A spatial analysis of international stock market linkages

Hossein Asgharian*: *Department of Economics, Lund University*

Wolfgang Hess: *Department of Statistics, Ludwig Maximilian University of Munich*

Lu Liu: *Department of Economics, Lund University*

Abstract

We employ spatial econometrics techniques to investigate to what extent countries' economic and geographical relations affect their stock market co-movements. We propose an econometric model that is particularly suitable for financial data, where common time trends prevail. In general, among the relations that we analyze, bilateral trade and exchange rate stability prove to be best suited to capture return co-variations. An analysis of three regionally dominant countries shows that bilateral trade is the most important relation regarding the transmission of shocks from the US and Japan to other countries, whereas the UK affects mostly its geographical neighbors.

Keywords: stock market synchronization; spatial econometrics; feedback effects

JEL classification: G15, C23

* Tel.: +46 46 222 8667; fax: +46 46 222 4118;

Department of Economics, Lund University, Box 7082, S-22007 Lund, Sweden.

Hossein.Asgharian@nek.lu.se; wolfgang.hess@nek.lu.se; lu.liu@nek.lu.se

We are very grateful to *Jan Wallanders and Tom Hedelius Foundation, The Swedish Bank Research Foundation* and *Torsten Söderbergs Foundation* for funding this research.

A spatial analysis of international stock market linkages

Abstract

We employ spatial econometrics techniques to investigate to what extent countries' economic and geographical relations affect their stock market co-movements. We propose an econometric model that is particularly suitable for financial data, where common time trends prevail. In general, among the relations that we analyze, bilateral trade and exchange rate stability prove to be best suited to capture return co-variations. An analysis of three regionally dominant countries shows that bilateral trade is the most important relation regarding the transmission of shocks from the US and Japan to other countries, whereas the UK affects mostly its geographical neighbors.

Keywords: stock market synchronization; spatial econometrics; feedback effects;
JEL classification: G15, C23

I. Introduction

The severe global economic impacts of the recent financial crises have intensified the need for analyzing linkages between different financial markets. In order to conduct risk hedging through global diversification, financial investors need to understand co-movements of financial markets and the sensitivity of the markets to exogenous shocks. Therefore, it is essential to explore the underlying economic structures that affect the transmission of country (market)-specific shocks to other countries (markets). In this study, we employ spatial econometrics tools to analyze to what extent different linkages between countries affect the degree of their stock market co-movements.

Interactions among international stock markets have been investigated by a number of earlier studies (see e.g., Longin and Solnik 1995, Karolyi and Stulz 1996, Bekaert and Harvey 1995, Asgharian and Bengtsson 2006, Asgharian and Nossman 2011). The majority of previous studies have solely focused on assessing the degree of dependence among markets, whereas the channels through which stock markets are related to each other have received insufficient attention. Previous research on the latter subject relied primarily on gravity models, where the correlation or co-exceedance among national stock markets is regressed on economic sizes (GDP or market capitalization) and distances (measured by cross-country-specific variables) between the markets (see e.g. Flavin et al. 2002, Beine and Candelon 2010, and Wälti 2011).

Recent developments in spatial econometrics have provided an alternative tool for analyzing the economic structures that affect the co-movement of financial markets. Applying spatial econometrics makes it possible to incorporate factors related to location and distance in the analysis. Using this approach, the structure of the relationship between observations at different locations is connected to the relative position of the observations in a hypothetical space. Unlike gravity models, this approach is not purely bilateral, i.e. it does not capture the average effects of different economic linkages on any purely bilateral correlation but rather their average effects on the relationships between one country and many other countries at once. Moreover, the spatial econometrics approach allows us to model asymmetric relationships between countries. Lastly, the spatial econometrics approach is dynamic in nature and allows us to investigate how a specific shock transmits throughout the system. It can therefore reveal how shocks in returns or in macroeconomic conditions in one country affect the stock markets of other countries, while taking into account the feedback effects that amplify the impact of shocks. Thus, our study can be helpful for analyzing potential channels through which adverse shocks may induce a systemic risk.

Although spatial modeling of dependence structures has become very popular in recent years, it has hardly been used in financial applications. Two recent exceptions are the studies on firm level data by Fernandez (2011), who employs variables such as market capitalization and book-to-market ratio to measure the spatial distances among firms, and Arnold et al. (2011), who consider two firms as neighbors if they belong to the same country or industry. However, none of these two studies uses bilateral economic variables to measure spatial distances. In fact, using firm characteristics as distance measures in a spatial autoregressive model is not coherent with the concept of spatial relationships; for example, the stock returns of two firms with high book-to-market ratios may have a similar pattern without having any impact on each other.

We investigate several different linkages between countries: geographical neighborhood, the volume of countries' bilateral trades, bilateral foreign direct investment (FDI), convergence in expected inflation, and the stability of the bilateral exchange rate. We analyze data for 41 national stock market indexes over a period from 1995 to 2010. We also perform a simulation analysis which shows that the commonly used spatial autoregressive model with one spatial lag, SAR(1), is not suitable for return data which are frequently exposed to common global shocks. We therefore propose an SAR(2) model, which enables us to mitigate this problem.

Our empirical results indicate that bilateral trade and exchange rate stability contribute to stock market synchronization to a greater extent than the other linkages considered. Due to the spatial transmission and feedback effects among markets, a unit shock in a country can be amplified by more than 20 percent via these two channels. We also investigate the transmission of shocks from three regionally dominant countries, namely the US, the UK, and Japan, to other countries. We find a strong effect of a unit shock to the US market on other countries, particularly through the trade channel. For the UK, the geographical channel appears to be the most important one, as the location in Europe makes the UK an important geographical neighbor to many other countries. For Japan, the trade channel appears to be the most important one.

Our study provides several important contributions to the literature. To our knowledge, this is the first in-depth analysis of the economic structures underlying the (global) co-movements of stock market indexes that employs spatial econometrics techniques. In addition, we propose a spatial econometric model that is particularly suitable for financial market data, where the observations have common time trends.

Finally, we provide new insights into the mechanism of transmission and feedback effects between stock markets. More specifically, we analyze to what extent shocks (or changes in macroeconomic conditions) affecting the stock market returns in one country are transmitted to other countries via various spatial linkages, and to what extent the impact of shocks is amplified by feedback effects. Our approach and results can be interesting for further analyses of the channels through which adverse shocks may generate global crashes.

The remainder of the paper is organized as follows. Section II presents the spatial econometrics methods used in this paper. Section III presents the data and selected variables. Section IV contains a simulation analysis of model behavior. Section V contains the empirical results, and section VI concludes.

II. Econometric Modeling

The concept of spatial dependence in regression models reflects a situation where the values of the dependent variable at one location depend on the values of neighboring observations at nearby locations. Such dependencies can originate from spatial spillovers stemming from contagion effects or from unobserved heterogeneity caused by omitted explanatory variables (see e.g. LeSage and Pace 2009). Our study focuses on the former concept. Depending on the source of the spatial correlation, a variety of alternative spatial regression structures can arise. The most commonly applied spatial regression models specify a spatial autoregressive (SAR) process in the dependent variable or the error term. These models are frequently referred to as the *spatial lag model* and the *spatial error model*, respectively.

Formally, the spatial lag model can be expressed as:

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\boldsymbol{y}$ is a vector of observations on a dependent variable, $\boldsymbol{X}$ is a matrix of observations on exogenous (explanatory) variables with an associated vector of coefficients $\boldsymbol{\beta}$, $\boldsymbol{\varepsilon}$ is a vector of idiosyncratic errors, $\boldsymbol{W}$ is a spatial weights matrix, and ρ is the SAR parameter. Similarly, the spatial error model can be expressed as:

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\nu}, \tag{2}$$

where $\boldsymbol{\nu} = \lambda \boldsymbol{W}\boldsymbol{\nu} + \boldsymbol{\varepsilon}$, with λ being the SAR parameter.

In this study, we focus solely on spatial lag models, i.e. models with an SAR process in the dependent variable. Using this model specification ensures that shocks to both the error term and the explanatory variables at one location are transmitted to all other locations within the spatial system (see e.g. LeSage and Pace 2009).[1] Prominent empirical applications of spatial econometrics models including spatially lagged dependent variables are Case (1991, 1992), Case et al. (1993), and, more recently, Kelejian et al. (2006) and Hondronyiannis et al. (2009).

In this study, we consider an SAR specification with two spatial lags, henceforth denoted SAR(2):

$$\boldsymbol{y} = \rho_1 \boldsymbol{W_1}\boldsymbol{y} + \rho_2 \boldsymbol{W_2}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{3}$$

[1] By contrast, when using a spatial error model, only shocks in the error term but not shocks to the explanatory variables are transmitted to other locations. In other words, provided that unexpected inflation has an effect on stock market returns, a shock to the US inflation rate would, in the spatial error model framework, affect stock market returns in the USA only.

Since we have both cross-sectional and time-series variations in our data, we employ a panel data specification:

$$\boldsymbol{y} = \rho_1(\boldsymbol{I}_T \otimes \boldsymbol{W_1}(t))\mathbf{y} + \rho_2(\boldsymbol{I}_T \otimes \boldsymbol{W_2}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}, \tag{4}$$

where $\rho_1$and ρ_2 are SAR parameters, and $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ are (possibly time-varying) spatial weights matrices describing the spatial arrangement of the cross-section units. The dimension of $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ is $N \times N$, where N is the number of cross-sectional observations in the sample. The model specification above is expressed in a stacked matrix form. The vector $\boldsymbol{y}$ contains NT observations of the dependent variable (monthly return), where T is the time-series dimension. Similarly, $\boldsymbol{X}$ is a $NT \times k$ matrix containing the stacked observations of k explanatory variables (including country-specific intercepts and the lagged dependent variable) and $\boldsymbol{\beta}$ is the corresponding $k \times 1$ vector of parameters. Finally, $\boldsymbol{\varepsilon}$ is an $NT \times 1$ vector of idiosyncratic error terms, $\boldsymbol{I}_T$ is an identity matrix of dimension T, and $\otimes$ denotes the Kronecker product.

The model can be written in reduced form as:

$$\boldsymbol{y} = \left(\boldsymbol{I}_{NT} - \rho_1\big(\boldsymbol{I}_T \otimes \boldsymbol{W_1}(t)\big) - \rho_2\big(\boldsymbol{I}_T \otimes \boldsymbol{W_2}(t)\big)\right)^{-1} (\boldsymbol{X\beta} + \boldsymbol{\varepsilon}). \tag{5}$$

This implies that any event, such as changes in economic variables or unexpected shocks, in one country will also affect other countries through the spatial relationship among countries (see e.g. Anselin (2006) or LeSage and Pace (2009) for detailed discussions of this so-called spatial multiplier effect).

The distinctive feature of this model specification is that it contains linear combinations of the dependent variable as additional explanatory variables. This induces an endogeneity problem that typically renders conventional OLS estimates of the model parameters inconsistent.[2] Maximum likelihood estimation can be used as an alternative to OLS that yields consistent parameter estimates. The log-likelihood function that is to be maximized is given by:

$$\ln \mathrm{L} = \sum_{t=1}^{T} \ln |\boldsymbol{I}_N - \rho_1 \boldsymbol{W}_{\mathbf{1}}(t) - \rho_2 \boldsymbol{W}_{\mathbf{2}}(t)| - \frac{NT}{2} \ln(2\pi\sigma^2) - \frac{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}}{2\sigma^2}, \tag{6}$$

where

$$\boldsymbol{\varepsilon} = \boldsymbol{y} - \rho_1(\boldsymbol{I}_T \otimes \boldsymbol{W}_{\mathbf{1}}(t))\boldsymbol{y} - \rho_2(\boldsymbol{I}_T \otimes \boldsymbol{W}_{\mathbf{2}}(t))\boldsymbol{y} - \boldsymbol{X\beta},$$

and σ^2 is the error variance that is to be estimated along with the structural model parameters (see e.g. Anselin 2006).

Since this study focuses on the identification of linkages through which markets are interconnected, the specification of $\boldsymbol{W}_{\mathbf{1}}$ and $\boldsymbol{W}_{\mathbf{2}}$ is of crucial importance. In our empirical analysis, we define these matrices in a way that allows for asymmetric dependencies between any pair of markets. In specifying $\boldsymbol{W}_{\mathbf{1}}$ and $\boldsymbol{W}_{\mathbf{2}}$ we start out by constructing a contiguity matrix $\boldsymbol{C}$ that indicates for any pair of markets in the sample whether market *j* is a neighbor to market i according to various factors defining closeness or distance among countries. If F_{ij} is a factor measuring the closeness between countries *i* and *j*, the elements in the i^{th} row and the j^{th} column of $\boldsymbol{C}$ are given by:

$$C_{ij} = 1 - \frac{\max_j F_{ij} - F_{ij}}{\max_j F_{ij} - \min_j F_{ij}} \tag{7}$$

for all $i \neq j$, and zero otherwise. By contrast, if F_{ij} is a factor measuring the distance between countries *i* and *j*, the elements in the i^{th} row and the j^{th} column of $\boldsymbol{C}$ are given by:

[2] Kelejian and Prucha (2002) and Lee (2002) have shown that under certain conditions the OLS estimator of the parameters of a linear spatial model containing a spatially lagged dependent variable is consistent and asymptotically normal. These estimates, however, are biased in finite samples.

$$C_{ij} = 1 - \frac{F_{ij} - \min_j F_{ij}}{\max_j F_{ij} - \min_j F_{ij}} \tag{8}$$

for all $i \neq j$, and zero otherwise. This definition of contiguity ensures that all elements of $\boldsymbol{C}$ lie between zero and one, with $C_{ij} = 1$ if country j has the shortest distance to country i and $C_{ij} = 0$ if country j has the longest distance to country i.

For each country i, the 20 remaining countries (i.e. 50% of all remaining countries) that are closest according to the respective definitions of neighborhood are considered to be neighbors. These neighboring countries are captured by the matrix $\boldsymbol{W}_1$ with elements $W_{1,ij} = C_{ij}$ if $C_{ij} \geq \underset{j}{\text{median}}\, C_{ij}$, and zero otherwise. Similarly, the 20 non-neighboring countries are captured by the matrix $\boldsymbol{W}_2$ with elements $W_{2,ij} = 1$ if $C_{ij} < \underset{j}{\text{median}}\, C_{ij}$, and zero otherwise. Following common practice, the elements of $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are row standardized, such that for each i, $\sum_j W_{1,ij} = \sum_j W_{2,ij} = 1$. Consequently, the first spatial lag, $\boldsymbol{W}_1\boldsymbol{y}$, can be interpreted as a weighted average of the dependent variable of all neighbors, and the second spatial lag, $\boldsymbol{W}_2\boldsymbol{y}$, as a simple, non-weighted average of the dependent variable of all non-neighbors.

Using an SAR(2) model with spatial weights matrices as defined above has three noteworthy implications. First, this model specification allows us to directly compare the spatial dependencies existing among neighbors with those existing among non-neighbors. Second, our specification of $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ allows for asymmetric dependencies between any pair of markets. For example, when defining neighborhood based on the amount of bilateral trade, the US is contiguous to the Philippines, since the volume of trade between the Philippines and the US is above the median volume of trade between the Philippines and all other countries. The Philippines, however, is not a first-order neighbor to the US, since their bilateral trade is below the median volume of trade between the US and all other countries. Third, the SAR(2) specification above accounts for spatial dependencies that are due to common time trends. Specifically, the SAR(2) specification above allows for two common time trends, which may differ between the group of neighbors and the group of non-neighbors. Moreover, the time effects are not eliminated, which implies that the SAR parameters ρ_1 and ρ_2 capture cross-sectional dependencies due to both spillover effects and common time trends.[3]

Although the focus of this study is on spatial dependencies among markets, we also account for spatial heterogeneity among markets by including a number of fundamental explanatory variables, which may affect market returns, in the model. A number of researchers have noted that SAR models require a special interpretation of the $\boldsymbol{\beta}$-parameters associated with these explanatory variables (see e.g. Anselin and Le Gallo 2006; Kelejian *et al*. 2006). In essence, $\boldsymbol{\beta}$ is no longer equivalent to the marginal effects of changes in the fundamentals. The reason for this is that a change in fundamentals in one country, say country i, affects the return of that country, which in turn affects the returns in nearby locations, which then feeds back to the return of country i. The values of $\boldsymbol{\beta}$ should thus be interpreted as average *immediate* effects of changes in the explanatory variables, which do not include such spillover and feedback effects.

[3] Lee and Yu (2010) propose an alternative estimation procedure for a linear panel data model with a spatially lagged dependent variable and unobserved time effects. Their method is based on a data transformation that eliminates the common time components. However, Lee and Yu (2010) assume an unobserved time component, which is common to all cross-sectional units. This induces equicorrelation between any two cross-sectional units no matter how far these units are apart, which is not in agreement with spatial interaction theory (see Anselin et al. 2008).

In order to maximize the likelihood function in equation (6) we employ the simulated annealing algorithm (see Goffe et al. 1994). For complex likelihood functions with potentially many local maxima, this algorithm outperforms conventional gradient-based methods, such as the Newton-Raphson algorithm, in finding the global maximum.

III. Variable Selection and Data

This section describes the selected channels of spatial dependence and defines the spatial distances between markets. It also presents the explanatory variables included in the model and the data sources used.

A. Potential channels of spatial dependence

To capture the relative distance/closeness of the financial markets to one another, we use five bilateral factors. Exchange rate volatility and the absolute difference between two countries' inflation rates are related to the degree of their monetary integration, while bilateral trade and bilateral FDI capture their economic linkages. As an additional factor, we use geographical distance. The values of all factors except geographical distance vary on a yearly basis. We would like to point out that we do not intend to provide an exhaustive analysis of all the potential channels through which stock markets may be interrelated. Our aim is rather to thoroughly analyze a selection of possibly important linkages and to provide an idea of how various bilateral factors can be used to generate distance measures between the markets.

a. *Exchange rate volatility*

Less volatile exchange rates should reduce cross-currency risk premiums, implying more similar discount rates and thereby decreasing the cost of hedging currency risk. This should give a more homogeneous valuation of equities and increase incentives to invest in foreign markets, thereby leading to higher market integration. However, empirical evidence on the role of exchange rate stability for international market dependence is mixed. Bekaert and Harvey (1995), for instance, find no evidence that exchange rate changes are related to market integration. On the contrary, Bodart and Reding (1999), Fratzscher (2002), and Beine et al. (2010) all find a significant negative impact of exchange rate volatility on financial market co-movements.

We compute exchange rate volatility as the standard deviation of daily log changes in bilateral exchange rates each year.

b. Absolute difference between inflation expectations

The convergence of inflation expectations induces investors to be less home-biased, as they no longer need to hedge local inflation risk by investing more in local assets. In addition, the convergence of inflation rates may also imply an environment with stable exchange rates and thus increase incentives to invest in foreign markets. Previous research has merely shed light on the role of inflation for regional stock market dependence. Johnson and Soenen (2002) and Hardouvelis et al. (2006) find negative impacts of inflation differentials on stock market integration among Asian countries and EMU countries, respectively.

We calculate yearly inflation rate as the average change in CPI for every month of the year compared with the respective month in the preceding year. Assuming the series of inflation rates are Martingale, expected inflation is equal to realized inflation in the preceding year. Then, we compute the bilateral factor by taking the absolute differences between expected inflation rates across countries.

c. Bilateral trade

We expect international trade to foster business cycle synchronization across countries. A large value of trade between two countries should imply a higher dependence between these countries and thus increase the degree of stock market dependence. Wälti (2010), Beine and Candelon (2010), and Beine et al. (2010), among a vast literature, find that bilateral trade contributes to larger stock market co-movements.

We calculate the factor of bilateral trade as:

$$F_{ij,t}^{BT} = \frac{exp_{ij,t} + imp_{ij,t}}{\sum_{k=1}^{k=N} exp_{ik,t} + \sum_{k=1}^{k=N} imp_{ik,t}} \quad (9)$$

where exp and imp are, respectively, yearly nominal export and import values in US dollars. Thus, $F_{ij,t}^{BT}$ represents the value of trade between country i and country j relative to the total value of trade of country i.

d. Bilateral FDI

Another factor that may affect stock market dependence is bilateral FDI[4]. "FDI provides a means for creating direct, stable and long-lasting links between economies" (OECD 2008). Countries having larger values of bilateral FDI may be more exposed to common shocks. However, only a limited number of empirical studies have investigated the impact of bilateral FDI on stock market integration. Among these few studies, Chinn and

[4] According to the OECD benchmark definition of FDI (fourth edition, 2008), direct investment is a category of cross-border investment made by a resident in one economy (the direct investor) with the objective of establishing a lasting interest in an enterprise (the direct investment enterprise) that is resident in an economy other than that of the direct investor.

Forbes (2004) find the impact of bilateral FDI to be insignificant. They argue that this could partially result from the noises in FDI statistics[5].

We calculate the variable of bilateral FDI in the same manner as the variable of bilateral trade:

$$F_{ij,t}^{FDI} = \frac{outflow_{ij,t} + inflow_{ij,t}}{\sum_{k=1}^{k=N} outflow_{ik,t} + \sum_{k=1}^{k=N} inflow_{ik,t}} \tag{10}$$

where $outflow$ and $inflow$ are the yearly nominal positions of FDI outflow and inflow in US dollars. Thus, $F_{ij,t}^{FDI}$ represents the relative importance of the direct investment relationship with country j for country i.

e. Geographical distance

A country's stock market is prone to be affected by its nearby countries because of close economic relations and business cycle synchronization. Investors are more likely to invest in nearby markets because they have better information about them compared with more distant markets. Empirical studies, such as Flavin et al. (2002), have documented the positive impact of geographical closeness on stock market integration.

To measure geographical neighborhood, we use the distance between capital cities for every pair of countries.

B. Selection of control variables

In addition to the factors assessing spatial dependence, a number of explanatory macro variables are included in the model. These variables are changes in exchange rate, unexpected inflation, GDP growth, and sovereign default rate.

[5] The FDI data are reported by each national government and thus they are subject to different reporting standards.

A positive change in exchange rate (i.e. local currency depreciation) is expected to have a negative impact on market returns, since the depreciation of a country's local currency is a proxy for economic distress. However, the empirical evidence regarding this effect is mixed. Ma and Kao (1990) find a positive relationship between currency and stock price movements, whereas Friberg and Nydahl (1999) document a negative relationship. We construct the variable as the monthly difference in a country's exchange rate to the US dollar.

Positive unexpected inflation indicates economic boom, and can therefore be expected to have a positive impact on market returns. However, empirical studies, such as Fama and Schwert (1977), have found a negative correlation between stock returns and unexpected inflation. We calculate monthly unexpected inflation as realized inflation minus expected inflation as described in section III-A.

GDP growth is a representative proxy for business cycle phases and is, therefore, expected to have a positive impact on stock market returns. The previous literature, for example Harvey (1995) and Fifield et al. (2002), has confirmed the impact of GDP growth on equity returns.

The sovereign default rate assesses a country's creditworthiness. Its impact on stock market returns may be ambiguous. On one hand, time-series empirical studies, such as Brooks et al. (2004) and Hooper et al. (2008), have shown that a country being credit-downgraded tends to have a decrease in its stock market returns. On the other hand, a higher sovereign default rate indicates higher market uncertainty, which may imply a higher risk premium. Thus, in a cross-sectional framework, countries with a higher sovereign default rate are expected to have larger stock market returns. We measure the sovereign default rate on an ordinal scale between 1 (AAA) and 20 (CC) according to the Standard & Poor’s foreign currency rating. Thus, a higher sovereign default rate value implies lower creditworthiness.

C. Dataset

Our data comprise observations on 41 equity markets (see Table 1 for the list of included countries in addition to the US). We extract the main indexes for these markets from MSCI and construct log returns between January 1995 and October 2010.

Data on bilateral trade are taken from the STAN Bilateral Trade Database (source: OECD). This database contains the values of the annual imports and exports of goods for all OECD counties and 17 non-OECD countries. These import and export values are given in US dollars at current prices. The data cover the period 1995 to 2009. We assume that the values in 2010 are equivalent to those in 2009.

We collect data on FDI positions from the OECD International Direct Investment Statistics. This source provides annual bilateral FDI positions in US dollars for the period 1995 to 2008. It also reports the positions of outward FDI from OECD countries to OECD countries and non-OECD countries as well as the positions of outward FDI from non-OECD countries to OECD countries. Some observations are confidential and therefore not reported. The observations of FDI from non-OECD countries to non-OECD countries are also not reported. However, the values of these observations are likely to be minor, so we treat them as zero. We also assume that the observations in 2009 and 2010 are equivalent to those in 2008.

We use exchange rates from GTIS and WM/Reuters. Data on monthly CPI[6] are taken from national sources on DataStream. Distances between capital cities are taken from CEPII (Research and Expertise on Major Issues for the World Economy). Data on foreign currency ratings are collected from the Standard & Poor's Sovereign Rating. Data on yearly GDP in purchasing power parity between 1994 and 2009 are from the World Bank. We assume that GDP growth rates in 2010 are equivalent to those in 2009.

IV. Simulation Analysis for Model Selection

In this section, we perform a simulation analysis in order to motivate the use of an SAR(2) model in our empirical analysis and the definition of neighborhood based on median values (see section II).

The most commonly used specification in spatial econometrics is the SAR(1) model, which in panel form can be written as:

$$\boldsymbol{y} = \rho(\mathbf{I}_T \otimes \boldsymbol{W}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}, \tag{11}$$

where $\boldsymbol{W}(t)$ is the $N \times N$ neighborhood matrix.

Figure 1 shows the estimated ρ-values obtained from an SAR(1) model with varying numbers of neighbors for each market, where, for each number of neighbors, we use 50 randomly generated neighborhood matrices. The figure shows that ρ is positive in all cases, which indicates a common trend among markets. The average value of ρ increases and the range between the minimum and the maximum estimates approaches

[6] The CPIs for Australia and New Zealand are reported on a quarterly basis. We generate monthly values using linear interpolation.

zero when we increase the number of neighbors. More specifically, ρ reaches its maximum value when we use around 28 neighbors for each country. This indicates that by increasing the number of neighbors we capture the entire spatial dependence among markets (i.e. all the countries are related to each other either directly or through their neighbors).

[Insert Figure 1]

One way to eliminate the common trend is to subtract the cross-sectional mean from each observation (within transformation). The first graph of Figure 2 shows the estimated $\rho-$values obtained from an SAR(1) model with demeaned returns. We now see a reverse pattern: by raising the number of neighbors, the estimated values of ρ become increasingly negative. The reason for this is that we regress the difference of each country from the mean on the weighted sum of the other countries' differences from the mean. If a particular country has a return above the mean, the average value of all other countries is below the mean and vice versa. However, we can obtain positive values of ρ when assigning only a few neighbors to each country since we may by chance pick neighboring countries that deviate from the cross-sectional mean in the same direction as the country under consideration. By increasing the number of neighbors we move towards an extreme scenario where each country's mean-adjusted return is regressed on the average of all other countries' mean-adjusted returns, implying a perfectly negative correlation (see the second graph of Figure 2).[7]

[7] Another alternative for eliminating the trend is to deduct the returns on a world market index from each country's return. However, this approach did not solve the problem of positive ρ in an SAR(1) model with a randomly defined neighborhood.

[Insert Figure 2]

The above results show that an SAR(1) model cannot be used in a panel data setting with a common trend in the data. We therefore use an SAR(2) model, which enables us to directly compare the spatial dependencies existing among neighbors with those existing among non-neighbors. For each country, the 50% of all remaining countries that are closest according to the various distance measures are defined as neighbors and the other 50% of the remaining countries are defined as non-neighbors. Using this definition of neighborhood ensures that common trends in the data affect both neighbors and non-neighbors to the same extent. The effect of neighborhood can then be investigated by comparing the estimated values of the two spatial autocorrelation coefficients.

V. Empirical Results

We analyze the spatial dependence among our selected markets over the entire sample period from January 1995 to October 2010. The section starts with a descriptive analysis of the neighborhood matrices, followed by an analysis of the estimation results. The last part of this section contains a robustness analysis.

A. Exploratory analysis of the neighborhood structures

To give a simple illustration of the neighborhood structures, we present the relative closeness of countries to the US and the relative closeness of the US to other countries according to the different factors over the entire period. For each factor, we take the average of the values over time to construct the contiguity matrix $\boldsymbol{C}$ and the associated neighborhood matrix $\boldsymbol{W}_1$. For each neighborhood factor, Table 1 presents the non-zero elements of the row of $\boldsymbol{W}_1$ associated with the US before row-standardization. This indicates the relative importance of those countries that are neighbors to the US according to the various factors.

[Insert Table 1]

According to exchange rate volatility, Hong Kong is always the closest to the US during the entire sample period. Countries of the Euro area are either the farthest neighbors (e.g. France, Italy, and Spain) or non-neighbors (e.g. Finland, Germany, and the Netherlands). If determined by the convergence of expected inflation, the relative closeness of neighbor markets varies very little (i.e. the values in the third column are between 0.93 and 0.99). Non-neighbors include countries that have had high inflation some time during the observation period, such as Argentina, China, Russia, and Turkey, as well as low-inflation countries such as Japan. In contrast to inflation, the factor of bilateral trade shows disparities in neighbor markets' relative closeness, since the closest neighbors (i.e. Canada, Mexico, China, and Japan) have such large values of trade with the US that the relative closeness of other neighbors is rather low. Notably, Canada is constantly the most important trading partner for the US. Geographically, many Western European countries are neighbors to the US in addition to North American countries. Lastly, only Canada and the UK are neighbors to the US in all cases.

Table 2 presents the non-zero elements of the column of $\boldsymbol{W}_1$ associated with the US before row-standardization. This shows which countries the US is a neighbor to according to the various factors. The values indicate the relative importance of the US as compared to other neighbor countries.

[Insert Table 2]

Table 2 shows that the US is a neighbor to all other countries when bilateral trade is used as neighborhood factor. For several countries (Brazil, Canada, Chile, India, Israel, and Mexico), the US is also the most important trading partner. With respect to exchange rate volatility, inflation, and foreign direct investment, the US is a neighbor to almost all countries. With respect to geographical distance, however, the US is a neighbor only to the five remaining American countries and New Zealand.

In order to investigate to what extent different definitions of neighborhood overlap, we present the proportion of overlapping non-zero elements between each pair of neighborhood matrices in Table 3. Under the null hypothesis that two different concepts of neighborhood are independent, the expected proportion is 0.5. A value of zero indicates that the respective definitions of neighborhood exhibit a perfectly negative correlation (neighborhood according to one definition implies non-neighborhood according to the other). A value equal to one, by contrast, indicates that the respective neighborhood definitions have a perfectly positive correlation (neighborhood according to one definition implies neighborhood according to the other).

Table 3 shows that almost all proportions are significantly different from 0.5, which indicates that there are systematic relationships between the various neighborhood definitions. However, the fractions are not particularly large, which shows that there are noticeable differences among the various neighborhood matrices. It is, therefore, worthwhile separately analyzing the dependencies among stock markets at proximate locations for each specific concept of neighborhood.

[Insert Table 3]

B. Estimation results

We present the results for the entire sample in Table 4. The estimated ρ_1s of all the factors are highly significant and positive. All the estimated ρ_2s are also significantly positive. This suggests that there are common trends and/or spillovers within both neighbors and non-neighbors. However, ρ_1 is substantially larger than ρ_2 in all cases except for foreign investment. Comparing the R-square values of the SAR(2) estimations with those of the restricted model, i.e. a model with $\rho_1 = \rho_2 = 0$, shows that allowing for spatial correlation substantially increases the explanatory power of the model. Further, we measure the contribution of each explanatory variable to the total variance of the dependent variable. The results show that the part of the total variance (explained by the spatial relationship with neighbor countries is apparently higher than that explained by the relationship with non-neighbors. This holds for all neighborhood definitions except bilateral FDI. Furthermore, the AIC values given in the last row of the table confirm the better fit of the SAR(2) model compared with the restricted model. According to likelihood ratio tests, all SAR(2) models significantly outperform the restricted model (results are not reported but are available upon request).

As argued previously in this paper, the global trend in international equity markets may result in positive spatial dependence even among markets that are not neighbors with one another. Therefore, in addition to examining the statistical significance of ρ_1 and ρ_2, we also evaluate whether the spatial neighborhoods defined by the selected factors outperform other possible definitions of neighborhood. We randomly generate 200 contiguity matrices from which we construct W_1 and W_2. This gives 200 pairs of estimated ρ_1 and ρ_2. The first and second diagrams of Figure 3 depict the estimated values of ρ_1 and ρ_2, respectively, for our five selected neighborhood factors. They also show the 99%, 95%, and 90% intervals for the empirical distribution of the estimated ρs.

[Insert Table 4]

The estimated ρ_1s lie above the 99% interval of the empirical distribution for all factors except FDI. This suggests that these factors are better than 99.5% of all possible measures of market relationships at capturing the spatial dependence among our selected markets. In addition, the estimated ρ_2s for all factors, except FDI, are below the 95% interval, implying that non-neighbor countries according to these factors have small degrees of spatial dependence compared with other possible definitions of neighborhood.

[Insert Figure 3]

We now compare our selected factors regarding the estimated spatial correlation. According to the results in Table 4, the most important factors are bilateral trade and exchange rate volatility, which have similar values for the spatial autocorrelation coefficients. We find bilateral FDI to be the worst factor at capturing spatial correlation. This may mainly be because of the low quality of the data on FDI. In addition, because of missing observations, several markets have fewer than 20 neighbors. This, as shown in section IV, tends to result in a smaller estimated spatial correlation coefficient among neighbors.

The failure of bilateral FDI at capturing stock market co-movements can also be observed from the part of the R-square values that is related to spatial relationships with neighbor countries (see the third row from the bottom in Table 4).

In order to compare the bilateral factors more rigorously with one another and rank them in terms of their importance to spatial dependence, we modify the econometric model by defining $\boldsymbol{W}_2$ in a different way. We use the spatial weights matrix of one factor as $\boldsymbol{W}_1$ and the spatial weights matrix of another factor as $\boldsymbol{W}_2$, i.e. both matrices contain relative weights. This enables us to perform a pair-wise comparison of the factors.

Table 5 shows the results of this comparison. For ease of exposition, we only show the sign of the difference between the estimated coefficients. A positive sign shows that the factor in that column has a larger value of ρ compared with the factor in the respective row. The differences in the estimated parameters for geographical distance, bilateral trade, and exchange rate volatility are not significant. This finding is consistent with the well-established empirical result that cross-country trade is strongly related to geographical distance and exchange rate volatility (see for example Chowdhury 1993, Glick and Rose 2002). In addition, inflation and FDI are significantly outperformed by other factors.

[Insert Table 5]

We also report the coefficients of the control variables in Table 4. Most coefficients are highly significant, except the coefficient on GDP growth. For default rate, the estimated coefficient is positive. Since default rates vary more between countries than they do over time, this finding implies a higher risk premium for high-risk countries. The sign of the coefficients for exchange rate is negative, which is consistent with the expectations discussed in section III-B. The estimated coefficient for the variable unexpected inflation is positive. This is in accordance with our expectation, although it conflicts with some previous findings (see for example Fama and Schwert 1977). The final row of Table 4 contains the coefficient on lagged return. This coefficient is extremely small in all cases and significant only in one case.

C. Robustness analysis

This section contains a robustness analysis evaluating the effects of sample selection and the treatment of (temporal) autocorrelation in sample returns.

First, we examine whether our results are robust to the choice of the sample period. We divide the sample into two chronological subgroups where the first period covers January 1995 to November 2002 and the second period starts in December 2002 and ends in October 2010. Table 6 shows that the ranking of the factors is almost unchanged during the sub-periods compared with the entire period. However, we find that the spatial dependence among neighbors tends to be higher during the first half of the sample period (until November 2002) than it is during the second half. The estimated ρ_1 for exchange rate volatility and geographical distance are similar in the second subperiod, which may be because of the introduction of the Euro.

[Insert Table 6]

It should be noted that the values of ρ_2 remain almost unchanged over the two sub-periods, except for exchange rate volatility, for which the value almost doubles in the second period (the results of ρ_2 are not reported but are available upon request).

Second, we examine the sensitivity of our results to the assumption of equal autocorrelation for all markets, by using returns adjusted for autocorrelation. We consider the returns as AR(1) processes and estimate their partial autocorrelation coefficients. The autocorrelation-adjusted returns are calculated by subtracting the product of the estimated partial autocorrelation coefficients and the first-order lagged returns from the original returns. Table 6 shows that the estimation using autocorrelation-adjusted returns yields similar results to the original estimation.

In addition, removing the lagged returns renders the original results almost unchanged. This is consistent with the results in Table 4, which indicate that lagged returns have very small and insignificant effects in almost all cases. This suggests that autocorrelation (or at least first-order autocorrelation) in returns has little impact on the estimation results.

D. Spatial transmission and feedback effects

This section presents the global spatial effects stemming from return movements in one particular country. Unlike the gravity approach, the spatial econometrics approach allows us to investigate how a change in the fundamentals or a shock affecting the stock market returns in one country transmits throughout the spatial system. The spatial approach is dynamic in nature, and return movements in one market affect the returns in all neighboring markets. The resulting movements in those markets will, in turn, affect their neighboring markets, and so forth. These transmissions of return movements take place within any given month, i.e. our sampling frequency, and continue until a new equilibrium is reached. A noteworthy property of the spatial econometrics model applied here is that any country is likely to be a second-order neighbor to itself, i.e. any country is likely to be a neighbor to some of its neighbors. This implies that return movements in one country will trigger return movements in neighboring countries, which in turn will feed back to the country itself, thereby increasing the effect of shocks (or changes in the fundamentals) beyond the effect that would have emerged in the absence of spatial correlation.

In order to illustrate the effects of this transmission and feedback mechanism, we consider the following two measures. First, to examine to what extent feedback effects amplify the impact of a shock in a particular country on its own market returns, we calculate the average own effect (including feedback) resulting from a unit shock. Second, to investigate how much shocks in one country affect other countries, we compute the average effect of a unit shock in one country on all other countries. To see how these effects are calculated, recall that, for any given month *t*, the SAR(2) model in equation (4) can be expressed as

$$\boldsymbol{y}_t = \sum_{k=1}^{K} \boldsymbol{V}_t \, \boldsymbol{x}_{kt} \beta_k + \boldsymbol{V}_t \boldsymbol{\varepsilon}_t, \tag{12}$$

where

$$\boldsymbol{V}_t = \left(\boldsymbol{I}_n - \rho_1 \boldsymbol{W}_1(t) - \rho_2 \boldsymbol{W}_2(t)\right)^{-1}.$$

The average own effect with feedback is then calculated as

$$\bar{V}_{own} = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{j=i}^{N} V_{ij,t}}{N}, \tag{13}$$

and the average effect on all other countries is calculated as

$$\bar{V}_{other} = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{i=1}^{N} \sum_{j \neq i}^{N} V_{ij,t}}{N(N-1)}. \tag{14}$$

Table 7 presents these two measures for three different neighborhood structures. As our previous results have shown that exchange rate volatility, bilateral trade, and geographical distance are not significantly outperformed by any factor (see Table 5), we focus on these three factors.

[Insert Table 7]

As Table 7 shows, the average own effect with feedback is markedly larger than one for all three neighborhood structures. The instant effect of one is amplified by more than 20 percent via the channel of exchange rate or trade, resulting in an average own effect of 1.21 and 1.25, respectively. The average feedback effect is less pronounced via the channel of geographical neighborhood, and amounts to only nine percent of the initial unit shock. The average effect of a unit shock in one country on all other countries is similar in magnitude to the average own effect and amounts to 0.22 and 0.28 for exchange rate volatility and trade, respectively, and to a somewhat lower 0.12 for geographical distance. These figures show that return movements in one market substantially affect other markets via the investigated spatial linkages. Moreover, the spatial interrelation among markets also amplifies the initial effect of a shock in one country on its own market returns to a substantial extent.

In what follows, we investigate the transmission and feedback effects among markets in more detail by analyzing how shocks in specific countries affect other countries. For that purpose, we calculate the effect of a unit shock in country j on all other countries as

$$V_j = \frac{1}{T}\sum_{t=1}^{T} \frac{\sum_{i \neq j}^{N} v_{ij,t}}{N-1}. \tag{15}$$

The countries we consider are the US, the UK, and Japan, since these countries play dominating roles in their respective geographical regions America, Europe, and Asia. To make the comparison between these countries more meaningful, we modify equation (4) in order to allow for separate spatial correlation coefficients for each of these countries. Figure 4 shows the results of this analysis. The effect of a unit shock in the US market through the trade channel is particularly striking and increases market returns in average by almost 1.4. This is because the US is a neighbor to all other countries with respect to trade, and it is also the most important trading partner for as many as six other countries (see Table 2). The effect of a unit shock in the US market through the exchange rate channel is also very pronounced. Here, the US is an important neighbor to most countries, in particular those with currencies pegged to the US dollar. The effect of a unit shock in the US market through the geographical channel is very small, as the US is a geographical neighbor to only six other countries. For the UK, the geographical channel appears to be the most important one, as the location in Europe makes the UK an important geographical neighbor to many other countries. The exchange rate channel, however, seems to be unimportant, and the effect of a shock is virtually zero. For Japan, the trade channel seems to be the most important one. This is not surprising, as Japan is an important trading partner for many of the World's economies.

[Insert Figure 4]

To complete this section, we take a closer look at how the effect of a unit shock to the US market is distributed among the various countries. Figure 5 plots the elements V_{ij}, for all $i \neq j$, where j stands for the US market. We report average values over all the periods. The figure shows that, via the trade channel, the US affects most countries to a roughly equal extent. However, Canada and Mexico are affected more heavily than the remaining countries. The effects of a US shock via the exchange rate channel are also similar in size for all countries, but slightly larger for countries with currencies pegged to the US dollar. Lastly, the effects of a US shock via the geographical channel differ more heavily. This is not surprising, since, as opposed to the trade and the exchange rate channel, the US is not a geographical neighbor to (almost) all other countries. Consequently, the few countries that the US is a neighbor to are affected much more by return movements in the US market than the remaining countries.

Finally, as pointed out earlier, an important merit of our approach is its ability to model asymmetric relationships between countries. As an example, consider the following case. A unit shock in the US affects the stock markets of Japan and the UK by, respectively, 1.52 and 1.36 units through the trade channel. By contrast, a unit shock in Japan (the UK) affects the US market only by 0.58 (0.22) units through the same channel.[8] This asymmetry is partly due to the differences in the countries' relative importance to each other as trade partners, and partly because the countries are not equally important globally. The former aspect is captured by allowing for asymmetries in the contiguity matrices, and the latter by allowing the spatial correlation parameters to vary between countries.

[Insert Figure 5]

VI. Summary and Conclusions

In this study, we apply spatial panel econometrics techniques to investigate to what extent different linkages among countries affect the dependence among their stock markets. Specifically, we use data on monthly returns for 41 markets between January 1995 and October 2010. We employ five linkages among countries in order to define their closeness in a hypothetical space: geographical distance, the volume of countries'

[8] To conserve space, we only report the spatial effect of the US to other countries. The results for the UK and Japan are available on request.

bilateral trades, bilateral FDI, convergence in expected inflation, and the stability of the bilateral exchange rate. Due to the long time period and the large number of countries that we study, an analysis of various other potential linkages, such as the number of cross-listed stocks, was prevented by a lack of complete data. In practice, shocks or changes in macroeconomic conditions in one country affect other countries' stock market returns through different linkages simultaneously. The purpose of our study is not to measure the total dependence among markets, but to investigate to what extent different linkages affect the degree of dependence among markets.

We propose an SAR(2) model which enables us to mitigate the problem of common trends in return data. We use a number of goodness of fit measures and find that the spatial correlation among neighbors contributes substantially to the return variations. The importance of the neighborhood factors is primarily assessed using the estimated spatial correlation parameters. The significance of these parameters is investigated by using their empirical distribution obtained from 200 randomly generated contiguity matrices. We find that the most important factors are bilateral trade and exchange rate volatility. We perform a number of robustness analyses and show that our findings are robust with regard to the choice of the sample period and the way we treat autocorrelation in returns. Moreover, an analysis of the average spatial effect of all countries shows that a country-specific shock can be amplified by more than 20 percent through the exchange rate and trade channels. However, the average feedback effect via the geographical channel is only around 10 percent.

We also estimate a model with different spatial correlation parameters for three regionally dominant countries, namely the US, the UK, and Japan, in order to investigate how a unit shock in these countries transmits to other countries. The results indicate, among other things, that bilateral trade is the most important channel for the transmission of shocks from the US and Japan to other markets, while the UK affects mostly its geographical neighbors.

To our knowledge, this is the first analysis of the (economic) linkages underlying global stock market co-movements that employs spatial econometrics methods. Our approach has two distinct advantages as compared to previously used methods, such as the panel gravity model. First, the approach allows us to model asymmetric relationships between countries. This asymmetry stems partly from the differences in countries' relative importance in their bilateral relationships. We capture this by allowing for asymmetries in the contiguity (neighborhood) matrices. In addition, different countries are not equally important globally. This source of asymmetry can be captured by allowing the spatial correlation parameters to vary between countries. Second, the approach allows us to study the dynamics of return transmissions. In particular, we are able to show how shocks or changes in macroeconomic conditions in one country transmit throughout the spatial system. Therefore, our proposed approach is not only important for analyzing stock market integration, it also provides a suitable framework to analyze the broad subject of contagion and systemic crises including systemic banking distress and sovereign credit risk spillover.

References

Anselin, L., 2006. *Spatial econometrics*, in: T.C. Mills and K. Patterson (Eds.), Palgrave Handbook of Econometrics: Volume 1, Econometric Theory. Basingstoke, Palgrave Macmillan, 901–969.

Anselin, L. and Le Gallo J., 2006. Interpolation of air quality measures in hedonic house price models: Spatial aspects. *Spatial Economic Analysis* 1, 31–52.

Anselin, L., Le Gallo, J., and Jayet, H., 2008. Spatial panel econometrics, in: L Mátyás and P. Sevestre (Eds.), *The Econometrics of Panel Data*. Berlin, Springer, 625–660.

Arnold, M., Stahlberg, S., and Wied, D., 2011. Modeling different kinds of spatial dependence in stock returns, *Empirical Economics*, online first.

Asgharian, H., and Bengtsson, C., 2006. Jump spillover in international equity markets. *Journal of Financial Econometrics* 4, 167–203.

Asgharian, H., and Nossman, M., 2011. Risk contagion among international stock markets. *Journal of International Money and Finance* 28, 22–38.

Beine, M., and Candelon, B., 2010. Liberalisation and stock market co-movement between emerging economies. *Quantitative Finance* 11, 299–312.

Beine, M., Cosma, A., and Vermeulen, R., 2010. The dark side of global integration: Increasing tail dependence. *Journal of Banking and Finance* 34, 184–192.

Bekaert, G., and Harvey, C.R., 1995. Time-varying world market integration. *Journal of Finance* 50, 403–444.

Bodart, V., and Reding, P., 1999. Exchange rate regime, volatility and international correlations of bond and stock markets. *Journal of International Money and Finance* 18, 133–151.

Brooks, R., Faff, R.W., Hiller, D., and Hiller, J., 2004. The national market impact of sovereign rating changes. *Journal of Banking and Finance* 28, 233–250.

Case, A.C., 1991. Spatial patterns in household demand. *Econometrica* 59, 953–965.

Case, A.C., 1992. Neighborhood influence and technological change. *Regional Science and Urban Economics* 22, 491–508.

Case, A.C., Rosen, H.S., and Hines, J.R., 1993. Budget spillovers and fiscal policy interdependence: Evidence from the States. *Journal of Public Economics* 52, 285–307.

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

Chowdhury, A.R., 1993. Does exchange rate volatility depress trade flows? Evidence from error correction models. *Review of Economics and Statistics* 75, 700–706.

Fama, E.F., and Schwert, G.W., 1977. Asset returns and inflation. *Journal of Financial Economics* 5, 115–146.

Fernandez, V., 2011. Spatial linkages in international financial markets, *Quantitative Finance* 11, 237-245.

Fifield, S.G.M., Power, D.M., and Sinclair, C.D., 2002, Macroeconomics factors and share returns: An analysis using emerging market data. *International Journal of Finance and Economics* 7, 51–62.

Flavin, T.J., Hurley, M.J., and Rousseau, F., 2002. Explaining stock market correlation: A gravity model approach. *The Manchester School Supplement* 2002, 87–106.

Fratzscher, M., 2002. Financial market integration in Europe: On the effects of EMU on stock markets. *International Journal of Finance and Economics* 7, 163–193.

Friberg, R., and Nydahl, S., 1999. Openness and the exchange rate exposure of national stock markets. *International Journal of Finance and Economics* 4, 55–62.

Glick, R., and Rose, A.K., 2002. Does a currency union affect trade? The time-series evidence. *European Economic Review* 46, 1125-1151.

Goffe, W.L., Ferrier, G.D., and Rogers, J., 1994. Global optimization of statistical functions with simulated annealing. *Journal of Econometrics* 60, 65–99.

Hardouvelis, G.A., Malliaropulos, D., and Priestley, R., 2006. EMU and European stock market integration. *Journal of Business* 79, 365.

Harvey, C.R., 1995. The risk exposure of emerging equity markets. *The World Bank Economic Review* 9, 19–50.

Hondronyiannis, G., Kelejian, H.H., and Tavlas, G.S., 2009. Spatial aspects of contagion among emerging economies. *Spatial Economic Analysis* 4, 191–211.

Hooper, V., Hume, T., and Kim, S.J., 2008. Sovereign rating changes: Do they provide new information for stock markets? *Economic Systems*, 32, 142–166.

Johnson, R., and Soenen, L., 2002. Asian economic integration and stock market comovement. *Journal of Financial Research* 15, 141–157.

Karolyi, G.A., and Stulz, R.M., 1996. Why do markets move together? An investigation of U.S.–Japan stock return comovements. *Journal of Finance* 51, 951–986.

Kelejian, H.H., and Prucha, I.R., 2002. 2SLS and OLS in a spatial autoregressive model with equal spatial weights. *Regional Science and Urban Economics* 32, 691–707.

Kelejian, H.H., Tavlas, G.S., and Hondronyiannis, G., 2006. A spatial modeling approach to contagion among emerging economies. *Open Economies Review* 17, 423–442.

Lee, L.-F., 2002. Consistency and efficiency of least squares estimation for mixed regressive, spatial autoregressive models. *Econometric Theory* 18, 252–277.

Lee, L.-F., and Yu, J., 2010. A spatial dynamic panel data model with both time and individual fixed effects. *Econometric Theory* 26, 564–597.

LeSage, J., and Pace, R.K., 2009, *Introduction to Spatial Econometrics*, Boca Raton: Chapman & Hall/CRC.

Longin, F., Solnik, B., 1995. Is correlation in international equity returns constant: 1960–1990. *Journal of International Money and Finance* 14, 3–26.

Ma, C.K., and Kao, G.W., 1990. On exchange rate changes and stock price reactions. *Journal of Business Finance & Accounting*, 17, 441–449.

OECD, OECD Benchmark Definition of Foreign Direct Investment - 4th Edition, 2008.

Wälti, S., 2010. Stock market synchronization and monetary integration. *Journal of International Money and Finance* 30, 96–110.

Table 1. Neighborhood with the US based on different factors

This table presents which are the neighboring countries of the US according to the values of exchange rate volatility, difference in expected inflation, bilateral trade, bilateral foreign investment, and geographical distance, which are denoted by F_{ij}. For simplicity, we calculate the average of the values, $\bar{F}_{ij}$, over the entire sample period from 1995 to 2010, for each factor. We then construct the contiguity matrix $\boldsymbol{C}$ with elements $C_{ij} = 1 - (\bar{F}_{ij} - \min_j \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures closeness between countries, and with $C_{ij} = 1 - (\max_j \bar{F}_{ij} - \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures distance between countries. Lastly, we construct the neighborhood matrix $\boldsymbol{W}_1$ with elements $\boldsymbol{W}_{1,ij}= \boldsymbol{C}_{ij}$ if $\boldsymbol{C}_{ij} \geqslant$ median $\boldsymbol{C}_{ij}$ over j, and zero otherwise. Each column of the table comprises the values in the row associated with the US in the respective neighborhood matrix $\boldsymbol{W}_1$ (zeros are not shown). The values describe the relative closeness of neighbor markets to the US.

	Exch. rate vol.	*Inflation*	*Trade*	*Foreign invest.*	*Geographical*
Argentina	0.78			0.47	
Australia		0.96		0.57	
Austria		0.95			0.67
Belgium		0.96	0.07		0.72
Brazil			0.08	0.48	
Canada	0.65	0.96	1.00	0.92	1.00
Chile	0.64			0.66	
China	0.95		0.47		
Czech		0.93			0.68
Denmark		0.94			0.70
Finland		0.93			0.68
France	0.58	0.95	0.12		0.72
Germany		0.94	0.24		0.71
Greece	0.59	0.96			
Hong Kong	1.00		0.06	0.53	
Hungary					0.66
India	0.75			0.46	
Indonesia				0.44	
Ireland	0.59		0.06	0.50	0.76
Israel	0.70		0.05	0.94	
Italy	0.59	0.96	0.09		0.67
Japan			0.47	0.75	
Korea		0.94	0.15	0.41	
Malaysia	0.84	0.96	0.09	0.46	
Mexico			0.57	0.97	0.85
Netherlands			0.09		0.72
New Zealand		0.97			
Norway					0.72
Philippines	0.70			0.56	
Poland					0.67
Portugal	0.58	0.97			0.74
Russia	0.72				
Singapore	0.80		0.09	0.61	
Spain	0.59	0.99			0.73
Sweden		0.93			0.70
Switzerland			0.05	0.46	0.70
Taiwan	0.81	0.93	0.14	0.72	
Thailand	0.70	0.94	0.06	0.45	
Turkey					
UK	0.61	0.94	0.20	0.57	0.74

Table 2. Relative importance of the US for other countries based on different factors

This table presents which countries the US is a neighbor to according to the values of exchange rate volatility, difference in expected inflation, bilateral trade, bilateral foreign investment, and geographical distance, which are denoted by F_{ij}. For simplicity, we calculate the average of the values, $\bar{F}_{ij}$, over the entire sample period from 1995 to 2010, for each factor. We then construct the contiguity matrix $\boldsymbol{C}$ with elements $C_{ij} = 1 - (\bar{F}_{ij} - \min_j \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures closeness between countries, and with $C_{ij} = 1 - (\max_j \bar{F}_{ij} - \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures distance between countries. Lastly, we construct the neighborhood matrix $\boldsymbol{W}_1$ with elements $\boldsymbol{W}_{1,ij} = \boldsymbol{C}_{ij}$ if $\boldsymbol{C}_{ij} \geqslant$ median $\boldsymbol{C}_{ij}$ over j, and zero otherwise. Each column of the table comprises the values in the column associated with the US in the respective neighborhood matrix $\boldsymbol{W}_1$ (zeros are not shown). The values indicate the relative importance of the US as compared to other neighbor countries.

	Exch. rate vol.	*Inflation*	*Trade*	*Foreign invest.*	*Geographical*
Argentina	1.00	0.66	0.53	0.24	0.60
Australia	0.73	0.96	0.78	0.09	
Austria	0.58	0.95	0.12		
Belgium	0.58	0.97	0.32	0.12	
Brazil	0.82	0.74	1.00	0.25	0.66
Canada	0.92	0.96	1.00	0.78	1.00
Chile	0.95	0.90	1.00	0.37	0.61
China	1.00	0.91	0.93	0.06	
Czech		0.93	0.08	0.04	
Denmark	0.68	0.95	0.23	0.08	
Finland	0.61	0.94	0.48	0.03	
France	0.59	0.95	0.44	0.19	
Germany	0.58	0.95	0.79	0.28	
Greece	0.61	0.95	0.29	0.14	
Hong Kong	1.00	0.92	0.30	0.42	
Hungary		0.77	0.11	0.14	
India	0.98	0.79	1.00	0.30	
Indonesia	0.93	0.66	0.58	0.18	
Ireland	0.63	0.94	0.61	0.46	
Israel	0.98		1.00	0.91	
Italy	0.63	0.96	0.37	0.18	
Japan	0.91	0.90	0.96	0.21	
Korea	0.92	0.94	0.84	0.06	
Malaysia	0.97	0.96	0.97	0.08	
Mexico	0.93	0.80	1.00	0.78	0.99
Netherlands	0.58	0.93	0.32	0.31	
New Zealand	0.70	0.96	0.62	0.04	0.29
Norway		0.93	0.40	0.08	
Philippines	0.99	0.82	0.88	0.25	
Poland		0.88	0.10		
Portugal	0.59	0.97	0.14		
Russia	1.00	0.43	0.51	0.06	
Singapore	0.98	0.92	0.89	0.41	
Spain	0.60	0.98	0.26	0.06	
Sweden		0.94	0.49	0.05	
Switzerland	0.70	0.92	0.33	0.32	
Taiwan	0.99	0.94	0.80	0.45	
Thailand	0.97	0.94	0.72	0.18	
Turkey	0.85	0.30	0.47	0.05	
UK	0.86	0.94	0.93	0.65	

Table 3. The relationship between neighborhood variables

This table shows the results of the test that two different concepts of neighborhood are independent. For each factor, we calculate the average of the values, $\bar{F}_{ij}$, over the entire sample period from 1995 to 2010. We then construct the contiguity matrix $\boldsymbol{C}$ with elements $C_{ij} = 1 - (\bar{F}_{ij} - \min_j \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures closeness between countries, and with $C_{ij} = 1 - (\max_j \bar{F}_{ij} - \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$ if F_{ij} measures distance between countries. Lastly, we construct the neighborhood matrix $\boldsymbol{W}_1$ with elements $\boldsymbol{W}_{1,ij} = \boldsymbol{C}_{ij}$ if $\boldsymbol{C}_{ij} \geqslant$ median $\boldsymbol{C}_{ij}$ over j, and zero otherwise. The table reports the proportion of overlapping non-zero elements for each pair of neighborhood matrices. Under the null hypothesis that two neighborhood definitions are independent, the expected proportion is 0.5. The significance test is based on a binomial distribution. The values marked with one asterisk are significant at the 5% level and those with two asterisks are significant at the 1% level.

	Exch. rate vol.	*Inflation*	*Trade*	*Foreign invest.*	*Geographical distance*
Exch. rate vol.	-				
Inflation	0.62**	-			
Trade	0.66**	0.56**	-		
Foreign investment	0.54*	0.55**	0.66**	-	
Geographical distance	0.60**	0.51	0.65**	0.64**	-

Table 4. Estimated parameters over the entire sample period

This table presents the estimated results of the panel data spatial autoregressive with two spatial lags and with country-specific effect (equation 4):

$$\boldsymbol{y} = \rho_1(\boldsymbol{I}_T \otimes \boldsymbol{W}_1(t))\mathbf{y} + \rho_2(\boldsymbol{I}_T \otimes \boldsymbol{W}_2(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}.$$

The estimations are based on monthly stock market returns of 41 countries over the period from January 1995 to December 2010. $\boldsymbol{W}_1$ describes relations between neighboring countries and $\boldsymbol{W}_2$ describes relations between non-neighboring countries, according to various factors: exchange rate volatility, difference in expected inflation, bilateral trade, bilateral foreign investment, and geographical distance. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The control variables $\boldsymbol{X}$ include changes in exchange rate to U.S. dollars, unexpected inflation rate, default rating, GDP growth, and lagged return. Results are also reported for a restricted model with $\rho_1 = \rho_2 = 0$. Additionally, the table reports the total R-square as well as the return variations explained by the spatial relationships between neighbors and non-neighbors, respectively. The final row of the table shows the AIC values. The parameter values marked with one asterisk are significant at the 5% level and those with two asterisks are significant at the 1% level.

	Exch. rate vol.	*Inflation*	*Trade*	*Foreign invest.*	*Geograph.*	*Restricted*
ρ_1	0.729**	0.603**	0.732**	0.336**	0.654**	
ρ_2	0.121**	0.234**	0.150**	0.460**	0.164**	
Exchange rate	-0.318**	-0.325**	-0.317**	-0.335**	-0.315**	-0.524**
Unexp. inf.	0.014**	0.011**	0.015**	0.015**	0.015**	0.019**
Default rating	0.002**	0.002**	0.001**	0.002**	0.002**	0.002**
GDP growth	-0.008	0.047	-0.016	0.114**	-0.040	-0.187**
Lagged return	-0.001	-0.001	0.008**	-0.006	-0.006	0.067**
R-square	0.531	0.524	0.541	0.522	0.533	0.239
Due to neighb.	0.320	0.260	0.310	0.151	0.314	
Due to non-neighb.	0.054	0.107	0.066	0.212	0.067	
AIC	-344	418	-1309	719	-607	34410

Table 5. Comparison of different neighborhood factors

This table presents the results of the comparison between the degrees of spatial dependence implied by various factors. The results are obtained from the panel data spatial autoregressive with two spatial lags and with country-specific effect (equation 4):

$$\boldsymbol{y} = \rho_1(\boldsymbol{I_T} \otimes \boldsymbol{W_1}(t))\mathbf{y} + \rho_2(\boldsymbol{I_T} \otimes \boldsymbol{W_2}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon},$$

with $\boldsymbol{W}_1$ describing relations between neighboring countries according to one factor and $\boldsymbol{W}_2$ describing relations between neighboring countries according to an alternative factor. ρ_1 and ρ_2 are spatial coefficients that capture the degree of spatial dependence within correspondingly defined neighborhood. A positive sign indicates that the factor in that column has a larger spatial coefficient thus implying a higher degree of spatial dependence compared with the factor in the row and vice versa. The estimations are based on monthly stock market returns of 41 countries over the period from January 1995 to December 2010. Significant values are marked with asterisks. An asterisk indicates that the difference between the estimated ρ_1 and ρ_2 is significant at the 5% level.

	Exch. rate vol.	*Inflation*	*Trade*	*Foreign invest.*	*Geographical*
Exch. rate vol.		-*	+	-*	-
Inflation	+*		+*	-*	+*
Trade	-	-*		-*	-
Foreign invest.	+*	+*	+*		+*
Geographical	+	-*	+	-*	

Table 6. Robustness analysis

This table presents the estimated ρ_1 from the robustness analysis of the panel data spatial autoregressive with two spatial lags and with country-specific effect (equation 4):

$$\boldsymbol{y} = \rho_1(\boldsymbol{I}_T \otimes \boldsymbol{W_1}(t))\mathbf{y} + \rho_2(\boldsymbol{I}_T \otimes \boldsymbol{W_2}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}.$$

$\boldsymbol{W}_1$ describes relations between neighboring countries and $\boldsymbol{W}_2$ describes relations between non-neighboring countries, according to various factors: exchange rate volatility, difference in expected inflation, bilateral trade, bilateral foreign investment, and geographical distance. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The full sample consists of stock market returns of 41 countries from January 1995 to December 2010. The first row of the table shows ρ_1 of the main model over the entire sample period, while the second and third rows give the estimated values over two sub-periods, namely January 1995 to November 2002 and December 2002 to October 2010. In the fourth row, we relax the assumption of constant return autocorrelation over all countries by using the autocorrelation-adjusted returns, while the fifth row gives the results obtained after removing the lagged return from the model. The parameter values marked with one asterisk are significant at the 5% level and those with two asterisks are significant at the 1% level.

Model	Sample	*Exchange rate volatility*	*Inflation*	*Bilateral trade*	*Bilateral FDI*	*Geographical distance*
Main model	Entire	0.729**	0.603**	0.732**	0.336**	0.654**
	Period 1	0.800**	0.657**	0.880**	0.355**	0.682**
	Period 2	0.604**	0.545**	0.675**	0.295**	0.616**
AR_1 adj. Y_t	Entire	0.732**	0.599**	0.733**	0.317**	0.651**
Without Y_{t-1}		0.730**	0.602**	0.732**	0.336**	0.654**

Table 7. Average spatial feedback effect

The table shows the average effect of a unit shock in a particular country on its own stock market returns and on other markets' returns. The own effect is calculated using equation (13):

$$\bar{V}_{own} = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{j=i}^{N} V_{ij,t}}{N},$$

and the average effect to other countries is based on equation (14):

$$\bar{V}_{other} = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{i=1}^{N}\sum_{j\neq i}^{N} V_{ij,t}}{N(N-1)},$$

based on the reduced form of spatial autoregressive with lags

$$\boldsymbol{y}_t = \sum_{k=1}^{K} \boldsymbol{V}_t\, \boldsymbol{x}_{kt}\beta_k + \boldsymbol{V}_t\boldsymbol{\varepsilon}_t.$$

where $V_{ij,t}$ is the element of $\boldsymbol{V}_t = \left(\boldsymbol{I}_n - \rho_1\boldsymbol{W}_1(t) - \rho_2\boldsymbol{W}_{\boldsymbol{2}}(t)\right)^{-1}$ with $\boldsymbol{W}_1$ describing relations between neighboring countries and $\boldsymbol{W}_2$ describing relations between non-neighboring countries, according to various factors. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The instant effect of a unique shock is also presented for the sake of comparison. The results are reported for the three neighborhood factors, which, according to Table 5, are not significantly outperformed by any other factor.

	Exch. rate vol.	*Trade*	*Geographical distance*
Instant effect	1.00	1.00	1.00
Own effect with feedback	1.21	1.25	1.09
Mean effect to all other countries	0.22	0.28	0.12

Figure 1. Estimated spatial autocorrelation coefficients for returns with randomly generated neighborhood matrices

This figure shows the estimated values of ρ obtained from the panel data spatial autoregressive with one spatial lag and with country-specific effect (equation 11)

$$\boldsymbol{y} = \rho(\mathbf{I}_T \otimes \boldsymbol{W}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon},$$

with varying numbers of neighboring countries for each market. For various numbers of neighbors (between 1 and 40), we use 50 randomly generated neighborhood matrices, $\boldsymbol{W}$. The figure also shows the range between the minimum and the maximum estimates for each case. The data cover 41 equity markets over the period from January 1995 to December 2010.

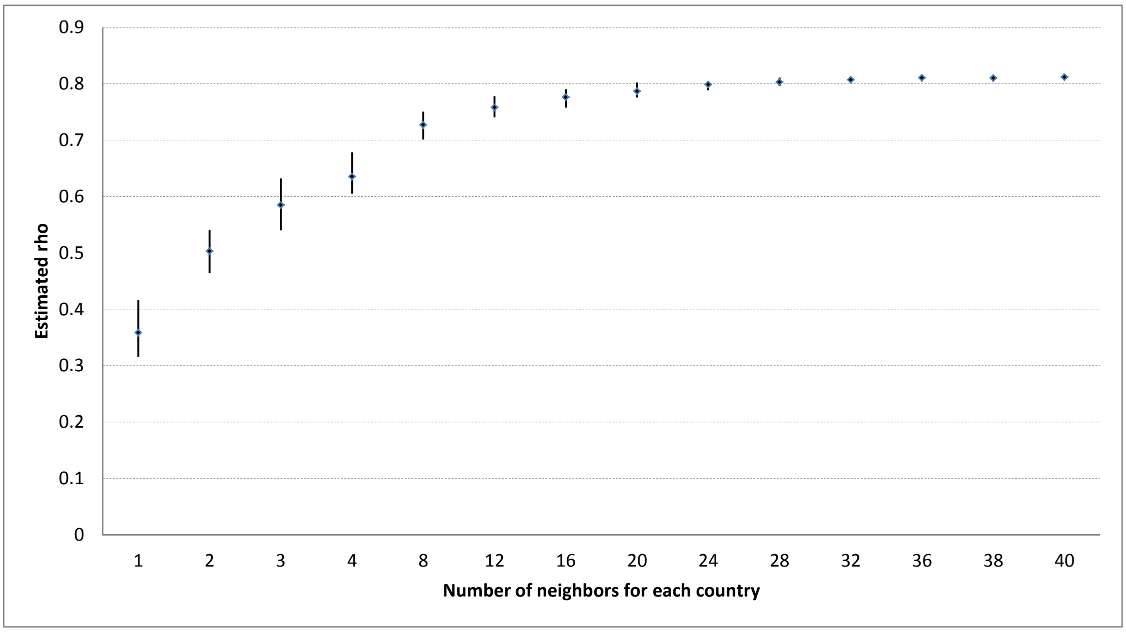


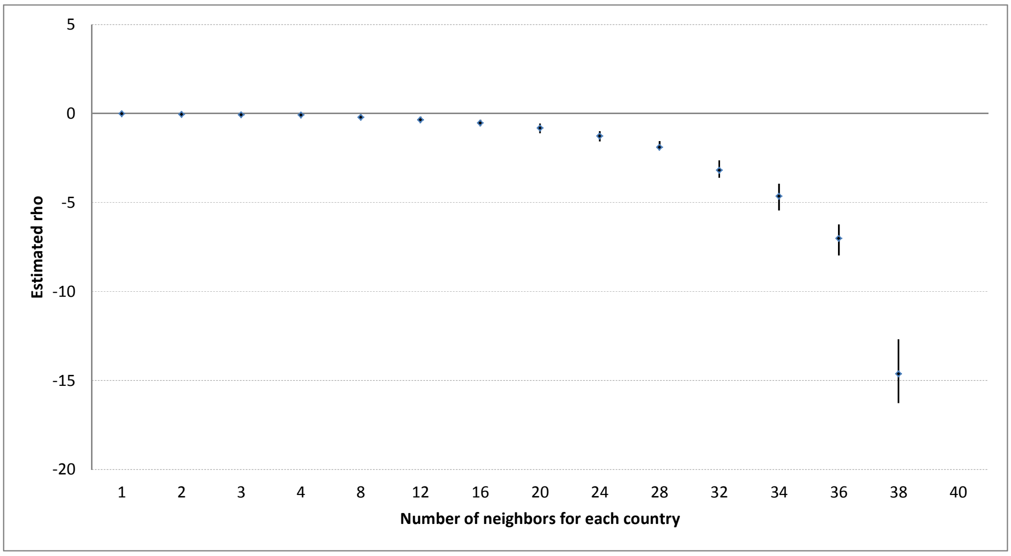
Figure 2. Estimated spatial autocorrelation coefficients for demeaned returns with randomly generated neighborhood matrices

The first graph of this figure shows the average estimated values of ρ obtained the panel data spatial autoregressive with one spatial lag and with country-specific effect (equation 11)

$$\boldsymbol{y} = \rho(\mathbf{I}_T \otimes \boldsymbol{W}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon},$$

on demeaned returns, with varying numbers of neighbors for each market. For various numbers of neighbors (between 1 and 40), we use 50 randomly generated neighborhood matrices, $\boldsymbol{W}$. The figure also shows the range between the minimum and the maximum estimates for each case. The data cover 41 equity markets over the period from January 1995 to December 2010.

The second graph plots the correlation between each country's demeaned return and the average of all neighbor countries' demeaned returns. The plotted values are the average correlations over 50 randomly generated neighborhood matrices for any given number of neighbors for each market.



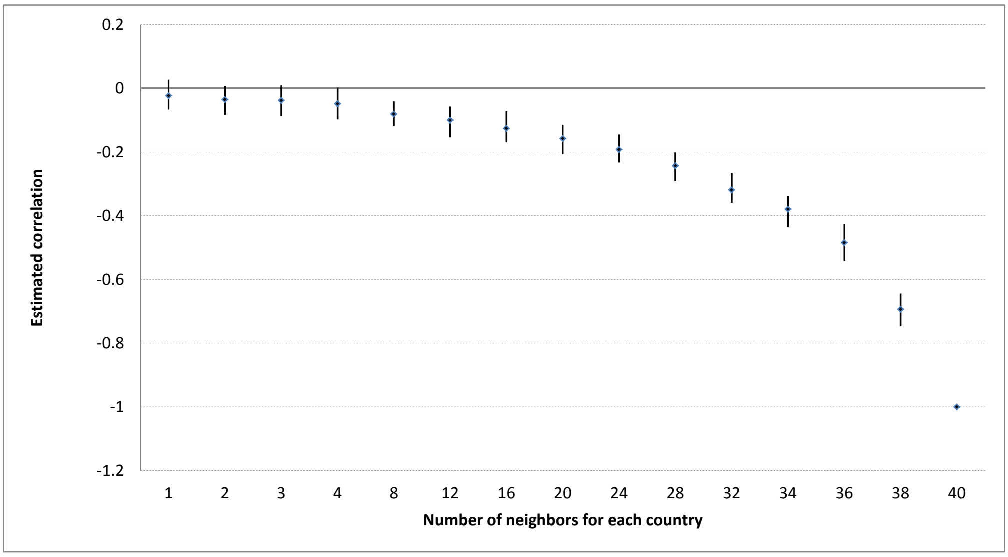
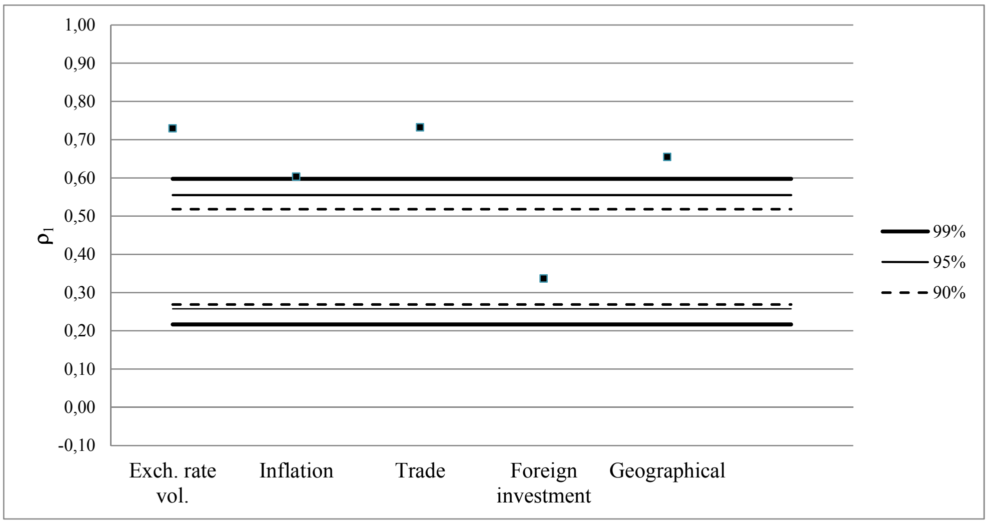


Figure 3. The estimated ρ_1 and ρ_2 for returns compared with the lower and upper quantiles of the empirical distribution of the estimated ρs

This figure compares the estimated values of spatial coefficients ρ_1 and ρ_2 from five selected neighborhood factors (the dots) with those from randomly generated neighborhood matrices. The estimated spatial coefficients ρ_1 and ρ_2 are obtained from the panel data spatial autoregressive with two spatial lags and with country-specific effect (equation 4):

$$\boldsymbol{y} = \rho_1(\boldsymbol{I_T} \otimes \boldsymbol{W_1}(t))\mathbf{y} + \rho_2(\boldsymbol{I_T} \otimes \boldsymbol{W_2}(t))\mathbf{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon},$$

with $\boldsymbol{W}_1$ describing relations between neighboring countries according to one factor and $\boldsymbol{W}_2$ describing relations between neighboring countries according to an alternative factor. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The lines show the 99%, 95%, and 90% intervals for the empirical distributions of the estimated ρ s from 200 randomly generated contiguity matrices. The data cover 41 equity markets over the period from January 1995 to December 2010.



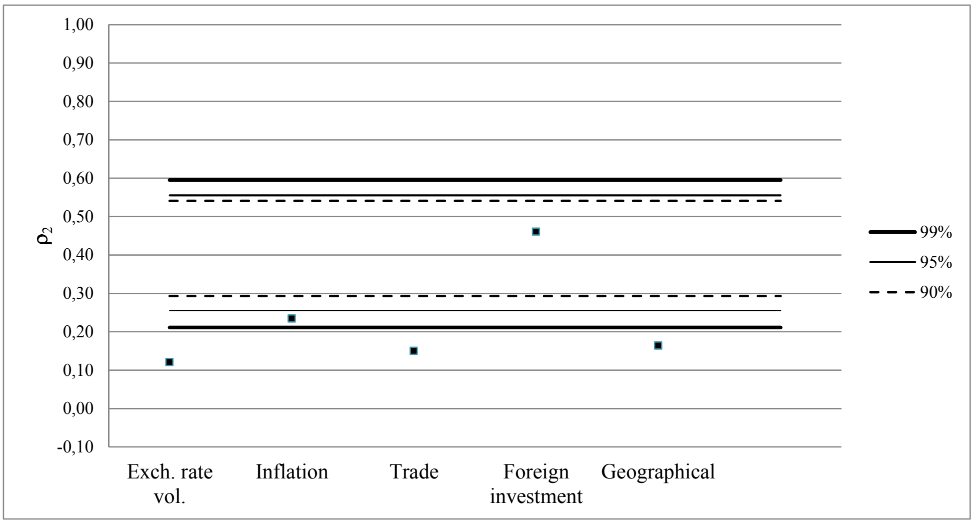


Figure 4. Mean spatial effect of regionally dominant countries

The figure shows the average effect of a unit shock in three regionally dominant countries on other countries. The effect is calculated using equation (15):

$$V_j = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{i\neq j}^{N} V_{ij,t}}{N-1},$$

based on the reduced form of spatial autoregressive with lags (equation 12):

$$\boldsymbol{y}_t = \sum_{k=1}^{K} \boldsymbol{V}_t\, \boldsymbol{x}_{kt}\beta_k + \boldsymbol{V}_t\boldsymbol{\varepsilon}_t.$$

$V_{ij,t}$ is the element of $\boldsymbol{V}_t = \left(\boldsymbol{I}_n - \rho_1\boldsymbol{W}_1(t) - \rho_2\boldsymbol{W}_2(t)\right)^{-1}$ with $\boldsymbol{W}_1$ describing relations between neighboring countries and $\boldsymbol{W}_2$ describing relations between non-neighboring countries, according to various factors. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The sample covers stock markets of 41 countries over the period from January 1995 to December 2010. The dominating countries considered are the US, the UK, and Japan. The spatial effects are reported for the three neighborhood factors, which, according to Table 5, are not significantly outperformed by any other factor.

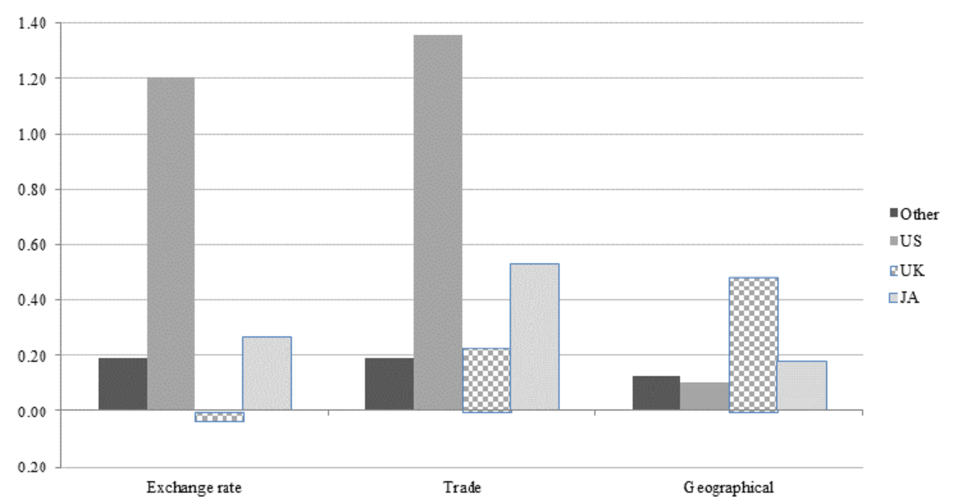


Figure 5. Spatial effect of the US on other countries

The figure shows the effect of a unit shock to the US on the stock market returns of other countries. The values shown are the elements V_{ij} averaged over time for all $i \neq j$, where j denotes the US. V_{ij} is calculated using $\boldsymbol{V}_t = \left(\boldsymbol{I}_n - \rho_1 \boldsymbol{W}_1(t) - \rho_2 \boldsymbol{W}_2(t)\right)^{-1}$ with $\boldsymbol{W}_1$ describing relations between neighboring countries and $\boldsymbol{W}_2$ describing relations between non-neighboring countries, according to various factors. ρ_1 captures the degree of spatial dependence within each defined neighborhood and ρ_2 captures the degree of spatial dependence among non-neighboring markets. The data cover 41 equity markets over the period from January 1995 to December 2010. The spatial effects are reported for the three neighborhood factors, which, according to Table 5, are not significantly outperformed by any other factor.