Essays on Financial Market Interdependence

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To My Parents

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Lund, March 2012
Lu Liu

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Chapter 1

Introduction

1.1 Background

The structure of interdependence between financial markets plays a crucial role in the field of finance. The degree to which investors reduce their risks by diversifying portfolios relies on the degree of interdependence between asset returns. Over the past few decades, ties between economies, such as international trade, foreign direct investment and monetary integration, have been strengthened more than ever before and have provided fundamental drivers for ever-increasing interdependence among international financial markets. Thanks to deregulation and advances in technologies, the growth of financial market interdependence has gained momentum along with worldwide capital mobilization and global diversification. At the same time, the breadth and depth of financial market interdependence have been blamed for their domino effects during recent financial crises. Profound studies on the structure of interdependence among financial markets are therefore useful for policy makers and investors.

Interdependence, in this thesis, is defined as a general relationship between financial assets/markets in a broad sense. Financial market interdependence has been studied using many frameworks. For example, the dependence in the second-order moments of asset returns has received a great deal of attention in both theoretical and empirical works. Volatility spillover, correlations, and covariances among asset returns have been examined by using variants of multivariate models of generalized autoregressive conditional heteroskedasticity (GARCH). Important applications have been implemented by Ng (2000), Engle (2002), and Baele (2005).

Although volatility and correlation are the core factors in diversification, they represent a limited amount of risk and dependence in the scenarios of extreme events. The fat-tail feature prevailing in most financial time series calls for studies that go beyond the second-order moments of asset returns to examine the interdependence of extreme movements. For example, interdependence may appear as cross-border spillover of extreme shocks, which can be modelled by spillover of jump processes (Asgharian and Bengtsson, 2006, and Asgharian and Nossman, 2011) or Granger causality of extreme downside movements (Hong *et al.*, 2009, among other methods).

While the behaviour of interdependence has attracted a great deal of attention, it is also vital to understand the mechanisms or factors that drive the interdependence. The unobserved latent factors that drive assets to switch from a low volatility state to a high volatility state have been addressed using hidden Markov chains in Edwards and Susmel (2003) and Larsson (2007). In this context, interdependence is not only about correlations or spillovers, but is also about if the latent driving factors for different assets are related to one another. Furthermore, observable fundamental ties between economies, such as economic integration and monetary integration are found to be important explanatory variables for cross-border stock market interdependence (Wälti, 2011, and Forbes and Chinn, 2004).

This thesis looks into interdependence among financial markets from several angles using various econometric methodologies. The first essay studies the spillover of extreme downside risk in stock markets. The second essay examines the nonlinear dependence between stocks and commodity futures, which is reflected by the assets' regime switches governed by hidden Markov chains. The third essay investigates the channels of national stock market interdependence.

1.2 From volatility to extreme downside scenario

Over the past few decades, many researchers have probed the interdependence or spillover of volatility among financial assets and markets. According to the theory of portfolio selection (founded by Markowitz, 1952), a security's risk is addressed by variance or volatility. Portfolio optimization is accomplished by maximizing the mean given the variance or volatility of the portfolio. Therefore, volatility is an important factor for making investment decisions. However, measuring risk by volatility subjects the analysis to many limitations. Advances in risk measurements have been one of the main issues in finance for both academics and practitioners.

The mean–variance rule depends on such assumptions as normally distributed asset returns and constant correlations between assets over time. However, most financial time series are asymmetric rather than normally distributed. Therefore, the benefit and risk of an asset cannot be adequately described by the mean and volatility of the returns. On the other hand, in reality, investors have downside risk aversion, that is to say, they care more about downside losses than upside gains. Another limitation of volatility is that volatility, in practice, represents a small risk . In the presence of large adverse market movements (e.g., financial crises), a risk measure associated with extreme downside movement of asset returns is more sensible than volatility.

In the same year as Markowitz (1952), Roy (1952) proposed the safety-first principal, according to which investors minimize chances of large losses. Markowitz (1959) also recognized the limitations of measuring risk by variance and proposed semivariance, the deviation below mean, which has been widely used as an important measure for downside risk among later developed third-moment measures. In 1994, J. P. Morgan proposed a more recent risk measure for extreme downside risk, Value at Risk (VaR). Although not perfect, VaR has become a standard and popular measure of extreme downside risk. VaR (left-tail) is defined based on the (left-tail) cumulative probabilities of return distributions, which is related to the likelihood of extreme (downside) movement of asset returns. Intuitively, it measures how much a portfolio or asset can lose given a prespecified probability level within a period of time. Because of its conceptual simplicity and adequacy, Chapter 2 in this thesis adopts VaR to measure extreme downside risk.

Using the left-tail VaR as the extreme downside risk measure, Chapter 2 studies the spillover of extreme downside risk from major stock markets to smaller ones. The method used is inspired by the concept of Granger causality in risk (Hong *et al.*, 2009), where an extreme downside risk is defined as an event where asset return falls below the left-tail VaR. According to Hong *et al.* (2009), the return of one market Granger causes the return of another market *in risk* if the probability that the return of the latter market falls below its left-tail VaR can be predicted from the information of the former market. Based on the concept of Granger causality in risk, Chapter 2 proposes an extreme-value regression to predict the likelihood of extreme downside risk of a stock market in the Asian-Pacific region given the information of extreme downside risks of two large markets, the U.S. and the Japanese markets.

Chapter 2 not only examines the occurrence of spillover as most other studies do (Asgharian and Bengtsson, 2006, Baele and Soriano, 2010, and Asgharian and Nossman, 2011), it also quantifies and predicts the likelihood of an extreme downside movement. The extreme downside risks in the U.S. and Japanese markets are found to be significantly predictive for the extreme downside risks in the Asian-Pacific markets, which is important for investors to consider when diversifying portfolios among these markets.

Furthermore, Chapter 2 adds to the literature by investigating extreme downside risks and risk-spillover effects from a state-dependence perspective. By using a Markov-switching model, VaR is estimated conditional on the volatile–tranquil state of the market, as is the risk-spillover effect. On one hand, this is sensible for the sake of dynamic asset allocation because investors change their expectations and valuations based on market conditions. On the other hand, due to the presence of contagion in financial crises, it is crucial to understand the interdependence of extreme market shocks under different market conditions.

1.3 Dependence and diversification with regime switching

It is well accepted that financial assets barely follow the constant normal distributions assumed by standard portfolio-selection theory and may have abrupt changes. Many financial assets have periodic dynamics that switch from the tranquil to the volatile regime and then back. Therefore, dependence between assets' regime switching is an important aspect of financial market interdependence. Empirical studies have shown the need to recognize regime switches in asset pricing and portfolio selection. For example, according to Ang and Bekaert (2002), the economic costs of ignoring regimes when doing international portfolio diversification can be substantial and even larger than the cost of not diversifying.

The dependence of financial assets' regime-switching dynamics is twofold. First, risk management requires knowledge about how common the volatile regimes of different assets are and how long they last. It is desirable that the regime switching of invested assets be driven by different (latent) factors, or more strongly, that the switches of assets be completely unrelated. Second, it is also crucial to understand the behaviours of correlations between assets along with the regime switches. Correlations among international financial markets tend to be higher in the volatile regime than in the tranquil regime. This undermines the benefit of diversification at the time that is needed most.

One typical method to tackle the prevalence of regime switching in financial assets is using Markov-switching models based on Hamilton (1989), where asset return is allowed to be drawn from two or more distributions (regimes) and the switch of the distributions is governed by a latent Markov variable. Based on Hamilton (1989), Hamilton and Susmel (1994) developed a Markov-switching model with autoregressive conditional heteroskedasticity (ARCH) that allows for abrupt changes in the ARCH process parameters. The parameterization of Hamilton and Susmel (1994) is parsimonious and enables inference of the high- and low-volatility regimes of financial asset returns.

The empirical literature has adopted the Markov-switching models to study the dependence of regime-switching dynamics between time series variables including financial assets. For instance, Hamilton and Lin (1996) test the dependence between the stock market and the business cycle by examining the combined regimes of stock returns and industrial production growth using a bivariate Markov-switching model. They find that economic recession is a main factor driving stock market volatility. Similar methods have been applied in the studies of financial market dependence. For example, by using a bivariate Markov-switching ARCH model, Edwards and Susmel (2003) find interconnections between the volatility regimes of emerging markets' interest rates while Larsson (2007) investigates the dependence among stock and bond markets.

Inspired by Hamilton and Lin (1996) and Edwards and Susmel (2003), Chapter 3 of this thesis delves into the regime switching dependence (described earlier in this section) between U.S. stocks and commodity futures. Although commodity futures are known for their good diversification potential with stocks, most literature (e.g., Kat and Oomen, 2006, Büyüksahin *et al.*, 2010, and Chong and Miffre, 2010) consider only the correlations among these two types of assets. This thesis is the first to tackle the nonlinear regime dependence between these two assets. By using a bivariate Markov-switching ARCH model, Chapter 3 adds to the knowledge about the diversification benefit between stocks and commodity futures in the following notions. First, the regime switches of commodity futures are not driven by the same latent factors as the regime switches of the U.S. stocks. The regime-switching patterns of certain categories of commodity futures are even independent from the dynamic of stocks. Second, the regime when both the U.S. stocks and commodity futures are volatile is infrequent and short-lived. Third, correlations between the U.S. stocks and commodity futures are low across all the regimes compared with the correlations between the U.S. stocks and the weighted average stocks of all the other countries.

1.4 Channels of interdependence

Chapters 2 and 3 mainly deal with the extent of financial markets' interrelation. Although Chapter 3 tackles the hypotheses that markets' regime switches are driven by the same or related factors, one does not explicitly observe the factors. One must study the channels or factors of interdependence to understand markets' dependence behaviour. Chapter 4, the last chapter of this thesis, aims at the factors that drive the correlations among financial markets, specifically among national stock markets, by using the dynamic panel data estimation method.

The changes in interdependence among national stock markets rise from linkages between economies. Most studies focus on the impact of trade and financial integration. For example, Forbes and Chinn (2004) find bilateral trade to be the primary channel through which the largest financial markets affect other markets. Fratzscher (2002) and Wälti (2011) find that the elimination of exchange-rate volatility and the process of monetary unification contribute to stock market integration. Other market linkages have also received attention. An example is industrial structure, which is documented to be the most important factor in Roll (1992). Time-invariant channels such as geographical closeness are also found to increase stock market interdependence (Flavin *et al.*, 2002).

In line with the literature regarding the well-known driving factors, Chapter 4 finds the important role of an unconventional factor—information capacity. Large information capacity, which refers more available communication technologies, provides easier access to information and fosters information diffusion across markets. Chapter 4 contains a discussion about information capacity and finds its impact to be unnegligible on stock market correlations when other factors such as trade and exchange rate volatility are also taken into account.

Furthermore, Chapter 4 stands out by distinguishing the marginal effects of the factors with respect to specific types of markets. It is well known that developing markets exhibit different features from developed markets, such as lower market liquidity and smaller market capitalization relative to the scales of the economies. Therefore, it is implausible to assume that the marginal effects of the market linkage factors are the same across the interdependence of all markets. For example, one may expect that developing stock markets are connected by bilateral trade to a different degree from those of developed markets. However, most related studies neglect the relation between the impacts of the factors and the heteroskedasticity (or idiosyncrasy) of markets. A few studies, such as Pretorius (2002) and Beine and Candelon (2011), circumvent this problem by studying developing or developed markets only. Unlike Pretorius (2002) and Beine and Candelon (2011), this thesis addresses the issue of market heteroskedasticity while keeping a comprehensive view over a large sample of national stock markets.

Chapter 4 adds to the literature that studies the EMU's effect on stock market integration. Although existing literature (e.g., Yang *et al.*, 2003) finds that stock market comovement among EMU countries increased after the introduction of the euro, the increase in integration may be attributable to a general tendency towards integration at the global level or the level of developed markets. Chapter 4 addresses this issue by examining whether joint EMU participation matters while controlling other factors driving interdependence markets' and different development levels. Results show that in the post monetary transition period (from year 2003 to 2010), the impact of the euro diminishes when we take into account integration through trade, elimination of exchange rate volatility, industrial similarity and information capacity among developed markets.

Bibliography

Ang, A. and Bekaert, G. (2002), "International asset allocation with regime shifts", *Review of Financial studies*, vol. 15(4), pp. 1137–1187.

Asgharian, H. and Bengtsson, C. (2006), "Jump spillover in international equity markets", *Journal of Financial Econometrics*, vol. 4(2), pp. 167–203.

Asgharian, H. and Nossman, M. (2011), "Risk contagion among international stock markets", *Journal of International Money and Finance*, vol. 30(1), pp. 22–38.

Baele, L. (2005), "Volatility spillover effects in European equity markets", *Journal of Financial and Quantitative Analysis*, vol. 40(2), pp. 373–401.

Baele, L. and Soriano, P. (2010), "The determinants of increasing equity market comovement: economic or financial integration?", *Review of World Economics*, vol. 146, pp. 573–589.

Beine, M. and Candelon, B. (2011), "Liberalisation and stock market co-movement between emerging economies", *Quantitative Finance*, vol. 11(2), pp. 299–312.

Büyüksahin, B., Haigh, M. and Robe, M. (2010), "Commodities and equities: ever a "market of one"?", *Journal of Alternative Investments*, vol. 12(3), pp. 76–95.

Chong, J. and Miffre, J. (2010), "Conditional correlation and volatility in commodity futures and traditional asset markets.", *Journal of Alternative Investments*, vol. 12(3), pp. 61 – 75.

Edwards, S. and Susmel, R. (2003), "Interest-rate volatility in emerging markets", *Review of Economics and Statistics*, vol. 85(2), pp. 328–348.

Engle, R. (2002), "Dynamic conditional correlation", *Journal of Business and Economic Statistics*, vol. 20(3), pp. 339–350.

Flavin, T. J., Hurley, M. J. and Rousseau, F. (2002), "Explaining stock market correlation: a gravity model approach", *The Manchester School*, vol. 70(S1), pp. 87–106.

Forbes, K. J. and Chinn, M. D. (2004), "A decomposition of global linkages in financial markets over time", *The Review of Economics and Statistics*, vol. 86(3), pp. 705–722.

Fratzscher, M. (2002), "Financial market integration in Europe: on the effects of EMU on stock markets", *International Journal of Finance & Economics*, vol. 7(3), pp. 165–193.

Hamilton, J. (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", *Econometrica*, vol. 57(2), pp. 357–384.

Hamilton, J. and Lin, G. (1996), "Stock market volatility and the business cycle", *Journal of Applied Econometrics*, vol. 11(5), pp. 573–593.

Hamilton, J. and Susmel, R. (1994), "Autoregressive conditional heteroskedasticity and changes in regime", *Journal of Econometrics*, vol. 64(1-2), pp. 307–333.

Hong, Y., Liu, Y. and Wang, S. (2009), "Granger causality in risk and detection of extreme risk spillover between financial markets", *Journal of Econometrics*, vol. 150(2), pp. 271–287.

Kat, H. and Oomen, R. (2006), "What every investor should know about commodities, Part II: Multivariate return analysis", *Alternative Investment Research Centre Working Paper No. 33, Cass Business School Research Paper.*

Larsson, O. (2007), *Essays on Risk in International Financial Markets*, Lund University.

Markowitz, H. M. (1952), "Portfolio selection", *Journal of Finance*, vol. 7(1), pp. 77–91.

Markowitz, H. M. (1959), *Portfolio Selection: Efficient Diversification of Investments*, John Wiley& Sons, Inc., New York Chapman & Hall, Limited, London.

Ng, A. (2000), "Volatility spillover effects from Japan and the US to the Pacific-Basin", *Journal of international money and finance*, vol. 19(2), pp. 207–233.

Pretorius, E. (2002), "Economic determinants of emerging stock market interdependence", *Emerging Markets Review*, vol. 3(1), pp. 84 – 105.

Roll, R. (1992), "Industrial structure and the comparative behavior of international stock market indices", *Journal of Finance*, vol. 47(1), pp. 3–41.

Roy, A. (1952), "Safety first and the holding of assets", *Econometrica*, pp. 431–449.

Wälti, S. (2011), "Stock market synchronization and monetary integration", *Journal of International Money and Finance*, vol. 30(1), pp. 96–110.

Yang, J., Min, I. and Li, Q. (2003), "European stock market integration: does EMU matter?", *Journal of business finance & accounting*, vol. 30(9-10), pp. 1253–1276.

Chapter 2

Extreme Downside Risk Spillover from the United States and Japan to Asian-Pacific Stock Markets

2.1 Introduction

As global financial markets have been increasingly deregulated and integrated, the risk in one financial market or asset is very likely to be transmitted to other markets or assets. When implementing global investment strategies, it is critical for the investors to model and forecast risk spillover effects. This paper examines whether and how extreme downside risk is transmitted from the globally dominant stock market (the U.S. market) and the regionally dominant stock market (the Japanese market) to Asian-Pacific stock markets. Asia-Pacific typically refers to East Asia, Southeast Asia, and Oceania. Specifically, this paper studies the national stock markets of Australia, mainland China, Hong Kong, South Korea, Singapore, and Taiwan, which are the main markets of the Asian-Pacific region judged by market capitalization.

For risk management, monitoring extreme downside risk is critical. First, most investors are downside-risk-averse (i.e., more sensitive to bad news than to good). Second, empirical research shows that market correlations increase more after negative shocks than after positive shocks of the same size. For example, Longin and Solnik (2001) find an increase in correlation in bear markets but not in bull markets. Consequently, during bad times, when portfolio diversification is the most needed for hedging risk, the intensified transmission of large negative shocks may significantly weaken the benefits of diversification. The standard dynamic portfolio choice problem should therefore be modified during bad times, to capture investors' downside-risk aversion and the effect of extreme downside risk spillover.

Risk spillovers between financial markets and assets have been widely studied. Among a number of frameworks, correlation analysis has been explored to explain the linkages between financial asset markets (e.g., King and Wadhwani, 1990, and Forbes and Rigobon, 2002). Volatility spillover across international markets has been usually tested by generalized autoregressive conditional heteroskedasticity (GARCH) processes (e.g., Baele, 2005). While GARCH processes allow for time variation in conditional volatility, extreme returns are assumed to follow the same distribution as other returns. Hartmann *et al.* (2004) circumvent this problem by looking at extremal dependence between markets in distress periods. Risk spillover has also been analyzed in the framework of volatility with jumps (e.g., Asgharian and Bengtsson, 2006, and Asgharian and Nossman, 2011). Other research (e.g., Bae *et al.*, 2003, Christiansen and Ranaldo, 2009, and Adrian and Brunnermeier, 2009) have studied extreme coexceedance or simultaneous extreme events of financial markets and financial institutions. However, extreme downside risk spillover still needs to be further explored. The ever-increasing integration of assets and markets calls for better measures of extreme downside risk and prediction of risk transmission.

This paper proposes a binary response model to investigate the spillover of extreme downside risk between different international stock markets. The approach is based on the concept of Granger causality in risk (Hong *et al.*, 2009), where an extreme downside risk is said to have occurred at a prespecified level if asset returns fall below the left-tail Value at Risk (VaR) at the given level. While Hong *et al.* (2009) develop kernel-based tests on extreme downside risk spillover, this paper proposes a regression approach to make ex-ante predictions of extreme downside risk in an Asian-Pacific market given the information about a dominant market (i.e., the U.S. or Japan).

In order to measure extreme downside risk, this paper forecasts VaR via a Markov switching ARCH (SWARCH) model (e.g., Hamilton and Susmel, 1994, and Cai, 1994), which allows the distribution of the variable to change across regimes. The use of SWARCH serves two purposes. First, SWARCH is expected to be more accurate in forecasting VaR than single-regime (G)ARCH models, because it captures potential shifts of the distribution and alleviates the problems of excess kurtosis and skewness (see, e.g., Timmermann, 2000, and Li and Lin, 2004). Next, by identifying high volatility regimes and low volatility regimes via SWARCH, we may examine whether the degree of the spillover effect also shifts when the regime shifts.

This paper's contribution is twofold: First, its model not only examines whether spillover takes place, but it is also able to predict and quantify the likelihood of extreme downside movement of a market given the information about extreme downside risks in the globally dominant market (the U.S.) and the regionally dominant market (Japan). Second, this paper looks at extreme downside risks and risk-spillover effects from a state-dependent perspective, which is critical for dynamic asset allocation. Overall, this study provides investors with implications about monitoring extreme downside risks in globally diversified portfolios.

The rest of this paper is organized as follows. Section 2.2 presents the model. It start by describing the concept of Granger causality in risk following Hong *et al.* (2009). Based on this concept, a binary response model is proposed for extreme downside risk spillover. Section 2.3 presents the estimation procedures. Section 2.4 describes the data. Section 2.5 presents an empirical analysis and Section 2.6 concludes.

2.2 Model of extreme downside risk spillover

This section presents first the concept of Granger causality in risk following Hong *et al.* (2009), which is the theoretical background for the binary response model of extreme value spillover. Then the extreme value model is elaborated, which predicts extreme downside risk in one market given the occurrence of extreme downside risk in a dominant market.

The concept of Granger causality in risk is designed to test "whether the past history of the occurrences of large risks in one market has predictive ability for the future occurrences of large risks in another market" (Granger, 1969, 1980). Let $r_{j,t}$ and $r_{i,t}$ be the returns of markets i and j. Put $\Psi_{t-1} = \{\Psi_{i,t-1}, \Psi_{j,t-1}\}$, where $\Psi_{i,t-1} = \{r_{i,t-1}, r_{i,t-2}, \ldots\}$ and $\Psi_{j,t-1} = \{r_{j,t-1}, r_{j,t-2}, \ldots\}$ are the information sets available at time t for markets i and j. Define $VaR^{\alpha}_{i,t}$ to be the α-quantile of the probability distribution of $r_{i,t}$ at time t, and $VaR^{\alpha}_{j,t}$ to be the same for $r_{j,t}$.

If the hypothesis H_0 below holds,

$$H_0 : P(r_{i,t} < VaR^{\alpha}_{i,t}|\Psi_{i,t-1}) = P(r_{i,t} < VaR^{\alpha}_{i,t}|\Psi_{t-1}) \text{ almost surely,} \tag{2.1}$$

the $r_{j,t}$ does not Granger-cause $r_{i,t}$ in risk at confidence level $1-\alpha$ with respect to the information set Ψ_{t-1}. On the other hand, if

$$H_1 : P(r_{i,t} < VaR^{\alpha}_{i,t}|\Psi_{i,t-1}) \neq P(r_{i,t} < VaR^{\alpha}_{i,t}|\Psi_{t-1}), \tag{2.2}$$

then $r_{j,t}$ Granger-causes $r_{i,t}$ in risk at level α with respect to the information set Ψ_{t-1}. In this sense, information about an extreme downside movement in $r_{j,t}$ can be used to predict risk in $r_{i,t}$.

To test the hypotheses above, Hong *et al.* (2009) formulate similar hypotheses on Granger causality in mean by defining a left-tail VaR-related risk indicator by

$$Z^{\alpha}_{t} \equiv 1(r_t < VaR^{\alpha}_{t}), \tag{2.3}$$

where $1(\cdot)$ is an indicator function that takes the value 1 when the stock market return is smaller than the VaR, and is 0 otherwise. Thus, the hypothesis (2.1) can be equivalently stated as

$$H_0 : E(Z^{\alpha}_{i,t}|\Psi_{i,t-1}) = E(Z^{\alpha}_{i,t}|\Psi_{t-1}) \text{ almost surely.} \tag{2.4}$$

Therefore, the Granger causality in risk between $r_{i,t}$ and $r_{j,t}$ can be viewed as a Granger causality in mean between $Z^{\alpha}_{i,t}$ and $Z^{\alpha}_{j,t}$. The Granger causality test is equivalent to a Granger-type procedure based on the regression

$$Z^{\alpha}_{i,t} = \beta_0 + \sum_{l=1}^{L}(\beta_l Z^{\alpha}_{j,t-l}) + u_t, \tag{2.5}$$

which checks whether the coefficients $\{\beta_l\}_{l=1}^{L}$ are jointly zero.

Based on the concept of Granger causality in risk, this paper develops a simple binary response model for predicting extreme downside risk, analogous to the regression (2.5). The paper uses the left-tail VaR-related risk indicator (defined in Equation (2.3)) as the extreme downside risk measure, and sets up a binary extreme value regression,

$$Pr(\hat{Z}_{i,t} = 1 | \boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp\,(\boldsymbol{x}_t'\boldsymbol{\beta})\}, \tag{2.6}$$

where $\boldsymbol{x}_t'\boldsymbol{\beta} = \beta_0 + \beta_1 \hat{Z}_{j,t-1} + \beta_2 \hat{Z}_{i,t-1}$.

The extreme value regression is based on the cumulative distribution function for the Gumbel extreme value distribution[1]. Thanks to its asymmetrical response curve, an extreme value model is particularly appropriate for this study because the event of a predefined extreme downside risk occurs rarely. Cameron and Trivedi (2009), among many other papers in the literature, has argued for the use of an extreme value model when there is a high proportion of zeros (absence of events) in the binary variable. Symmetric models such as Probit and Logit are inappropriate for this study since their response curves approach zero and one at the same rate.

In Equation (2.6), the probability that an extreme downside movement takes place in market i depends on its own past movement and on the occurrence of an extreme downside movement in market j. "β_1" indicates the intensity of an extreme downside risk spillover from market j to market i. And if "$\beta_2 = 0$", an extreme downside event in market i is irrelevant to its own lagged value.

This study takes the U.S. and Japan as the dominant markets for the Asian-Pacific region, thus $\hat{Z}_{j,t-1} = \hat{Z}_{\mathrm{US},t-1}$ or $\hat{Z}_{\mathrm{JP},t-1}$, where $\hat{Z}_{\mathrm{US},t-1}$ and $\hat{Z}_{\mathrm{JP},t-1}$ are the risk indicators for the S&P 500 and Nikkei 225.

[1]The cumulative distribution function of the Gumbel extreme value distribution is $F(x; \mu, \sigma) = exp\{-exp(-(x - \mu)/\sigma)\}$.

2.3 Estimation approach

The proposed risk spillover model described in Section 2.2 relies on the estimation of VaR, which is obtained from SWARCH. The estimation approach consists of three steps. First, we estimate SWARCH for each series of the stock market index returns. Second, by using the estimated parameters for the SWARCH, we calculate the VaR and the extreme downside risk indicator for each market. The last step is to estimate the model of risk spillover using the extreme downside risk indicators.

The first step is to estimate a two-regime SWARCH after Hamilton and Susmel (1994) and Cai (1994) for each series of stock market returns. There are two advantages in adopting SWARCH. First, SWARCH is expected to be more accurate at forecasting VaR than single-regime (G)ARCH models. As VaR is calculated from the first two moments of the asset returns, understanding the distribution of the returns is crucial for forecasting VaR. Financial asset returns are typically skewed and fat-tailed. SWARCH is able to mitigate such problems, because skewness may be replicated by the Markov switching process with different means in the different regimes and excess kurtosis may also be obtained along with certain probabilities of staying in the regimes (see Timmermann, 2000) for theoretical elaboration and Li and Lin (2004) for empirical evidence). SWARCH is also able to capture potential structural breaks or regime shifts, thus avoiding the spuriously high persistence that exists in single-regime (G)ARCH models. In addition to the estimation accuracy, another advantage of using SWARCH is that we may examine whether the degree of the spillover effect also changes when the regime shifts, as the two-regime SWARCH in this study identifies the probabilities of a high volatility regime and that of a low volatility regime. Unlike backward-looking measures for business cycle or turning points (e.g., NBER's business cycle reference dates), the predicted probabilities of the regimes obtained via SWARCH are forward-looking, and therefore serve the purpose of predicting extreme downside risk.

As in Hamilton and Susmel (1994) and Cai (1994), set up the two-regime SWARCH,

$$r_t = \mu_{s_t} + e_t \tag{2.7}$$

$$e_t = \sqrt{g_{s_t}} \cdot u_t \tag{2.8}$$

$$u_t = \sqrt{h_t} \cdot v_t,\ \ v \sim N(0,1) \tag{2.9}$$

$$h_t = a_0 + a_1 \cdot u_{t-1}^2 + \lambda \cdot d_{t-1} \cdot u_{t-1}^2, \tag{2.10}$$

where $d_{t-1} = 1$ if $u_{t-1} < 0$ and $d_{t-1} = 0$ otherwise.

Here, s_t denotes an unobserved random variable that can take on the values 1 or 2, and s_t is regarded as the "state" or "regime" that the process is in at date t. It is assumed to follow a first order Markov chain with transition probabilities

$$P\left(s_t = n | s_{t-1} = m\right) = p_{mn} \tag{2.11}$$

for $m, n = 1, 2$ and $\sum_{n=1}^{2} p_{mn} = 1$ for all m. Although the state variable, s_t, is unobservable, one can estimate $p(s_t | r_{t-1}, r_{t-2}, \ldots)$, namely the predicted probability of regime s_t at time t, as in the filtering algorithm of Hamilton (1989).

In Equation (2.8), the underlying ARCH variable, u_t, is multiplied by the scaling parameter $\sqrt{g_1}$ when the process is in the regime represented by $s_t = 1$, but multiplied by the scaling parameter $\sqrt{g_2}$ when the process is in the regime represented by $s_t = 2$; thus the scale of the ARCH process changes as the regime changes. For the sake of identification, the value of g_1 is standardized to 1 and the value of g_2 is constrained to be larger than 1. Therefore, the first regime in the estimation is the low volatility regime and the second regime is the high volatility regime.

Conditional on knowing the current and past regimes, estimate the conditional variance implied for the residual e_t.

$$\begin{aligned} \sigma_t^2 &= E\left(e_t^2 | s_t, s_{t-1}, e_{t-1}\right) \\ &= g_{s_t}\left[a_0 + a_1(e_{t-1}^2/g_{s_{t-1}}) + \lambda d_{t-1}(e_{t-1}^2/g_{s_{t-1}})\right] \end{aligned} \tag{2.12}$$

The second step is to calculate the VaR for each series of stock market returns by using the mean, conditional volatility, and predicted regime probability $p(s_t | r_{t-1}, r_{t-2}, \ldots)$ estimated via SWARCH. The mixture distribution of returns is derived as the weighted average of the individual regime distributions using the ex-ante predicted regime probabilities as weights. The one-day-ahead VaR at time t at the $1-\alpha$ confidence level is hence calculated as the α-quantile of the mixture distribution,

$$\alpha = \sum_{s_t}\sum_{s_{t-1}} \hat{p}(s_t, s_{t-1}|r_{t-1}, r_{t-2}, \ldots) \int_{\infty}^{VaR_t^{\alpha}} N(x, \hat{\mu}^{(s_t)}, \hat{\sigma}_t^{(s_t,s_{t-1})}|r_{t-1}, r_{t-2}, \ldots)\mathrm{d}x, \tag{2.13}$$

where $\hat{p}(s_t, s_{t-1}|r_{t-1}, r_{t-2}, \ldots)$ is the estimated predicted probability, $\hat{\mu}^{(s_t)}$ is the mean conditional on state s_t, and $\hat{\sigma}_t^{(s_t,s_{t-1})}$ is the volatility conditional on s_t and s_{t-1}. Given the one-day-ahead VaR from Equation (2.13), calculate the extreme downside risk indicators according to Equation (2.3).

The last step is to examine and predict the spillover of extreme downside risks: this is the ultimate aim of this study. Instead of looking at the simple spillover model given by Equation (2.6), we extend the model in order to examine whether the risk spillover effects become intensified when the dominant market shifts into the volatile regime. This is done by introducing a dummy variable, d_t, that indicates the regime at time t. The ultimate estimation regression is thus[2]

$$Pr(\hat{Z}_{i,t} = 1|\boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp(\beta_0 + \beta_1\hat{Z}_{j,t-1} + \gamma\hat{Z}_{j,t-1}d_{j,t-1} + \beta_2\hat{Z}_{i,t-1})\}, \tag{2.14}$$

where $j = \{\mathrm{US}, \mathrm{JP}\}$ and $d_{j,t-1}$ is unity if market j is in a volatile regime and zero otherwise.

Although the volatile and the tranquil regimes are not explicitly observable, one can date the regimes based on their probabilities. According to Hamilton (1989), a time series is in one of the two regimes at time t if the smoothed probability of that regime is larger than 0.5 at time t. However, since this paper delves into the ex-ante forecast of risk spillover, the regimes are dated based on predicted probabilities rather than smoothed probabilities: $d_{j,t} = 1$ if $p(s_t = 2|r_{t-1}, r_{t-2}, \ldots) > 0.5$, and zero otherwise.

Based on Equation (2.14), we can find the discrete effect of $\hat{Z}_{j,t-1}$ on

[2] Although in the model specification the explanatory variable $\hat{Z}_{j,t-1}$ is lagged by one day, the contemporaneous observation is used for $\hat{Z}_{\mathrm{JP},t-1}$, thus remaining consistent with the previous analysis.

$Pr(\hat{Z}_{i,t})$ by calculating the discrete change in $Pr(\hat{Z}_{i,t})$ as $\hat{Z}_{j,t-1}$ changes from 0 to 1, following Anderson and Newell (2003):

$$\text{Discrete effect of } \hat{Z}_{j,t-1} = Pr(\hat{Z}_{i,t} = 1|\hat{Z}_{j,t-1} = 1) - Pr(\hat{Z}_{i,t} = 1|\hat{Z}_{j,t-1} = 0). \tag{2.15}$$

2.4 Data

The data in this article consists of the time series of daily stock market indices at closing time, denominated in U.S. dollars, extracted from Datastream. The S&P 500 is selected for the U.S. market, the Nikkei 225 for the Japanese market, the ASX all ordinaries for Australia, the Shanghai Stock Exchange Composite for the equity market of mainland China, the Hang Seng Index for Hong Kong, the Korean Stock Exchange Composite, the Singapore Straits Times Index, and the Taiwan Stock Exchange Weighted. The data covers the period from January 4, 1993 to April 17, 2009. All stock-market indices are transformed into daily log returns.

Given that the stock markets in this study operate in different time zones with different opening and closing times, it is important to know the operating hours of each market relative to other markets in coordinated universal time, for the purpose of interpreting the empirical results (see Table 2.1).

The New York Stock Exchange and the NASDAQ stock market operating times do not overlap with those of the Asian-Pacific markets and they are closed after all the Asian-Pacific markets on the same day, so this paper uses one-day lagged observations of the S&P 500 to analyze the spillover effects from the U.S. to the Asian-Pacific markets. In addition, all the Asian-Pacific stock exchanges (except the Taiwan Stock Exchange) in this study close no earlier than the Tokyo Stock Exchange. Therefore, the paper uses the same day observations for the analysis of the Japanese spillover effects.

According to the descriptive statistics (see Table 2.2), most of the markets trend upwards in the sample period except for Japan, judged by the means of the market returns. Additionally, the developed markets tend to have smaller volatility than the developing markets. For example, the U.S. market has the

Table 2.1: The closing times (UTC) of the stock exchanges

Stock exchanges	Closing time (UTC)
New York Stock Exchange	21:00 (standard time), 20:00 (daylight saving time)
Tokyo Stock Exchange	06:00
Australian Securities Exchange	06:00
Shanghai Stock Exchange	07:00
Hong Kong Stock Exchange	08:00
Korean Exchange	06:00
Singapore Stock Exchange	09:00
Taiwan Stock Exchange	05:30

Table 2.2: Descriptive statistics of the logarithmic returns of the stock market indices

	Mean	Std Dev	Kurtosis	Skewness	Minimum	Maximum
US	0.0002	0.0120	9.8454	−0.1992	−0.0947	0.1096
Japan	−0.0001	0.0162	4.2573	0.0756	−0.1119	0.1257
Australia	0.0002	0.0136	13.9260	−1.0874	−0.1585	0.0811
China	0.0002	0.0237	33.6404	−0.0935	−0.3896	0.2889
Hong Kong	0.0002	0.0175	9.4939	0.0956	−0.1471	0.1727
South Korea	0.0000	0.0237	15.0735	0.0647	−0.2144	0.2634
Singapore	0.0001	0.0141	5.6492	−0.0326	−0.0863	0.1071
Taiwan	0.0001	0.0168	2.8557	−0.1524	−0.1135	0.0772

smallest standard deviation (0.0120), whereas China and South Korea have the highest (0.0237). In addition, the market returns of Japan, Hong Kong, and South Korea are positively skewed, while the returns of all the other markets are negatively skewed. we also find that all the markets are leptokurtic. With the highest excess kurtosis (33.6404), mainland China has the largest risk in tails. In comparison, Taiwan has the fewest outliers. The skewness and the excess kurtosis of the market returns provide further incentives for us to adopt the Markov switching method.

2.5 Empirical analysis

This section begins with the empirical estimation of the VaRs and extreme downside risk indicators. Next, a simpler method is used in the spirit of Asgharian and Bengtsson (2006) for a preliminary analysis of risk spillover. The last subsection presents the empirical results of the exteme downside risk spillover model given by Equation (2.14).

2.5.1 Empirical estimation of value at risk and risk indicators

For all the stock market index samples, the SWARCH model[3] is estimated with nine rolling estimation windows, each of which consists of 2,000 daily log returns. The estimation window moves by 250 trading days. With each window's estimated parameters, we can forecast the predicting probabilities and the day-by-day conditional volatilities for 250 trading days following each estimation window to calculate the one-day-ahead VaRs for the period from September 4, 2000 to April 17, 2009. The SWARCH model is estimated by maximum likelihood employing the filtering algorithm of Hamilton (1989). The Matlab code of Asgharian (2002) for simulated annealing is used to locate a good approximation of the global maximum point of the likelihood function. The estimated SWARCH results and predicted probability of the high volatile regime for the S&P 500 and Nikkei 225 are displayed in Appendix A.

Given the estimated SWARCH results, the one-day-ahead VaRs are calculated with confidence levels 95% and 90% via Equation (2.13). The performance of the estimation is judged by the widely used Christoffersen (1998) conditional coverage test (described in Appendix B), which jointly tests whether the frequency of VaR exceedances predicted by the model is consistent with the empirical frequency of exceedances (i.e., the failure rate) and whether the exceedances are independent. The result of testing is summarized in Table 2.3. The extreme downside risk indicators are subsequently calculated via Equation (2.3).

[3] I also calculate the VaR with a Markov switching variance model (Turner *et al.*, 1989), in which the volatilities are constant within regimes. Judged by failure rates, the SWARCH models perform better than the Markov switching variance models.

Table 2.3: Failure rates and likelihood ratio statistics for the conditional coverage test in the out-of-sample period from Sep. 4, 2000 to Apr. 14, 2009

	$\alpha = 0.10$			$\alpha = 0.05$		
	Failure rate	LR_{cc}	p-value	Failure rate	LR_{cc}	p-value
US	0.1058	0.9811	0.6131	0.0627	7.0625	0.0293
JP	0.0987	5.1221	0.0772	0.0507	0.0303	0.9850
AU	0.1009	0.8601	0.3872	0.0604	1.2727	0.0542
CN	0.1098	4.8720	0.0875	0.0658	12.6470	0.0018
HK	0.0960	1.2762	0.5283	0.0480	2.9535	0.2284
KR	0.0916	1.9102	0.3847	0.0547	2.5770	0.2757
SG	0.0844	9.5895	0.0083	0.0458	1.9375	0.3796
TW	0.0982	0.8601	0.6505	0.0542	1.2727	0.5292

Note: LR is the likelihood ratio statistics for Christoffersen's (1998) test of conditional coverage, which is the sum of the likelihood ratio statistics for Kupiec's (1995) unconditional coverage test and the likelihood ratio statistics for the independence test. The LR conforms to the $\chi^2(2)$ distribution.

2.5.2 Preliminary risk spillover analysis

Before describing the empirical results for the spillover model, this paper presents a preliminary overview of the extreme downside risk spillover between the markets, by investigating the simultaneity and dependence between the extreme downside risk indicators. This preliminary analysis is analogous to the jump-spillover analysis of Asgharian and Bengtsson (2006). First, we look at the simultaneous risk intensities between pairs of markets, which reveal the existence of systematic risk spillovers. Then we perform an analysis of the conditional risk spillover probabilities, examining to what extent extreme downside movements in the dominant markets increase the probability of extreme downside movements in other markets. It is worth noting that this paper examines the same-day spillover from Japan and the previous-day spillover from the U.S. to individual Asian-Pacific markets due to the different operating hours, as shown in Table 2.1.[4]

[4]"Simultaneous occurrence," in this article, always refers to the same trading date in Japan but to the previous trading date in the U.S.

Table 2.4: Simultaneous risk intensities of $\hat{Z}^{0.1}$

	AU	CN	HK	JP	KR	SG	TW	US
AU	0.1009							
CN	0.0261***	0.1098						
HK	0.0430***	0.0280***	0.0960					
JP	0.0384***	0.0215***	0.0387***	0.0987				
KR	0.0414***	0.0264***	0.0453***	0.0385***	0.0916			
SG	0.0401***	0.0206***	0.0494***	0.0363***	0.0393***	0.0844		
TW	0.0356***	0.0251***	0.0438***	0.0374***	0.0467***	0.0432***	0.0932	
US	0.0477***	0.0222***	0.0395***	0.0382***	0.0346***	0.0328***	0.0343***	0.1058

Note: *** denotes the 99% confidence level. The implied risk intensities are on the diagonals. The test statistics used can be found in Miller and Miller (2004).

Simultaneous risk intensities

The simultaneous risk intensity between two markets reveals the simultaneity of their extreme downside risks. It is defined as the number of simultaneous occurrences of extreme downside movements divided by the number of "same events." An extreme downside movement is identified by a risk indicator equal to 1, and equality of events is defined as the equality of the risk indicators of the two markets. A market's simultaneous risk intensity with itself is called the implied risk intensity and is equivalent to the failure rate shown in Table 2.3.

Tables 2.4 and 2.5 give the estimated simultaneous risk intensities and whether the estimated values are significant. The significance levels of the simultaneous risk intensities are obtained by testing whether the estimated intensities are greater than what they would be under the null hypothesis that the different markets' large losses are completely independent. Under this null hypothesis, the simultaneous risk intensity of two markets is equal to the product of the markets' implied risk intensities. For example, the simultaneous risk intensity between the Nikkei 225 and the Hang Seng Index at the 0.05 level of VaR under the null hypothesis is equal to 0.0507 multiplied by 0.0480.

One obvious finding in Tables 2.4 and 2.5 is that the estimated simultaneous risk intensities are all significant at the 99% confidence level, which suggests the

Table 2.5: Simultaneous risk intensities of $\hat{Z}^{0.05}$

	AU	CN	HK	JP	KR	SG	TW	US
AU	0.0604							
CN	0.0100***	0.0658						
HK	0.0192***	0.0118***	0.0480					
JP	0.0192***	0.0069***	0.0158***	0.0507				
KR	0.0198***	0.0118***	0.0181***	0.0149***	0.0547			
SG	0.0196***	0.0108***	0.0211***	0.0157***	0.0181***	0.0458		
TW	0.0160***	0.0099***	0.0154***	0.0135***	0.0196***	0.0172***	0.0542	
US	0.0218***	0.0090***	0.0174***	0.0170***	0.0142***	0.0150***	0.0113***	0.0627

Note: *** denotes the 99% confidence level. The implied risk intensities are on the diagonals. The test statistics used can be found in Miller and Miller (2004).

existence of systemic risk spillover between these markets. Another observation is that the simultaneous risk intensities of the mainland Chinese market are the weakest. This is consistent with previous research, showing that the Chinese financial market is highly insulated from international markets. For example, Johansson (2009) shows that the Shanghai and Shenzhen markets both have a low average systematic risk when measured against the world market. In addition, Australia, mainland China, and Hong Kong appear to be more sensitive to the U.S. market than to the Japanese market, as their simultaneous intensities with the U.S. are higher than those with Japan. By contrast, the markets of South Korea, Singapore, and Taiwan have more simultaneous extreme downside movements with Japan.

Conditional risk spillover probabilities

Conditional risk spillover probability is the likelihood that an extreme downside movement takes place in one market conditional on an extreme downside movement in another market. It reveals the dependence of the extreme downside risk of the former market on that of the latter. The probability conditional on the dominant market is estimated as the number of simultaneous extreme downside movements with the chosen dominant market divided by the number of extreme downside movements of the dominant market. Table 2.6 shows the estimated conditional spillover probabilities

Table 2.6: Conditional risk spillover probabilities

	Dominant Markets			
	U.S.		JP	
	$\hat{Z}^{0.1}$	$\hat{Z}^{0.05}$	$\hat{Z}^{0.1}$	$\hat{Z}^{0.05}$
AU	0.3950***	0.3191***	0.3378***	0.3509***
CN	0.1723***	0.1277***	0.1802***	0.1228***
HK	0.3235***	0.2553***	0.3423***	0.2895***
KR	0.2815***	0.2057***	0.3423***	0.2719***
SG	0.2689***	0.2199***	0.3243***	0.2895***
TW	0.2773***	0.1631***	0.3288***	0.2456***

Note: *** denotes the 99% confidence level. The test statistics used can be found in Miller and Miller (2004).

of each Asian-Pacific market, one conditional on the U.S. and another on Japan. The significance levels are obtained by testing the equality of the estimated spillover probabilities with the corresponding probabilities under the null hypothesis of no risk spillover. A market's conditional risk spillover probability under the null is equal to that market's implied risk intensity.

The results show that all the estimated probabilities are significant at the 99% confidence level. This provides preliminary evidence for the existence of both U.S. and Japanese spillover effects. Notably, we observe that the Australian risk probabilities conditional on the U.S. and those conditioned on Japan are among the highest. This finding reflects Australia's high sensitivity to extreme negative shocks from either dominant market. By contrast, the Chinese market is the most insulated from both global and regional extreme negative shocks, as its risk probabilities are smaller than all the other Asian-Pacific markets. Furthermore, the spillover probabilities conditional on Japan are larger than those conditional on the U.S. for all but the Australian and Chinese markets, implying that the Japanese market might better predict the extreme downside risks of most Asian-Pacific markets. This may be due to the fact that the activities in the U.S. market take place before the opening of the Asian-Pacific markets whereas the Japanese and the Asian-Pacific markets hours of operation overlap. This is consistent with the previous empirical finding of Flavin *et al.* (2002): more hours of common trading are associated with greater degree of stock price co-movements, because more hours of common trading indicate ease of trading and less information asymmetry. However in the mean time, we do not rule out the possibility that the U.S. shocks affect the Asian-Pacific markets via Japan.

2.5.3 Empirical analysis of the extreme downside risk spillover model

This section describes the estimated results of the extreme value model of extreme downside risk spillover given by Equation (2.14).

First, the results with the U.S market as the dominant market are presented in Tables 2.7 and 2.8, for, respectively, VaR levels of 0.1 and 0.05. β_1 is statistically significant for all of the Asian-Pacific markets (except for China at the 0.05 level of VaR), implying broad sensitivity to the extreme downside risk of the U.S. market. Positive signs for all instances of β_1 suggest that extreme negative shocks in the S&P 500 Granger-cause downside movements in the Asian-Pacific markets.

Furthermore, intensified spillover in periods of high volatility in the U.S. is found only for Taiwan, as γ for the Taiwanese market is positive and strongly significant at the 0.1 VaR level. This finding reveals contagion between the S&P 500 and the Taiwanese market by the World Bank's very restrictive definition of financial contagion. However, this additional spillover effect in the crisis period loses both size and significance when we consider a higher level of risk, the 0.05 VaR level.

In addition, the lagged extreme downside movement is irrelevant to current movement for almost all the selected Asian-Pacific markets. The exceptions are Korea (for 0.1 VaR) and Hong Kong (for 0.05 VaR).

The pseudo R^2 in the last row of Tables 2.7 and 2.8 indicates that the extreme downside risk in the U.S. has the most predictive power for the Australian market (0.117 for 0.1 VaR and 0.0985 for 0.05 VaR), which is consistent with the finding in Section 2.5.2. In contrast, an extreme downside movement of the Chinese stock market is the least predictable by the U.S. market, which may be mainly due to the fact that the Chinese stock market

Table 2.7: Estimated extreme downside risk spillover from the S&P 500 at the 0.1 VaR level, September 4, 2000 to April 17, 2009.

Parameter	AU	CN	HK	KR	SG	TW
β_0	-0.999^{***}	-0.809^{***}	-0.966^{***}	-0.981^{***}	-1.024^{***}	-0.929^{***}
	(0.032)	(0.030)	(0.032)	(0.032)	(0.032)	(0.031)
β_1	1.114^{***}	0.289^{**}	0.788^{***}	0.748^{***}	0.630^{***}	0.364^{***}
	(0.156)	(0.144)	(0.147)	(0.146)	(0.145)	(0.145)
γ	-0.062	-0.046	0.143	-0.002	0.162	0.489^{***}
	(0.185)	(0.172)	(0.177)	(0.174)	(0.173)	(0.174)
β_2	0.003	-0.143	-0.230	-0.018^{**}	0.061	-0.150
	(0.097)	(0.090)	(0.106)	(0.099)	(0.103)	(0.099)
Pseudo R^2	0.117	0.008	0.083	0.060	0.065	0.098

Note: The estimated extreme value regression is given by (2.14): $Pr(\hat{Z}_{i,t} = 1|\boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp(\beta_0 + \beta_1 \hat{Z}_{US,t-1} + \gamma \hat{Z}_{US,t-1} d_{US,t-1} + \beta_2 \hat{Z}_{i,t-1})\}$, where $\hat{Z}_{i,t}$ is the risk indicator of market i at the 0.1 VaR level, $\hat{Z}_{US,t-1}$ is the risk indicator of S&P 500 at the 0.1 VaR level, and $d_{US,t-1}$ is the dummy variable that indicates the volatile regime of S&P500. ***, **, and * denote 0.01, 0.05 and 0.10 levels of significance, respectively. Standard errors are in parentheses.

Table 2.8: Estimated extreme downside risk spillover from the S&P 500 at the 0.05 VaR level, September 4, 2000 to April 17, 2009

Parameter	AU	CN	HK	KR	SG	TW
β_0	-1.151^{***}	-1.015^{***}	-1.206^{***}	-1.139^{***}	-1.219^{***}	-1.112^{***}
	(0.034)	(0.031)	(0.035)	(0.033)	(0.035)	(0.033)
β_1	1.120^{***}	0.312	1.053^{***}	0.590^{***}	0.907^{***}	0.401^{**}
	(0.211)	(0.207)	(0.207)	(0.202)	(0.203)	(0.206)
γ	-0.153	-0.015	-0.189	0.110	-0.151	0.171
	(0.244)	(0.240)	(0.239)	(0.234)	(0.235)	(0.238)
β_2	0.095	-0.167	-0.373^{*}	0.086	0.046	-0.123
	(0.124)	(0.128)	(0.202)	(0.130)	(0.148)	(0.144)
Pseudo R^2	0.0985	0.0086	0.0961	0.0450	0.0725	0.0267

Note: The estimated extreme value regression is given by (2.14): $Pr(\hat{Z}_{i,t} = 1|\boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp(\beta_0 + \beta_1 \hat{Z}_{US,t-1} + \gamma \hat{Z}_{US,t-1} d_{US,t-1} + \beta_2 \hat{Z}_{i,t-1})\}$ is the risk indicator of S&P 500 at 0.05 VaR level, and $d_{US,t-1}$ is the dummy variable that indicates the volatile regime of S&P500. ***, **, and * denote 0.01, 0.05 and 0.10 levels of significance, respectively. Standard errors are in parentheses.

has been heavily insulated from world markets.

Tables 2.9 and 2.10 present the results of regression (2.14) with the Japanese market as the dominant markets. As with the U.S., the spillover

Table 2.9: Estimated extreme downside risk spillover from the Nikkei 225 at the 0.1 VaR level, September 4, 2000 to April 17, 2009

Parameter	AU	CN	HK	KR	SG	TW
β_0	-0.955^{***}	-0.810^{***}	-0.972^{***}	-1.009^{***}	-1.059^{***}	-0.948^{***}
	(0.031)	(0.030)	(0.032)	(0.032)	(0.033)	(0.031)
β_1	0.808^{***}	0.315^{***}	0.724^{***}	0.816^{***}	0.756^{***}	0.850^{***}
	(0.107)	(0.104)	(0.106)	(0.106)	(0.105)	(0.108)
γ	0.195	-0.086	0.648^{***}	0.413^{**}	0.545^{***}	0.061
	(0.192)	(0.183)	(0.204)	(0.197)	(0.198)	(0.189)
β_2	0.032	-0.151	-0.128	-0.011	0.149	-0.172^{*}
	(0.094)	(0.090)	(0.101)	(0.101)	(0.100)	(0.101)
Pseudo R^2	0.074	0.009	0.093	0.095	0.102	0.074

Note: The estimated extreme value regression is given by (2.14): $Pr(\hat{Z}_{i,t} = 1|\boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp(\beta_0 + \beta_1\hat{Z}_{JP,t-1} + \gamma\hat{Z}_{JP,t-1}d_{JP,t-1} + \beta_2\hat{Z}_{i,t-1})\}$ where $\hat{Z}_{i,t}$ is the risk indicator of market i at 0.1 VaR level, $\hat{Z}_{JP,t-1}$ is the risk indicator of Nikkei 225 at 0.1 VaR level, and $d_{JP,t-1}$ is the dummy variable that indicates the volatile regime of Nikkei 225. ***, **, and * denote 0.01, 0.05 and 0.10 levels of significance, respectively. Standard errors are in parentheses.

from Japan is also positive and significant in all the investigated Asian-Pacific stock markets. β_1 is highly significant for nearly all the markets at both the 0.1 and the 0.05 VaR levels.

In comparison with the U.S. spillover, we find wide contagion between Japan and the Asian-Pacific markets. γ is positive and significant for Hong Kong and South Korea at both the 0.1 and the 0.05 VaR levels, for Singapore at the 0.1 VaR level, and for Australia at the 0.05 VaR level. This suggests that extreme downside co-movements of these markets with Japan are intensified when the Japanese market is in turmoil. By contrast, such an intensified effect of spillover is not found on mainland China or Taiwan.

The prediction for the extreme downside risk of the Singapore market based on that of Japan achieves the largest pseudo R^2: 0.102 at the 0.1 VaR level and 0.103 at the 0.05 VaR level. This suggests that the Singapore market is the most sensitive to the regionally dominant effect, compared to the other Asian-Pacific markets. In contrast, the extreme downside risk of the Chinese market is the least predictable by the Japanese market, judged by its pseudo R^2's being the smallest of all.

Table 2.10: Estimated extreme downside risk spillover from the Nikkei 225 at the 0.05 VaR level, September 4, 2000 to April 17, 2009

Parameter	AU	CN	HK	KR	SG	TW
β_0	-1.135^{***}	-1.008^{***}	-1.196^{***}	-1.151^{***}	-1.233^{***}	-1.131^{***}
	(0.033)	(0.031)	(0.034)	(0.033)	(0.035)	(0.033)
β_1	0.929^{***}	0.309^{**}	0.832^{***}	0.640^{***}	0.881^{***}	0.772^{***}
	(0.147)	(0.147)	(0.148)	(0.145)	(0.145)	(0.146)
γ	0.488^{*}	-0.082	0.629^{**}	0.710^{***}	0.399	0.121
	(0.275)	(0.259)	(0.270)	(0.270)	(0.262)	(0.254)
β_2	0.051	-0.187	-0.583^{**}	0.087	0.076	-0.175
	(0.126)	(0.130)	(0.266)	(0.132)	(0.147)	(0.151)
Pseudo R^2	0.097	0.007	0.108	0.073	0.103	0.055

Note: The estimated extreme value regression is given by (2.14): $Pr(\hat{Z}_{i,t} = 1|\boldsymbol{x}_t, \boldsymbol{\beta}) = 1 - exp\{-exp(\beta_0 + \beta_1 \hat{Z}_{JP,t-1} + \gamma \hat{Z}_{JP,t-1} d_{JP,t-1} + \beta_2 \hat{Z}_{i,t-1})\}$, where $\hat{Z}_{i,t}$ is the risk indicator of market i at 0.05 VaR level, $\hat{Z}_{JP,t-1}$ is the risk indicator of Nikkei 225 at 0.05 VaR level, and $d_{JP,t-1}$ is the dummy variable that indicates the volatile regime of Nikkei 225. ***, **, and * denote 0.01, 0.05 and 0.10 levels of significance, respectively. Standard errors are in parentheses.

For most of the Asian-Pacific markets, current market movement is unpredictable by the markets' own previous performance, since β_2 is mostly insignificant. Only for Hong Kong and Taiwan do the one-day lagged movements of the market itself provide relevant information.

Based on the estimates obtained, we can forecast the probabilities that the returns of Asian-Pacific markets will fall below the VaR given the information about the U.S. and Japan. Using Equation (2.15), we can calculate the discrete effect of the dominant market's extreme downside movement on the probability of an extreme downside movement in another market. For example, given that the Singapore market had no extreme downside movement at $t-1$, a fall of Japanese market returns below its 0.1 VaR will raise the likelihood of a corresponding downside movement in Singapore by about 22.9% if the Japanese market is in a tranquil period at t. If the Japanese market is in a period of turmoil, this likelihood will be instead raised by 42.7%.

2.6 Conclusion

This paper studies the extreme downside risk spillover from the U.S. and Japanese stock markets to six Asian-Pacific stock markets. Previous research has investigated risk spillover usually as the spillover of volatility or jumps. In contrast to those typical approaches, this study address the spillover of extreme downside risk measured by Value at Risk. This paper models a binary extreme value regression to find out whether an extreme downside movement in a dominant market (the U.S. or Japan) has predictive ability for downside movements in smaller markets (the individual Asian-Pacific stock markets) and if this (Granger-)causality increases significantly during a period of market turbulence. The estimation framework allows the distribution of the returns to vary with a change in regime: this provides flexibility for risk estimations and feasibility for spillover investigation under different market conditions.

This paper finds strong evidence for the existence of systemic risk across the U.S., Japan, and Asian-Pacific markets. Both the U.S. and Japanese extreme downside risks have significant predictive ability for the possibility of extreme losses in all six Asian-Pacific markets. While Australia shows the highest sensitivity in the Asian-Pacific region to the extreme downside risk of the S&P 500, Singapore is the most vulnerable to that of the Nikkei 225. In contrast, the mainland Chinese market is overall the least affected by the extreme downside risks of either the U.S. or the Japanese market.

Results reveal that these spillover effects may be intensified during the volatile regime of the dominant markets. Asian-Pacific markets, except for mainland China and Taiwan, tend to become more sensitive to Japan's extreme downside risk when the Japanese market is in a period of high volatility. Yet the U.S. spillover effect increases only on Taiwan when the U.S. market turns turbulent.

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Appendix A: SWARCH estimates

Table A.1: U.S. SWARCH estimates

	1/4/93– 1/9/00	12/20/93– 8/17/01	12/5/94– 8/2/02	11/20/95– 7/18/03	11/4/96– 7/2/04	10/20/97– 6/17/05	10/5/98– 6/2/06	9/20/99– 5/18/07	9/4/00– 5/2/08
p_{11}	0.9918***	0.9892***	0.9801***	0.9899***	0.9905***	0.9886***	0.9950***	0.9937***	0.9936***
	(0.0051)	(0.0054)	(0.0075)	(0.0041)	(0.0037)	(0.0039)	(0.0030)	(0.0030)	(0.0032)
p_{22}	0.9892***	0.9905***	0.9877***	0.9786***	0.9789***	0.9863***	0.9961***	0.9921***	0.9922***
	(0.0065)	(0.0051)	(0.0052)	(0.0077)	(0.0077)	(0.0049)	(0.0024)	(0.0039)	(0.0041)
μ_1	0.0008***	0.0009***	0.0013***	0.0007***	0.0006***	0.0005**	0.0003*	0.0005**	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
μ_2	0.0004	0.0000	−0.0003	−0.0007	−0.0008	−0.0005	−0.0002	−0.0005	−0.0007
	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
g_2	4.9959***	4.9181***	5.1734***	3.4162***	3.3909***	3.8013***	4.1307***	4.8542***	4.8378***
	(0.4251)	(0.3908)	(0.3911)	(0.2665)	(0.2660)	(0.2698)	(0.2766)	(0.3366)	(0.3455)
a_0	2.8e5***	3.1e−5***	3.1e−5***	8.1e−5***	8.3e−5***	6.0e−5***	4.3e−5***	4.1e−5***	3.9e−5***
	(1.8e−6)	(2.0e−6)	(2.2e−6)	(6.1e−6)	(5.6e−6)	(4.6e−6)	(2.4e−6)	(2.4e−6)	(2.2e−6)
a_1	3.0e−7***	2.1e−6***	6.5e−6***	3.0e−6***	2.8e−6***	2.6e−7**	1.5e−6***	4.5e−6***	1.2e−7
	(1.5e−7)	(1.5e−7)	(1.5e−7)	(1.6e−7)	(1.6e−7)	(1.5e−7)	(1.5e−7)	(1.5e−7)	(1.5e−7)
λ	0.1982***	0.2244***	0.2343***	0.0803**	0.0829**	0.1406***	0.1495***	0.1409***	0.1354***
	(0.0537)	(0.0538)	(0.0535)	(0.0393)	(0.0398)	(0.0457)	(0.0418)	(0.0421)	(0.0413)

Note: $r_t = \mu_{s_t} + e_t$, $e_t = \sqrt{g_{s_t}} \cdot u_t$, $u_t = \sqrt{h_t} \cdot v_t$, $v \sim N(0,1)$, and $h_t = a_0 + a_1 \cdot u_{t-1}^2 + \lambda \cdot d_{t-1} \cdot u_{t-1}^2$, where $d_{t-1} = 1$ if $u_{t-1} < 0$ and zero otherwise. Standard errors are in parentheses. ***, **, and * denote, respectively, the 99%, 95%, and 90% levels of significance.

Table A.2: Japan SWARCH estimates

	1/4/93– 1/9/00	12/20/93– 8/17/01	12/5/94– 8/2/02	11/20/95– 7/18/03	11/4/96– 7/2/04	10/20/97– 6/17/05	10/5/98– 6/2/06	9/20/99– 5/18/07	9/4/00– 5/2/08
p_{11}	0.9796***	0.9811***	0.9796***	0.9801***	0.9811***	0.9860***	0.9863***	0.9872***	0.9868***
	(0.0061)	(0.0062)	(0.0062)	(0.0063)	(0.0059)	(0.0045)	(0.0044)	(0.0041)	(0.0041)
p_{22}	0.9726***	0.9666***	0.9637***	0.9611***	0.9551***	0.9544***	0.9550***	0.9542***	0.9510***
	(0.0117)	(0.0126)	(0.0118)	(0.0123)	(0.0134)	(0.0133)	(0.0131)	(0.0134)	(0.0142)
μ_1	0.0002	−0.0001	−0.0003	−0.0005	−0.0006	−0.0006	−0.0005	−0.0004	−0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
μ_2	−0.0001	−0.0005	−0.0003	−0.0006	−0.0001	−0.0002	−0.0002	−0.0002	−0.0004
	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
g_2	4.2800***	4.1039***	4.1280***	3.9297***	3.6798***	3.7122***	3.6872***	3.5008***	3.4211***
	(0.3080)	(0.3200)	(0.3140)	(0.3130)	(0.2970)	(0.3210)	(0.3190)	(0.3080)	(0.3050)
a_0	0.0001***	0.0001***	0.0001***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(1.2e−5)	(1.3e−5)	(9.8e−6)	(1.0e−5)	(1.0e−5)	(9.5e−6)	(9.5e−6)	(9.4e−6)	(9.7e−6)
a_1	1.1e−5***	1.80e−5	4.4e−6***	1.4e−5	1.8e−6***	6.1e−7***	3.1e−6***	4.2e−7***	1.8e−7
	(1.6e−7)	(3.5e−2)	(1.6e−7)	(3.6e−2)	(1.6e−7)	(1.6e−7)	(1.6e−7)	(1.7e−7)	(1.7e−7)
λ	2.7e−4	3.0e−5	5.0e−6	4.4e−6	6.8e−7	6.8e−6	7.4e−6	4.8e−7	6.8e−7
	(0.0303)	(0.0405)	(0.0300)	(0.0449)	(0.0342)	(0.0368)	(0.0374)	(0.0427)	(0.0485)

Note: $r_t = \mu_{s_t} + e_t$, $e_t = \sqrt{g_{s_t}} \cdot u_t$, $u_t = \sqrt{h_t} \cdot v_t$, $v \sim N(0,1)$, $h_t = a_0 + a_1 \cdot u_{t-1}^2 + \lambda \cdot d_{t-1} \cdot u_{t-1}^2$, where $d_{t-1} = 1$ if $u_{t-1} < 0$ and $d_{t-1} = 0$ otherwise. Standard errors are in parentheses. ***, **, and * denote, respectively, the 99%, 95% and 90% levels of significance.

Appendix B: Likelihood ratio test of correct unconditional coverage

The LR test of conditional coverage (Christoffersen, 1998) combines the LR test of unconditional coverage (Kupiec, 1995) with the LR test of independence.

The LR test of unconditional coverage suggested by (Kupiec, 1995) measures whether the frequency of VaR exceedances predicted by the model is consistent with the empirical frequency of exceedances (i.e., the failure rate). The null hypothesis for the test is

$$H_0 : \alpha = \frac{x}{T}, \tag{2.16}$$

where $\frac{x}{T}$ is the observed failure rate and α is the failure rate suggested by the confidence level. The test statistics take the form

$$LR_{uc} = -2ln\left(\frac{(1-\alpha)^{T-x}\alpha^x}{(1-\frac{x}{T})^{T-x}(\frac{x}{n})^x}\right), \tag{2.17}$$

and conforms to the χ^2 distribution with one degree of freedom.

The LR test of independence measures whether the probability of an exceedance on any day depends on the outcome of the previous day. As described in Section 2.2, the risk indicator $Z_t^\alpha = 1$ if exceedance occurs, and equals zero if no exceedance occurs. Define n_{ij} as the number of observations having $Z^\alpha = i$ followed by $Z^\alpha = j$. In addition, let π_i be the probability of observing an exceedance conditional on $Z^\alpha = i$ on the previous day. Put

$$\begin{aligned} \pi_0 &= \frac{n_{01}}{n_{00}+n_{01}}, \\ \pi_1 &= \frac{n_{11}}{n_{10}+n_{11}}, \\ \pi &= \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}. \end{aligned} \tag{2.18}$$

The test statistic for the independence test is given by

$$LR_{ind} = -2ln\left(\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}}\right), \tag{2.19}$$

and conforms to the χ^2 distribution with one degree of freedom.

The LR test of conditional coverage is the joint test of coverage and independence given by

$$LR_{cc} = LR_{uc} + LR_{ind}, \tag{2.20}$$

and conforms to the χ^2 distribution with two degrees of freedom.

Bibliography

Adrian, T. and Brunnermeier, M. (2009), "CoVaR", *Federal Reserve Bank of New York Staff Reports*, vol. 348, pp. 1–8.

Anderson, S. and Newell, R. (2003), "Simplified marginal effects in discrete choice models", *Economics Letters*, vol. 81(3), pp. 321–326.

Asgharian, H. (2002), Matlab code for simulated annealing. Manuscript.

Asgharian, H. and Bengtsson, C. (2006), "Jump spillover in international equity markets", *Journal of Financial Econometrics*, vol. 4(2), pp. 167–203.

Asgharian, H. and Nossman, M. (2011), "Risk contagion among international stock markets", *Journal of International Money and Finance*, vol. 30(1), pp. 22–38.

Bae, K., Karolyi, G. and Stulz, R. (2003), "A new approach to measuring financial contagion", *Review of Financial Studies*, vol. 16(3), p. 717.

Baele, L. (2005), "Volatility spillover effects in European equity markets", *Journal of Financial and Quantitative Analysis*, vol. 40(2), pp. 373–401.

Cai, J. (1994), "A Markov model of switching-regime ARCH", *Journal of Business & Economic Statistics*, vol. 12(3), pp. 309–316.

Cameron, A. and Trivedi, P. (2009), *Microeconometrics using stata*, vol. 5, Stata Press College Station, TX.

Christiansen, C. and Ranaldo, A. (2009), "Extreme coexceedances in new EU member states' stock markets", *Journal of Banking & Finance*, vol. 33(6), pp. 1048–1057.

Christoffersen, P. F. (1998), "Evaluating Interval Forecasts", *International Economic Review*, vol. 39(4), pp. 841–862.

Flavin, T. J., Hurley, M. J. and Rousseau, F. (2002), "Explaining stock market correlation: a gravity model approach", *The Manchester School*, vol. 70(S1), pp. 87–106.

FORBES, K. and RIGOBON, R. (2002), "No contagion, only interdependence: Measuring stock market comovements", *Journal of Finance*, vol. 57(5), pp. 2223–2261.

GRANGER, C. (1980), "Testing for causality: A personal viewpoint", *Journal of Economic Dynamics and Control*, vol. 2, pp. 329–352.

GRANGER, C. W. J. (1969), "Investigating Causal Relations by Econometric Models and Cross-spectral Methods", *Econometrica*, vol. 37(3), pp. 424–438.

HAMILTON, J. (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", *Econometrica*, vol. 57(2), pp. 357–384.

HAMILTON, J. and SUSMEL, R. (1994), "Autoregressive conditional heteroskedasticity and changes in regime", *Journal of Econometrics*, vol. 64(1-2), pp. 307–333.

HARTMANN, P., STRAETMANS, S. and VRIES, C. (2004), "Asset market linkages in crisis periods", *Review of Economics and Statistics*, vol. 86(1), pp. 313–326.

HONG, Y., LIU, Y. and WANG, S. (2009), "Granger causality in risk and detection of extreme risk spillover between financial markets", *Journal of Econometrics*, vol. 150(2), pp. 271–287.

JOHANSSON, A. (2009), "An analysis of dynamic risk in the Greater China equity markets", *Journal of Chinese Economics and Business Studies*, vol. 7(3), pp. 299–320.

KING, M. and WADHWANI, S. (1990), "Transmission of volatility between stock markets", *Review of Financial Studies*, vol. 3(1), p. 5.

KUPIEC, P. (1995), "Techniques for verifying the accuracy of risk measurement models", *Journal of Derivatives*, vol. 3(2), pp. 73–84.

Li, M. and Lin, H. (2004), "Estimating value-at-risk via Markov switching ARCH models–an empirical study on stock index returns", *Applied Economics Letters*, vol. 11(11), pp. 679–691.

Longin, F. and Solnik, B. (2001), "Extreme correlation of international equity markets", *Journal of Finance*, vol. 56(2), pp. 649–676.

Miller, I. and Miller, M. (2004), *John E. Freund's mathematical statistics with applications*, Prentice Hall.

Timmermann, A. (2000), "Moments of Markov switching models", *Journal of Econometrics*, vol. 96(1), pp. 75–111.

Turner, C., Startz, R. and Nelson, C. (1989), "A Markov model of heteroskedasticity, risk, and learning in the stock market", *Journal of Financial Economics*, vol. 25(1), pp. 3–22.

Chapter 3

Volatility Behavior and Dependence Structure of Commodity Futures and Stocks

with Lin Gao

3.1 Introduction

Risk management and portfolio diversification have been receiving more and more attention especially since the financial crisis which started in 2007. It is naive to rely on correlations for asset allocation assuming asset returns will continue to follow the same distribution over time. Empirical studies show that financial assets such as stocks and bonds periodically switch from a low volatility regime to a high volatility regime, and then back. Furthermore, assets tend to have larger co-movements with one another in crises despite their low correlations in tranquil periods (see Hartmann *et al.*, 2004, and Norden and Weber, 2009). Therefore, it is crucial for investors to understand the periodic regime-switching of financial assets and the dependence structure between the switching processes.

As an alternative investment opportunity, commodity futures returns tend to have low correlations with the returns of traditional assets such as stocks (see, for example, Gorton and Rouwenhorst, 2006, and Erb and Harvey, 2006) and are thus an ideal option for portfolio diversification. In the meantime, from a risk management perspective, it is desirable that the regime switching of commodity futures be driven by different (latent) factors from those driving the regime switching of stocks, or more strongly, that the switches of commodity futures be completely unrelated with the factors driving the switches of stocks. Previous research has not yet paid sufficient attention to such non-linear dependence structures between commodity futures and stocks. Our paper fills this gap.

The aim of this paper is to reveal the benefit of risk diversification between commodity futures and stocks by investigating the dependence structure between them. To examine the periodic dynamics of commodity futures and stocks, the present paper employs a bivariate model of switching autoregressive conditional heteroskedasticity (SWARCH), in which asset returns switch between different distributions. This model allows testing several interesting hypotheses on the dependence structure. First, by making hypotheses about the transition probabilities between the regimes of low and high volatility, we examine whether the regime switches (or the Markov chains) of the two assets are the same or are unrelated. Moreover, by comparing the conditional correlations in the different regimes, this paper investigates whether the conditional correlation tends to vary with the switching process of the stocks or that of the commodity futures.

This study investigates the weekly data of seven groups of commodity futures from the American commodity exchanges: animal products, energy, grains, industrial materials, industrial metals, precious metals, and softs. The S&P 500 index is selected as the stock index. The results demonstrate that none of the commodity futures are governed by the same regimes as those of the stocks. However, the degrees of regime-dependence with stocks differ among commodities. Besides energy and precious metals, which are typically closely related to the stock market, animals also exhibit dependence on the regime switching of stocks. By contrast, regime-independence is discovered between all the other commodities and stocks. In addition, the switches in animals are better at capturing the changes in its correlations with stocks, whereas the switches in stocks are more decisive for the correlation with precious metals.

This study differs from earlier research in three key aspects. First, as far as we know, this is the first study of the regime dependence structure between commodity futures and stocks. Previous studies mainly focus on comovement (e.g., Erb and Harvey, 2006, or Chong and Miffre, 2010). Moreover, this paper investigates regime changes of both assets in a joint framework with bivariate SWARCH instead of dealing with them in a separate modeling context (e.g., Choi and Hammoudeh, 2010, and Fong and See, 2001) or in a common regime, namely when both are in their volatile regimes at the same time (e.g., Chan *et al.*, 2011). In addition, this regime-dependent analysis of the conditional correlation provides inductive evidence for diversification potential, compared to previous research into dynamic correlation analysis on stocks and commodities, such as Kat and Oomen (2006); Büyüksahin *et al.* (2010); and Chong and Miffre (2010). The identification of "originator" in the correlation changes—stocks or commodities that lead the correlations—is useful for risk hedging. Last and remarkably, unlike the recent studies that document a one-sided effect and predictability of oil on stocks (see Apergis and Miller, 2009, and Driesprong *et al.*, 2008), this paper shows that the influences between the two asset categories are mutual.

The rest of this paper is organized as follows. Section 3.2 presents the preliminary data analysis. Section 3.4.2 specifies the statistical model based on SWARCH. Section 3.4 contains the empirical analysis for volatility behavior and dependence structure between commodity futures and stocks. Section 3.5 concludes.

3.2 Data description and preliminary analysis

To compare commodity futures returns with stock returns, the S&P 500 Composite Index close price and the settlement prices for commodity futures traded on American exchanges are collected (see Table A.1). Rebalanced and equally weighted commodity futures portfolios are constructed in the spirit of Bodie and Rosansky (1980) and Gorton and Rouwenhorst (2006).

Table 3.1: Descriptive statistics of the index logarithmic returns

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs	S&P 500
Mean	0.00013	0.00034	0.00011	0.00006	0.00039	0.00047	0.00003	0.00066
Median	0.00030	0.00124	-0.00012	0.00025	0.00077	0.00068	0.00002	0.00138
Std. Dev.	0.01140	0.02062	0.01220	0.01309	0.01579	0.01374	0.01275	0.01001
Kurtosis	1.60142	3.24401	2.00160	15.48079	4.51702	7.47411	21.11919	6.41339
Skewness	0.03416	-0.49865	-0.11862	-1.18982	-0.77664	-0.34063	1.28209	-0.74493
Min	-0.05004	-0.12554	-0.05659	-0.16492	-0.11422	-0.09602	-0.08591	-0.08722
Max	0.05452	0.09629	0.04483	0.05621	0.05267	0.10571	0.17052	0.04932
Corr.	0.07225	0.02363	0.14817	0.18602	0.25325	0.12613	0.07759	1

Note: Descriptive statistics for log-returns of the investigated indexes: mean, median, standard deviation, excess kurtosis, skewness, minimum value, maximum value and correlation with S&P 500.

Seven groups of commodities are formed, based on their natural characteristics, similarly to Gorton and Rouwenhorst (2005)'s classification: animal products (animals), energy, grains, industrial materials (industrials), industrial metals (metals), precious metals (precious m.), and softs (the index compositions and data sources are displayed in Table A.1 in the Appendix). The descriptive statistics of the data are depicted in Table 3.1.

Usually, researchers assume that commodity futures are fully collateralized and hence add the riskless interest rate component earned during holding the futures to the commodity futures returns. However, in that way commodity futures returns will be "extorted" by interest rates. This paper drops this component in the returns calculation and use the returns resulting directly from the futures contracts, which is defined as excess returns in the literature.

Despite the fact that commodities are traded and consumed worldwide, we restrict our analysis to the U.S. markets for the following reasons. First, the commodity futures selected are all traded on the U.S. futures exchanges. Second, the U.S. stock market is still representative of the world financial markets.

Because of the different introduction dates and availability of the commodities, the indexes contain only those commodities with equal length of time series in order to avoid discontinuities in the volatility estimation. The sample period of all the time series is from January 5, 1979 to April 30, 2010, except that energy runs from April 8, 1983, and metals run from August 9, 1989, due to the limited data availability. All data are downloaded from Datastream. Log returns are constructed from the time series. The data frequency is weekly[1]. Last, the time span of the U.S. business cycle of expansion and contraction is adopted from the announcement by the National Bureau of Economic Research (NBER).

The commodities in the sample provide a very diverse set in terms of such factors as seasonality (e.g., harvest time), country of origin, and perishability, despite their common exchange location—the U.S.. In this sense, there does not exist a common market called "the commodity market" compared to stocks and bonds. For instance, animal products are perhaps the most domestic commodity because of their perishability, whereas grains or other commodities are produced and traded internationally. Storability may be informative for the volatility process. Grains, metals, and oil are storable, and so their intertemporal arbitrage is possible. Softs and animals are not storable, which means futures prices are an unbiased predictor of the future spot price (see Power and Turvey, 2010). According to Beck (2001), autoregressive conditional heteroskedasticity is evident in storable but not in non-storable commodity prices. Hence, because of the diversity of commodities, different categories of commodity futures are distinguished instead of being investigated in one single index.

As shown in Table 3.1, all the time series display a positive trend in the sample period, as the mean of every series is positive. Compared with the commodity futures indexes, the S&P 500 has a higher mean and a lower standard deviation. In addition, all the time series are leptokurtic, but the level of kurtosis varies. Most commodity futures, such as animals, energy, grains, and metals, have smaller kurtosis than the S&P 500, whereas industrials and softs have a much larger "fat tail" risk. Furthermore, most time series, excluding animals and softs, are negatively skewed. Table 3.1 also displays

[1]Monthly and daily data were also examined. The daily data contain much noise, disturbing the regime-shift identification with additional spikes. Moreover, with a long sample period and many data points, the regimes are compacted and less evident. Using monthly data, the regime division is similar to the weekly data, but the quality of regime identification is inferior to that with the weekly data.

the simple correlations between the commodities and the S&P 500. Metals has the largest correlation during the sample period, whereas energy has the smallest. However, as argued previously, simple correlation is not sufficient for understanding the dependence between the assets. Judged from the various properties of the commodity futures, they are expected to have distinct behaviours as to volatility, and diverse dependences on the S&P 500.

3.3 Model and estimation framework

This study examines the dependence between the S&P 500 and commodity futures in a bivariate switching ARCH (SWARCH) modeling framework. Based on the bivariate estimations, two types of hypotheses are tested to make in-depth inferences about the dependence structures between stocks and each group of commodity futures.

3.3.1 Bivariate SWARCH model (Model A)

The bivariate SWARCH model we use is a variant of the bivariate SWARCH of Hamilton and Lin (1996) and Edwards and Susmel (2003), which were developed based on the univariate SWARCH of Cai (1994) and Hamilton and Susmel (1994). For the sake of brevity, our bivariate SWARCH model is called *Model A*. It is

$$\boldsymbol{r}_t = \boldsymbol{\mu}_{s_t} + \boldsymbol{u}_t, \tag{3.1}$$

$$\boldsymbol{u}_t | \boldsymbol{I}_{t-1} \sim N(0, \boldsymbol{H}_t), \tag{3.2}$$

$$\boldsymbol{H}_t = \begin{pmatrix} h_t^+ & \rho_{s_t}\sqrt{h_t^+ h_t^*} \\ \rho_{s_t}\sqrt{h_t^+ h_t^*} & h_t^* \end{pmatrix}, \tag{3.3}$$

$$h_t^+ = g^+_{s_t^+}[a^+ + b^+({u^+_{t-1}}^2 / g^+_{s^+_{t-1}})], \tag{3.4}$$

$$h_t^* = g^*_{s_t^*}[a^* + b^*({u^*_{t-1}}^2 / g^*_{s^*_{t-1}})], \tag{3.5}$$

where the superscript $+$ stands for the S&P500, and $*$, for commodity futures. $r_t = (r_t^+, r_t^*)'$, and $\mu_{s_t} = (\mu^+_{s_t^+}, \mu^*_{s_t^*})'$, where r_t^+ denotes the returns of the S&P

500, and r_t^* is the commodity futures returns. $\mu^+_{s_t^+}$ and $\mu^*_{s_t^*}$ are the state-dependent means of stocks and the commodity futures.

S_t^+ is an unobserved state variable that reflects the volatility state of the S&P 500, and S_t^* represents the volatility phase of the individual commodity futures. We assume that each time series switches between two regimes: a low volatility regime and a high volatility regime, and $S_t^+ = 1$ and $S_t^* = 1$ denote the low-volatility states of stocks and of commodity futures, while $S_t^+ = 2$ and $S_t^* = 2$ denote their high-volatility states. Since each time series has binary regimes, in the bivariate case there are four combinations of regimes, specified by the latent variable S_t.

$$
\begin{aligned}
S_t &= 1 \text{ if } S_t^+ = 1 \text{ and } S_t^* = 1 \\
S_t &= 2 \text{ if } S_t^+ = 2 \text{ and } S_t^* = 1 \\
S_t &= 3 \text{ if } S_t^+ = 1 \text{ and } S_t^* = 2 \\
S_t &= 4 \text{ if } S_t^+ = 2 \text{ and } S_t^* = 2
\end{aligned}
$$

S_t is assumed to follow a first-order Markov chain, with transition probabilities

$$P(S_t = j | S_{t-1} = i) = p_{ij}, \tag{3.6}$$

for $i, j = 1, \ldots, 4$ and $\sum_{j=1}^4 p_{ij} = 1$ for all j.

The transition probability matrix is

$$P = \begin{pmatrix} p_{11} & p_{21} & p_{31} & p_{41} \\ p_{12} & p_{22} & p_{32} & p_{42} \\ p_{13} & p_{23} & p_{33} & p_{43} \\ p_{14} & p_{24} & p_{34} & p_{44} \end{pmatrix} \tag{3.7}$$

The conditional covariance matrix $\boldsymbol{H}_t$ is specified in Equation (3.3). The conditional variance of stocks, h_t^+, and the conditional variance of the commodity futures, h_t^*, each follow a SWARCH process. The scaling factors $g^+_{s_t^+}$ and $g^*_{s_t^*}$ measure the scales of the ARCH processes for the S&P 500 and commodity futures. The factors for the low volatility regimes, g_1^+ and g_1^*, are normalized at unity, and both $g_2^+ > 1$ and $g_2^* > 1$. The correlation coefficient ρ varies across the four different states.

Although the state variable S_t is unobservable, we can date the regimes based on their probabilities. First, we use all the information in the sample to

Table 3.2: Dependence hypotheses testing

Dependence of Markov chains	
Model B	$S_t^+ = S_t^*$
Model C	S_t^+ is independent of S_t^*
Correlation structure	
Model D	$\rho_{S_t=1} = \rho_{S_t=3}$ and $\rho_{S_t=2} = \rho_{S_t=4}$
Model E	$\rho_{S_t=1} = \rho_{S_t=2}$ and $\rho_{S_t=3} = \rho_{S_t=4}$

estimate the probability at time t: $P(S_t|r_T, r_{T-1}, \ldots)$, namely the smoothed probability, using the algorithm of Kim and Nelson (1999). Second, using the dating technique of Hamilton (1989), we infer which regime the time series is in at time t using the criterion that the smoothed probability of that regime should be larger than 0.5.

For estimation, we employ Hamilton's (1989) filtering algorithm for Markov switching models in Matlab. We use Asgharian (2002)'s Matlab code for simulated annealing to locate a good approximation to the global maximum point of the likelihood function.

3.3.2 Dependence hypotheses testing (Model B-E)

An in-depth investigation of the dependence structure between two assets is carried out by testing two types of hypotheses, which impose restrictions on the general Model A. The first type of hypothesis is about the dependence of the Markov chains of commodities and stocks. The second type is about the correlation between the returns. For the sake of clarity, we briefly describe the hypotheses as Model B-E in Table (3.2).

The first type of hypothesis, namely Model B and Model C, regards the regime shift dependence between the Markov chains of the two assets in the spirit of Hamilton and Lin (1996). Model B, assumes that the commodity futures and the S&P 500 share a common pattern of regime switches: $S_t^+ = S_t^*$. Namely, the states $S_t = 2$ and $S_t = 3$ are excluded. In this case, the transition probability matrix is reduced to a 2×2 matrix:

$$\begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11}^{+} & p_{21}^{+} \\ p_{12}^{+} & p_{22}^{+} \end{pmatrix} = \begin{pmatrix} p_{11}^{*} & p_{21}^{*} \\ p_{12}^{*} & p_{22}^{*} \end{pmatrix} \tag{3.8}$$

Another hypothesis, Model C assumes that the regime switching pattern of the S&P 500 is unrelated to that of the commodity futures, in which case S_t^* is independent of S_t^+ for all t. More precisely, the transition probabilities defined in Equation (3.6) are calibrated as a product of those for the independent chains governing S_t^+ and S_t^*.

$$\begin{pmatrix} p_{11} & p_{21} & p_{31} & p_{41} \\ p_{12} & p_{22} & p_{32} & p_{42} \\ p_{13} & p_{23} & p_{33} & p_{43} \\ p_{14} & p_{24} & p_{34} & p_{44} \end{pmatrix} = \begin{pmatrix} p_{11}^{+}p_{11}^{*} & p_{21}^{+}p_{11}^{*} & p_{11}^{+}p_{21}^{*} & p_{21}^{+}p_{21}^{*} \\ p_{12}^{+}p_{11}^{*} & p_{22}^{+}p_{11}^{*} & p_{12}^{+}p_{21}^{*} & p_{22}^{+}p_{21}^{*} \\ p_{11}^{+}p_{12}^{*} & p_{21}^{+}p_{12}^{*} & p_{11}^{+}p_{22}^{*} & p_{21}^{+}p_{22}^{*} \\ p_{12}^{+}p_{12}^{*} & p_{22}^{+}p_{12}^{*} & p_{12}^{+}p_{22}^{*} & p_{22}^{+}p_{22}^{*} \end{pmatrix} \tag{3.9}$$

The second type of hypothesis is about the correlation structure: First, Model D assumes that the change of correlation is primarily governed by the regime switching of the S&P 500: $\rho_{S_t=1} = \rho_{S_t=3}$ and $\rho_{S_t=2} = \rho_{S_t=4}$. In this model, the S&P 500 is called the "originator." Second, Model E attributes the variation of the correlation to the changes in commodity volatility: $\rho_{S_t=1} = \rho_{S_t=2}$ and $\rho_{S_t=3} = \rho_{S_t=4}$. Here, the commodity futures are called the originator.

For both types of hypothesis tests, the general Model (Model A) with unrestricted transition probabilities and correlations serves as the benchmark case. To test each null hypothesis, we implement a likelihood ratio test to compare the likelihood of the unrestricted model (Model A) with that of the particular restricted model. The likelihood ratio approximately follows a chi-squared distribution with k degrees of freedom under the null hypothesis, where k is the number of additional parameters estimated for the unrestricted model compared to the restricted one.

3.4 Empirical analysis

This section addresses the research questions raised in the first part of the paper using bivariate SWARCH analysis and its affiliated tests. First, we present the results of the general case (Model A). Next, bivariate tests of independent and common regimes of commodity futures and stocks are implemented. Last, the conditional correlation is analyzed in different regime contexts and on this basis the hypotheses about the correlation structure are tested.

3.4.1 Bivariate analysis of the dependence structures

This section presents the estimation results of the general case (Model A) and the results of the regime-dependence hypothesis tests described by Models B and C.

The estimated parameters of Model A are given in Table 3.3.[2] (The estimated transition probability matrices are given in Table A.3 and the estimated smoothed probabilities are given in Figures A.1–A.7 in the Appendix.) For the sake of brevity, the name of each commodity refers to the respective bivariate model with stocks in the following analysis. In contrast to stocks, high volatility is not necessarily associated with low or negative average returns in commodity futures. All commodity futures, except energy and precious metals, yield higher returns in their high volatility regimes than in their low volatility regimes. This phenomenon is consistent with the argument in Gorton *et al.* (2007), in which they observe infrequent upward spikes in the prices of commodity futures, but no downward spikes.

The fact that commodity futures prices are more prone to upward than to downward price spikes can be attributed to the production costs of commodities. As long as demand exists, there will exist a floor for commodity prices, which has to do with production costs. The upper bound of commodity prices is relatively open. This is how commodity futures differ from stocks, bonds, or other financial futures, which possess substantial intangible assets such as brand or credibility and could have a value of zero.

[2]Estimated results of univariate two-state SWARCH are presented in Table A.2 to explore the assets' properties. The transition probabilities p_{12} and p_{21} are statistically significant for the S&P 500 and all the commodity futures, which indicates the existence of regime switch in all cases. ARCH effects disappear for many commodities in the Switching ARCH estimation, which is consistent with the previous empirical findings (e.g., Lamoureux and Lastrapes, 1990) that the high persistence of ARCH may be spurious because of uncaptured structural breaks. Only stocks, precious metals, and grains still retain a statistically significant ARCH coefficient b. In order to compare the results between all the series without loss of generality, we continue to use SWARCH in the following analysis.

Table 3.3: Maximum likelihood estimates for the bivariate SWARCH (Model A)

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs
μ_1^+	0.0014***	0.0013***	0.0013***	0.0013***	0.0009***	0.0013***	0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
μ_2^+	-0.0006	-0.0007	-0.0005	9.2e-005	0.0006	-0.0001	-0.0004
	(0.0007)	(0.0009)	(0.0008)	(0.001)	(0.0005)	(0.0006)	(0.0006)
μ_1^*	0.0001	0.0011**	-0.0002	0.0001	0.0004	0.0005*	-5.4e-005
	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.000)
μ_2^*	0.0002	-0.0031	0.0013	0.0004	0.0009	0.0003	0.0001
	(0.0010)	(0.0021)	(0.0011)	(0.0006)	(0.0024)	(0.0015)	(0.0009)
g_2^+	3.875***	4.017***	4.280***	3.811***	3.832***	3.812***	3.907***
	(0.351)	(0.458)	(0.412)	(0.335)	(0.373)	(0.351)	(0.335)
g_2^*	3.591***	4.383***	4.644***	2.339***	4.278***	6.538***	2.971***
	(0.401)	(0.448)	(0.479)	(0.213)	(0.445)	(0.511)	(0.284)
a^+	4.4e-005***	4.5e-005***	4.2e-005***	3.8e-005***	3.1e-005***	4.2e-005***	4.0e-005***
	(2.5e-006)	(2.5e-006)	(2.8e-006)	(2.7e-006)	(2.5e-006)	(2.5e-006)	(2.5e-006)
b^+	0.160***	0.180***	0.147***	0.150***	0.198***	0.177***	0.152***
	(0.029)	(0.032)	(0.028)	(0.023)	(0.033)	(0.027)	(0.027)
a^*	8.3e-005***	0.0002***	7.0e-005***	9.1e-005***	0.0002***	8.3e-005***	8.9e-005***
	(5.0e-006)	(1.2e-005)	(4.7e-006)	(6.0e-006)	(9.8e-006)	(4.1e-006)	(6.5e-006)
b^*	8.1e-005	0.045	0.070*	0.030	7.6e-006	0.068**	1.8e-005
	(0.035)	(0.035)	(0.042)	(0.029)	(0.032)	(0.029)	(0.031)
ρ_1	0.0030	0.112***	0.080*	0.158***	0.051	0.057	0.116**
	(0.036)	(0.036)	(0.042)	(0.050)	(0.050)	(0.035)	(0.046)
ρ_2	0.188**	-0.194	0.136	-0.069	0.151***	0.030	0.076
	(0.081)	(0.085)	(0.092)	(0.087)	(0.048)	(0.065)	(0.080)
ρ_3	-0.075	-0.359	0.215**	0.083	0.164	0.134	-0.104
	(0.082)	(0.067)	(0.088)	(0.064)	(0.152)	(0.106)	(0.109)
ρ_4	0.201*	0.357***	0.200***	0.345***	0.521***	0.302***	0.130*
	(0.108)	(0.089)	(0.063)	(0.043)	(0.052)	(0.076)	(0.072)
LogL.	10448.769	8294.017	10411.7	10323.84	6614.531	10321.49	10368.45

Note: The table shows the results of the general bivariate SWARCH (Model A) of 4 states composed of 2 states for commodity futures and 2 states for the S&P 500. In the first column, + stands for the S&P 500 and * stands for commodity futures. In the other columns, * indicates significance at the 10%, ** at the 5% level, and *** at the 1% level. Standard errors are in parentheses.

Table 3.4: Duration and empirical frequency of the general bivariate SWARCH (Model A)

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs
				Duration			
state 1	57.78	79.79	14.62	24.25	107.20	61.47	15.10
state 2	3.57	9.63	4.99	25.62	102.73	13.33	35.58
state 3	9.69	6.83	6.72	102.52	12.23	9.51	4.65
state 4	1.42	15.49	13.86	24.84	26.15	4.26	13.53
				Empirical frequency			
state 1	57%	64%	63%	39%	41%	60%	56%
state 2	23%	14%	11%	13%	47%	20%	17%
state 3	12%	11%	10%	23%	4%	8%	7%
state 4	2%	7%	11%	22%	9%	7%	14%

Note: Expected durations and empirical frequencies of all states for the general bivariate SWARCH of the commodity futures. The duration of state j is how many weeks, on average, regime j will last. The empirical frequency is estimated as the number of weeks that are in state j divided by the total number of weeks in the sample period.

In order to illustrate the persistence of the regimes, Table 3.4 gives the empirical frequency and the estimated duration for each state of Model A. The empirical frequency is estimated as the number of weeks that are in state j divided by the total number of weeks in the sample period. The duration of state j, calculated as $1/(1 - p_{jj})$ following Kim and Nelson (1999), gives how many weeks, on average, regime j lasts. The table shows that the mutual volatile state (i.e., the fourth state) occupies only 10% on average of the stock–commodity combinations. Except for metals, the mutual tranquil state (state 1) has the highest empirical frequency (54% on average of the whole sample) among the four states for all the bivariate models. The expected durations of the mutual volatile state is also on average smaller than those of the other states. Animals is advantageous in risk diversification to a portfolio of stocks, as its mutual volatile state with stocks occurs in 2% of the entire sample period and tends to last for only 1.43 weeks.

Next, the dependence tests of Model B and Model C are implemented, in order to examine whether commodities and stocks are driven by the same or by unrelated forces. The results are shown in Table 3.5. The null hypothesis that commodity futures and stocks are driven by common latent forces (Model

Table 3.5: Likelihood ratio test against the independent and common models (Model B and Model C)

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs
				Commonality (Model B)			
LogL. Model B(14)	10414.44	8162.55	10372.50	10284.95	6563.72	10287.53	10334.64
Likelihood Ratio	68.66***	262.93***	78.40***	77.79***	101.61***	67.91***	67.62***
Conclusion	uncom	uncom	uncom	uncom	uncom	uncom	uncom
				Independence (Model C)			
LogL. Model C(18)	10439.42	8279.85	10406.55	10317.43	6612.22	10314.63	10362.53
Likelihood Ratio	18.69**	28.33***	10.30	12.82	4.61	13.72*	11.83
Conclusion	dep	dep	indep	indep	indep	dep	indep

Note: LogL. Model B(14) and LogL. Model C(18) are, respectively, the likelihood values of Model B and Model C. The numbers in parentheses are the number of parameters for each model.
Model B assumes that the commodity futures have the same regimes with the S&P 500. The likelihood ratio is approximately distributed as χ^2_{12}, as the unrestricted model A has 12 more parameters than the restricted model B. Model B is rejected in all cases, implying that none of the commodity futures share common regimes with the S&P 500.
Model C assumes that the regime switching patterns of commodity futures and the S&P 500 are independent. The likelihood ratio is approximately distributed as χ^2_8, as the unrestricted model A has 8 more parameters than Model C. Model C is rejected for animals, energy, and precious metals, suggesting that the factors that drive the regime-switch of these assets are dependent on the factors that drive the S&P 500.
*, ** and *** indicate that the restricted model (null hypothesis) is rejected at, respectively, significance levels of 10%, 5%, and 1%.

B) is rejected for all commodities at the 5% level of significance. This result is in line with the market-segmentation point of view. Further, Model C is not rejected for grains, industrials, metals, or softs, implying that the latent driving factors of these commodity futures are independent of the latent factors driving stocks. Dependence is found only in energy and precious metals, which are known to be closely related with stock markets, and in animal products. The property of non-mutual and independent regime switches between most commodity futures and stocks favors the diversification between these two assets.

To summarize, the results detect three attractive properties of commodity futures that are favorable for risk diversification in a portfolio. First, the mutual volatile regime of commodity futures and stocks tend to be infrequent and short-lived. Second, commodity futures tend to be subject to upward instead of downward price changes. Finally, the conditional variances of stocks and commodities are not necessarily subject to the same or interdependent driving factors, as manifested in the independent and uncommon regime identification between them.

As a byproduct of our analysis, a mutual transmission effect is detected between stocks and energy. In the transition matrix of energy-stocks shown in Appendix Table A.3 for the unrestricted model A, p_{23} and p_{32} are statistically significant at the 5% level, suggesting that the individual volatile state of energy or stocks can easily switch to the volatile state of its counterpart. As shown by the smoothed conditional probabilities in Figure A.2 in Appendix A, during the energy crisis of 1985 and 1986, the turmoil in the energy market spreads to the stock market. Moreover, volatile stock market state also affects energy, which is featured in the stock market crash in 1987 and in the recent financial crisis since mid-2007.

3.4.2 Correlation tests and analysis

In addition to the dependence of regime switching patterns between asset returns, correlations that are conditional on various regimes also play a key role in asset diversification. The bottom part of Table 3.3 displays the conditional correlation coefficients ρ for the general bivariate model (Model A), in which ρ:s are allowed to vary across the four regimes. The small value of ρ over all the regimes favors diversification between stocks and commodity futures.

Particularly interesting are the correlation coefficients in the fourth regime when both stock markets and commodity futures are volatile. As displayed in Table 3.3, the ρ:s are all significantly positive in the fourth regime. These values also increase for all commodity futures except for grains. However, the magnitude of the increase is very mild in all cases except for metals, suggesting that the benefit of diversification still prevails. Although the correlation between metals and stocks is large in the fourth regime ($\rho = 0.521$), the fourth regime of metals takes up only 9% time of the whole sample, according to the empirical frequency shown in Table 3.4. In comparison, the lowest correlation during the mutual volatile regime is between softs and the stock market (0.130).

Table 3.6: Selected estimation results of the bivariate model A between the world stock index (excluding the U.S. market) and the S&P 500 index

	State 1	State 2	State 3	State 4
Duration	24.17	1.01	6.08	10.13
Empirical Frequency	61%	7%	9%	23%
ρ	0.541***	0.462***	0.039	0.717***
	(0.027)	(0.080)	(0.128)	(0.027)

Note: Selected results of the bivariate SWARCH between world stock index (excluding the U.S. market) and S&P 500 index. Duration, empirical frequency, and correlation are shown for each state. Standard errors of ρ are in parentheses. *** denotes the 1% significance level.

In order to intuitively demonstrate the diversification potential of commodity futures, we consider the benefit of diversification between the S&P 500 and the world stock index (excluding the U.S. market) as a benchmark. Table 3.6 presents the estimated duration, empirical frequency, and correlation coefficients between the world stock index and the S&P 500 using the bivariate model A. The sample period is from January 5, 1979 to April 30, 2010, the same as most of the selected samples of the commodity futures. The results show that the returns correlations between the S&P 500 and the stock index of the rest of the world are significantly positive and much larger than those with commodity futures in states 1, 2, and 4. Although the correlation for state 3 is insignificantly different from zero, the benefit of diversification is almost negligible given the short duration (6.08 weeks) and small empirical frequency (9%) of this state. Besides, the hypothesis of independence (Model B) between the S&P 500 and the world stock index (excluding the U.S. market) is rejected. Therefore, we conclude that commodity futures are superior to the world stock index in terms of diversification with the U.S. stock market.

Among the groups of commodity futures, industrials and softs demonstrate small and statistically insignificant correlations with the S&P 500 in the second and third states. Hence, investors in U.S. stocks can benefit from portfolio diversification with industrials and softs when these two assets are in different regimes from stocks. Given the positive (though not significant) means of industrials and softs in volatile times (see Table 3.3), their low correlation with stocks becomes even more attractive in the third state. Notably, the third state of industrials and the S&P 500 tends to be long-lasting compared to other states, as the duration of the third state (see Table 3.4) is 102.52 weeks. Therefore, one can gain relatively stable benefits from diversifying investments into industrials futures and the S&P 500.

Precious metals lives up to its role as a "safe haven." First, the correlations in the first three states are not statistically different from zero. Second, the correlation of the mutual volatile state is merely 0.302, though significant. Finally, the empirical frequency of the mutual volatile state is very small.

It is worth mentioning that the correlation of energy with stocks is significant and varies substantially across regimes. The correlation coefficients are negative in the second and the third states, suggesting "decoupling" and hedging between these two assets. This may partly be explained by a "flight to quality" because a high realized mean is associated with low volatility for both the assets, which is described in Section (3.4.1). Empirically, we observe a large spike in the smoothed probability of the third state in 1990 caused by the Persian Gulf War (see Figure A.2 in the Appendix), which brought about fears of a decreasing oil supply but unremarkable impact on the stock market. In addition, the positive and large correlation in the fourth regime can be explained by stressed market liquidity or a pessimistic economic forecast during the financial crises (e.g., after the dot-com bubble burst and in the recent financial crisis starting in late 2007).

Furthermore, two hypotheses regarding the change in the correlations (described as Model D and Model E in Section 3.3) are tested. Model D assumes that the S&P is the "originator" (i.e., the correlations change when stocks switch from one of its regimes to the other), whereas Model E assumes that commodity futures are the originator. Table 3.7 shows the test results for Models D and E. The correlations become larger when the stock market turns volatile in all cases except for energy. However, the likelihood ratios demonstrate that only the correlations of animals, grains, and softs are associated with the volatility-regime switches of stocks. The likelihood ratio test shows that Model E is not rejected for grains, precious metals, or softs. The correlation coefficient between grains and the S&P 500 doubles as

Table 3.7: Likelihood ratio test against Model D and Model E

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs
				Model D			
$\rho_1 = \rho_3$	-0.008	0.087**	0.115***	0.104***	0.067	0.025	0.067*
	(0.082)	(0.036)	(0.033)	(0.037)	(0.048)	(0.035)	(0.035)
$\rho_2 = \rho_4$	0.175	-0.063	0.168***	0.259***	0.242***	0.188***	0.090*
	(0.108)	(0.045)	(0.049)	(0.036)	(0.039)	(0.041)	(0.049)
LogL. Model D(24)	10448.53	8286.93	10410.31	10320.75	6609.76	10319.12	10366.77
Likelihood Ratio	0.48	14.17***	2.77	6.19**	9.54***	4.73*	3.36
				Model E			
$\rho_1 = \rho_2$	0.036	0.015	0.095***	0.139***	0.116***	0.056*	0.090**
	(0.032)	(0.033)	(0.033)	(0.036)	(0.034)	(0.031)	(0.038)
$\rho_3 = \rho_4$	0.084	0.020	0.208***	0.214***	0.449***	0.237***	0.050
	(0.057)	(0.060)	(0.050)	(0.035)	(0.060)	(0.058)	(0.058)
LogL. Model E(24)	10444.81	8285.06	10411.47	10318.77	6612.02	10320.80	10366.86
Likelihood Ratio	7.92**	17.91***	0.45	10.15***	5.02*	1.37	3.18
Originator	stocks	neither	both	neither	neither	commodity	both

Note: Estimated correlations between commodity futures and S&P 500 of Model D and Model E. Also shown are the results of likelihood ratio tests for the general bivariate SWARCH (Model A) against Model D and E. The likelihood ratio is approximately distributed as χ^2_2, as Model A has 2 more parameters than Model D. Model D is rejected for energy, industrials, metals, and precious metals. Model E is rejected for animals, energy, industrials, and metals. ***, **, and * denote null hypothesis rejected at, respectively, the 1%, 5%, and 10% significance levels.

grains turn from their tranquil to their volatile state, whereas the correlation coefficient of precious metals triples. We therefore ascribe the correlation of precious metals mainly to the volatility state itself. In addition, both models are rejected for energy, industrial materials, and metals, suggesting that the correlation changes are not aligned with either side of the assets.

3.5 Conclusion

The main finding of this paper is that commodity futures can be a good instrument for risk diversification. They do not share common volatility regimes with U.S. stocks, which is in line with the segmented market view. Furthermore, regime-switching dependence is only found in energy and precious metals, which are known to be closely related to the stock market, and in animals. The mutual volatile regime of commodity futures and stocks tend to be infrequent and short-lived.

The correlations between U.S. stock returns and the investigated commodity futures are generally much lower than the correlation between the U.S. stock returns and world (excluding U.S.) stock index returns. Correlations between U.S. stocks and the commodity futures do increase in periods in which both are volatile. However, animals, grains, and softs typically have low correlations with stocks. Even in their volatile regimes, the correlations of these three commodity groups with stocks remain as low as about 0.2. Moreover, regarding the short duration of mutual volatile regimes, the temporary increase in correlation is not a severe issue. Overall, the results of this paper support risk diversification between commodity futures and stocks.

This paper also infers that the changes in correlations can be related to the regime switches of assets. For animals, the changes in its correlation with stocks are associated with the regime switches of stocks, whereas the correlation changes of precious metals seem to stem from the regime switches of precious metals itself.

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Appendix A

Table A.1: Data sources

No.	Name	Quotes start	Market	Sector
1	Frozen Pork Bellies	5/1/1979	Chicago Mercantile Exchange	Animals
2	Live Cattle	5/1/1979	Chicago Mercantile Exchange	Animals
3	Lean Hogs	5/1/1979	Chicago Mercantile Exchange	Animals
4	Feeder Cattle	5/1/1979	Chicago Mercantile Exchange	Animals
5	Heating Oil	8/4/1983	New York Mercantile Exchange	Energy
6	Crude Oil	8/4/1983	New York Mercantile Exchange	Energy
7	Wheat	5/1/1979	Chicago Board of Trade	Grains
8	Corn	5/1/1979	Chicago Board of Trade	Grains
9	Soybeans	5/1/1979	Chicago Board of Trade	Grains
10	Soybean Oil	5/1/1979	Chicago Board of Trade	Grains
11	Soybean meal	5/1/1979	Chicago Board of Trade	Grains
12	Oats	5/1/1979	Chicago Board of Trade	Grains
13	Cotton	5/1/1979	Coffee, Sugar, and Cocoa Exchange	Industrials
14	Lumber	5/1/1979	Chicago Mercantile Exchange	Industrials
15	Copper	1/9/1989	New York Commodities Exchange	Metals
16	Platinum	5/1/1979	New York Mercantile Exchange	Precious Metals
17	Gold	5/1/1979	New York Commodities Exchange	Precious Metals
18	Palladium	5/1/1979	New York Mercantile Exchange	Precious Metals
19	Cocoa	5/1/1979	Coffee, Sugar and Cocoa Exchange	Softs
20	Sugar	5/1/1979	Coffee, Sugar and Cocoa Exchange	Softs
21	Orange Juice	5/1/1979	New York Commodities Exchange	Softs
22	Coffee	5/1/1979	Coffee, Sugar and Cocoa Exchange	Softs

Table A.2: Maximum likelihood estimates for the univariate two-state model

	Animals	Energy	Grains	Industrials	Metals	Precious M.	Softs	S&P 500
p_{11}	0.979***	0.985***	0.964***	0.990***	0.993***	0.978***	0.960***	0.985***
	(0.007)	(0.005)	(0.010)	(0.005)	(0.003)	(0.006)	(0.015)	(0.005)
p_{12}	0.021***	0.015***	0.036***	0.010*	0.007**	0.022***	0.04***	0.015***
	(0.007)	(0.005)	(0.010)	(0.005)	(0.003)	(0.006)	(0.015)	(0.005)
p_{22}	0.963***	0.910***	0.898***	0.993***	0.929***	0.938***	0.862***	0.980***
	(0.012)	(0.028)	(0.026)	(0.004)	(0.034)	(0.015)	(0.046)	(0.007)
p_{21}	0.037***	0.090***	0.102***	0.007*	0.071**	0.062***	0.138***	0.020***
	(0.012)	(0.028)	(0.026)	(0.004)	(0.034)	(0.015)	(0.046)	(0.007)
μ_1	0.00041	0.00109**	-0.00017	-0.00012	0.00050	0.00052*	-0.00002	0.00128***
	(0.00032)	(0.00050)	(0.00029)	(0.00040)	(0.00043)	(0.00028)	(0.00033)	(0.00022)
μ_2	-0.00036	-0.00466*	0.00092	0.00041	-0.00071	0.00034	0.00001	0.00024
	(0.00067)	(0.00274)	(0.00103)	(0.00047)	(0.00362)	(0.00108)	(0.00113)	(0.00049)
g_2	2.831***	5.263***	4.574***	2.339***	5.859***	6.043***	3.089***	3.609***
	(0.242)	(0.602)	(0.480)	(0.206)	(0.869)	(0.427)	(0.343)	(0.290)
a	7.7E-5***	2.5E-4***	7.1E-5***	8.3E-5***	1.7E-4***	7.7E-5***	9.5E-5***	3.7E-5***
	(6.0E-6)	(2.0E-5)	(6.1E-6)	(7.2E-6)	(1.1E-5)	(7.6E-6)	(7.1E-6)	(2.8E-6)
b	0.000	0.032	0.075*	0.041	0.000	0.051**	0.000	0.162***
	(0.028)	(0.038)	(0.040)	(0.029)	(0.034)	(0.023)	(0.032)	(0.022)
LogL.	5046	3600	5003	4897	3025	4914	4968	5389
Dur.	27.105	11.155	9.832	142.361	14.157	16.146	7.265	49.075
E.f.	0.349	0.110	0.222	0.590	0.083	0.244	0.156	0.446

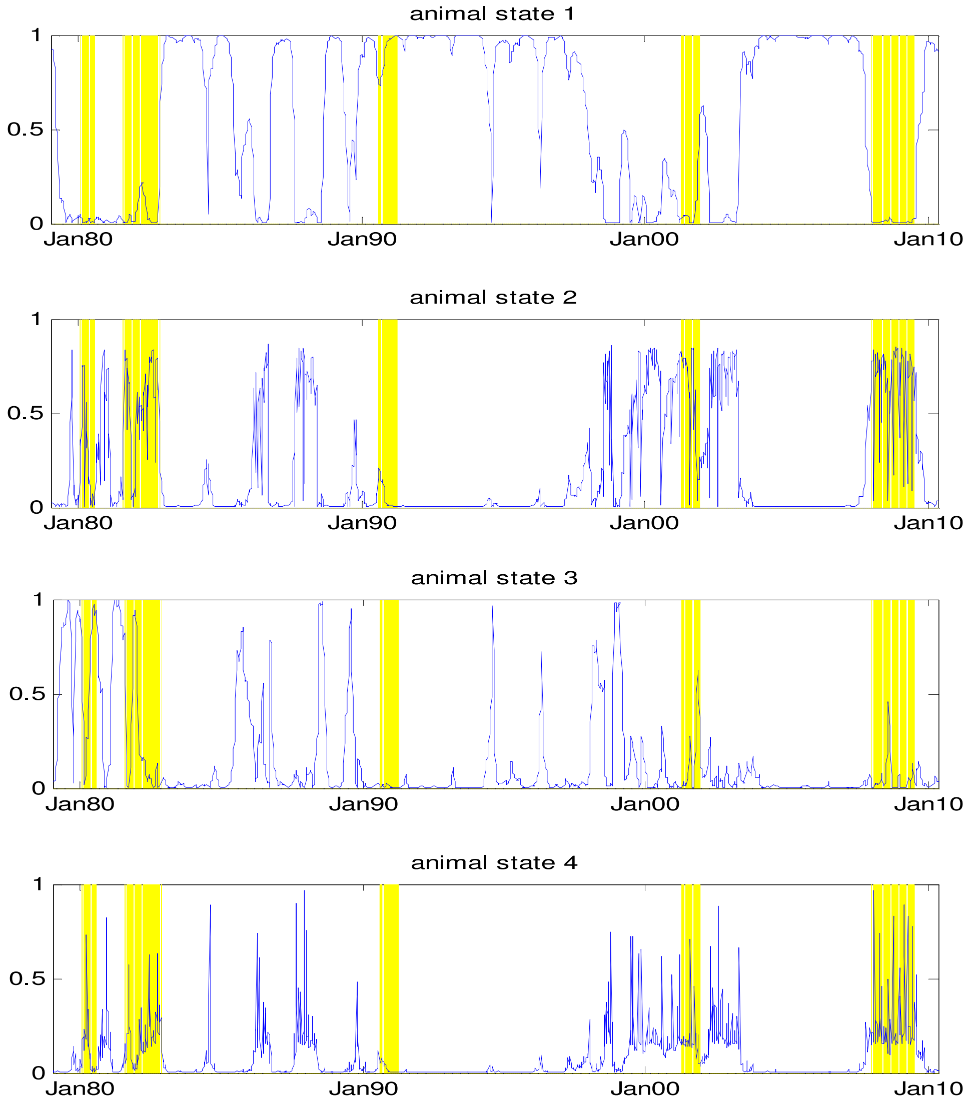
Note: Results for the univariate SWARCH model of each commodity futures and S&P 500. Standard errors are in parentheses. The first four rows of the table are the transition probabilities. The last two rows are the duration and empirical frequency of the high volatility regime of the asset. The duration is defined as $1/(1-p_{jj})$. The empirical frequency is estimated as the number of weeks that are in the high volatility regime divided by the total number of weeks in the sample period. Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.3: Transition probability matrices in the general bivariate SWARCH (Model A)

Animals				Energy			
0.9827***	6.4E-06	0.0418*	0.0559	0.9875***	4.2E-06	0.0268	0.0645**
3.1E-07	0.7201***	0.0614	0.6442*	0.0080*	0.8962***	0.0829**	1.9E-05
0.0087	0.0462	0.8968***	0.0021	0.0045	0.1038***	0.8535***	4.1E-06
0.0086	0.2337*	0.0000	0.2977	4.6E-08	3.5E-05	0.0368	0.9355***
Grains				Industrials			
0.9316***	0.1433**	0.1286**	4.9E-05	0.9588***	0.0390*	0.0097	0.0346**
0.0326*	0.7998***	0.0201	0.0721	0.0147	0.9610***	2.1E-07	0.0002
0.0358**	0.0001	0.8512***	1.6E-05	0.0020	6.0E-06	0.9902***	0.0055
5.6E-07	0.0568	5.5E-06	0.9278***	0.0245**	2.8E-06	5.3E-06	0.9597***
Metals				Precious M.			
0.9907***	0.0036	0.0346	4.8E-05	0.9837***	5.0E-06	0.0121	0.0855**
1.4E-06	0.9903***	0.0239	0.0382	0.0101*	0.9250***	5.4E-06	0.0893*
0.0093	4.4E-06	0.9182***	9.5E-07	0.0061	2.2E-06	0.8949***	0.0597
1.5E-06	0.0061	0.0232	0.9618***	1.1E-06	0.0750**	0.0930	0.7655***
Softs							
0.9338***	0.0001	0.1798**	0.0739**				
0.0088	0.9719***	4.4E-05	1.7E-06				
0.0443*	0.0280	0.7851***	3.3E-05				
0.0131	0.0001	0.0351	0.9261***				

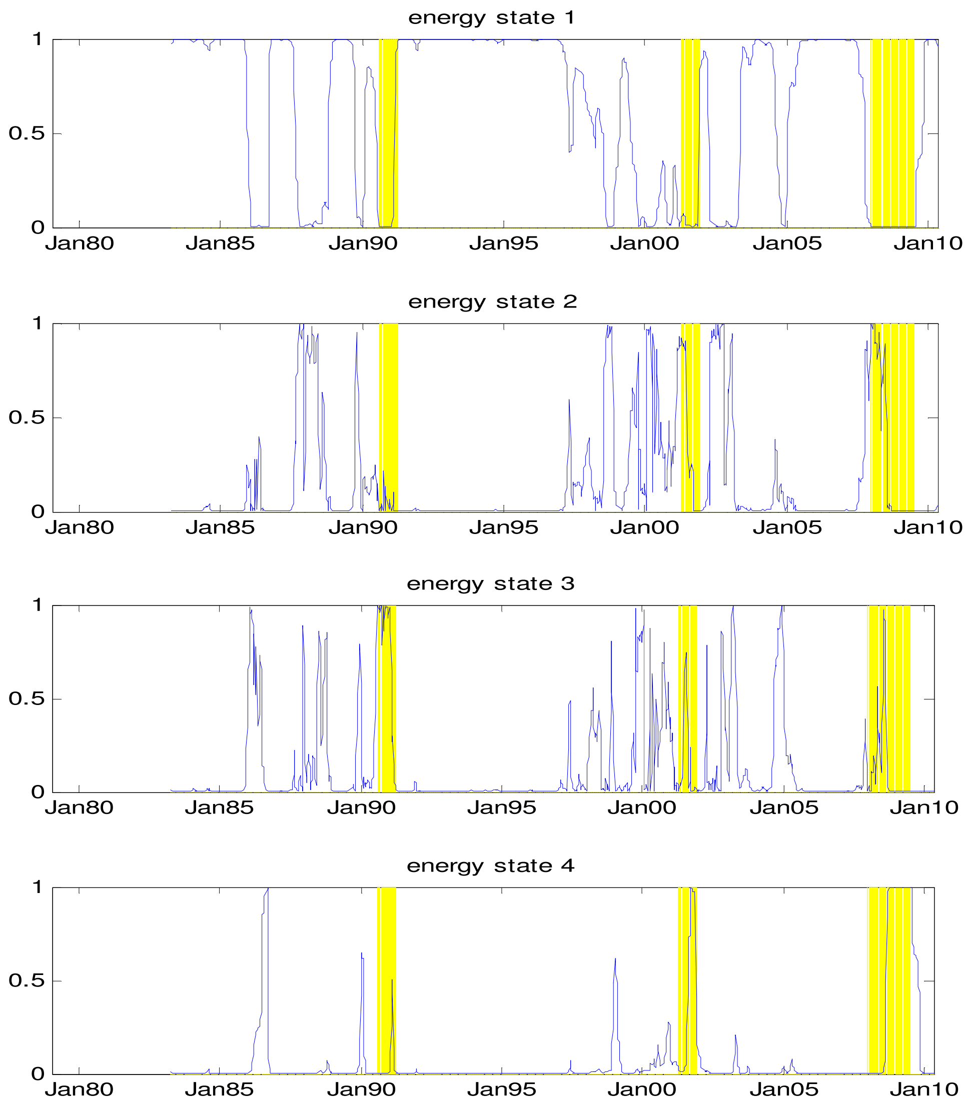
Note: Transition probabilities for every bivariate model. For example, the first row of "animals" shows the probabilities of transiting to state 1: p_{11}, p_{21}, p_{31}, and p_{41}. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure A.1: Smoothed probabilities in the bivariate SWARCH model for animals and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



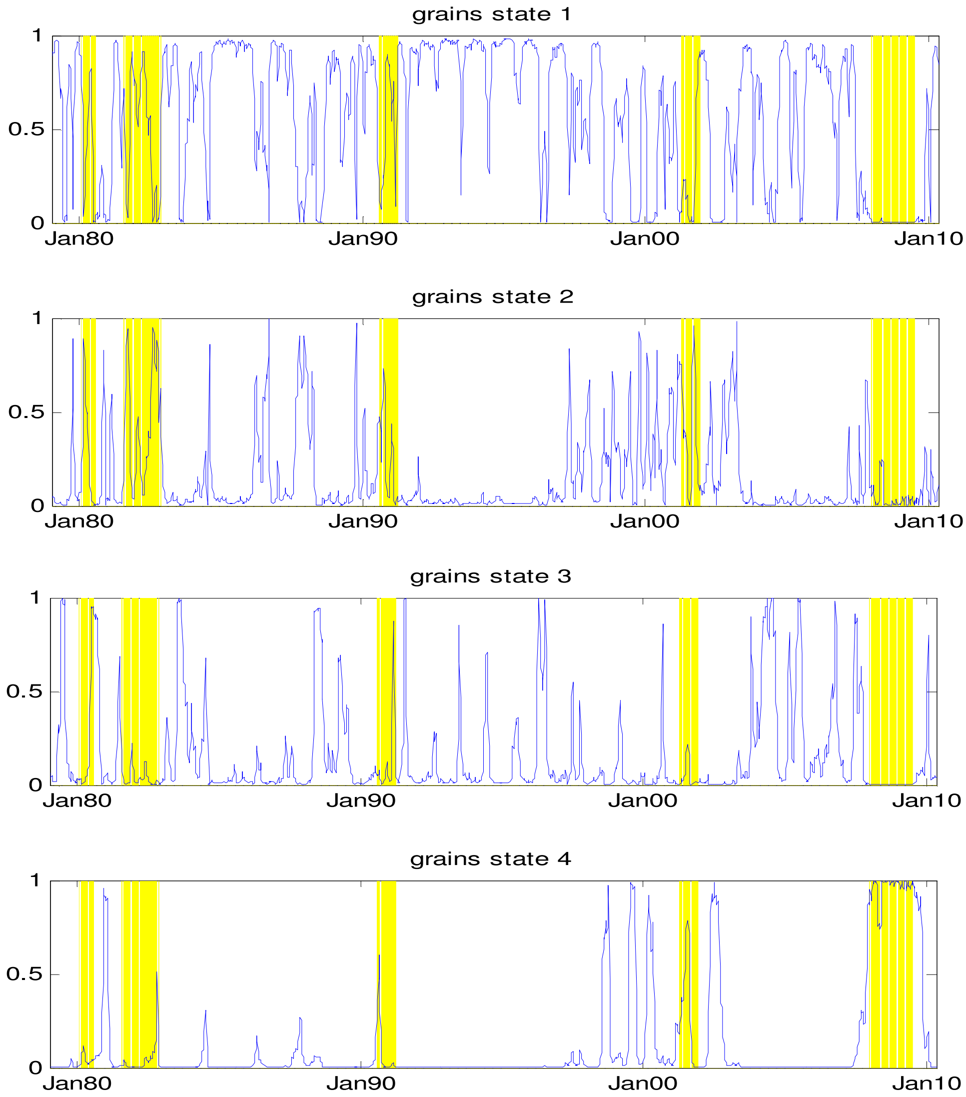
The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of animals and stocks are displayed, based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.2: Smoothed probabilities in the bivariate SWARCH model for energy and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



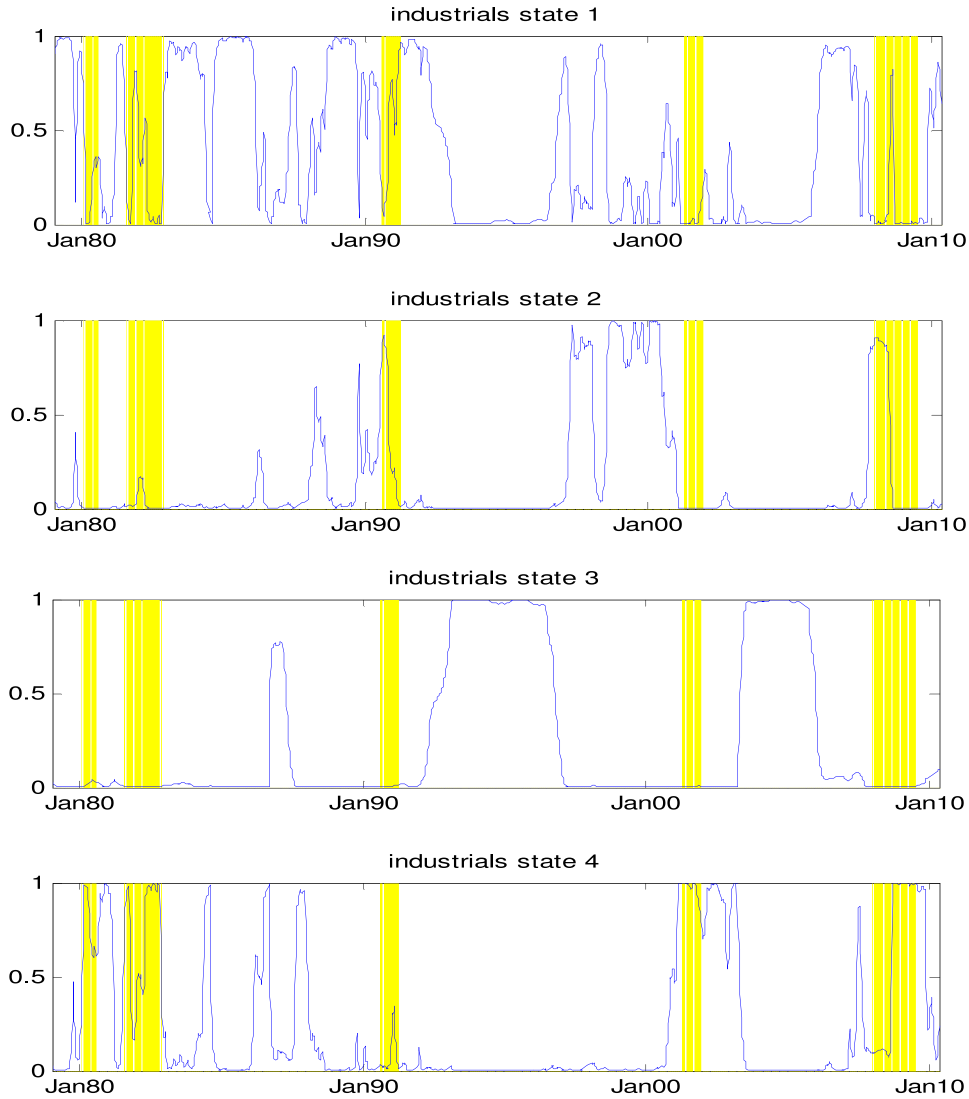
The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of energy and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.3: Smoothed probabilities in the bivariate SWARCH model for grains and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



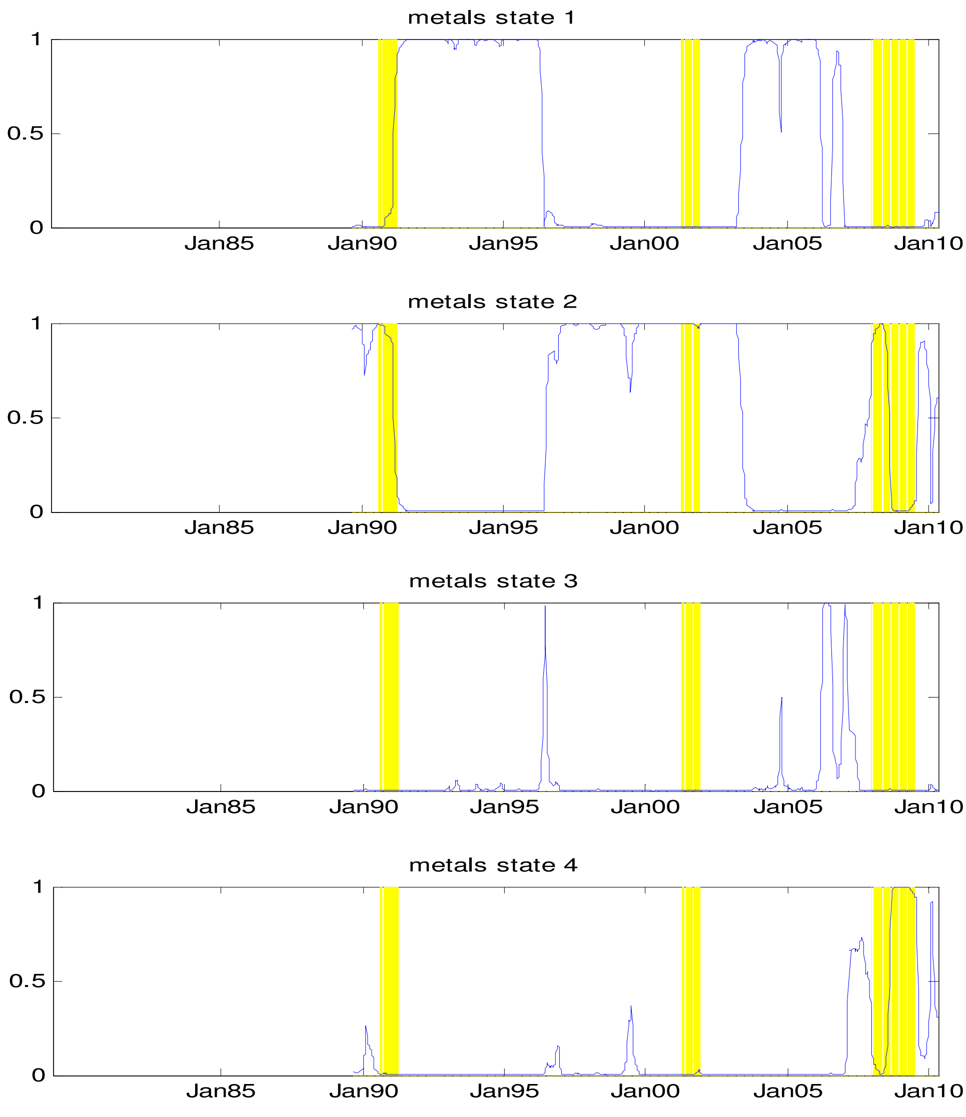
The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of grains and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.4: Smoothed probabilities in the bivariate SWARCH model for industrials and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



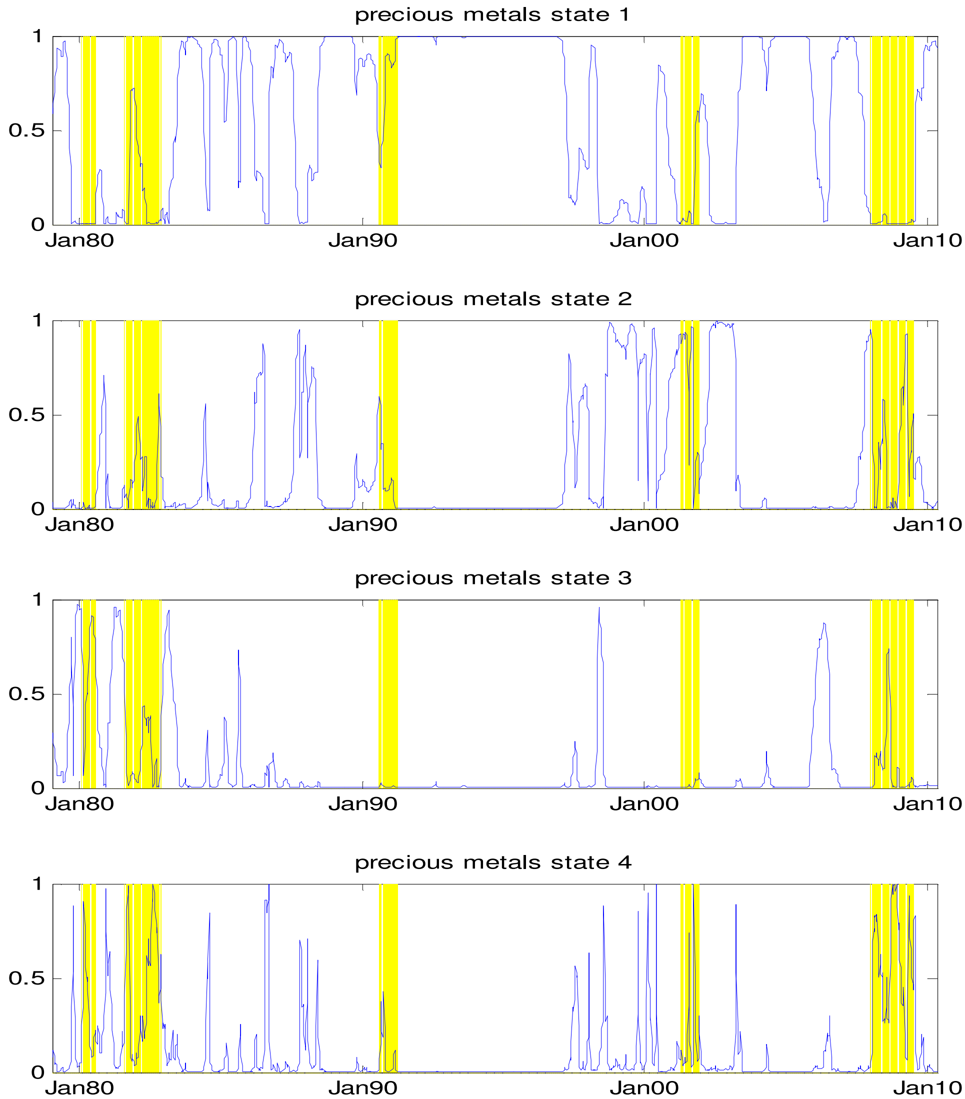
The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of the industrials and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.5: Smoothed probabilities in the bivariate SWARCH model for metals and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



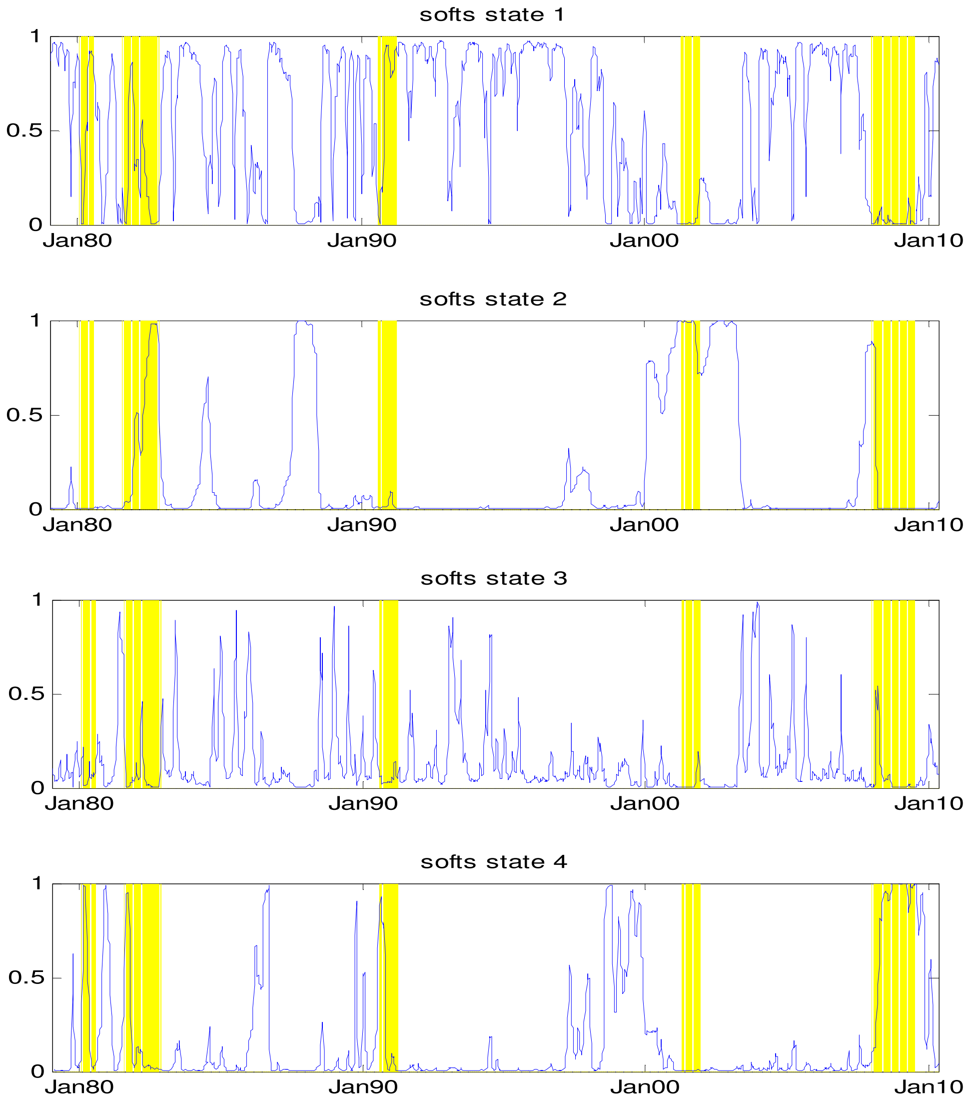
The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of metals and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.6: Smoothed probabilities in the bivariate SWARCH model for precious metals and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of precious metals and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Figure A.7: Smoothed probabilities in the bivariate SWARCH model for softs and S&P 500 vs. the U.S. business cycle contraction phase announced by NBER



The smoothed probabilities $p(S_t = i|r_T, r_{T-1}, \ldots)$ of softs and stocks are displayed based on the bivariate SWARCH model. The periods of U.S. business cycles announced by NBER are illustrated in bars.

Bibliography

Apergis, N. and Miller, S. (2009), "Do structural oil-market shocks affect stock prices?", *Energy Economics*, vol. 31(4), pp. 569–575.

Asgharian, H. (2002), Matlab code for simulated annealing. Manuscript.

Beck, S. (2001), "Autoregressive conditional heteroscedasticity in commodity spot prices", *Journal of Applied Econometrics*, vol. 16(2), pp. 115–132.

Bodie, Z. and Rosansky, V. I. (1980), "Risk and return in commodity futures", *Financial Analysts Journal*, vol. 36(3), pp. 27–31+33–39.

Büyüksahin, B., Haigh, M. and Robe, M. (2010), "Commodities and equities: ever a "market of one"?", *Journal of Alternative Investments*, vol. 12(3), pp. 76–95.

Cai, J. (1994), "A Markov model of switching-regime ARCH", *Journal of Business & Economic Statistics*, vol. 12(3), pp. 309–316.

Chan, K., Treepongkaruna, S., Brooks, R. and Gray, S. (2011), "Asset market linkages: Evidence from financial, commodity and real estate assets", *Journal of Banking & Finance*, vol. 35(6).

Choi, K. and Hammoudeh, S. (2010), "Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment", *Energy Policy*, vol. 38(8), pp. 4388–4399.

Chong, J. and Miffre, J. (2010), "Conditional correlation and volatility in commodity futures and traditional asset markets.", *Journal of Alternative Investments*, vol. 12(3), pp. 61 – 75.

Driesprong, G., Jacobsen, B. and Maat, B. (2008), "Striking oil: Another puzzle?", *Journal of Financial Economics*, vol. 89(2), pp. 307–327.

Edwards, S. and Susmel, R. (2003), "Interest-rate volatility in emerging markets", *Review of Economics and Statistics*, vol. 85(2), pp. 328–348.

ERB, C. and HARVEY, C. (2006), "The strategic and tactical value of commodity futures", *Financial Analysts Journal*, pp. 69–97.

FONG, W. and SEE, K. (2001), "Modelling the conditional volatility of commodity index futures as a regime switching process", *Journal of Applied Econometrics*, vol. 16(2), pp. 133–163.

FORBES, K. and RIGOBON, R. (2002), "No contagion, only interdependence: Measuring stock market comovements", *Journal of Finance*, vol. 57(5), pp. 2223–2261.

GORTON, G., HAYASHI, F. and ROUWENHORST, K. (2007), "The fundamentals of commodity futures returns", *NBER Working Paper 13249*.

GORTON, G. and ROUWENHORST, K. (2005), "Facts and fantasies about commodity futures", *Yale ICF Working Paper*.

GORTON, G. and ROUWENHORST, K. (2006), "Facts and fantasies about commodity futures", *Financial Analysts Journal*, vol. 62(2), pp. 47–68.

HAMILTON, J. (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", *Econometrica*, vol. 57(2), pp. 357–384.

HAMILTON, J. and LIN, G. (1996), "Stock market volatility and the business cycle", *Journal of Applied Econometrics*, vol. 11(5), pp. 573–593.

HAMILTON, J. and SUSMEL, R. (1994), "Autoregressive conditional heteroskedasticity and changes in regime", *Journal of Econometrics*, vol. 64(1-2), pp. 307–333.

HARTMANN, P., STRAETMANS, S. and VRIES, C. (2004), "Asset market linkages in crisis periods", *Review of Economics and Statistics*, vol. 86(1), pp. 313–326.

KAT, H. and OOMEN, R. (2006), "What every investor should know about commodities, Part II: Multivariate return analysis", *Alternative Investment*

Research Centre Working Paper No. 33, Cass Business School Research Paper.

Kim, C. and Nelson, C. R. (1999), *State-space models with regime switching*, vol. Cambridge, MA: MIT Press.

Lamoureux, C. and Lastrapes, W. (1990), "Persistence in variance, structural change, and the GARCH model", *Journal of Business & Economic Statistics*, vol. 8(2), pp. 225–234.

Norden, L. and Weber, M. (2009), "The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis", *European financial management*, vol. 15(3), pp. 529–562.

Power, G. and Turvey, C. (2010), "Long-range dependence in the volatility of commodity futures prices: Wavelet-based evidence", *Physica A: Statistical Mechanics and its Applications*, vol. 389(1), pp. 79–90.

Chapter 4

Multiple Stock Market Interdependence in a Dynamic Panel Data Estimation

4.1 Introduction

Global stock markets are undergoing ever-increasing integration. International investors need to understand the driving forces behind stock market interdependence in order to evaluate the potential benefits and risks of global diversification.

There is an important literature documenting stock market synchronization being driven by linkages between economies, but there is hardly a consensus among economists over the importance of these linkages. For instance, Wälti (2011) finds that monetary integration leads to stronger stock market synchronization, but Roll (1992) finds similarity in industrial structure to be the most important driving factor. Forbes and Chinn (2004) find bilateral trade to be the primary channel through which the largest financial markets affect other markets, while Flavin *et al.* (2002) argue for the impact of geographic location. The diversity of these conclusions, as stated by Beine and Candelon (2011), may be attributable to the heterogeneous characteristics of the markets.

And it may also stem from variation in time.

The present paper studies the impact of several bilateral market linkages on the pairwise correlations between the returns of 41 national stock market indexes. We pay attention to the overall magnitudes of the impacts, as well as to their heterogeneity across markets and across time. The investigated linkages are information capacity, economic integration, financial integration, and industrial dissimilarity. Specifically, it classifies the pairwise market correlations into three groups: *among developed markets*, *among developing markets*, and *between developing & developed markets*. And thereby one can distinguish the impacts of the linkages on different groups of stock market correlations. We also implement a sub-period analysis to examine the time-variation of the impacts of the linkages. The present paper attempts to answer three questions. First, which linkages drive stock markets' comovement? Second, how do the mechanisms of interdependence (i.e., the effects of market linkages on stock market correlations) differ in different groups of markets? For example, does financial integration drive the correlations among developed markets to the same extent as it drives the correlations among developing markets? Third, when the selected bilateral linkages are taken into account, does joining the currency union (i.e., the European Economic and Monetary Union (EMU)) still matter for stock market integration?

This paper relies on the gravity model with a dynamic panel specification. The gravity model in economics, mimicking the gravitational interaction in Newton's law of gravity, explains the relationship between two economies based on their masses and the distance (or closeness) between them. The gravity model is widely used in the empirical study of international trade, and has become popular in the study of capital market synchronization (see Flavin *et al.*, 2002, Beine *et al.*, 2010, and Beine and Candelon, 2011 for example). In our study, the relationship between two economies is the correlation between their primary national stock markets, while the sizes of the markets are regarded as the masses, and the cross-market linkages, as the distances. One merit of the gravity model approach, particularly for our study, is its flexibility in describing cross-market heterogeneity.

This paper differs from the existing literature in several respects. First, it provides a comprehensive view of a large sample of national stock markets while distinguishing the impact of the linkages with respect to specific types of markets. There exist studies of the interdependence of developing or developed markets only (see for example Pretorius, 2002, and Beine and Candelon, 2011), while others investigate a combination of developed and developing countries without allowing for potential heterogeneity. However, it is implausible that the stock markets in developed economies are linked via the same mechanism as are developing markets. The present paper provides new insight for understanding stock market interdependence.

Second, this paper addresses the important role of information capacity in explaining stock markets' comovement. According to Sims (2006), the information capacity of a country includes its wiring capacity and internal human capacity. Wiring capacity refers to the availability of communication technologies that allow investors to access information, whereas internal human capacity refers to investor's capability and efficiency of using the information. We expect an increase in stock market correlations as information capacity increases, since a large information capacity implies easier access to information, which in turn reduces information asymmetries and fosters cross-country investment in equities. Moreover, a market with a large information capacity may have a fast information diffusion process, and therefore may respond faster to external shocks, whereas a market with a very small information capacity tends to be isolated from other markets.

Third, this paper adds to the literature that studies the EMU effect on stock market integration. The existing literature (e.g., Yang *et al.*, 2003) finds that the EMU has significantly strengthened stock market integration among its member countries; however, the increase in integration may also be attributable to other factors such as larger volumes of bilateral trade and faster information transmission. The present paper examines whether joint EMU participation matters after controlling for the selected bilateral linkages defined above.

Fourth, our dynamic panel specification is able to capture the dynamics of stock market correlations, which is ignored by the existing related studies (e.g., Wälti, 2011, and Flavin *et al.*, 2002). Empirical evidence (see Kim *et al.*, 2005 for example) shows that stock market integration is a persistent process and one of its main determinant is the existing level of integration. Estimation of the impacts of bilateral factors may be spurious if autocorrelation is not taken into account.

Our empirical findings show that all the linkages have significant impacts on stock market interdependence overall. However, the mechanism of interdependence differs between markets and in time. Specifically, information capacity has a stronger impact on the correlations between developed markets than on the other two groups of correlations. There is a negative relation between industrial dissimilarity and stock market interdependence in the second half of the sample period, 2003–2010, which is more evident for developed markets. Joint EMU membership increases stock market integration, but this effect becomes insignificant in the post monetary transition period, 2003–2010, when we control for heterogeneous mechanisms across markets at different levels of development.

The remainder of this paper is organized as follows. Section 4.1 presents the dynamic panel gravity model. Section 4.3 presents the selected variables and data. Section 4.4 contains the estimation results and Section 4.5 concludes.

4.2 Econometric modelling

The econometric model is a gravity model with dynamic panel specification allowing for both cross-section effects and time-specific effects. To answer the research questions proposed in Section 4.1, we sequentially design four econometric specifications.

The baseline regression, namely specification I, is

$$\begin{aligned} \rho_{ij,t} &= \alpha + \gamma\rho_{i,t-1} + \lambda Size_{ij,t} + X_{ij,t}\beta + \textstyle\sum_{t=2}^{T} \delta_t d_t + u_{ij,t}, \\ u_{ij,t} &= \eta_{ij} + \epsilon_{ij,t}, \\ &(i \times j) \in (1, ...N)^2, i < j, t = 1, \ldots, T, \end{aligned} \tag{4.1}$$

where $\rho_{ij,t}$ is the daily returns correlation between stock market i and j in year t. The lagged dependent variable $\rho_{i,t-1}$ captures the potential dynamics of stock market correlation. $Size_{ij,t}$ is the joint mass of markets i and j, which is defined as the sum of the logarithms of the market capitalizations in market i and j in year t. $X_{ij,t}$ is a $1 \times K$ vector consisting of the variables that describe the market linkages, such as information capacity, economic integration, financial integration, and industrial similarity. The measurement of these variables is described in Section 4.3. d_t is the time dummy variable for year t. η_{ij} is the cross-section fixed effect and is independent of $\epsilon_{ij,t}$. N is the number of markets, which is 41 in our study. The number of time periods, T, is 16 (years).

Unobserved heterogeneity in the cross-section and time-series dimensions is controlled for by the fixed effect η_{ij} and the time dummy variable d_t. The cross-section fixed effect makes the model specification parsimonious, because it is able to account for unincluded time invariant variables (e.g., geographical distance) that may be correlated with the included variables. Likewise, the time dummy variable is able to capture the impact of common shocks. This is particularly important for our study, because our sample contains several international crisis periods such as the Asian financial crisis and the global financial crisis beginning in 2007 when common shocks prevailed regionally and globally.

Although unobserved heterogeneity is controlled for by fixed effects, the baseline regression I assumes the influences of the bilateral linkages to be homogeneous on all pairwise market correlations, which is implausible because of the different characteristics of these markets. We extend the baseline specification I to specification II, in regression (4.2), in order to examine the interdependence mechanism for markets across different levels of economic development.

$$\begin{aligned}\rho_{ij,t} = {} & \gamma\rho_{i,t-1} + \lambda Size_{ij,t} + X_{ij,t}\beta_0 + d_{ij}^{mm}X_{ij,t}\beta_1 + d_{ij}^{mh}X_{ij,t}\beta_2 \\ & + \textstyle\sum_{t=2}^{T}\delta_t d_t + \eta_{ij} + \epsilon_{ij,t},\end{aligned} \tag{4.2}$$

where d_{ij}^{mm} is 1 if both markets i and j are developing markets, and is 0 otherwise. Likewise, d_{ij}^{mh} is 1 if either i or j is a developing market, and is 0 otherwise. Hence, the impact of factor $X_{ij,t}$, respectively, on the correlations between developed markets, on those between developing markets, and on those between developed and developing markets, is β_0, $\beta_0 + \beta_1$, and $\beta_0 + \beta_2$.

Table 4.1: Specification outline

	Levels of development	EMU effect
I	No	No
II	Yes	No
III	No	Yes
IV	Yes	Yes

Furthermore, in order to examine the effect of joining the EMU on stock market integration, two more specifications are designed. The following regression, namely specification III, extends specification I by introducing a dummy variable for pairs of countries that are simultaneously EMU members.

$$\rho_{ij,t} = \alpha + \gamma\rho_{i,t-1} + \lambda Size_{ij,t} + X_{ij,t}\beta + \phi d_{ij,t}^{EMU} + \sum_{t=2}^{T}\delta_t d_t + \eta_{ij} + \epsilon_{ij,t}, \tag{4.3}$$

where $d_{ij,t}^{EMU}$ is one if both markets i and j are members of the EMU, and zero otherwise. If ϕ is positive, one can say that the degree of interdependence among EMU stock markets is larger than can be explained by the linkages between markets when assuming the interdependence mechanism to be homogeneous across markets.

The most extended specification, IV, examines the EMU effect while taking into account the heterogeneity across developing and developed countries:

$$\begin{aligned}\rho_{ij,t} &= \gamma\rho_{i,t-1} + \lambda Size_{ij,t} + X_{ij,t}\beta_0 + d_{ij}^{mm}X_{ij,t}\beta_1 + d_{ij}^{mh}X_{ij,t}\beta_2 \\ &+\phi d_{ij,t}^{EMU} + \sum_{t=2}^{T}\delta_t d_t + \eta_{ij} + \epsilon_{ij,t}.\end{aligned} \tag{4.4}$$

Since EMU countries are a subset of the developed countries, a positive ϕ in specification IV indicates that stock market correlations in EMU are more than can be explained by the interdependence mechanism of developed countries. If ϕ loses its scale and statistical significance, integration among EMU stock markets is merely attributable to market linkages via the same mechanism as the interdependence of other developed markets. That is to say, there is no "pure" EMU effect. For the sake of clarity, Table 4.1 presents an outline of the characteristics of specifications I–IV.

To estimate our dynamic panel regressions, we will use the general method of moments (GMM). Since we have 41 markets in the dataset, there are 820 pairwise correlations in total. This means that the panel dataset has a very large number of cross-sections (820) and a relatively small number of time periods (16). It is well-known that the fixed effects estimator is biased and inconsistent for such dynamic panels (see Nickell, 1981). The random effects GLS estimator is also biased (see Baltagi, 2008). We therefore estimate the model with Arellano and Bover (1995)/Blundell and Bond (1998) GMM, which is designed for dynamic panels with a large number of cross sections and a small number of time periods. The Arellano and Bover (1995)/Blundell and Bond (1998) estimation is based on the study of Arellano and Bond (1991), which carries out a first difference transformation and uses GMM. Arellano and Bover (1995) and Blundell and Bond (1998) augment the Arellano and Bond (1991) estimator by assuming that the first differences of the instrumenting variables are uncorrelated with the fixed effects. This allows the introduction of more instruments and dramatically improves the efficiency (see Roodman, 2006). Another merit of the Arellano–Bover/Blundell–Bond GMM estimation is the ability to estimate the coefficients of the time invariant variables by introducing more moment equations. This is particularly useful when we come to examine the EMU effect in the second sub-period (2003-2010) when the dummy variable $d_{ij,t}^{EMU}$ varies over cross-sections but not over time.

4.3 Selected variables and data

This section presents the selected variables and data sources, focusing on the expected impacts of the bilateral linkages.

4.3.1 National market indexes and correlations

Our sample of interest contains the main market indexes of 41 economies. The data are extracted from the MSCI for the period from the beginning of 1995 to the end of 2010. Following Flavin *et al.* (2002), cross-country stock market interdependence is measured as the correlation of the daily logarithmic returns of the national market indexes in each year. [1]

[1] Wälti (2011) transforms the correlations by Fisher's z transformation. This transformed dependent variable yields the same statistically significance for each independent variable as using the untransformed dependent variable in the present paper. For ease of interpretation, the untransformed correlation coefficient is retained.

Table 4.2: Selected markets

High-income economies (Developed markets)		Middle-income economies (Developing markets)	
1	Australia	1	Argentina
2	Austria*	2	Brazil
3	Belgium*	3	Chile
4	Canada	4	China
5	Czech Republic	5	India
6	Denmark	6	Indonesia
7	Finland*	7	Malaysia
8	France*	8	Mexico
9	Germany*	9	The Philippines
10	Greece*	10	Russia
11	Hong Kong	11	Thailand
12	Hungary	12	Turkey
13	Ireland*		
14	Israel		
15	Italy*		
16	Japan		
17	Korea		
18	The Netherlands*		
19	New Zealand		
20	Norway		
21	Poland		
22	Portugal*		
23	Singapore		
24	Spain*		
25	Sweden		
26	Switzerland		
27	Taiwan		
28	UK		
29	USA		

Note: The sample contains the main market indexes of 41 economies, among which 29 are high income countries and 12 are middle income countries according to the classification of the World Bank. * indicates that the country is a member of the EMU.

As there is no convention for the classification of developed countries and developing countries, income level is used as a proxy for the level of economic development, and so high income countries are designated as developed economies and middle income countries, as developing economies. The sample consists of 29 high income countries and 12 middle income countries according to the World Bank[2] (see Table 4.2). Eleven countries, marked with *, among the developed countries are members of the EMU. The pairwise correlations of markets are categorized into three groups: those among developed markets, those among developing markets, and those between developed & developing markets.

4.3.2 Selected determinants of stock market interdependence

Size

The size of a stock market is measured as the logarithm of the total market capitalization of its listed stocks. The correlations between markets with large capitalization are expected to be large, as international stock markets are sensitive to shocks coming from large markets. The data for the market capitalization of Taiwan is drawn from the World Federation of Exchanges database, whereas the data for the other markets is collected from the World Bank's World Development Indicators Database. The total size of two markets is

$$Size_{ij,t} = \log\left(MarkCap_{i,t}\right) + \log\left(MarkCap_{j,t}\right). \tag{4.5}$$

Information capacity

To measure information capacity, wiring capacity is used since its measurement is less subjective than that of internal human capacity, following Mondria and Wu (2010). A market's information capacity is

$$Info_{i,t} = \log(telephone_{i,t} + mobile_{i,t} + internet_{i,t}), \tag{4.6}$$

[2]See http://data.worldbank.org/about/country-classifications/country-and-lending-groups.

where $telephone_{i,t}$ is the number of telephone lines per 100 persons, $mobile_{i,t}$ is the number of mobile cellular subscription per 100 persons, and $internet_{i,t}$ is the number of internet users per 100 persons. The data is collected from the World Bank's World Development Indicators database. The cross-country linkage of the information capacity for two markets is measured as their total information capacity.

$$Info_{ij,t} = Info_{i,t} + Info_{j,t}. \tag{4.7}$$

Information capacity is expected to have a positive impact on stock market correlations. First, as illuminated by Portes and Rey (2005), market segmentation is mainly attributable to information asymmetries. A high information capacity provides investors with easier access to information and more advanced tools for analyzing the information, and may therefore lead to less information asymmetries between domestic and foreign investors and hence less market segmentation. Second, a high information capacity may also foster information diffusion between markets. Markets with a high information capacity tend to react promptly to external shocks and hence comove more with other markets. The existing literature, for example Ivkovich and Weisbenner (2007), has found the presence of an information diffusion effect on investment behavior. Furthermore, the development of information capacity advances the form of stock trading services, noticeably reduces the transaction cost, and therefore encourages cross-border trading.

Financial integration

One expects financial integration to enhance the degree of stock market interdependence. In this study, exchange rate volatility is used to assess the financial integration between two markets. A less volatile exchange rate, which means higher financial integration, decreases the cost of hedging currency risk and leads to convergence in cross-country discount rates, which should imply a more homogeneous valuation of assets across markets and hence a larger degree of stock market interdependence. The exchange rate volatility is calculated as the standard deviation of daily logarithmic changes in bilateral exchange rates for each year. The data for exchange rates are collected from GTIS and WM/Reuters.

Economic integration

Economic integration facilitates the convergence of cash flows between countries, fosters business cycle synchronization, and hence is expected to increase stock market interdependence. Since economic integration mainly refers to trade unification, the economic integration of two countries is measured by the intensity of their bilateral trade. Following Beine and Candelon (2011), the relative trade intensity is defined as

$$Econ_{ij,t} = \frac{exp_{ij,t} + imp_{ij,t}}{exp_{i,t} + imp_{i,t}} + \frac{exp_{ij,t} + imp_{ij,t}}{exp_{j,t} + imp_{j,t}}, \tag{4.8}$$

where $exp_{ij,t}$ and $imp_{ij,t}$ are, respectively, the values of the exports and imports from country i to country j. $exp_{i,t}$ and $imp_{i,t}$ are the values of the total exports and imports of country i, and similarly for j. Hence $Econ_{ij,t}$ is the intensity of trade between countries i and j relative to their total value of trade.

The data for bilateral trade is taken from the STAN Bilateral Trade Database (source: OECD), which contains the values of annual imports and exports of goods for all countries in the sample. All values are in U.S. dollars at current prices.

Dissimilarity in industrial exposure

Stock markets with similar industrial structure may be highly correlated, as they are more likely to be driven by the same global industry-specific factors. Following Asgharian and Bengtsson (2006), the risk exposures (betas) of national stock markets to the Datastream world industry indexes will be a proxy for industrial dissimilarity: the industrial dissimilarity of two markets is defined as the average absolute difference in these betas.

Variable descriptions

In order to obtain some prior knowledge of the interdependence within the different groups of markets, Table 4.3 gives the average values of the pairwise correlations and the linkage variables for the three subgroups of country pairs across periods. There is a common time trend in all subgroups. The countries are becoming more and more closely linked to one another in their stock

Table 4.3: Average level of stock market pairwise correlations and explanatory linkages

	All	Developed	Developing	Developed & Developing
		Entire period, 1996–2010		
ρ	0.3297	0.3951	0.2607	0.2664
Info	5.3527	5.6283	4.4451	5.2033
Fin	0.0075	0.0061	0.0092	0.0088
Econ	0.0502	0.0604	0.0412	0.0400
Ind	0.4093	0.3368	0.5285	0.4713
Number of obs.	13120	6496	1056	5568
		First Sub-Period, 1996–2002		
ρ	0.2235	0.2899	0.1672	0.1566
Info	4.8976	5.2538	3.6565	4.7175
Fin	0.0080	0.0062	0.0110	0.0096
Econ	0.0501	0.0626	0.0319	0.0391
Ind	0.4461	0.3481	0.6024	0.5309
Number of obs.	6560	3248	528	2784
		Second Sub-Period, 2003–2010		
ρ	0.4168	0.4839	0.3307	0.3550
Info	5.7703	5.9781	5.1460	5.6463
Fin	0.0071	0.0060	0.0081	0.0082
Econ	0.0502	0.0585	0.0492	0.0407
Ind	0.3715	0.3274	0.4449	0.4091
Number of Obs.	7380	3654	594	3132

Note: This table presents the average values of the pairwise correlation ρ and of the linkages broken down by different groups of markets.

market correlations and explanatory linkages except for economic integration. The degree of economic integration of developed markets drops in the second sub-period, though still being the largest among the three subgroups. In all sample periods, pairwise correlations between developed countries are larger on average than those between developing countries and those between developed and developing countries. The selected linkages also appear to be the strongest between developed countries, whereas developing countries have the lowest degree of integration with each other in all cases except for economic integration. The economic integration between developing countries increases dramatically in the second sample period and surpasses that between developing and developed countries.

4.4 Empirical analysis

This section starts with an analysis of the entire sample period, and then implements analyses over two chronological sub-periods (from 1996 to 2002 and from 2003 to 2010) in order to examine the time variation of market interdependence. Then we examine whether the EMU increases stock market integration even when controlling for the selected linkages. It is noteworthy that the monetary transition of EMU was accomplished in 2002[3]. In this way we examine the effect of the EMU before and after the monetary transition. Finally, we examine the sensitivity of our results to the large economies.

4.4.1 Entire sample period analysis

This section implements an empirical analysis based on the econometric models of Section 4.2 for the entire sample from 1996 to 2010. In this GMM estimation, three lags of the dependent variable are adopted as instruments and robust standard errors are used. In addition, we will take into account potential predetermined and endogenous independent variables. Bilateral trade and exchange rate volatility are likely to be predetermined, as they may be influenced by shocks (e.g., unexpected inflation rate) that may affect at the same time stock market returns. Industrial dissimilarity is potentially endogenous, as its proxy is estimated from the returns of stock market indexes. Two lags of these regressors are used as instruments. The issue of potential endogeneity in a panel gravity model is also tackled in Wälti (2011). They regress each of the endogenous variables on different sets of exogenous variables

[3]The conversion rates between the 11 participating national currencies and the Euro were established on 31 December 1998. In the beginning of 1999, the Euro became a real currency and a single monetary policy was introduced. Greece, the last to join the EMU in our sample, adopted the Euro on 1 January 2001. On 1 January 2002, the Euro notes and coins were introduced.

and then use the predicted values of the endogenous variables in the main estimation. Wälti (2011)'s method, however, is subject to estimation errors.

Table 4.4 presents the results for various specifications of our econometric models. The first column presents the results of the baseline specification I, omitting time fixed effects. The complete specification I and specification II are presented in the second and third columns.

First, we see the importance of controlling for a common trend in this sample, which contains several regional and global crisis periods. By comparing the first and the second columns in Table 4.4, the negative effect of exchange rate volatility appears statistically significant in the first column but loses both its scale and significance in the second column. This is because ignoring a common trend in the data biases the estimates of the causal effect of the market linkages. For example, during the Asian financial crisis of the late 1990s, an extremely large exchange rate volatility was associated with coincident stock market slumps in many Asian markets, though there is no apparent causality between these two incidents. This may undermine the overall estimate of the negative causal effect of exchange rate volatility on stock market interdependence if the common trend is not controlled for by time dummy variables. Furthermore, the hypothesis that the time effects are jointly zero in column two is rejected. (The estimates of the time dummy variables of all specifications are presented in the Appendix).

Second, the coefficients for all the selected linkages are statistically significant in column two. Consistent with what was expected, information capacity and economic integration increase stock market interdependence, and a less volatile exchange rate is associated with a higher stock market interdependence. The positive coefficient for dissimilarity of industrial exposure, however, is contrary to one's expectations, which might be due to potential cross-country heterogeneity in the industrial similarity effect.

Furthermore, the existence of cross-country heterogeneity in the linkage effects is examined by using specification II. First, we reject the hypothesis that the additional regressors in specification II compared with the baseline specification I are jointly equal to zero, thus verifying the existence of heterogeneity in the linkage effects. Specifically, heterogeneity is found in

Table 4.4: Estimated results over the entire sample period 1996–2010

	(I)	(I)	(II)
ρ_{t-1}	0.525***	0.352***	0.370***
	(44.02)	(3.77)	(21.44)
Info	0.130***	0.0541**	0.0331***
	(27.17)	(2.59)	(3.32)
Fin	-0.482	-2.966***	-4.078***
	(-1.14)	(-4.92)	(-4.33)
Econ	0.493**	0.654**	0.337*
	(3.09)	(2.88)	(2.19)
Ind	0.0660***	0.0435**	-0.100***
	(5.72)	(2.84)	(-5.29)
Size	-0.0251***	0.0156*	0.00386
	(-20.20)	(2.12)	(0.57)
Info$\times d^{mm}$			-0.0252***
			(-6.43)
Info$\times d^{mh}$			-0.0167***
			(-6.82)
Fin$\times d^{mm}$			1.639
			(1.57)
Fin$\times d^{mh}$			0.920
			(0.96)
Econ$\times d^{mm}$			0.252
			(1.08)
Econ$\times d^{mh}$			0.00784
			(0.04)
Ind$\times d^{mm}$			0.151***
			(4.44)
Ind$\times d^{mh}$			0.140***
			(6.77)
Time effect	no	yes	yes
Pseudo R^2	0.7301	0.8423	0.8524
AR(1)	0.00	0.00	0.00
AR(2)	0.00	0.70	0.83
Number of obs.	12300	12300	12300

Note: This table presents the results of the entire-sample period analysis. The first column presents the results of specification I (4.1) without a time dummy. Specification I in the second column includes time fixed effects. The third column is specification II (4.2), where bilateral linkages interact with the dummy d^{mm} for correlation between two developing countries and with the dummy d^{mh} for the correlation between a developing country and a developed country. The AR tests yield the p-values of the Arellano–Bond test with the null hypotheses of no first-order serial correlation and no second-order serial correlation in the first-differenced errors. The pseudo R^2 is the square of the correlation between the original dependent variable and its fitted value. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the impact of information capacity. β_0 for $Info$, which is now interpreted as the impact of information capacity on the interdependence among developed markets, is positive and significant at the 0.1% level of significance. β_1 and β_2, which are the additional impacts of information capacity on the interdependence of the other two groups, are negative and significant but smaller in size. This implies that the effect of information capacity is overall positive and is more substantial in developed markets. Besides information capacity, industrial dissimilarity also has heterogeneous effects. The negative sign of Ind indicates that developed markets with similar industrial exposure tend to comove. By contrast, a developing market has less comovement with other markets (either developing markets or developed markets) with similar industrial exposure, as implied by the positive and large coefficients for $Ind \times d^{mm}$ and $Ind \times d^{mh}$. This may be due to too much noise in the equity prices of developing markets and thus explains why the impact of industrial dissimilarity is overall positive in the specifications of type I, which assume no heterogeneity. Additionally, the effects of financial and economic integration remain positive in specification II. Judged from the sign and scale, financial integration seems to be a more important channel for interdependence between developed markets than for that between developing markets or that between developed and developing markets, whereas economic integration appears to be more important for the interdependence of developing markets, although both the effects are statistically insignificant.

Moreover, specifications I and II correctly capture the dynamics of the stock market correlations as the Arellano–Bond test does not reject the hypothesis of no second-order serial correlation in the first-differenced errors. The effect of the one-year lagged dependent variable remains positive and statistically significant across all the specifications, which conforms to the finding of Kim *et al.* (2005) that stock market integration is persistent and that one of its main determinants is the existing level of integration. In addition, the effect of market size is positive in specifications I (including time fixed effects), implying that markets with a large capitalization are more influential on other markets. However, this effect diminishes in specification II, where heterogeneity is allowed for.

4.4.2 Sub-period analysis

This section examines the impacts of the explanatory linkages and their cross-market heterogeneity over two periods. Chronologically divide the sample into two sub-samples: 1996–2002 and 2003–2010.

The results for specifications I and II for each sub-period are presented in Table 4.5. In specification I, none of the estimated coefficients change sign over time except industrial dissimilarity and market size. Industrial dissimilarity seems to increase stock market correlations in the first period, but the effect becomes negative in the second period. The effect of market size is positive in the first period but becomes almost zero in the second period. Judged by the scales of the coefficients, the marginal effect of information capacity becomes slightly larger in the second period, while the effect of economic integration becomes much smaller.

Furthermore, we observe significant heterogeneity in the impacts of information capacity and industrial similarity in both sub-periods in specification II. The effect of information capacity remains positive and stronger among developed markets in both sub-periods. The industrial dissimilarity effect and its heterogeneity are, however, distinct across periods. From 1996 to 2002, industrial dissimilarity shows no significant impact on the interdependence among developed markets but shows positive impact on the correlations of developing markets with other markets (either developing markets or developed markets). By contrast, from 2003 to 2010, the industrial dissimilarity effect appears to be negative to all pair-wise correlations and is stronger among developed markets.

As in the whole period, financial integration is a more important channel for stock market interdependence among developed countries in both sub-periods judged by the sign and scale of the coefficients. Economic integration seems to be more important for developing markets than for developed markets in the first period, but the difference diminishes in the second period.

Table 4.5: Estimated results over the sub-periods 1996–2002 and 2003–2010

	(I-period1)	(I-period2)	(II-period1)	(II-period2)
ρ_{t-1}	0.288***	0.395***	0.335***	0.401***
	(8.37)	(4.43)	(12.86)	(5.03)
Info	0.0563**	0.0701***	0.0428**	0.0440**
	(3.15)	(3.36)	(3.04)	(2.66)
Fin	-4.247***	-4.392	-5.308***	-5.689*
	(-9.02)	(-1.03)	(-3.42)	(-2.21)
Econ	1.385**	0.816***	0.514*	0.414*
	(2.75)	(3.90)	(2.47)	(2.13)
Ind	0.117***	-0.0663	-0.00504	-0.142***
	(8.10)	(-1.94)	(-0.15)	(-6.23)
Size	0.0331**	-0.0171	0.0206*	-0.0142
	(2.91)	(-1.67)	(2.47)	(-1.82)
Info$\times d^{mm}$			-0.0140*	-0.0147**
			(-2.18)	(-2.64)
Info$\times d^{mh}$			-0.0156***	-0.0124*
			(-3.77)	(-2.37)
Fin$\times d^{mm}$			1.210	3.175
			(0.69)	(1.56)
Fin$\times d^{mh}$			2.157	1.205
			(1.32)	(0.56)
Econ$\times d^{mm}$			0.293	0.00308
			(1.16)	(0.01)
Econ$\times d^{mh}$			0.222	-0.0660
			(0.55)	(-0.19)
Ind$\times d^{mm}$			0.117**	0.0482
			(2.79)	(1.31)
Ind$\times d^{mh}$			0.0659*	0.110*
			(1.97)	(1.98)
PseudoR^2	0.7581	0.8654	0.7799	0.8663
AR(1)	0.00	0.00	0.00	0.00
AR(2)	0.78	0.27	0.36	0.46
No. of obs.	5740	6560	5740	6560

Note: Results for specifications I and II for the two sub-periods. The AR tests give the p-value of the Arellano–Bond test with the null hypotheses of no first-order serial correlation and no second-order serial correlation in first-differenced errors. The pseudo R^2 is the square of the correlation between the original dependent variable and its fitted value. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.4.3 The EMU effect

This section examines whether joint EMU membership matters for stock market interdependence. By using specifications III and IV that control for bilateral linkages and their heterogeneous impacts, we can see whether stock market interdependence in the EMU is higher than can be explained by the predefined linkages across markets. We can also examine the EMU stock market interdependence before and after the EMU monetary transition by looking at the sub-periods separately.

Table 4.6 gives the coefficient for the joint EMU dummy, which is significantly positive in both specifications III and IV in the entire sample period, which indicates the existence of a "pure" EMU effect that is not explained by the predefined market linkages. Both specifications III and IV indicate "pure" EMU effect in the first sub-sample, which includes the period of monetary transition from 1998 to 2002, because the coefficients of the joint EMU membership dummy are positive and statistically significant.

For the second sub-period, the EMU effect also remains significant and positive in specification III. However, when it comes to specification IV, which allows for heterogeneity across markets of different levels of development, the coefficient of the EMU dummy loses both its statistical significance and scale. This indicates that after the EMU monetary transition, the stock market integration in EMU can be mostly explained by the same mechanisms of interdependence as among other developed markets and there is no "pure" EMU effect beyond this.

4.4.4 Sensitivity analysis

To examine the sensitivity of our findings to the selection of markets, we will exclude the U.S market and the Chinese market, which are the giants respectively from developed markets and from developing markets, from our sample, and check the robustness of the estimates of specifications I–IV. Table A.1-A.3 in the Appendix shows that the signs and scales of the linkage coefficients and the cross-market heterogeneous coefficients are similar to those in the main estimation results. Furthermore, as in the main estimation, the

Table 4.6: The EMU effect

	(III-entire)	(III-period1)	(III-period2)	(IV-entire)	(IV-period1)	(IV-period2)
ρ_{t-1}	0.346***	0.293***	0.382***	0.361***	0.325***	0.396***
	(19.26)	(4.62)	(15.78)	(4.21)	(12.57)	(18.57)
d_t^{EMU}	0.142***	0.0745**	0.142*	0.117***	0.110***	0.0847
	(6.01)	(2.61)	(2.37)	(5.15)	(4.41)	(1.75)
Info	0.0503***	0.0539	0.0630**	0.0343***	0.0469***	0.0415**
	(4.34)	(1.89)	(3.09)	(3.35)	(3.40)	(2.60)
Fin	-2.957***	-4.189***	-3.563**	-4.010	-4.905**	-5.049***
	(-7.53)	(-5.93)	(-2.89)	(-1.91)	(-3.19)	(-3.70)
Econ	0.529***	1.318**	0.555**	0.219	0.438*	0.256
	(3.33)	(2.64)	(2.79)	(1.39)	(2.30)	(1.30)
Ind	0.0380***	0.111***	-0.0632***	-0.101***	-0.0322	-0.138***
	(3.53)	(6.53)	(-4.32)	(-4.35)	(-0.96)	(-6.27)
Info$\times d^{mm}$				-0.0251***	-0.0145*	-0.0152**
				(-3.49)	(-2.29)	(-2.75)
Info$\times d^{mh}$				-0.0164***	-0.0167***	-0.0128***
				(-3.80)	(-4.11)	(-4.03)
Fin$\times d^{mm}$				1.588	0.792	2.976
				(0.98)	(0.46)	(1.72)
Fin$\times d^{mh}$				0.893	1.819	1.018
				(0.63)	(1.13)	(0.94)
Econ$\times d^{mm}$				0.366	0.371	0.129
				(1.33)	(1.55)	(0.46)
Econ$\times d^{mh}$				0.0610	0.271	-0.00618
				(0.30)	(0.69)	(-0.02)
Ind$\times d^{mm}$				0.149***	0.139***	0.0435
				(4.87)	(3.29)	(1.21)
Ind$\times d^{mh}$				0.136***	0.0871*	0.107***
				(5.70)	(2.56)	(3.72)
Size	0.0184**	0.0307	-0.00536	0.00742	0.0182*	-0.00760
	(3.02)	(1.95)	(-0.62)	(1.09)	(2.25)	(-1.15)
Pseudo R^2	0.8434	0.7603	0.8665	0.8522	0.7810	0.8668
AR(1)	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	0.31	0.98	0.17	0.69	0.93	0.40
No. of obs.	12300	5740	6560	12300	5740	6560

Note: This table presents the results for specifications III (4.3) and IV (4.4) for the entire sample period and for the sub-periods separately. The AR tests give the p-value of the Arellano–Bond test with the null hypotheses of no first-order serial correlation and no second-order serial correlation in first-differenced errors. The pseudo R^2 is the square of the correlation between the original dependent variable and its fitted value. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

coefficient for the joint EMU membership dummy is large and significant before year 2003, but in the second sub-period, it loses its scale and significance not only in specification IV but also in III, which confirms that the EMU effect on stock market interdependence diminishes after the monetary transition.

4.5 Conclusion

This paper used a dynamic panel gravity model to explain the mechanism of interdependence between 41 national stock markets using four cross-market linkages: information capacity, financial integration, economic integration, and similarity in industrial structure. The overall magnitudes of the linkage effects were analyzed, as well as their heterogeneity across markets and time. All the linkages contribute to the overall stock market correlations. However, the mechanism of the interdependence between developed markets differs from that of developing markets and differs between the two sub-periods. Specifically, the positive effect of information capacity is stronger on the stock market correlations among developed markets. There is a negative relation between industrial dissimilarity and stock market interdependence in the second half of the sample period, 2003–2010, but it is more evident for the interdependence between developed markets.

While allowing for heterogeneous mechanisms of interdependence, the effect of joining the European Economic and Monetary Union (EMU) on stock market integration is examined. For 1996–2002, during which the EMU monetary transition took place, there is a "pure" positive effect of common EMU membership on stock market interdependence: the EMU stock market correlations are more than can be explained by the market linkages. However, in the post monetary transition sub-period, 2003–2010, this "pure" effect of the EMU diminishes. Therefore, after the common monetary policy was fully established, EMU stock market integration can be mostly explained by the same interdependence mechanisms as with other developed markets: the increase in correlations between stock markets of the EMU member countries are attributable to factors such as faster information transmission and larger industrial similarity.

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Appendix

Table A.1: Sensitivity analysis: Entire period, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
ρ_{t-1}	0.360***	0.367***	0.352***	0.356***
	(19.71)	(3.90)	(19.55)	(3.79)
d_t^{EMU}			0.140***	0.108***
			(5.87)	(4.69)
Info	0.0723***	0.0412***	0.0658***	0.0427***
	(5.25)	(3.58)	(5.07)	(3.75)
Fin	-2.452***	-4.322	-2.533***	-4.226
	(-5.95)	(-1.93)	(-6.23)	(-1.96)
Econ	0.681***	0.446**	0.544***	0.301*
	(4.25)	(2.88)	(3.57)	(2.03)
Ind	0.0263*	-0.123***	0.0214*	-0.125***
	(2.47)	(-4.00)	(1.99)	(-3.90)
Size	0.00489	-0.00131	0.00710	0.00167
	(0.80)	(-0.16)	(1.18)	(0.20)
Info$\times d^{mm}$		-0.0279***		-0.0284***
		(-3.48)		(-3.57)
Info$\times d^{mh}$		-0.0175***		-0.0179***
		(-3.53)		(-3.59)
Fin$\times d^{mm}$		1.803		1.691
		(1.07)		(1.04)
Fin$\times d^{mh}$		1.271		1.197
		(0.81)		(0.78)
Econ$\times d^{mm}$		0.185		0.345
		(0.86)		(1.60)
Econ$\times d^{mh}$		-0.197		-0.0972
		(-0.96)		(-0.50)
Ind $\times d^{mm}$		0.181***		0.182***
		(5.65)		(5.53)
Ind $\times d^{mh}$		0.160***		0.158***
		(5.63)		(5.36)

Note: This table presents the results when the U.S. and Chinese markets are excluded. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Sensitivity analysis: First sub-period, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
ρ_{t-1}	0.316***	0.341***	0.318***	0.322***
	(9.23)	(4.86)	(9.28)	(4.64)
d_t^{EMU}			0.0724*	0.120***
			(2.46)	(4.58)
Info	0.0787***	0.0473	0.0762***	0.0520
	(4.26)	(1.50)	(4.26)	(1.62)
Fin	-4.618***	-5.461*	-4.584***	-5.118*
	(-10.95)	(-2.52)	(-11.13)	(-2.35)
Econ	0.874*	0.543*	0.869*	0.517*
	(2.26)	(2.49)	(2.24)	(2.37)
Ind	0.127***	-0.0280	0.122***	-0.0552
	(9.24)	(-0.74)	(8.86)	(-1.43)
Size	0.0153	0.00349	0.0133	0.00220
	(1.53)	(0.29)	(1.35)	(0.19)
Info$\times d^{mm}$		-0.0165*		-0.0167*
		(-2.35)		(-2.34)
Info$\times d^{mh}$		-0.0134**		-0.0143***
		(-3.11)		(-3.34)
Fin$\times d^{mm}$		0.868		0.509
		(0.47)		(0.28)
Fin$\times d^{mh}$		1.873		1.598
		(1.10)		(0.93)
Econ$\times d^{mm}$		0.121		0.158
		(0.45)		(0.58)
Econ$\times d^{mh}$		-0.388		-0.376
		(-1.36)		(-1.33)
Ind $\times d^{mm}$		0.154*		0.178**
		(2.55)		(2.91)
Ind $\times d^{mh}$		0.0997*		0.120**
		(2.20)		(2.65)

Note: This table presents the results for the first sub-period if the U.S. and Chinese markets are excluded. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Sensitivity analysis: Second sub-period, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
ρ_{t-1}	0.406***	0.390***	0.404***	0.388***
	(16.20)	(6.59)	(6.60)	(17.75)
d_t^{EMU}			0.0508	0.0715
			(0.76)	(1.43)
Info	0.0898***	0.0788***	0.0876***	0.0781***
	(4.11)	(4.59)	(3.95)	(4.61)
Fin	-4.274***	-5.350*	-3.855	-4.840***
	(-3.36)	(-2.56)	(-1.18)	(-3.38)
Econ	1.055***	0.530**	0.930***	0.353
	(5.69)	(3.24)	(3.83)	(1.77)
Ind	-0.0930***	-0.153***	-0.0924**	-0.154***
	(-6.36)	(-5.97)	(-2.98)	(-6.72)
Size	-0.0317***	-0.0200**	-0.0285***	-0.0158*
	(-4.31)	(-3.05)	(-3.68)	(-2.14)
Info$\times d^{mm}$		-0.0172**		-0.0185**
		(-2.87)		(-3.07)
Info$\times d^{mh}$		-0.0130**		-0.0142***
		(-3.23)		(-3.90)
Fin$\times d^{mm}$		2.932		2.804
		(1.53)		(1.72)
Fin$\times d^{mh}$		1.048		0.979
		(0.60)		(0.84)
Econ$\times d^{mm}$		0.186		0.367
		(0.64)		(1.22)
Econ$\times d^{mh}$		0.376		0.519
		(0.76)		(1.36)
Ind $\times d^{mm}$		0.0762		0.0771
		(1.61)		(1.62)
Ind $\times d^{mh}$		0.0910*		0.0926**
		(2.02)		(3.12)

Note: This table presents the results for the second sub-period if the U.S. and Chinese markets are excluded. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Time dummies: The entire period as a whole.

	(II)	(III)
1996	-0.517**	-0.0897
	(-2.79)	(-0.66)
1997	-0.444*	-0.00537
	(-2.41)	(-0.04)
1998	-0.369*	0.0750
	(-2.05)	(0.55)
1999	-0.573**	-0.130
	(-3.13)	(-0.95)
2000	-0.488*	-0.0399
	(-2.48)	(-0.29)
2001	-0.482*	-0.0296
	(-2.49)	(-0.22)
2002	-0.485*	-0.0285
	(-2.48)	(-0.21)
2003	-0.546**	-0.0821
	(-2.73)	(-0.60)
2004	-0.395	0.0721
	(-1.90)	(0.52)
2005	-0.513*	-0.0400
	(-2.54)	(-0.28)
2006	-0.378	0.102
	(-1.81)	(0.72)
2007	-0.356	0.120
	(-1.77)	(0.84)
2008	-0.316	0.157
	(-1.63)	(1.13)
2009	-0.386	0.0958
	(-1.95)	(0.68)
2010	-0.337	0.153
	(-1.68)	(1.08)

Note: The table presents the estimated time effects for the entire period. The specifications II and III correspond to those in Table 4.4. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.5: Time dummies: The sub-periods

	(II-period1)	(II-period2)	(III-period1)	(III-period2)
1996	-0.959***		-0.537**	
	(-3.99)		(-2.85)	
1997	-0.880***		-0.457*	
	(-3.66)		(-2.41)	
1998	-0.817***		-0.379*	
	(-3.39)		(-1.97)	
1999	-1.008***		-0.582**	
	(-4.16)		(-3.00)	
2000	-0.926***		-0.494*	
	(-3.82)		(-2.55)	
2001	-0.914***		-0.484*	
	(-3.79)		(-2.50)	
2002	-0.917***		-0.484*	
	(-3.81)		(-2.50)	
2003		0.135		0.278
		(0.65)		(1.91)
2004		0.284		0.429**
		(1.30)		(2.86)
2005		0.178		0.322*
		(0.83)		(2.16)
2006		0.329		0.475**
		(1.48)		(3.10)
2007		0.334		0.478**
		(1.53)		(3.14)
2008		0.362		0.515***
		(1.85)		(3.51)
2009		0.304		0.455**
		(1.50)		(3.06)
2010		0.359		0.514***
		(1.72)		(3.40)

Note: The table presents the estimated time effects for the sub-periods 1996–2002 and 2003–2010 separately. Specifications II and III correspond to those in Table 4.5. t statistics are in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6: Time dummies: The EMU effect

	(IV-entire)	(IV-period1)	(IV-period2)	(V-entire)	(V-period1)	(V-period2)
1996	-0.553***	-0.891**		-0.167	-0.491**	
	(-4.06)	(-3.19)		(-1.08)	(-2.66)	
1997	-0.479***	-0.812**		-0.0828	-0.411*	
	(-3.49)	(-2.91)		(-0.52)	(-2.21)	
1998	-0.399**	-0.747**		-0.000428	-0.330	
	(-2.89)	(-2.67)		(-0.00)	(-1.76)	
1999	-0.611***	-0.940***		-0.212	-0.538**	
	(-4.39)	(-3.33)		(-1.28)	(-2.83)	
2000	-0.525***	-0.858**		-0.123	-0.453*	
	(-3.75)	(-3.12)		(-0.78)	(-2.38)	
2001	-0.519***	-0.847**		-0.113	-0.444*	
	(-3.72)	(-3.11)		(-0.70)	(-2.34)	
2002	-0.522***	-0.848**		-0.112	-0.444*	
	(-3.74)	(-3.13)		(-0.71)	(-2.34)	
2003	-0.584***		-0.0874	-0.167		0.144
	(-4.12)		(-0.46)	(-1.03)		(0.93)
2004	-0.433**		0.0608	-0.0144		0.295
	(-3.03)		(0.32)	(-0.09)		(1.89)
2005	-0.551***		-0.0458	-0.126		0.187
	(-3.82)		(-0.24)	(-0.76)		(1.19)
2006	-0.415**		0.102	0.0156		0.338*
	(-2.85)		(0.53)	(0.10)		(2.12)
2007	-0.395**		0.107	0.0329		0.340*
	(-2.71)		(0.55)	(0.19)		(2.13)
2008	-0.351*		0.139	0.0731		0.379*
	(-2.46)		(0.72)	(0.42)		(2.39)
2009	-0.421**		0.0809	0.0109		0.319*
	(-2.92)		(0.42)	(0.06)		(2.00)
2010	-0.372*		0.136	0.0687		0.378*
	(-2.56)		(0.70)	(0.40)		(2.35)

Note: The table presents the estimated time effects for the EMU effect. Specifications IV and V correspond to those in Table 4.6. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7: Time dummies: Entire period analysis, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
1996	-0.382*	-0.00326	-0.400**	-0.0791
	(-2.46)	(-0.01)	(-2.59)	(-0.34)
1997	-0.304	0.0925	-0.320*	0.0164
	(-1.95)	(0.38)	(-2.07)	(0.07)
1998	-0.239	0.164	-0.250	0.0900
	(-1.52)	(0.64)	(-1.60)	(0.36)
1999	-0.444**	-0.0407	-0.462**	-0.121
	(-2.79)	(-0.16)	(-2.93)	(-0.49)
2000	-0.366*	0.0460	-0.382*	-0.0362
	(-2.31)	(0.19)	(-2.43)	(-0.15)
2001	-0.365*	0.0535	-0.382*	-0.0281
	(-2.31)	(0.22)	(-2.43)	(-0.12)
2002	-0.373*	0.0504	-0.389*	-0.0313
	(-2.36)	(0.21)	(-2.48)	(-0.13)
2003	-0.433**	-0.00204	-0.451**	-0.0851
	(-2.71)	(-0.01)	(-2.83)	(-0.35)
2004	-0.273	0.158	-0.291	0.0724
	(-1.69)	(0.66)	(-1.81)	(0.31)
2005	-0.390*	0.0488	-0.406*	-0.0349
	(-2.39)	(0.19)	(-2.51)	(-0.14)
2006	-0.253	0.192	-0.269	0.108
	(-1.54)	(0.78)	(-1.65)	(0.44)
2007	-0.231	0.209	-0.247	0.125
	(-1.41)	(0.82)	(-1.51)	(0.50)
2008	-0.202	0.246	-0.212	0.165
	(-1.25)	(0.94)	(-1.32)	(0.65)
2009	-0.274	0.180	-0.285	0.0984
	(-1.68)	(0.69)	(-1.77)	(0.38)
2010	-0.218	0.242	-0.230	0.160
	(-1.33)	(0.93)	(-1.41)	(0.62)

Note: The table presents the estimated time effects for the sensitivity analysis. The specifications I–IV correspond to those in Table A.1. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.8: Time dummies: First sub-period, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
1996	-0.719**	-0.189	-0.654**	-0.164
	(-2.82)	(-0.80)	(-2.60)	(-0.73)
1997	-0.633*	-0.0973	-0.567*	-0.0720
	(-2.49)	(-0.41)	(-2.26)	(-0.32)
1998	-0.585*	-0.0290	-0.516*	-0.000652
	(-2.28)	(-0.12)	(-2.05)	(-0.00)
1999	-0.774**	-0.226	-0.709**	-0.203
	(-2.99)	(-0.94)	(-2.78)	(-0.89)
2000	-0.697**	-0.145	-0.630*	-0.127
	(-2.70)	(-0.64)	(-2.48)	(-0.59)
2001	-0.691**	-0.137	-0.626*	-0.119
	(-2.69)	(-0.61)	(-2.48)	(-0.56)
2002	-0.698**	-0.139	-0.633*	-0.121
	(-2.73)	(-0.63)	(-2.51)	(-0.57)

Note: The table presents the estimated time effects for the sensitivity analysis in the first sub-period. Specifications I–IV correspond to those in Table A.2. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.9: Time dummies: Second sub-period, but excluding the U.S. and China

	(I)	(II)	(III)	(IV)
2003	0.480*	0.295	0.408*	0.191
	(2.41)	(1.64)	(2.00)	(1.01)
2004	0.637**	0.448*	0.565**	0.343
	(3.18)	(2.51)	(2.78)	(1.81)
2005	0.535**	0.345	0.463*	0.240
	(2.64)	(1.89)	(2.24)	(1.25)
2006	0.690***	0.496**	0.617**	0.390*
	(3.38)	(2.71)	(2.97)	(2.02)
2007	0.689***	0.496**	0.616**	0.389*
	(3.34)	(2.68)	(2.94)	(2.00)
2008	0.708***	0.528**	0.636**	0.422*
	(3.48)	(2.79)	(2.98)	(2.19)
2009	0.653**	0.469*	0.580**	0.362
	(3.18)	(2.49)	(2.73)	(1.87)
2010	0.715***	0.531**	0.643**	0.425*
	(3.47)	(2.84)	(3.04)	(2.19)

Note: The table presents the estimated time effects for the sensitivity analysis in the second sub-period. Specifications I–IV correspond to those in Table A.3. t statistics are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Bibliography

ARELLANO, M. and BOND, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies*, vol. 58(2), pp. 277–297.

ARELLANO, M. and BOVER, O. (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics*, vol. 68(1), pp. 29 – 51.

ASGHARIAN, H. and BENGTSSON, C. (2006), "Jump spillover in international equity markets", *Journal of Financial Econometrics*, vol. 4(2), pp. 167–203.

BALTAGI, B. H. (2008), *Econometric Analysis of Panel Data*, John Wiley and Sons Ltd, 4th ed.

BEINE, M. and CANDELON, B. (2011), "Liberalisation and stock market co-movement between emerging economies", *Quantitative Finance*, vol. 11(2), pp. 299–312.

BEINE, M., COSMA, A. and VERMEULEN, R. (2010), "The dark side of global integration: Increasing tail dependence", *Journal of Banking and Finance*, vol. 34(1), pp. 184 – 192.

BLUNDELL, R. and BOND, S. (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, vol. 87(1), pp. 115 – 143.

FLAVIN, T. J., HURLEY, M. J. and ROUSSEAU, F. (2002), "Explaining stock market correlation: a gravity model approach", *The Manchester School*, vol. 70(S1), pp. 87–106.

FORBES, K. J. and CHINN, M. D. (2004), "A decomposition of global linkages in financial markets over time", *The Review of Economics and Statistics*, vol. 86(3), pp. 705–722.

Ivkovich, Z. and Weisbenner, S. (2007), "Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices", *Review of Financial Studies*, vol. 20(4), pp. 1327–1357.

Kim, S. J., Moshirian, F. and Wu, E. (2005), "Dynamic stock market integration driven by the European Monetary Union: An empirical analysis", *Journal of Banking and Finance*, vol. 29(10), pp. 2475 – 2502.

Mondria, J. and Wu, T. (2010), "The puzzling evolution of the home bias, information processing and financial openness", *Journal of Economic Dynamics and Control*, vol. 34(5), pp. 875 – 896.

Nickell, S. (1981), "Biases in Dynamic Models with Fixed Effects", *Econometrica*, vol. 49(6), pp. 1417–1426.

Portes, R. and Rey, H. (2005), "The determinants of cross-border equity flows", *Journal of International Economics*, vol. 65(2), pp. 269 – 296.

Pretorius, E. (2002), "Economic determinants of emerging stock market interdependence", *Emerging Markets Review*, vol. 3(1), pp. 84 – 105.

Roll, R. (1992), "Industrial structure and the comparative behavior of international stock market indices", *Journal of Finance*, vol. 47(1), pp. 3–41.

Roodman, D. (2006), "How to do Xtabond2: an introduction to difference and system GMM in Stata", *SSRN eLibrary*.

Sims, C. A. (2006), "Rational inattention: beyond the linear-quadratic case", *American Economic Review*, vol. 96(2), pp. 158–163.

Wälti, S. (2011), "Stock market synchronization and monetary integration", *Journal of International Money and Finance*, vol. 30(1), pp. 96–110.

Yang, J., Min, I. and Li, Q. (2003), "European stock market integration: does EMU matter?", *Journal of business finance & accounting*, vol. 30(9-10), pp. 1253–1276.

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