourth hypothesis is

$$H_0: \rho^l_{i,j} \geq \rho^{h*}_{i,j} \tag{9}$$

$$H_1: \rho^l_{i,j} < \rho^{h*}_{i,j},$$

where $\rho^{h*}_{i,j}$ are the correlations after adjustment during the turmoil period. A rejection of the null hypotheis in the t-test indicates the significant increase in comovements due to the subprime credit crisis.

In both the adjusted and unadjusted correlation coefficient t-tests, we employ a Fisher transformation. The Fisher transformation on the correlation coefficients is required to obtain a distribution closer to the normal, with the mean and variance as shown below.

$$\mu_t = \frac{1}{2} ln \left[\frac{1+\rho^t_{i,j}}{1-\rho^t_{i,j}}\right] \tag{10}$$

$$\sigma^2_t = \frac{1}{n_t - 3} \tag{11}$$

where t denotes h (h^*) or l indicating the turmoil or tranquil period. $\rho^t_{i,j}$ denotes the correlation between country i and country j during the turmoil or tranquil period. n_t indicates the observations during the turmoil or tranquil period. The two-sample t-statistics are calculated with

$$t = \frac{\mu_{h\,(h^*)} - \mu_l}{\sqrt{\sigma^2_{h\,(h^*)} + \sigma^2_l}}. \tag{12}$$

One-sided t-tests are used to examine whether the cross-market correlation coefficients during the turmoil period are higher than those during the tranquil period. The critical value for the t-test at a 5% significance level is 1.65. If the t-statistic is equal or greater than 1.65, we identify that there is a significant increase due to the subprime crisis; otherwise, there is no increase.

4 Data

We define the subprime crisis from July 27th, 2007 to January 5th, 2009[4]. In order to analyze the difference between the comovements during both the subprime crisis and non-crisis periods, we study the comovements during the tranquil period starting from January 7th, 2002 to July 26th, 2006. We use DataStream banking sector indices of G-7 countries following Jokipii and Lucey (2007). These indices are value-weighted indices, appropriate in that they can provide an accurate reflection of the major listed banks in each country. These indices are extracted based on local currency. We apply a logarithmic transformation on the banking sector indices.

In order to control for the influence of the fundamental factors, we use the following macroeconomic fundamentals variables: the growth rate of real GDP, growth rate of CPI, unemployment rate, inflation rate, short-term interest rate, depreciation rate of currency, growth rate of trading value in current account and growth rate of capital flows in capital accounts. The short-term interest rate, which is approximated with three-month Treasury bill rates, is adopted to control for the possible adverse effect from the rise of the short-term interest rate since the high interest rate will worsen bank balance sheets if banks' lending rates cannot be raised quickly enough. As has been shown in Galbis(1993), there is a direct connection between financial liberalization and the interest rate. The inclusion of short-term interest rates may also control the impact due to

[4] The starting date of the subprime credit crisis is determined according to Dungey et al. (2008) and the official website of the National Bureau of Economic Research. The subprime credit crisis is, at the time of this study, an on-going crisis. Therefore, the ending date of the subprime credit crisis in this study is the last date on which the data are available.

financial liberalization. Kaminsky and Reinhart (1996) suggest that financial liberalization has some predictive power on the occurrence of banking crises. Financial liberalization may increase the vulnerability of the banking sector to a crisis since it increases the opportunities for excessive risk taking and fraudulence. Following Demirgüç-Kunt and Detragiache (1998), the depreciation rate, which is calculated as the rate of change of the exchange rate, is applied to control for the effect that the crisis may be triggered by an excessive exchange risk exposure in the banking sector or among bank borrowers. Both the trade values of national current capital accounts are adopted to reflect changes in the strength of the trade and financial links among countries. Foreign direct investment (FDI) is one major component of the capital account as both public and private international investments flowing in and out will be recorded by the capital account. A global factor controlling for the impact of global shocks is approximated with the MSCI world index, which is a value-weighted index that monitors the performance of stocks from around the world.

We obtain the data of banking sector indices, GDP, CPI, unemployment rate, inflation rate, and depreciation rate from DataStream. The short-term interest rate, current account, capital account, and MSCI world index, we collect from Bloomberg and the websites of the centre banks of G-7 countries. Although daily data are recommended by a recent study (Hsin 2004), we apply weekly data of stock indices in our tests because most of the macroeconomic fundamental variables just have quarterly or monthly data.

5 Empirical results

5.1 Summary Statistics

Table 1 reports the summary statistics of log-transformed banking sector indices of G-7 countries. Panel A reports the full sample period. It shows that Japan is the most volatile country with an estimated standard deviation of 0.0513, while Canada is the least volatile market with a standard deviation of 0.0301. The kurtosis statistics for all G-7 countries appear to be excessively high. Averaged indices are negative, except in Canada. Jarque-Bera statistics indicate that the distributions of log indices depart from normal for all seven countries. Panel B reports the summary statistics during the pre-crisis period. We find that the means of log indices are all positive. Furthermore, these series appear to be less volatile by comparing the standard deviation of the full period with that of the non-crisis period. As has been further confirmed by panel C, all means of log indices are negative and the standard deviations reflect that the series are highly volatile during the subprime credit crisis.

Table 2 presents the correlations of G-7 countries. Panels A, B and C report the correlations of the full sample, pre-crisis and crisis periods, respectively. They show that stock indices of banking sectors are highly correlated among G-7 countries. However, we do not observe that the correlations increase for all pairs of countries during the turmoil period. Table 3 reports the Dickey Fuller test. Tests reject the null hypothesis of non-stationary and the presence of a unit root at 1% level. Both GARCH tests and correlation coefficients tests, therefore, proceed.

5.2 Two-stage Threshold AR(1)-GARCH(1,1)-in-mean Test Results

The results of the first stage GARCH model are shown in Table 4. The asymmetric effects in volatility have been identified for Canada, the U.K., and the U.S. The estimated coefficients of f_i (asymmetry) of the three countries are 0.0230, 0.2201, and 0.2482, respectively. This result suggests that the banking sectors of these countries are responding more strongly toward bad news than good news. However, the asymmetric coefficient for Italy is negatively significant (-0.2228). This may suggest that the market reacts more in favour of good news. The coefficients of lagged log indices are negative and significant for countries other than Japan. We observe that the depreciation rate and global factor are the most influential fundamental factors. The coefficient of the global factor for Germany is as high as 1.0676. Except for Canada, the coefficients of deprecation rates of the other countries in response to the U.S. dollar are significant. There is no significant response for the factors CPI, current account and capital account with the first stage GARCH tests. The log index of France shows a significantly negative reaction to GDP. Furthermore, only the log index of France reacts to the inflation rate and unemployment rate at a 1% significance level. As for the short-term interest rates, both Italy and Japan have significant negative responses.

Table 5 provides the test results of contagion using the second stage GARCH model. The contagion effects we identified in the second stage are conditional on the fundamental factors we controlled in the model. We observe some contagion effects, as shown in Panel A of Table 5. As shown in this panel, there are significant mutual contagion effects between the U.S. and the other four countries: Canada, France, Germany and the U.K. In terms of economic significance, Canada has the most important impact on the U.S. market, and Canada is also the one most affected by the U.S. We observe that the impact of Canada on the U.S. is larger than the impact of the U.S. on Canada. This may be due to the fact that the banking system of Canada is healthier than the banking system of the U.S. during this sample period. Specifically, Canada responds to the U.S. with coefficient $\delta_{7,1}$(US)=0.3648, while the U.S. reacts to Canada with coefficient $\delta_{1,7}$(CN)=0.4152. As for the U.K. and the U.S., however, it is the opposite. The U.S. casts more impact on the U.K.

Furthermore, Panel A shows that the contagion effects tend to be regional. For instance, there are significant regional contagion effects among European countries, but relatively weak effects between European countries and countries such as Canada or Japan. For instance, the excess comovement between Germany and France, $\delta_{3,2}$(GE), is 0.3412, while the excess comovement between Germany and Japan, $\delta_{3,5}$(GE), is only -0.0407. Similarly, there is a mutual contagion effect between North American countries: Canada and the U.S.

Panel B of Table 5 reports the transmission of volatility. Our results reflect relatively mild volatility transmission effects. This may be because both ARCH and GARCH effects in the model partially capture the variance spillovers and the first-moment transmission effects have also been controlled in the mean equation. Canada and the U.K. appear to be the influential ones among G-7 countries with respect to volatility transmissions. For instance, Canada affects Japan, the U.K. and the U.S. with estimated coefficients 0.2906, 0.0556, and 0.1518, respectively. We also observe positive and significant volatility transmissions from Japan to Germany and the U.S. Compared with the results in Panel A, we find that for some pairs of countries, there is evidence of volatility spillovers even though we do not observe any contagion effect. For instance, the innovation of Canada has a significant transmission effect on the volatilities of Japan, but no contagion effect has been identified between these countries.

Panel A of Table 6 reports the test results of additional contagion effects associated with the subprime credit crisis. The estimation results are very similar to Panel A of Table 5. It suggests that the contagion effects do exist during the pre-crisis period. Panel B of Table 6 studies whether the subprime crisis causes an additional contagion effect. We expect to find positive and significant coefficients, $d\delta_{7,j}(US)$, which indicate that the subprime crisis is associated with an innovation transmission from the U.S. to the other countries. However, we do not find the evidence to support this conjecture. In addition, we observe that some contagion effects existing among G-7 countries are additionally caused by the subprime credit crisis. The significant cases are the U.K. and Germany with $d\delta_{6,3}$ (UK)=0.2163; Italy and Japan with $d\delta_{5,4}$ (JP)=0.1317 and $d\delta_{4,5}$(IT)=0.6041. Moreover, the strength of the contagion effects from Canada to the U.S. and from France to the U.S. has been reinforced during the crisis. Especially for Canada, $d\delta_{1,7}$(CN) equals to 0.4603 at a 1% significance level. Panel C of Table 6 studies the volatility spillover effects. Again, the results are similar to previous findings in Panel C of Table 5.

5.3 Correlation Coefficient Test Results

Table 7 records the test results of vector autoregressive regression. We notice that the log indices are sensitive to some of the cross-market fundamental factors and lagged log indices. As for the U.S., the log index reacts positively to one lagged log index of Canada and Germany simultaneously. Furthermore, cross-market macro-fundamental factors, capital account, short-term interest rate of France and depreciation rate of Japan, cast statistically significant impacts on the log index of the U.S. This may explain the findings of panel B of Table 6 that the strength of the contagion effects from Canada and France to the U.S. has been reinforced during the subprime credit crisis. It may be due to these uncontrolled cross-market macro-fundamental effects that we identify the additional contagion effects between these two pairs of countries. In addition, we also notice that the influences of cross-market fundamental factors are exhibited among European countries.

Table 8 reports the unadjusted correlation coefficient t-test results. It shows that the correlations between the U.S. and the other three countries, Canada; France; and the U.K., increase significantly due to the crisis. Except the correlation between Japan and Germany, all other correlation coefficients are higher in the turmoil period than those in the tranquil period, which is an indispensible prerequisite for the occurrence of contagion. Furthermore, there is no increase identified between the U.S. and Germany nor the U.S. and Italy. This is identical to the preliminary results obtained with simple cross-market correlation statistics based on the log indices. When Italy or Japan is treated as a leading country, there is no increase identified.

However, when the adjustment takes place, the increases in correlation coefficients disappear, as shown in Table 9. Particularly, the correlations between the U.S.

and the other six countries do not increase during the subprime crisis. This indicates that the correlations among G-7 countries during the crisis period result largely from the increase in the volatilities of innovation. The adjustment correcting the heteroscedasticity bias reduces the strength of the correlation during the crisis. This result is, as we expected, identical to the results generated with the GARCH model.

6 Conclusion

This paper studies the financial contagion of banking sectors among G-7 countries by examining the excess comovement of stock indices of banking sectors during the first 18 months of the subprime credit crisis of 2007. Weekly indices of the banking sector obtained from DataStream are employed to facilitate the study. We first employ a two-stage threshold AR(1)-GARCH(1,1)-in-mean model in order to test whether there is any excess comovement among banking sectors during the subprime credit crisis. By adding eight fundamental factors and one global factor into our models, we control for the fundamental-related interdependence. Furthermore, we apply vector autoregressive regression, followed by the correlation coefficient tests, to study the changes in strength of the comovement of indices after controlling for cross-market fundamentals.

In general, there are significant mutual contagion effects among G-7 countries during the full sample period according to the GARCH test. The mutual contagion effects tend to be regional. Specifically, there are contagion effects within European countries, but relatively weak effects between European countries and countries such as Canada and Japan. Similarly, there are contagion effects between Canada and the U.S. In addition, the U.S. market is highly related and affected by other countries, such as France, Germany and the U.K.

The surprising finding is that the subprime credit crisis does not necessarily contribute to the contagion effects as expected. Specifically, we do not observe contagion effects transmitted from the U.S. to other markets during the subprime crisis. Meanwhile, Canada and France exhibit additional impacts on the U.S. during the crisis. These marginal contagion effects brought by the crisis from either Canada or France to the U.S. may be due to the cross-market fundamental factors such as international trade and capital flows, which are not controlled in the GARCH model.

In the VAR model, the unadjusted correlation coefficient test shows that the subprime credit crisis does result in significant increases in market comovements. The correlations are strengthened between the U.S. and three countries, Canada, France and the U.K., due to the crisis. However, this result is subject to the heteroscedasticity bias. With the appropriate adjustment, the strength of correlations during the crisis turns out to be the same as that during the non-crisis period. This result is consistent with the findings of the GARCH model. It suggests that the correlations of G-7 banking sectors during the crisis largely depend on the increase in volatility. In this respect, the excess comovements of banking sectors of G-7 countries during the subprime credit crisis are indeed not as strong as we expected.

In light of the mutual contagion effects during either the crisis or the non-crisis period, we observe that, whether there is a crisis or not, the banking sectors of these developed countries are closely related, especially within their geographic region. Risk diversification driven investments among the banking sectors of countries within the same geographic region may not exhibit good performances. We cannot ignore that, as the center of the world economy, the U.S. has more or less influence over the other nations. From this perspective, the banking system of the U.S. may need to place more emphasis on the nations which possess the least contagion effects, for instance Italy or

Japan. Though we do not observe that the subprime credit crisis strengthens contagion effects from the banking sector of the U.S. to the other countries, we cannot safely draw the conclusion that the subprime credit crisis does no harm to the banking sectors either. In a highly globalized financial world, no economy can be fully exempt from a world-wide financial crisis. Therefore, international cooperation on financial surveillance is necessary to maintain global stability.

Table 1 Descriptive Statistics of Stock Indices of Banking Sectors in G-7 Countries

	CN	FR	GE	IT	JP	UK	US
Panel A: Total period: January 7, 2002-January 5, 2009							
Observations	366	366	366	366	366	366	366
Mean	0.0005	-0.0016	-0.0026	-0.0010	-0.0002	-0.0025	-0.0018
Median	0.0011	0.0036	0.0039	0.0039	0.0026	-0.0002	0.0007
Maximum	0.1639	0.1315	0.1614	0.1312	0.1467	0.1505	0.2695
Minimum	-0.1630	-0.2084	-0.2541	-0.1875	-0.2998	-0.2544	-0.1933
Std. Dev.	0.0301	0.0431	0.0417	0.0338	0.0513	0.0397	0.0454
Skewness	-0.4940	-0.8126	-1.2977	-0.8578	-0.5621	-1.2447	0.4662
Kurtosis	10.2400	6.7120	9.1420	7.7307	6.0683	10.2812	10.6374
Jarque-Bera	814.2471***	250.4112***	678.0076***	386.1775***	162.8442***	903.0004***	902.7757***
Panel B: Pre-crisis period: January 7, 2002- July 26, 2007							
Observations	290	290	290	290	290	290	290
Mean	0.0024	0.0022	0.0013	0.0018	0.0022	0.0004	0.0009
Median	0.0026	0.0048	0.0051	0.0048	0.0040	0.0010	0.0020
Maximum	0.0842	0.1315	0.1040	0.1001	0.1467	0.1046	0.1051
Minimum	-0.0903	-0.1584	-0.1421	-0.1250	-0.1717	-0.1466	-0.1294
Std. Dev.	0.0198	0.0328	0.0328	0.0277	0.0435	0.0274	0.0255
Skewness	-0.1497	-0.2999	-0.6256	-0.4020	-0.0480	-0.6502	-0.3559
Kurtosis	6.3333	7.0156	4.9264	6.2183	4.1697	7.8876	8.3633
Jarque-Bera	135.3430***	199.1859***	63.7559***	132.9650***	16.6436***	309.0883***	353.6969***
Panel C: Crisis period: July 27, 2007-January 5, 2009							
Observations	76	76	76	76	76	76	76
Mean	-0.0068	-0.0159	-0.0174	-0.0117	-0.0097	-0.0132	-0.0120
Median	-0.0106	-0.0092	-0.0128	-0.0074	-0.0016	-0.0148	-0.0149
Maximum	0.1639	0.1234	0.1614	0.1312	0.1180	0.1505	0.2695
Minimum	-0.1630	-0.2084	-0.2541	-0.1875	-0.2998	-0.2544	-0.1933
Std. Dev.	0.0531	0.0682	0.0636	0.0495	0.0734	0.0680	0.0861
Skewness	-0.0497	-0.3814	-0.9323	-0.6081	-0.6457	-0.6432	0.6982
Kurtosis	4.5481	3.2431	5.8166	5.1159	4.6663	4.5187	4.0564
Jarque-Bera	7.6203**	2.0296	36.1310***	18.8612***	14.0731***	12.5431***	9.7097***

This table reports summary statistics of log-transformed indices of banking sectors in G-7 countries. The sample contains weekly data from January 7, 2002 to January 5, 2009. The test statistic of Jarque-Bera is calculated as $JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$, where n is the number of observations. S is the sample skewness. K is the sample kurtosis. JB is applied to test a joint null hypothesis that the sample data are from a normal distribution with both the skewness and the excess kurtosis equal to zero. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 2 Correlations of Stock Indices of Banking Sectors in G-7 Countries

	CN	FR	GE	IT	JP	UK	US
Panel A: Total period: January 7, 2002-January 5, 2009							
CN	1	0.5968***	0.6153***	0.5589***	0.4195***	0.6493***	0.6744***
FR	0.5968***	1	0.7920***	0.7696***	0.3022***	0.7956***	0.7082***
GE	0.6153***	0.7920***	1	0.8066***	0.4384***	0.8069***	0.6667***
IT	0.5589***	0.7696***	0.8066***	1	0.4052***	0.7469***	0.5811***
JP	0.4195***	0.3022***	0.4384***	0.4052***	1	0.3774***	0.2748***
UK	0.6493***	0.7956***	0.8069***	0.7469***	0.3774***	1	0.6806***
US	0.6744***	0.7082***	0.6667***	0.5811***	0.2748***	0.6806***	1
Panel B: Pre-crisis period: January 7, 2002- July 26, 2007							
CN	1	0.6127***	0.5436***	0.5492***	0.2339***	0.4349***	0.6474***
FR	0.6127***	1	0.8163***	0.8224***	0.2183***	0.7793***	0.7496***
GE	0.5436***	0.8163***	1	0.8099***	0.3633***	0.7047***	0.7034***
IT	0.5492***	0.8224***	0.8099***	1	0.2487***	0.7472***	0.6269***
JP	0.2339***	0.2183***	0.3633***	0.2487***	1	0.1910***	0.2822***
UK	0.4349***	0.7793***	0.7047***	0.7472***	0.1910***	1	0.5855***
US	0.6474***	0.7496***	0.7034***	0.6269***	0.2822***	0.5855***	1
Panel C: Crisis period: July 27, 2007-January 5, 2009							
CN	1	0.5800***	0.6684***	0.5717***	0.5856***	0.7645***	0.6845***
FR	0.5800***	1	0.7569***	0.7060***	0.3755***	0.8050***	0.7078***
GE	0.6684***	0.7569***	1	0.7924***	0.5114***	0.8920***	0.6744***
IT	0.5717***	0.7060***	0.7924***	1	0.5870***	0.7551***	0.5862***
JP	0.5856***	0.3755***	0.5114***	0.5870***	1	0.5471***	0.2828**
UK	0.7645***	0.8050***	0.8920***	0.7551***	0.5471***	1	0.7272***
US	0.6845***	0.7078***	0.6744***	0.5862***	0.2828**	0.7272***	1

This table reports pairwise correlations of log-transformed indices of banking sectors in G-7 countries. The sample contains weekly data from January 7, 2002 to January 5, 2009. The test hypothesis is $H_0: \rho_{i,j} = 0$; $H_1: \rho_{i,j} \neq 0$. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 3 Dickey Fuller Tests of Stock Indices of Banking Sectors in G-7 Countries

	CN	FR	GE	IT	JP	UK	US
No. Obs	365	365	365	365	365	365	365
Lag 1	-1.2360***	-1.0163***	-0.9923***	-1.0630***	-1.1421***	-1.1486***	-1.3254***
	(-23.9800)	(-19.2300)	(-18.8700)	(-20.2000)	(-21.9300)	(-22.0100)	(-26.6500)

The Dickey-Fuller test has been applied to test whether a unit root is present in an autoregressive model. The DF test takes the form: Δr_t = (ρ-1). r_{t-1} + μ_t , where: $\mu_t \sim N(0, \sigma_\mu^2)$. r_t is a log-transformed DataStream banking sector stock index. Δ is the first difference operator. *t* is a time index. ρ is a coefficient. u_t is an error term. The time series r_t converges to a stationary time series if | ρ | < 1. If | ρ | = 1, the time series is not stationary and a unit root is present. If | ρ | >1, the time series is not stationary and the variance of the time series grows exponentially as t increases (Dickey and Fuller 1979). The test hypothesis is H_0: | ρ | ≥ 1; H_1: | ρ | < 1. Z-statistics are in parentheses. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 4 GARCH Tests of Stock Indices in Response to Fundamental Factors

Market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
α_j	0.0105	-0.1781***	-0.0270	0.0111	0.0137	0.0012	-0.0295
	(0.5661)	(-2.8357)	(-0.9229)	(0.7615)	(0.4610)	(0.0625)	(-0.8929)
β_j	-0.2125***	-0.1868***	-0.0771*	-0.1039**	-0.0783	-0.1682***	-0.2225***
	(-3.6340)	(-4.8633)	(-1.9028)	(-2.4274)	(-1.6339)	(-3.5990)	(-4.9461)
γ_j(GARCH M)	-0.3028	-0.0568	-1.4293	-2.2368	-0.0030	-0.3884	1.2542
	(-0.0921)	(-0.0247)	(-0.5654)	(-0.8175)	(-0.0011)	(-0.2039)	(0.8168)
Capital Acc.	-0.0047	0.0000	-0.0001	-0.0002	-0.0003	-0.0007	-0.0001
	(-1.3129)	(0.4287)	(-1.6344)	(-1.0176)	(-0.5736)	(-0.7788)	(-0.1439)
CPI	-0.0722	-0.5509	-0.1275	-0.8578	-0.5165	-0.1632	-0.1514
	(-0.2953)	(-1.2321)	(-0.3387)	(-1.1890)	(-0.8420)	(-0.5244)	(-0.7221)
Current Acc.	0.0004	0.0001	0.0014	0.0001	0.0012	0.0002	-0.0055
	(0.7358)	(0.0840)	(1.2169)	(0.4418)	(0.3844)	(0.1939)	(-0.5995)
GDP	-0.1866	-0.5819*	-0.1617	-0.1407	-0.0058	-0.0238	0.3809
	(-0.7652)	(-1.6576)	(-0.5518)	(-0.4199)	(-0.0138)	(-0.0540)	(1.4189)
Inflation	0.0001	0.0110***	-0.0020	-0.0004	-0.0002	-0.0018	0.0005
	(0.1154)	(0.0065)	(-0.4746)	(-0.1771)	(-0.0371)	(-0.8745)	(0.4492)
Short-term r	-0.0018	0.0047	0.0000	-0.0033**	-0.0206*	-0.0004	0.0012
	(-1.0783)	(1.4740)	(-0.0132)	(-2.3384)	(-1.6724)	(-0.1497)	(0.6931)
Unemployment	-0.0005	0.0166***	0.0033	0.0002	-0.0021	0.0009	0.0039
	(-0.2366)	(2.6929)	(1.4044)	(0.1470)	(-0.3382)	(0.1848)	(0.7204)
Depreciation	0.0168	0.6374***	0.5570***	0.3976***	0.4081**	0.6156***	-
	(0.1801)	(7.4136)	(6.7255)	(5.2742)	(2.2617)	(7.6088)	-
Global factor	0.4874***	1.0328***	1.0676***	0.7967***	1.0425***	0.7797***	0.6894***
	(10.3791)	(15.6097)	(12.9933)	(11.5636)	(8.3576)	(12.5516)	(11.8178)
ω_j	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
	(1.1580)	(1.5408)	(0.9390)	(1.4316)	(1.3268)	(0.8338)	(1.3732)
a_j(ARCH)	-0.0125	0.2763***	0.1467	0.3054***	0.1413***	0.0506	0.0219
	(-0.2669)	(2.7143)	(1.4917)	(3.8731)	(2.8121)	(0.8716)	(0.4839)
b_j(GARCH)	0.9055***	0.7529***	0.8612***	0.8237***	0.8655***	0.8621***	0.8654***
	(21.1335)	(13.9709)	(23.1955)	(22.7303)	(14.5702)	(20.8279)	(33.5227)
f_j(Asymmetry)	0.2030***	-0.0319	0.0126	-0.2228**	-0.0937	0.2201**	0.2482**
	(2.6406)	(-0.3015)	(0.1046)	(-2.5279)	(-1.3547)	(2.2512)	(2.5374)

This table reports the estimation results of model; $r_{i,t} = \alpha_i + \beta_i r_{i,t-1} + \gamma_i h_{i,t} + \sum_{\pi=1}^{n} \kappa_{i,\pi} I_{i,\pi,t} + e_{i,t}$; $h_{i,t} = \omega_j + a_i e_{i,t-1}^2 + b_i h_{i,t-1} + f_i T_i e_{i,t-1}^2$ where $e_{i,t}|\Omega_{t-1} \sim N(0, h_{i,t})$. $r_{i,t}$ is the log-transformed banking sector index of market i at time t. $I_{i,\pi,t}$ denotes macro-fundamental variables for market i at time t. n denotes the number of fundamental factors. $e_{i,t}$ is the innovation, which is assumed to be serially uncorrelated, mutually independent and following the GARCH process. T_i a threshold dummy variable. $T_i = 1$ when the innovation at time t-1 is negative and 0 otherwise. $h_{i,t}$ is the conditional variance. Ω_{t-1} is the information matrix at time t-1. Z-statistics are in parentheses. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 5 GARCH Tests of Contagion across Countries

Panel A: Transmissions of innovations

	Responding market						
Innovative market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
$\delta_{1,j}$(CN)		0.0491	-0.0716**	0.0682	0.0345	0.0558	0.4152***
		(0.9885)	(-1.9602)	(1.6038)	(0.2904)	(1.0203)	(7.8199)
$\delta_{2,j}$(FR)	0.0925*		0.3375***	0.2291***	-0.0765	0.2868***	0.1929***
	(1.6517)		(8.8266)	(5.9735)	(-0.6337)	(5.5015)	(4.2388)
$\delta_{3,j}$(GE)	-0.0808*	0.3412***		0.2932***	-0.0407	0.0704	0.2040***
	(-1.8446)	(7.6783)		(7.1970)	(-0.3275)	(1.3494)	(5.1121)
$\delta_{4,j}$(IT)	0.0849	0.2972***	0.3246***		0.1992	0.2216***	-0.1008**
	(1.6262)	(6.4063)	(7.6587)		(1.5378)	(4.0302)	(-2.3727)
$\delta_{5,j}$(JP)	0.0150	0.0066	0.0176	-0.0010		0.0109	0.0046
	(0.9880)	(0.5360)	(1.0322)	(-0.0529)		(0.7884)	(0.2331)
$\delta_{6,j}$(UK)	0.0014	0.3231***	0.0917**	0.2383***	-0.0147		0.1496***
	(0.0244)	(6.7672)	(2.1774)	(4.6974)	(-0.1173)		(2.6406)
$\delta_{7,j}$(US)	0.3648***	0.1632***	0.1329***	-0.0738*	0.0793	0.1889***	
	(8.9140)	(3.8290)	(4.1566)	(-1.8213)	(1.0071)	(4.4216)	

Panel B: Transmissions of volatility of innovations

	Responding market						
Innovative market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
$\lambda_{1,j}$(CN)		0.0240	-0.0034	0.0046	0.2906**	0.0556**	0.1518***
		(1.2386)	(-0.5439)	(0.3241)	(2.2382)	(2.4743)	(3.9583)
$\lambda_{2,j}$(FR)	0.0623		0.0021	0.0112	-0.0485	0.0525*	-0.0071
	(1.5051)		(0.3673)	(0.5420)	(-0.6098)	(1.8764)	(-0.7368)
$\lambda_{3,j}$(GE)	-0.0156	0.0482***		-0.0132*	0.1345**	-0.0375***	-0.0268***
	(-1.0755)	(3.1988)		(-1.6612)	(2.5328)	(-4.0254)	(-3.9022)
$\lambda_{4,j}$(IT)	0.0268	0.0000	0.0051		0.0246	0.0722***	-0.0677***
	(1.2460)	(-0.0006)	(0.7565)		(0.2929)	(3.0187)	(-7.0427)
$\lambda_{5,j}$(JP)	-0.0086***	-0.0071***	0.0019**	0.0037		-0.0030	0.0136***
	(-3.3447)	(-7.1832)	(2.0621)	(1.6310)		(-1.3601)	(3.2780)
$\lambda_{6,j}$(UK)	0.1004***	0.0398*	0.0130*	0.0018	-0.0384		0.1130***
	(2.7439)	(1.7717)	(1.8230)	(0.1176)	(-0.7327)		(5.1949)
$\lambda_{7,j}$(US)	0.0084	-0.0048	0.0031	0.0086	-0.0452	-0.0133*	
	(0.6416)	(-0.4228)	(1.0633)	(1.0460)	(-1.6252)	(-1.6998)	
a_j(ARCH)	-0.0188	0.1238**	-0.0798***	0.1577*	0.1560***	-0.0085	0.0070
	(-0.5143)	(2.0210)	(-2.9317)	(1.9266)	(3.1819)	(-0.2634)	(0.1791)
b_j(GARCH)	0.2379***	0.6714***	1.0099***	0.8346***	0.7932***	0.7356***	0.6647***
	(2.7139)	(8.9659)	(51.5028)	(11.8235)	(11.7952)	(12.5069)	(14.7135)
f_j(Asymmetry)	-0.0412	-0.1949***	0.0249	-0.1194	-0.1119	0.0279	0.1993**
	(-0.8338)	(-3.5431)	(0.9218)	(-1.3843)	(-1.3910)	(0.4596)	(2.2110)

Panel C: Sensitivities to fundamental factors

	Responding market						
Fundamental factors	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
Lagged R_j	-0.1107***	-0.1497***	-0.1131***	-0.0970***	-0.0905**	-0.1428***	-0.2040***
	(-2.7643)	(-7.057)	(-5.2772)	(-3.4896)	(-1.9753)	(-4.4618)	(-6.1086)
Capital Acc.	-0.0001	0.0000	0.0000	-0.0001	-0.0001	-0.0021**	0.0006
	(-0.0159)	(1.3299)	(-0.7196)	(-1.1514)	(-0.2409)	(-2.4015)	(1.6318)
CPI	-0.0230	-0.2546	-0.3880**	-0.5145	-0.8166	-0.2278	-0.2684
	(-0.1179)	(-0.8911)	(-2.1934)	(-0.9601)	(-1.4045)	(-0.9636)	(-1.6040)
Current Acc.	0.0005	-0.0003	0.0000	0.0003	-0.0001	0.0012	-0.0090
	(1.1081)	(-0.7269)	(-0.0577)	(1.5442)	(-0.0503)	(1.5118)	(-1.1507)
GDP	-0.1976	-0.1788	-0.1559	-0.0370	-0.0018	0.1016	0.2506
	(-0.9846)	(-0.7700)	(-0.9804)	(-0.1917)	(-0.0045)	(0.3688)	(1.4047)
Inflation	0.0000	0.0039**	-0.0001	0.0009	0.0042	0.0002	0.0021**
	(0.0056)	(2.2717)	(-0.0474)	(0.3694)	(1.2357)	(0.1540)	(1.9972)
Short-term r	-0.0013	-0.0002	-0.0007	-0.0030***	-0.0145	0.0001	0.0012
	(-0.8583)	(-0.1172)	(-0.4217)	(-2.7971)	(-1.328)	(0.0696)	(0.8202)
Unemployment	-0.0007	0.0067**	0.0031**	-0.0005	0.0007	-0.0088**	0.0061
	(-0.4007)	(2.2915)	(2.1633)	(-0.4477)	(0.1374)	(-2.5674)	(1.3538)
Depreciation	0.0832	0.4836***	0.4578***	0.4445***	0.2803*	0.4934***	-
	(1.1784)	(8.6212)	(8.9903)	(7.8827)	(1.6629)	(9.8081)	-
Global factor	0.5253***	0.9959***	1.0955***	0.7462***	0.9784***	0.8486***	0.7139***
	(11.1627)	(24.5950)	(33.4741)	(18.0246)	(9.4693)	(18.2597)	(16.6908)
γ_j(GARCH M)	0.8138	0.8452	-2.9533	-4.4678	-0.1439	2.3060	1.5411
	(0.1887)	(0.1864)	(-0.5365)	(-0.7418)	(-0.0686)	(0.4846)	(0.6100)

This table reports the estimation results of model: $r_{j,t} = \alpha_j + \beta_j r_{j,t-1} + \gamma_j h_{j,t} + \sum_{\pi=1}^{n} \kappa_{j,\pi} I_{j,\pi,t} + \sum_{i=1}^{I} \delta_{i,j} \hat{e}_{i,t} + v_{j,t}$; $h_{j,t} = \omega_j + a_j v_{j,t-1}^2 + b_j h_{j,t-1} + \sum_{i=1}^{I} \lambda_{i,j} \hat{e}_{i,t}^2 + f_j T_j v_{j,t-1}^2$ where $v_{j,t} | \Omega_{t-1} \sim N(0, h_{j,t})$. $r_{j,t}$ is the log-transformed banking sector index of market j at time t. $I_{j,\pi,t}$ denotes macro-fundamental variables for market j at time t. n denotes the number of fundamental factors. $\hat{e}_{i,t}$ is the estimated residual of innovative country i in the first stage model. $\delta_{i,j}$ is the transmission coefficient of index j in response to the unexpected innovation from market i. $\lambda_{i,j}$ is the volatility transmission coefficient, which captures the dynamics of volatility in response to the unexpected innovations from the other market. T_j denotes a threshold dummy variable. $T_j = 1$ when the innovation at time t-1 is negative and 0 otherwise. $h_{j,t}$ is the conditional variance. Ω_{t-1} is the information matrix at time t-1. The test hypothesis is H_0: $\delta_{i,j} \leq 0$; H_1: $\delta_{i,j} > 0$. Z-statistics are in parentheses. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 6 GARCH Tests of Marginal Contagion during the Subprime Credit Crisis

Panel A: Transmissions of innovation

	Responding market						
Innovative market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
$\delta_{1,j}$(CN)		0.0488	-0.0736*	0.1106**	0.0729	0.0116	0.3722***
		(0.7594)	(-1.839)	(2.3293)	(0.5000)	(0.1776)	(6.2483)
$\delta_{2,j}$(FR)	0.0903		0.3444***	0.2001***	-0.2322	0.2720***	0.1321**
	(1.5205)		(8.5738)	(4.9032)	(-1.6367)	(4.4122)	(2.5358)
$\delta_{3,j}$(GE)	-0.0245	0.2794***		0.3190***	0.3124**	0.0608	0.1571***
	(-0.4677)	(4.4641)		(6.7264)	(2.3176)	(1.0590)	(3.7404)
$\delta_{4,j}$(IT)	0.0711	0.3289***	0.3332***		-0.0262	0.2235***	-0.0725
	(1.1629)	(5.1013)	(7.3194)		(-0.1742)	(3.5098)	(-1.5465)
$\delta_{5,j}$(JP)	0.0186	0.0156	0.0352**	-0.0174		0.0122	0.0194
	(1.1342)	(0.5834)	(1.9973)	(-0.8347)		(0.8524)	(0.9449)
$\delta_{6,j}$(UK)	0.0240	0.2340***	0.0494	0.2692***	-0.0214		0.1081*
	(0.3862)	(3.5237)	(0.9758)	(4.7313)	(-0.1509)		(1.8258)
$\delta_{7,j}$(US)	0.2872***	0.2113***	0.2169***	-0.0355	-0.1307	0.1304*	
	(4.8208)	(2.8303)	(4.8399)	(-0.6629)	(-0.8324)	(1.8052)	

Panel B: Marginal contagion effect during the subprime crisis

	Responding market						
Innovative market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
$d\delta_{1,j}$(CN)		-0.0230	0.0300	-0.1895*	0.3070	0.2071	0.4603***
		(-0.1456)	(0.3438)	(-1.9131)	(1.2005)	(1.4234)	(2.9081)
$d\delta_{2,j}$(FR)	-0.0503		-0.0457	0.0689	0.1403	0.0132	0.2964**
	(-0.3478)		(-0.5176)	(0.7178)	(0.6287)	(0.1299)	(2.3367)
$d\delta_{3,j}$(GE)	-0.0885	-0.0403		-0.1099	-0.6179***	0.1415	-0.0766
	(-0.6417)	(-0.2836)		(-1.0783)	(-2.6705)	(1.4995)	(-0.5185)
$d\delta_{4,j}$(IT)	-0.1549	0.0204	-0.0659		0.6041**	0.0211	0.1369
	(-1.1168)	(0.1124)	(-0.6685)		(2.4178)	(0.1570)	(0.7891)
$d\delta_{5,j}$(JP)	0.0536	0.0236	-0.0942*	0.1317**		0.0126	-0.0942
	(0.8792)	(0.3036)	(-1.8858)	(2.3198)		(0.2297)	(-1.0149)
$d\delta_{6,j}$(UK)	0.0830	0.0642	0.2163**	-0.1079	0.1903		0.1789
	(0.6509)	(0.4255)	(2.1898)	(-0.8225)	(0.8641)		(1.3063)
$d\delta_{7,j}$(US)	0.0918	0.0504	-0.1714**	-0.0088	0.0327	0.0059	
	(1.0103)	(0.4698)	(-2.554)	(-0.1093)	(0.1636)	(0.0576)	

Panel C: Transmissions of volatility of innovations

	Responding market						
Innovative market	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
$\lambda_{1,j}$(CN)		0.0099	-0.0075	0.0020	0.1994	0.0873**	0.1530***
		(0.1936)	(-1.1209)	(0.1406)	(-1.2615)	(2.5166)	(4.1954)
$\lambda_{2,j}$(FR)	0.0231		0.0042	0.0089	-0.0200	0.0543**	-0.0023
	(0.5961)		(0.6705)	(0.4271)	(-0.2251)	(2.1630)	(-0.1525)

$\lambda_{3,j}$(GE)	0.0214	-0.0018		-0.0066	0.2307**	-0.0358*	-0.0183**
	(0.9228)	(-0.0356)		(-0.6755)	(-2.3005)	(-1.9339)	(-1.9801)
$\lambda_{4,j}$(IT)	0.0209	0.0110	0.0070		0.0072	0.0735*	-0.0567***
	(0.8129)	(0.3597)	(0.9911)		(-0.0854)	(1.8950)	(-6.0233)
$\lambda_{5,j}$(JP)	-0.0146***	-0.0074	0.0020**	0.0037*		-0.0054*	0.0115***
	(-7.7894)	(-1.1902)	(2.2555)	(1.6496)		(-1.6861)	(3.3308)
$\lambda_{6,j}$(UK)	0.0267	0.0097	0.0123*	0.0083	-0.1030		0.1256***
	(0.8590)	(0.1867)	(1.9070)	(0.5494)	(-1.6129)		(4.9900)
$\lambda_{7,j}$(US)	0.0190	0.0111	0.0025	0.0033	0.0032	-0.0176*	
	(1.2608)	(0.5857)	(0.8282)	(0.6060)	-0.0843	(-1.8599)	
a_j(ARCH)	0.0318	0.1184	-0.0862***	0.1836**	0.1679**	0.0249	-0.0649**
	(0.7643)	(1.6145)	(-2.6648)	(2.1782)	(2.2907)	(0.5468)	(-2.1067)
b_j(GARCH)	0.4010***	0.4019***	1.0087***	0.8211***	0.4385***	0.6342***	0.6328***
	(3.6237)	(2.7225)	(43.4876)	(12.3068)	(6.2703)	(7.5156)	(11.5505)
f_j(Asymmetry)	0.0736	0.2517	0.0262	-0.1570*	-0.0474	-0.0074	0.1028*
	(1.1232)	(1.5657)	(0.9368)	(-1.7429)	(-0.3958)	(-0.0929)	(1.8505)

Panel D: Sensitivities to fundamental factors

	Responding market						
Fundamental factors	CN(j=1)	FR(j=2)	GE(j=3)	IT(j=4)	JP(j=5)	UK(j=6)	US(j=7)
Lagged R_j	-0.1227***	-0.0653*	-0.1146***	-0.0943***	-0.0959**	-0.1468***	-0.2379***
	(-2.9788)	(-1.9569)	(-5.3173)	(-3.2607)	(-2.0060)	(-4.4924)	(-7.2016)
Capital Acc.	-0.0025	0.0000	0.0000	-0.0001	-0.0004	-0.0019**	0.0003
	(-0.7659)	(-0.2069)	(-0.5490)	(-0.9923)	(-0.8223)	(-2.0753)	(0.7668)
CPI	-0.1309	-0.4205	-0.4022**	-0.4558	-0.5193	-0.2324	-0.2452
	(-0.6326)	(-1.2945)	(-2.3725)	(-0.8704)	(-0.8396)	(-0.9029)	(-1.3983)
Current Acc.	0.0009**	-0.0009**	-0.0002	0.0002	0.0001	0.0013	-0.0114
	(2.1445)	(-2.0226)	(-0.3845)	(1.1774)	(0.0197)	(1.4429)	(-1.398)
GDP	-0.1316	-0.0470	-0.1352	0.0470	0.1798	0.0126	0.2606
	(-0.6141)	(-0.1792)	(-0.8612)	(0.2522)	(0.4740)	(0.0475)	(1.2818)
Inflation	0.0003	0.0003	-0.0003	0.0011	0.0003	0.0001	0.0016
	(0.2343)	(0.1283)	(-0.2288)	(0.4772)	(0.0750)	(0.0470)	(1.5325)
Short-term r	-0.0001	-0.0009	-0.0008	-0.0024**	-0.0149	-0.0001	0.0017
	(-0.1001)	(-0.4294)	(-0.5239)	(-2.4945)	(-1.2612)	(-0.0381)	(1.1486)
Unemployment	0.0001	0.0004	0.0029**	0.0004	0.0001	-0.0071**	0.0074*
	(0.0477)	(0.1032)	(2.1088)	(0.3876)	(0.0143)	(-2.0575)	(1.6505)
Depreciation	-0.0019	0.2150***	0.4493***	0.4321***	0.2137	0.5321***	-
	(-0.0268)	(2.9355)	(9.3220)	(7.4749)	(1.1438)	(8.7418)	-
Global factor	0.4093***	0.5685***	1.0724***	0.7584***	0.9198***	0.8644***	0.6999***
	(8.7292)	(10.7653)	(33.0697)	(19.1764)	(9.6828)	(16.1056)	(14.9181)
γ_j(GARCH M)	0.0150	0.0260	-0.7154	-8.7059	0.8490	1.2225	4.4037
	(0.0029)	(0.0059)	(-0.1355)	(-1.4389)	(0.2556)	(0.2380)	(1.3003)

This table reports the estimation results of model $r_{j,t} = \alpha_j + \beta_j r_{j,t-1} + \gamma_j h_{j,t} + \sum_{\pi=1}^{n} \kappa_{j,\pi} I_{j,\pi,t} + \sum_{i=1}^{I} (\delta_{i,j} + d\delta_{i,j} D_t)\hat{e}_{i,t} + v_{j,t}$; $h_{j,t} = \omega_j + a_j v_{j,t-1}^2 + b_j h_{j,t-1} + \sum_{i=1}^{I} \lambda_{i,j} \hat{e}_{i,t}^2 + f_j T_j v_{j,t-1}^2$ where

$v_{j,t}|\Omega_{t-1} \sim N(0, h_{j,t})$. $r_{j,t}$ is the log-transformed banking sector index of market j at time t. $I_{j,\pi,t}$ denotes macro-fundamental variables for market j at time t. n denotes the number of fundamental factors. $\hat{e}_{i,t}$ is the estimated residual of innovative country i in the first stage model. $\delta_{i,j}$ is the transmission coefficient of index j in response to the unexpected innovation from market i. $\lambda_{i,j}$ is the volatility transmission coefficient, which captures the dynamics of volatility in response to the unexpected innovations from the other market. $d\delta_{i,j}$ denotes the additional contagion effect from the subprime credit crisis. $D_t = 1$ if the time period is from July 27, 2007 to January 5, 2009; otherwise, $D_t = 0$. T_j denotes a threshold dummy variable. $T_j = 1$ when the innovation at time t-1 is negative and 0 otherwise. $h_{j,t}$ is the conditional variance. Ω_{t-1} is the information matrix at time t-1. The test hypothesis is H_0: $d\delta_{i,j} \leq 0$; H_1: $d\delta_{i,j} > 0$. Z-statistics are in parentheses. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 7 VAR Tests of Stock Indices in Response to Fundamental Factors

	CN	FR	GE	IT	JP	UK	US
C	0.1309	-0.0905	0.2806	0.2790	0.4833	-0.2074	-0.2983
	(0.6500)	(-0.3100)	(1.0400)	(1.2200)	(1.3500)	(-0.8100)	(-0.8800)
$r^{CN}_{L=1,t}$	-0.2743***	0.2820***	0.0661	0.1019	-0.2846**	-0.0126	0.2377**
	(-4.3500)	(3.0800)	(0.7800)	(1.4200)	(-2.5200)	(-0.1600)	(2.2400)
$r^{FR}_{L=1,t}$	0.0367	-0.3014***	0.0364	0.0681	0.0930	-0.1216	0.1577
	(0.5500)	(-3.0900)	(0.4000)	(0.8900)	(0.7700)	(-1.4200)	(1.3900)
$r^{GE}_{L=1,t}$	-0.0520	0.2004**	-0.0001	0.1253	0.0958	0.0217	0.3015***
	(-0.7600)	(2.0200)	(0.0000)	(1.6100)	(0.7800)	(0.2500)	(2.6200)
$r^{IT}_{L=1,t}$	0.0178	-0.3792***	-0.1594*	-0.3951***	-0.0290	-0.0816	-0.4254***
	(0.2600)	(-3.8600)	(-1.7500)	(-5.1300)	(-0.2400)	(-0.9500)	(-3.7400)
$r^{JP}_{L=1,t}$	0.0172	-0.0762*	-0.0174	-0.0225	-0.1686***	0.0153	-0.0186
	(0.6100)	(-1.8700)	(-0.4600)	(-0.7000)	(-3.3600)	(0.4300)	(-0.3900)
$r^{UK}_{L=1,t}$	0.0128	0.3792***	0.0003	0.0131	-0.1668	-0.0236	0.0643
	(0.2100)	(4.2100)	(0.0000)	(0.1900)	(-1.5000)	(-0.3000)	(0.6200)
$r^{US}_{L=1,t}$	-0.0336	-0.2676***	-0.1169*	-0.0870	0.1386	-0.0733	-0.6609***
	(-0.7000)	(-3.8200)	(-1.8000)	(-1.5800)	(1.6100)	(-1.2000)	(-8.1400)
$r^{CN}_{L=2,t}$	-0.3053***	-0.1644*	-0.1421	-0.0757	-0.2169*	-0.1315	-0.2816***
	(-4.7300)	(-1.7500)	(-1.6400)	(-1.0300)	(-1.8800)	(-1.6100)	(-2.5900)
$r^{FR}_{L=2,t}$	-0.0142	-0.0244	0.0407	0.1917***	0.3694***	-0.0602	-0.0543
	(-0.2200)	(-0.2600)	(0.4700)	(2.6400)	(3.2400)	(-0.7400)	(-0.5100)
$r^{GE}_{L=2,t}$	0.1004	0.0949	0.0116	0.0521	0.1202	0.2188***	0.1034
	(1.5300)	(1.0000)	(0.1300)	(0.7000)	(1.0300)	(2.6300)	(0.9400)
$r^{IT}_{L=2,t}$	-0.0420	0.0048	0.0579	-0.0540	-0.1459	-0.1330	0.1488
	(-0.5300)	(0.0400)	(0.5500)	(-0.6000)	(-1.0400)	(-1.3300)	(1.1200)
$r^{JP}_{L=2,t}$	-0.0119	0.0249	0.0351	-0.0366	-0.1503***	0.0508	0.0345
	(-0.4100)	(0.5900)	(0.9000)	(-1.1100)	(-2.8900)	(1.3700)	(0.7100)
$r^{UK}_{L=2,t}$	0.0292	-0.0141	0.0334	-0.1698**	-0.2281*	-0.1198	-0.0451
	(0.4200)	(-0.1400)	(0.3600)	(-2.1500)	(-1.8400)	(-1.3600)	(-0.3900)
$r^{US}_{L=2,t}$	0.0626	-0.1747**	-0.0807	-0.0385	-0.0067	-0.0734	-0.0829
	(1.3000)	(-2.4900)	(-1.2400)	(-0.7000)	(-0.0800)	(-1.2000)	(-1.0200)
CNcap	-0.0134	-0.0323**	-0.0218*	-0.0263**	0.0103	-0.0184	-0.0235
	(-1.4000)	(-2.3300)	(-1.7000)	(-2.4200)	(0.6000)	(-1.5100)	(-1.4600)
FRcap	0.0000	0.0005*	0.0000	0.0000	-0.0006**	0.0002	0.0005*
	(0.0400)	(1.7900)	(0.1400)	(0.0600)	(-1.9900)	(1.1000)	(1.8300)
GEcap	-0.0001	-0.0001	-0.0001	-0.0001	-0.0003	0.0000	0.0000
	(-1.0400)	(-0.6900)	(-0.6500)	(-0.9600)	(-1.4600)	(0.0500)	(-0.1400)
ITcap	-0.0002	-0.0002	-0.0003	-0.0002	0.0005	-0.0002	-0.0002
	(-0.7600)	(-0.7100)	(-1.1500)	(-0.9200)	(1.1700)	(-0.7100)	(-0.4600)
JPcap	-0.0004	-0.0009**	-0.0002	-0.0005	-0.0003	-0.0002	-0.0004
	(-1.4100)	(-2.0700)	(-0.5300)	(-1.3500)	(-0.6000)	(-0.5800)	(-0.7900)
UKcap	-0.0045	-0.0072	-0.0048	-0.0041	-0.0028	-0.0047	-0.0088

	(-1.3900)	(-1.5100)	(-1.1000)	(-1.0900)	(-0.4700)	(-1.1300)	(-1.6000)
UScap	-0.0006	0.0000	-0.0011	-0.0016	0.0032	0.0012	-0.0019
	(-0.4400)	(-0.0200)	(-0.5500)	(-1.0000)	(1.2500)	(0.6700)	(-0.7800)
CNcpi	0.3507	0.0853	-0.1116	-0.5176	1.6214	0.8000	-1.0692
	(0.5900)	(0.1000)	(-0.1400)	(-0.7700)	(1.5400)	(1.0700)	(-1.0800)
FRcpi	2.7780***	-1.2798	-1.8036	-1.0903	4.9932***	-1.7989	0.5674
	(2.9400)	(-0.9300)	(-1.4200)	(-1.0200)	(2.9600)	(-1.5000)	(0.3600)
GEcpi	0.1347	1.2420*	-0.1627	0.6586	0.4860	0.6180	0.5519
	(0.2800)	(1.7500)	(-0.2500)	(1.1800)	(0.5600)	(1.0000)	(0.6700)
ITcpi	-0.4261	-4.1695**	0.3807	-0.5343	-3.1980	-0.0819	0.8994
	(-0.3200)	(-2.1600)	(0.2100)	(-0.3500)	(-1.3400)	(-0.0500)	(0.4000)
JPcpi	0.0214	2.2669**	1.5504*	1.1861	-2.6762**	0.3308	-0.2751
	(0.0300)	(2.3600)	(1.7400)	(1.5700)	(-2.2600)	(0.3900)	(-0.2500)
UKcpi	-1.8193***	-0.4869	1.3610	0.8137	-1.1687	0.4972	-0.9824
	(-2.9100)	(-0.5400)	(1.6200)	(1.1400)	(-1.0500)	(0.6300)	(-0.9400)
UScpi	-1.7029**	-0.6177	0.0753	0.1976	0.6203	-1.3596	-1.1229
	(-2.5500)	(-0.6400)	(0.0800)	(0.2600)	(0.5200)	(-1.6000)	(-1.0000)
CNcur	0.0000	0.0003	0.0003	0.0020	-0.0017	0.0000	-0.0031
	(0.0200)	(0.1900)	(0.2000)	(1.5100)	(-0.8200)	(0.0100)	(-1.6200)
FRcur	0.0028***	0.0012	0.0009	0.0009	0.0027	-0.0009	-0.0003
	(2.7000)	(0.8000)	(0.6400)	(0.7400)	(1.4700)	(-0.6700)	(-0.1700)
GEcur	0.0027	0.0012	0.0017	0.0035*	0.0068**	0.0032	0.0007
	(1.6400)	(0.5200)	(0.7900)	(1.8700)	(2.3400)	(1.5200)	(0.2400)
ITcur	-0.0001	0.0003	-0.0003	0.0006*	0.0003	-0.0002	-0.0002
	(-0.4500)	(0.6600)	(-0.7700)	(1.7700)	(0.5100)	(-0.4800)	(-0.3100)
JPcur	-0.0003	0.0022	-0.0001	-0.0021	-0.0004	0.0009	0.0017
	(-0.1200)	(0.6700)	(-0.0400)	(-0.800)	(-0.1000)	(0.3200)	(0.4400)
UKcur	-0.0018	0.0006	0.0005	0.0029	-0.0023	0.0017	0.0004
	(-0.7700)	(0.1900)	(0.1500)	(1.1100)	(-0.5700)	(0.5700)	(0.1100)
UScur	0.0019	0.0622*	0.0275	0.0216	0.0005	0.0553*	-0.0189
	(0.0800)	(1.7500)	(0.8400)	(0.7800)	(0.0100)	(1.7800)	(-0.4600)
CNgdp	0.1085	0.8083	-0.1708	0.7998	-1.0476	2.0968*	0.3761
	(0.1100)	(0.5700)	(-0.1300)	(0.7200)	(-0.6000)	(1.7000)	(0.2300)
FRgdp	1.1440	-1.0130	-0.7974	-0.3445	2.5384*	-1.0611	0.6166
	(1.4600)	(-0.8900)	(-0.7600)	(-0.3900)	(1.8200)	(-1.0700)	(0.4700)
GEgdp	-1.0379	0.9988	-0.6846	1.1244	0.1869	1.9990*	-1.0628
	(-1.2300)	(0.8100)	(-0.6000	(1.1700)	(0.1200)	(1.8600)	(-0.7500)
ITgdp	-1.5584	-0.7025	0.7583	-0.9154	2.2950	-1.8237	-1.1215
	(-1.5400)	(-0.4800)	(0.5600)	(-0.7900)	(1.2700)	(-1.4200)	(-0.6600)
JPgdp	0.6587	0.9418	-0.0638	0.1470	-3.7492***	0.1065	1.1448
	(1.3500)	(1.3300)	(-0.1000)	(0.2600)	(-4.2900)	(0.1700)	(1.3900)
UKgdp	0.3670	2.2401*	2.2778**	1.8991**	-1.5905	0.5527	1.7877
	(0.4400)	(1.8600)	(2.0500)	(2.0200)	(-1.0800)	(0.5300)	(1.2800)

USgdp	1.0411**	-0.0220	-0.3336	-0.5076	-1.5137	0.6923	0.7893
	(1.9600)	(-0.0300)	(-0.4700)	(-0.8400)	(-1.600)	(1.0300)	(0.8800)
CNinf	-0.0037	-0.0055	-0.0099	-0.0001	-0.0240***	-0.0117**	-0.0050
	(-0.8200)	(-0.8400)	(-1.6300)	(-0.0200)	(-2.9700)	(-2.0400)	(-0.6700)
FRinf	0.0035	-0.0199	-0.0035	0.0065	-0.0618***	0.0216*	0.0037
	(0.3500)	(-1.3800)	(-0.2600)	(0.5700)	(-3.4800)	(1.7100)	(0.2200)
GEinf	-0.0215***	0.0124	0.0108	0.0074	-0.0171	-0.0068	-0.0306**
	(-2.6200)	(1.0500)	(0.9800)	(0.7900)	(-1.1700)	(-0.6500)	(-2.2200)
ITinf	0.0038	-0.0172	-0.0322*	-0.0367**	0.0674***	-0.0457***	-0.0136
	(0.3000)	(-0.9300)	(-1.8900)	(-2.5500)	(2.9700)	(-2.8400)	(-0.6400)
JPinf	-0.0062	-0.0080	-0.0028	0.0062	-0.0331***	-0.0128	-0.0131
	(-0.8600)	(-0.7700)	(-0.2900)	(0.7600)	(-2.5800)	(-1.4100)	(-1.0900)
UKinf	0.0152**	0.0198**	0.0142*	0.0155**	0.0170	0.0258***	0.0020
	(2.5000)	(2.2500)	(1.7400)	(2.2400)	(1.5600)	(3.3400)	(0.2000)
USinf	0.0100	0.0264***	0.0145	0.0035	0.0256**	0.0166*	0.0264**
	(1.4400)	(2.6000)	(1.5400)	(0.4400)	(2.0500)	(1.8800)	(2.2500)
CN r	-0.0146*	-0.0186*	-0.0036	-0.0041	-0.0014	-0.0077	-0.0210*
	(-1.9100)	(-1.6800)	(-0.3600)	(-0.4700)	(-0.1000)	(-0.8000)	(-1.6400)
FR r	0.0177	0.0449**	0.0167	-0.0400**	-0.0232	0.0692***	0.0668***
	(1.1700)	(2.0500)	(0.8200)	(-2.3300)	(-0.8600)	(3.6100)	(2.6300)
GE r	-0.0148	-0.0181	0.0057	0.0364**	0.0205	-0.0152	-0.0221
	(-1.1200)	(-0.9400)	(0.3200)	(2.4200)	(0.8700)	(-0.9100)	(-1.0000)
IT r	0.0000	-0.0001	0.0040	-0.0047	-0.0055	-0.0030	0.0063
	(0.0000)	(-0.0200)	(0.7400)	(-1.0400)	(-0.7700)	(-0.6000)	(0.9500)
JP r	-0.0539	-0.0557	-0.0372	-0.1323***	0.0239	-0.0690	-0.0557
	(-1.2800)	(-0.9100)	(-0.6600)	(-2.7700)	(0.3200)	(-1.3000)	(-0.7900)
UK r	0.0056	-0.0203	-0.0393***	-0.0068	-0.0118	-0.0299**	0.0049
	(0.6000)	(-1.4900)	(-3.1100)	(-0.6300)	(-0.7000)	(-2.5100)	(0.3100)
US r	-0.0009	-0.0146	-0.0075	-0.0070	0.0193	-0.0172*	-0.0307**
	(-0.1200)	(-1.3300)	(-0.7400)	(-0.8100)	(1.4300)	(-1.7900)	(-2.4100)
CNue	0.0005	0.0392**	0.0036	0.0060	-0.0336	0.0109	0.0323
	(0.0400)	(2.2400)	(0.2200)	(0.4400)	(-1.5600)	(0.7100)	(1.5900)
FRue	-0.0076	-0.0064	-0.0171	-0.0441**	0.0277	-0.0119	-0.0143
	(-0.4300)	(-0.2500)	(-0.7200)	(-2.2000)	(0.8800)	(-0.5300)	(-0.4800)
GEue	-0.0053	0.0067	0.0151	0.0037	-0.0343	0.0248	0.0325
	(-0.4200)	(0.3700)	(0.8900)	(0.2600)	(-1.5100)	(1.5400)	(1.5200)
ITue	-0.0086	-0.0265	-0.0239	-0.0152	0.0086	-0.0192	-0.0475**
	(-0.7200)	(-1.5300)	(-1.4900)	(-1.1200)	(0.4000)	(-1.2700)	(-2.3700)
JPue	0.0247*	0.0422**	0.0318*	0.0262*	-0.0010	0.0282	0.0222
	(1.8000)	(2.1200)	(1.7200)	(1.6700)	(-0.0400)	(1.6100)	(0.9600)
UKue	0.0122	0.0142	-0.0207	0.0439	-0.1130***	0.0229	0.0585
	(0.5100)	(0.4100)	(-0.6400)	(1.6100)	(-2.6400)	(0.7500)	(1.4500)
USue	-0.0298*	-0.0389*	-0.0039	-0.0181	0.0561**	-0.0127	-0.0290

	(-1.9000)	(-1.7100)	(-0.1800)	(-1.0200)	(2.0100)	(-0.6400)	(-1.1000)
CNdep	0.0381	-0.2853	-0.3023*	-0.2597*	-0.1023	-0.3470**	-0.5512***
	(0.3200)	(-1.6400)	(-1.8700)	(-1.9000)	(-0.4800)	(-2.2800)	(-2.7300)
FRdep	28.5095	-3.6665	-3.4821	-28.4844	96.3237*	-23.7781	68.2032
	(0.9400)	(-0.0800)	(-0.0900)	(-0.8300)	(1.7800)	(-0.6200)	(1.3400)
GEdep	-24.7097	4.2993	7.0078	31.8870	-91.7720*	25.1246	-67.6423
	(-0.8100)	(0.1000)	(0.1700)	(0.9200)	(-1.6900)	(0.6500)	(-1.3200)
ITdep	-3.5706	0.0538	-2.8575	-2.7841	-4.0244	-0.8942	0.1920
	(-1.6200)	(0.0200)	(-0.9600)	(-1.1100)	(-1.0200)	(-0.3200)	(0.0500)
JPdep	0.4552***	0.4181***	0.5349***	0.5472***	0.5401***	0.7404***	0.5020***
	(4.7700)	(3.0200)	(4.1600)	(5.0400)	(3.1700)	(6.1100)	(3.1300)
UKdep	-0.1615	-0.0198	-0.1758	-0.1732	-0.3547	-0.0011	-0.2881
	(-1.2400)	(-0.1000)	(-1.0000)	(-1.1600)	(-1.5200)	(-0.0100)	(-1.3100)
Global fac	0.6418***	0.8928***	0.9044***	0.6337***	0.9789***	0.7196***	0.6278***
	(11.4500)	(10.9700)	(12.0000)	(9.9400)	(9.7800)	(10.1200)	(6.6600)

This table reports the estimation results of model: $R_t = C + \sum_{L=1}^{m} \phi_L R_{L,t} + \sum_{\pi=1}^{n} \Phi_\pi I_{\pi,t} + \eta_t$; $R_t \equiv \{r_t^{CN}, r_t^{FR}, r_t^{GE}, r_t^{IT}, r_t^{JP}, r_t^{UK}, r_t^{US}\}$; $R_{L,t} \equiv \{r_{L,t}^{CN}, r_{L,t}^{FR}, r_{L,t}^{GE}, r_{L,t}^{IT}, r_{L,t}^{JP}, r_{L,t}^{UK}, r_{L,t}^{US}\}'$; $I_{\pi,t} \equiv \{i_{\pi,t}^{CN}, i_{\pi,t}^{FR}, i_{\pi,t}^{GE}, i_{\pi,t}^{IT}, i_{\pi,t}^{JP}, i_{\pi,t}^{UK}, i_{\pi,t}^{US}\}'$ with $E(\eta_t) = 0$; $E(\eta_t, \eta_t') = \sum$; $E(\eta_t, \eta_s') = 0$ if $t \neq s$. r_t is a vector of DataStream banking sector log index. R_t is a transposed vector of log indices in G-7 countries. $R_{L,t}$ is a transposed vector of lagged log indices. ϕ_L is a vector of the coefficients of lagged log indices. n denotes the number of fundamental factors. $I_{\pi,t}$ is a transposed vector of exogenous fundamental variables for G-7 countries. Φ_π is a vector of the coefficients of fundamental variables. η_t is a vector of error terms. m denotes the autoregressive order. We estimate m with the autoregressive order of two according to the Hannan-Quinn information criterion. Z-statistics are in parentheses. '*', '**' and '***' indicate significance levels of 10%, 5% and 1%, respectively.

Table 8 T-Tests of Unadjusted Correlation Coefficients

Country	Tranquil ρ^l	Turmoil ρ^h	Full ρ	Test Stat	Increase
CN					
FR	0.3365	0.5188	0.4236	1.6881	Y
GE	0.2384	0.5106	0.3657	2.4093	Y
IT	0.3092	0.4024	0.3494	0.8034	N
JP	0.1117	0.2207	0.1462	0.8438	N
UK	0.2086	0.5649	0.3805	3.2204	Y
US	0.4682	0.7081	0.5947	2.8243	Y
FR					
CN	0.3365	0.5188	0.4236	1.6881	Y
GE	0.7037	0.8034	0.7539	1.7561	Y
IT	0.6968	0.6852	0.6928	-0.1669	N
JP	0.0374	0.1250	0.0665	0.6641	N
UK	0.6918	0.7670	0.7317	1.2159	N
US	0.5917	0.7357	0.6661	1.9595	Y
GE					
CN	0.2384	0.5106	0.3657	2.4093	Y
FR	0.7037	0.8034	0.7539	1.7561	Y
IT	0.6796	0.7051	0.6919	0.3678	N
JP	0.1684	0.0773	0.1343	-0.6961	N
UK	0.5621	0.7997	0.6784	3.4734	Y
US	0.5423	0.6445	0.5926	1.1916	N
IT					
CN	0.3092	0.4024	0.3494	0.8034	N
FR	0.6968	0.6852	0.6928	-0.1669	N
GE	0.6796	0.7051	0.6919	0.3678	N
JP	0.1016	0.1789	0.1250	0.5935	N
UK	0.6415	0.6722	0.6545	0.4066	N
US	0.4339	0.5137	0.4626	0.7747	N
JP					
CN	0.1117	0.2207	0.1462	0.8438	N
FR	0.0374	0.1250	0.0665	0.6641	N
GE	0.1684	0.0773	0.1343	-0.6961	N
IT	0.1016	0.1789	0.1250	0.3678	N
UK	0.0537	0.1226	0.0763	0.5220	N
US	0.0855	0.1259	0.0952	0.3075	N
UK					
CN	0.2086	0.5649	0.3805	3.2204	Y
FR	0.6918	0.7670	0.7317	1.2159	N
GE	0.5621	0.7997	0.6784	3.4734	Y
IT	0.6415	0.6722	0.6545	0.4066	N
JP	0.0537	0.1789	0.0763	0.5220	N
US	0.4499	0.6921	0.5843	2.7616	Y
US					
CN	0.4682	0.7081	0.5947	2.8243	Y

FR	0.5917	0.7357	0.6661	1.9595	Y
GE	0.5423	0.6445	0.5926	1.1916	N
IT	0.4339	0.5137	0.4626	0.7747	N
JP	0.0855	0.1259	0.0952	0.3075	N
UK	0.4499	0.6921	0.5843	2.7616	Y

This table reports unadjusted cross-market correlation coefficients for G-7 countries. The tranquil period is defined as January 7, 2002 to July 26, 2007. The turmoil period is defined as July 27, 2007 to January 5, 2009. The full period is the combination of the two sub-sample periods. The correlation coefficients are estimated using estimated residuals from the VAR model reported in Table 7. The coefficients are transformed with a Fisher transformation. In transformation, the correlation coefficients are approximately normally distributed with mean $\mu_t = \frac{1}{2} ln\left[\frac{1+\rho_{i,j}^t}{1-\rho_{i,j}^t}\right]$, and variance $\sigma_t^2 = \frac{1}{n_t - 3}$, where $t = h\ or l$ indicating the turmoil or tranquil period. $\rho_{i,j}^t$ denotes the correlation between country i and country j during the turmoil or tranquil period. n_t indicates the observations during the turmoil or tranquil period. The two-sample t-statistics are calculated with $t = \frac{\mu_h - \mu_l}{\sqrt{\sigma_h^2 + \sigma_l^2}}$. The critical value for the t-test at a 5% significance level is 1.65. Any test statistic greater than this critical value is recorded as a significant increase, denoted "Y"; otherwise, no increase, denoted "N". The test hypothesis is H_0: $\rho_{i,j}^l \geq \rho_{i,j}^h$; H_1: $\rho_{i,j}^l < \rho_{i,j}^h$.

Table 9 T-Tests of Heteroscedasticity-Adjusted Correlation Coefficients

Country	Tranquil ρ^l	Turmoil ρ^{h*}	Full ρ	Test Stat	Increase
CN					
FR	0.3365	0.3283	0.4236	-0.0693	N
GE	0.2384	0.3220	0.3657	0.6828	N
IT	0.3092	0.2442	0.3494	-0.5299	N
JP	0.1117	0.1286	0.1462	0.1283	N
UK	0.2086	0.3651	0.3805	1.2860	N
US	0.4682	0.4981	0.5947	0.2933	N
FR					
CN	0.3365	0.3245	0.4236	-0.1017	N
GE	0.7037	0.6065	0.7539	-1.2880	N
IT	0.6968	0.4695	0.6928	-2.6435	N
JP	0.0374	0.0711	0.0665	0.2542	N
UK	0.6918	0.5599	0.7317	-1.6439	N
US	0.5917	0.5232	0.6661	-0.7489	N
GE					
CN	0.2384	0.3241	0.3657	0.7000	N
FR	0.7037	0.6142	0.7539	-1.1949	N
IT	0.6796	0.4975	0.6919	-2.1232	N
JP	0.1684	0.0447	0.1343	-0.9423	N
UK	0.5621	0.6093	0.6784	0.5408	N
US	0.5423	0.4373	0.5926	-1.0413	N
IT					
CN	0.3092	0.2825	0.3494	-0.2200	N
FR	0.6968	0.5332	0.6928	-2.0031	N
GE	0.6796	0.5544	0.6919	-1.5314	N
JP	0.1016	0.1210	0.1250	0.1474	N
UK	0.6415	0.5197	0.6545	-1.3889	N
US	0.4339	0.3723	0.4626	-0.5534	N
JP					
CN	0.1117	0.2062	0.1462	0.7296	N
FR	0.0374	0.1166	0.0665	0.5995	N
GE	0.1684	0.0720	0.1343	-0.7361	N
IT	0.1016	0.1670	0.1250	0.5010	N
UK	0.0537	0.1143	0.0763	0.4587	N
US	0.0855	0.1174	0.0952	0.2424	N
UK					
CN	0.2086	0.3463	0.3805	1.1246	N
FR	0.6918	0.5418	0.7317	-1.8391	N
GE	0.5621	0.5834	0.6784	0.2386	N
IT	0.6415	0.4397	0.6545	-2.1712	N
JP	0.0537	0.0665	0.0763	0.0962	N
US	0.4499	0.4593	0.5843	0.0884	N
US					
CN	0.4682	0.3754	0.5947	-0.8504	N

FR	0.5917	0.4017	0.6661	-1.9151	N
GE	0.5423	0.3223	0.5926	-2.0543	N
IT	0.4339	0.2350	0.4626	-1.6934	N
JP	0.0855	0.0512	0.0952	-0.2590	N
UK	0.4499	0.3611	0.5843	-0.8008	N

This table reports heteroscedasticity-adjusted cross-market correlation coefficients for G-7 countries. The tranquil period is defined as January 7, 2002 to July 26, 2007. The turmoil period is defined as July 27, 2007 to January 5, 2009. The full period is the combination of the two sub-sample periods. The correlation coefficients are calculated using estimated residuals from the VAR model reported in Table 7.The correlations for the turmoil period are adjusted with the formula: $\rho_{i,j}^{h*} = \frac{\rho_{i,j}^{h}}{\sqrt{1+\delta\left[1-\left(\rho_{i,j}^{h}\right)^2\right]}}$, $\delta = \frac{\sigma_{xx}^{h}}{\sigma_{xx}^{l}} - 1$, where σ_{xx}^{h} and σ_{xx}^{l} are the variances of the crisis country x in the turmoil and tranquil periods, respectively. $\rho_{i,j}^{h}$ is the correlation between country i and j during the turmoil period. The adjusted correlation coefficients are then transformed with a Fisher transformation. In the transformation, the correlation coefficients are approximately normally distributed with mean $\mu_t = \frac{1}{2} ln\left[\frac{1+\rho_{i,j}^{t}}{1-\rho_{i,j}^{t}}\right]$, and variance $\sigma_t^2 = \frac{1}{n_t-3}$, where $t = h*\ orl$ indicating the turmoil or tranquil period. $\rho_{i,j}^{t}$ denotes the correlation between country i and country j during the turmoil or tranquil period. n_t indicates the observations during the turmoil or tranquil period.The two-sample t-statistics are calculated with $t = \frac{\mu_{h*}-\mu_l}{\sqrt{\sigma_{h*}^2+\sigma_l^2}}$. The critical value for the t-test at a 5% significance level is 1.65. Any test statistic greater than this critical value is recorded as a significant increase, denoted "Y"; otherwise, no increase, denoted "N". The test hypothesis is $H_0: \rho_{i,j}^{l} \geq \rho_{i,j}^{h*}$; $H_1: \rho_{i,j}^{l} < \rho_{i,j}^{h*}$.

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