A spatial analysis of international stock market linkages

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Abstract

Using spatial panel econometric techniques, this paper analyzes the impact of various linkages between countries on the interdependence of their stock markets. This is the first in-depth analysis of the underlying economic structures of financial market interactions using spatial econometric techniques. Our empirical results indicate that similarity in industrial structure is the most important linkage. Other important linkages include geographic closeness, bilateral trade, and exchange rate stability. We also show that the identified spatial relationships can be useful in a Bayesian framework in order to obtain a proper prior for the return covariance matrix.

1. Introduction

The severe global economic impacts of the recent financial crises have intensified the need for analyzing linkages between different financial markets. It is important for financial investors to understand how country (market)-specific shocks are transmitted to other countries (markets), because this affects their ability to conduct risk hedging through global diversification.

Interactions among international stock markets have been studied by a number of earlier studies. Some empirical works, e.g. Erb et al. (1994), Longin and Solnik (1995), and Karolyi and Stulz (1996), have focused on correlations between stock market returns, while others, e.g. Bekaert and Harvey (1995, 1997), Bekaert et al. (2005), Asgharian and Bengtsson (2006), and Asgharian and Nossman (2011), have addressed the issue of risk spillover across markets. 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.

Exploring the underlying economic structures that affect the co-movements of financial markets helps us properly assess the sensitivity of the markets to exogenous shocks. Recent developments in spatial econometrics have provided appropriate tools to analyze this subject. 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 will be connected to the relative position of the observations in a hypothetical space, for example the geographical location of a country. Spatial econometrics is primarily used in urban and real estate economics and economic geography. Some recent applications in other areas have included spatial price competition (Pinkse et al. 2002) and R&D spillovers (Lychagin et al. 2010). Noticeable 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 employ spatial econometrics tools to investigate which attributes affect the degree of dependence among different stock markets. Our aim is to identify to what extent different linkages between markets affect the degree of market co-movements. We use different attributes to map the spatial locations (distance/closeness) of financial markets and analyze the degree of spatial dependence among them. The existence of spatial dependence can be motivated by two different concepts, one that relies on omitted explanatory variables and a second that is based on spatial spillovers stemming from contagion effects (see e.g. LeSage and Pace 2009). Our study focuses on the latter concept.

A limited number of previous studies have attempted to explain the impact of various factors on financial market co-movements or correlations. These studies have relied primarily on the estimation of panel gravity models. For example, Flavin et al. (2002), Beine and Candelon (2010), and Wälti (2011) regress the correlation or co-exceedance among national stock markets on economic sizes (GDP or market capitalization) and distances between the markets (measured by cross-country-specific variables). They find that correlations depend on trade linkages, monetary integration, geographical variables, and the industrial compositions of markets. Compared with the gravity model approach, our study is not purely bilateral, i.e. we do not capture the average effect of distances on any purely bilateral correlation but rather the average effect of distances on the correlations between one country and many other countries at once. More importantly, our study allows for feedback effects among related markets.

We analyze a number of different linkages: geographical neighborhood, similarity in industrial structure, the volume of countries' bilateral trades, bilateral foreign direct investment (FDI), convergence in expected inflation, and the stability of the bilateral exchange rate. The analysis is performed on data for 41 national stock market indexes over a period from 1995 to 2010.

Our empirical results indicate that similarity in industrial structure is the most important economic linkage explaining the correlations among international stock markets. Geographic closeness, bilateral trade, and exchange rate volatility contribute to stock market synchronization to a greater extent than does inflation convergence. Countries that have larger volumes of FDI between each other do not show higher interdependence in their stock markets.

Our study provides three important contributions to the literature. First, to our knowledge, this is the first in-depth analysis of the underlying economic structures of financial market interactions using spatial econometrics techniques. Second, we employ several different concepts of neighborhood that have not previously been used in the literature. Third, by identifying several linkages through which stock markets are connected with each other and assessing the relative importance of these linkages, we provide new insights, which can be used by financial investors for risk hedging through global diversification. A critical issue in risk management is to obtain precise estimates of the future co-variances between markets. Such estimates are usually sensitive to the choice of estimation method and the time-series dimension of the data sample. Our results provide additional cross-sectional information that can be used to improve correlation predictions when making investment decisions. We show that the identified spatial relationship can be useful in a Bayesian framework to obtain a proper prior for the return covariance matrix. This prior, namely the spatial covariance matrix, is especially advantageous when the data sample has a small time-series dimension compared with the number of assets.

The remainder of the paper is organized as follows. Section 2 presents the spatial econometrics methods used in this paper. Section 3 presents the data and selected variables. Section 4 contains a simulation analysis of model behavior. Section 5 contains the empirical results, and section 6 concludes.

2. 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.[1] 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).[2] 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).

[1] Other specifications, such as a spatial moving average model or a spatial Durbin model, are also possible (see e.g. Anselin (2003) for an extensive overview of the taxonomy of spatial econometric model specifications).

[2] 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.

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

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

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

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

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.[3] 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:

$$\ln \mathrm{L} = \sum_{t=1}^{T} \ln |\boldsymbol{I}_N - \rho_1 \boldsymbol{W_1}(t) - \rho_2 \boldsymbol{W_2}(t)| - \frac{NT}{2} \ln(2\pi\sigma^2) - \frac{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}}{2\sigma^2}, \qquad (6)$$

where

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

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 $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ 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 $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ 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

[3] 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.

among countries.[4] 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:

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

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

[4] The various neighborhood factors are explained in detail in Section 3.

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. Lee and Yu (2010) propose an estimation procedure for a linear panel data model with a spatially lagged dependent variable and unobserved time effects, which can be applied even if T is substantially larger than N. Their method is based on a data transformation, where both sides of the regression equation are pre-multiplied by a projection matrix to eliminate 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). By contrast, 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.

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.

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.

3. 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.

3.1. Potential channels of spatial dependence

To capture the relative distance/closeness of the financial markets to one another, we use six 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 additional factors, we use similarity in industrial structure and geographical distance. The values of all factors except geographical distance vary on a yearly basis.

3.1.1 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.

3.1.2 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, 2003) 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.

3.1.3 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:

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

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.

3.1.4 Bilateral FDI

Another factor that may affect stock market dependence is bilateral FDI[5]. "FDI provides a means for creating direct, stable and long-lasting links between economies" (OECD

[5] 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

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 Forbes (2004) find the impact of bilateral FDI to be insignificant. They argue that this could partially result from the noises in FDI statistics[6].

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.

3.1.5 Similarity of industrial structure

Stock markets with similar industrial structures are exposed to the same types of global industry shocks and are, therefore, more likely to co-move. Roll (1992) argues that industrial composition is a more important explanatory element for stock market co-movement than is geographic closeness. Beine et al. (2010) confirm this finding by demonstrating that industrial similarity increases stock market dependence across all quantiles.

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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.

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

We construct a proxy for industrial dissimilarity in the spirit of Asgharian and Bengtsson (2006). We first calculate the countries' respective exposures (betas) to 10 DataStream world industry indexes.[7] For every pair of countries, we then measure their industrial dissimilarities as the average absolute difference in betas.

3.1.6 Geographic 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.

3.2. 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.

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

[7] We use weekly return data between January 6, 1995 and October 29, 2010. The industries used are oil and gas, basic materials, industrials, consumer goods, health care, consumer services, telecom, utilities, financials, and technology.

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 3.1.

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.

3.3. Dataset

There are 41 equity markets in our spatial analysis (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[8] are taken from national sources on DataStream. Distances between capital cities are taken from

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

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.

4. 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 2).

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 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 ρ−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).[9]

[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

[9] 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.

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.

5. 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 third subsection presents our robustness analysis.

5.1. Exploratory Analysis of the Neighborhood

In order to obtain prior knowledge of the relationships among the selected markets, we present a world map depicting the monthly return correlations of the selected equity markets with the US market (see Figure 3). The map illustrates that the markets of several Western European countries (e.g. France, Germany, and the UK), Canada, and Australia are highly correlated with the US market. The markets least correlated with the US are mostly emerging markets, such as Argentina, China, India, Indonesia, and Russia.

[Insert Figure 3]

To give a simple illustration of the neighborhood structures, we present the relative closeness of the neighborhoods of different markets with the US market according to the different factors over the entire period in Table 1. For each factor, we take the average of the values over time to construct the contiguity matrix $\boldsymbol{C}$ and the associated neighborhood matrix $\boldsymbol{W}_1$.

[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). In terms of industrial structure similarity, Switzerland is the nearest neighbor to the US, while Mexico, Israel, and Canada are the closest neighbors in terms of FDI. 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, 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.

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 2. 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 2 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 2]

5.2. Estimation results of SAR(2)

We present the results for the entire sample in Table 3. The estimated ρ_1s of all the factors are highly significant and positive. All the estimated ρ_2s, except the one for industrial structure, 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. 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.[10] 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 4 depict the estimated values of ρ_1 and ρ_2, respectively, for our six selected neighborhood factors. They also show the 99%, 95%, and 90% intervals for the empirical distribution of the estimated ρs.

[Insert Table 3]

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%

[10] We measure the contribution of each explanatory variable to the total variance of the dependent variable as $r_j = \beta_j \sum_{k=1}^{K} \beta_k \sigma_{jk}$, where σ_{jk} is the covariance between variable j and variable k, where $j = 1, \dots, K$ and $k = 1, \dots, K$.

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 4]

We now compare our selected factors regarding the estimated spatial correlation. The results in Table 3 show that markets with similar industrial structures tend to have the highest degree of spatial dependence in returns (ρ_1 = 0.888). The corresponding value of ρ_2 is not statistically significant, suggesting that there is no spatial dependence among countries that are non-neighbors according to this factor. Further 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 4, tends to result in a smaller estimated spatial correlation coefficient among neighbors.

The ability of similarity in industrial structure and 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 3).

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 W_2 in a different way. We use the spatial weights matrix of one factor as W_1 and the spatial weights matrix of another factor as W_2, i.e. both matrices contain relative weights. This enables us to perform a pair-wise comparison of the factors.

Table 4 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. We find that industrial structure significantly outperforms all other factors at capturing dependence among returns, which confirms that countries with similar industry compositions are sensitive to the same business conditions. 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 4]

We also report the coefficients of the control variables in Table 3. 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 3.2. 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 3 contains the coefficient on lagged return. This coefficient is extremely small in all cases and significant only in one case.

5.3. 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 5 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 5]

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 5 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 3, 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.

Finally, we estimate the model using return volatility (estimated as the standard deviation of daily returns for each month) instead of returns. The last row of Table 5 shows that the ranking of the factors for the spatial relationships of returns is also applicable to the spatial relationship of stock market volatility. Industrial structure is the most important factor, followed by exchange rate volatility, geographical distance, and trade. Inflation and FDI remain the least important factors.

5.4 Spatial covariance matrix

The sample covariance matrix estimated on time-series observations is an unbiased estimate of the return covariance matrix. However, since it has no structure it may be exposed to non-negligible estimation errors, particularly when the number of assets is large. Furthermore, the sample covariance matrix is not invertible when the number of assets is larger than is the number of historical return observations. It should also be noted that prolonging the historical estimation window is not desirable if the covariance structure changes over time. These issues may have important consequences for portfolio selection and risk assessment. Numerous studies (e.g. Daniels and Kass (1999), Yang and Berger (1994), Frost and Savarino (1986), and Ledoit and Wolf (2003)) have attempted to find a solution to this problem using a Bayesian framework. The general idea is to impose a certain prior structure on the covariance matrix in order to decrease its estimation error and to ensure that the estimated matrix is invertible. A drawback of this approach is the possibility of estimation errors because of a wrongly specified prior.

We argue that the spatial relationship between countries can be used to obtain a proper prior structure in such a Bayesian framework. Our starting point is a basic SAR relationship of the form $y = \rho W y + \varepsilon$, where ρ measures the intensity of spatial dependence among countries. We use the contiguity matrix $\boldsymbol{C}$ (described in section 2), defined according to different neighborhood factors, to form a symmetric spatial correlation matrix as:

$$\boldsymbol{corr}_s = \boldsymbol{I} + \rho\left(\frac{1}{2}(\boldsymbol{C} + \boldsymbol{C}')\right) \tag{12}$$

where $\boldsymbol{I}$ is an identity matrix of the same dimension as $\boldsymbol{C}$. The spatial covariance matrix is then defined as:

$$\boldsymbol{cov}_s = \boldsymbol{D}\boldsymbol{corr}_s\boldsymbol{D} \tag{13}$$

where $\boldsymbol{D}$ is the diagonal matrix of the estimated standard deviations of the returns.

We choose the value 0.8 for ρ, since our simulation analysis with an SAR(1) model in section 4 shows that the estimated ρ is roughly equal to 0.8 for all random neighborhood matrices with more than 20 neighbors for each country.

In order to examine the relevance of the spatial relationships to the estimation of the covariance matrix, we employ a simple portfolio analysis. We estimate the out-of-sample standard deviation of the minimum variance portfolio obtained from the spatial covariance matrix and compare it with that of the minimum variance portfolio obtained from sample covariance estimates and with that of an equally weighted portfolio. The sample covariance matrix is estimated using three alternative windows (four, five, and six years, respectively), while the spatial covariance matrices are based on the contiguity matrices and the sample variances from a one-year estimation window. It should be noted that the covariance matrix based on an estimation window of three years or less is not invertible. For each covariance matrix, we calculate the weights of the minimum variance portfolio and the corresponding monthly out-of-sample portfolio returns in the succeeding year. Figure 5 shows the standard deviations of the out-of-sample portfolio returns along with the standard deviation of an equally weighted portfolio.

[Insert Figure 5]

As shown in Figure 5, when we decrease the width of the estimation window, the out-of-sample standard deviation obtained from the sample covariance matrix increases, probably because of an increase in estimation error. In particular, the sample covariance matrix of the four-year window performs only marginally better than does the equally weighted portfolio. We find that most of our spatial covariance matrices (except those defined according to trade and investment) outperform the sample covariance matrix of the four-year estimation window. If we increase the window width to five years, the spatial relationships based on exchange rate volatility and geographical distance are still able to provide a superior structure to the covariance matrix estimation. It is no surprise that the spatial relationship based on investment performs as poorly as does the equally weighted portfolio because investment is found to be an unimportant factor to stock market dependence in section 5.2. Bilateral trade, which is important to stock market dependence, also shows a bad performance. This may be because the great disparities in the factor of bilateral trade (described in section 5.1) result in extreme values of the spatial covariance.[11]

6. Summary and Conclusions

In this study, we apply spatial panel econometric techniques to investigate to what extent different linkages among countries affect the dependence among their stock markets. Specifically, we use monthly data on returns for 41 markets between January 1995 and October 2010. We use six linkages among countries in order to define their closeness (neighborhood) in a hypothetical space: geographical neighborhood, similarity in industrial structure, the volume of countries' bilateral trades, bilateral FDI, convergence in expected inflation, and the stability of the bilateral exchange rate.

Our preliminary simulation analysis shows the limitation of the commonly used SAR(1) model in the presence of a common trend in the data. We therefore employ an SAR model with two spatial lags, which allows us to directly compare the spatial dependencies among neighbors with those among non-neighbors.

The estimated spatial correlation coefficients for all linkages are positive and statistically significant. Furthermore, these coefficients outperform 99.5% of those obtained by using

[11] The portfolio weights are restricted to be no less than –1.

200 randomly generated neighborhood matrices. Our results indicate that similarity in industrial structure significantly outperforms all other factors at capturing dependence among returns. Other important linkages that explain stock market dependence include geographic closeness, bilateral trade, and exchange rate stability. The pair-wise comparison of these factors confirms this result.

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. In addition, we find that the ranking of the neighborhood factors with respect to their capacity to capture market co-movements remains unchanged when we use market volatility instead of returns as the dependent variable.

By identifying the linkages through which stock markets are connected, we provide new insights for estimating future correlations between markets. We conduct a simple portfolio analysis and find that the majority of spatial covariance matrices perform well in terms of the out-of-sample standard deviation of the minimum-variance portfolio. This indicates that the spatial relationship between countries conveys important cross-sectional information, which can be used to obtain a proper prior structure for covariance matrix estimation.

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Table 1. Neighborhood with the US market based on different factors

This table presents the neighborhoods of different markets with the US market according to the different factors. For simplicity, we choose to present the values over the entire sample period from 1995 to 2010. For each factor, we calculate the average of the values over time, $\bar{F}_{ij}$. We then construct the contiguity matrix $\boldsymbol{C}$ with elements $C_{ij} = 1 - (\bar{F}_{ij} - \min_j \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$. Lastly, we construct the neighborhood matrix $\boldsymbol{W}_1$ with elements $\boldsymbol{W}_{1,ij} = \boldsymbol{C}_{ij}$ if $\boldsymbol{C}_{ij} \geq$ median $\boldsymbol{C}_{ij}$ over j, and zero otherwise. The values describe the relative closeness of neighbor markets to the US. For example, the value 1 for Hong Kong according to the factor exchange rate volatility implies that Hong Kong is the closest neighbor to the US in every year from 1995 to 2010 according to this factor.

	Exch. rate vol.	*Ind. structure*	*Inflation*	*Trade*	*Foreign invest.*	*Geographical*
Argentina	0.78				0.47	
Australia		0.72	0.96		0.57	
Austria			0.95			0.67
Belgium		0.82	0.96	0.07		0.72
Brazil				0.08	0.48	
Canada	0.65	0.86	0.96	1.00	0.92	1.00
Chile	0.64	0.75			0.66	
China	0.95			0.47		
Czech			0.93			0.68
Denmark		0.77	0.94			0.70
Finland			0.93			0.68
France	0.58	0.84	0.95	0.12		0.72
Germany		0.73	0.94	0.24		0.71
Greece	0.59		0.96			
Hong Kong	1.00	0.82		0.06	0.53	
Hungary						0.66
India	0.75	0.72			0.46	
Indonesia					0.44	
Ireland	0.59	0.75		0.06	0.50	0.76
Israel	0.70	0.85		0.05	0.94	
Italy	0.59	0.81	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		0.79		0.09		0.72
New Zealand		0.73	0.97			
Norway						0.72
Philippines	0.70				0.56	
Poland						0.67
Portugal	0.58	0.73	0.97			0.74
Russia	0.72					
Singapore	0.80	0.81		0.09	0.61	
Spain	0.59	0.82	0.99			0.73
Sweden		0.72	0.93			0.70
Switzerland		0.87		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	0.86	0.94	0.20	0.57	0.74

Table 2. 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 $C_{ij} = 1 - (\bar{F}_{ij} - \min_j \bar{F}_{ij})/(\max_j \bar{F}_{ij} - \min_j \bar{F}_{ij})$. Lastly, we construct the neighborhood matrix $\boldsymbol{W}_1$ with elements $\boldsymbol{W}_{1,ij} = \boldsymbol{C}_{ij}$ if $\boldsymbol{C}_{ij} \geq$ 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 with two asterisks are significant at the 1% level.

	Exch. rate vol.	*Inflation*	*Ind. structure*	*Trade*	*Foreign invest.*
Inflation	0.62**				
Ind. structure	0.65**	0.62**			
Trade	0.66**	0.56**	0.58**		
Foreign investment	0.54*	0.55**	0.56**	0.66**	
Geographical distance	0.60**	0.51	0.58**	0.65**	0.64**

Table 3. Estimated parameters over the entire sample period

This table presents the estimated results of the panel data SAR(2) model with country-specific effects (see equation (4)) and those of a restricted model with $\rho_1 = \rho_2 = 0$, where ρ_1 is the degree of spatial dependence within each defined neighborhood and ρ_2 implies the degree of spatial dependence among non-neighboring markets. The coefficients of the control variables are also presented. Additionally, the table reports the total *R*-square as well as the return variations explained by the spatial relationship between neighbors and non-neighbors, respectively. The final row of the table shows the AIC values. The estimations are based on monthly data of 41 countries over the period from January 1995 to December 2010. The parameter values marked with one asterisk are significant at the 5% level and with two asterisks are significant at the 1% level.

	Exch. rate vol.	*Ind. struct.*	*Inflation*	*Trade*	*Foreign invest.*	*Geograph.*	*Restricted*
ρ_1	0.729**	0.888**	0.603**	0.732**	0.336**	0.654**	
ρ_2	0.121**	-0.014	0.234**	0.150**	0.460**	0.164**	
Exchange rate	-0.318**	-0.303**	-0.325**	-0.317**	-0.335**	-0.315**	-0.524**
Unexp. inf.	0.014**	0.018**	0.011**	0.015**	0.015**	0.015**	0.019**
Default rating	0.002**	0.002**	0.002**	0.001**	0.002**	0.002**	0.002**
GDP growth	-0.008	-0.014	0.047	-0.016	0.114**	-0.040	-0.187**
Lagged return	-0.001	0.002	-0.001	0.008**	-0.006	-0.006	0.067**
R-square	0.531	0.548	0.524	0.541	0.522	0.533	0.239
Due to neighb.	0.320	0.397	0.260	0.310	0.151	0.314	
Due to non-neighb.	0.054	-0.006	0.107	0.066	0.212	0.067	
AIC	-344	-2271	418	-1309	719	-607	34410

Table 4. Comparison of different neighborhood factors

This table presents the results of the comparison between the estimated ρ_1 and ρ_2 for any pair of alternative neighborhood matrices. The results are obtained from the panel data SAR(2) model with country-specific effects (see equation (4)) but with $\boldsymbol{W}_2$ being a neighborhood matrix defined based on an alternative factor. A positive sign indicates that the factor in that column implies a higher degree of spatial dependence compared with the factor in the row and vice versa. The estimations are based on monthly data of 41 countries over the period from January 1995 to December 2010. Significant values are marked with asterisks.

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

Table 5. Robustness analysis

This table presents the estimated ρ_1 from the robustness analysis of the panel data SAR(2) model (see equation (4)). The first row of the table shows ρ_1 of the main model over the entire sample period of January 1995 to December 2010, 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 SAR(2) model. The final row presents the results of the main model when we replace return-by-return volatility (the standard deviation of daily returns over each month).

Model	Sample	*Exchange rate volatility*	*Industrial structure*	*Inflation*	*Bilateral trade*	*Bilateral FDI*	*Geographical distance*
Main model	Entire	0.729**	0.888**	0.603**	0.732**	0.336**	0.654**
	Period 1	0.800**	1.083**	0.657**	0.880**	0.355**	0.682**
	Period 2	0.604**	0.849**	0.545**	0.675**	0.295**	0.616**
AR_1 adj. Y_t	Entire	0.732**	0.888**	0.599**	0.733**	0.317**	0.651**
Without Y_{t-1}		0.730**	0.888**	0.602**	0.732**	0.336**	0.654**
Volatility	Entire	0.609**	0.709**	0.462**	0.551**	0.289**	0.567**

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

This figure shows the estimated values of ρ obtained from an SAR(1) model (see equation 11) with varying numbers of neighbors for each market. For various numbers of neighbors (between 1 and 40), we use 50 randomly generated neighborhood matrices. 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.

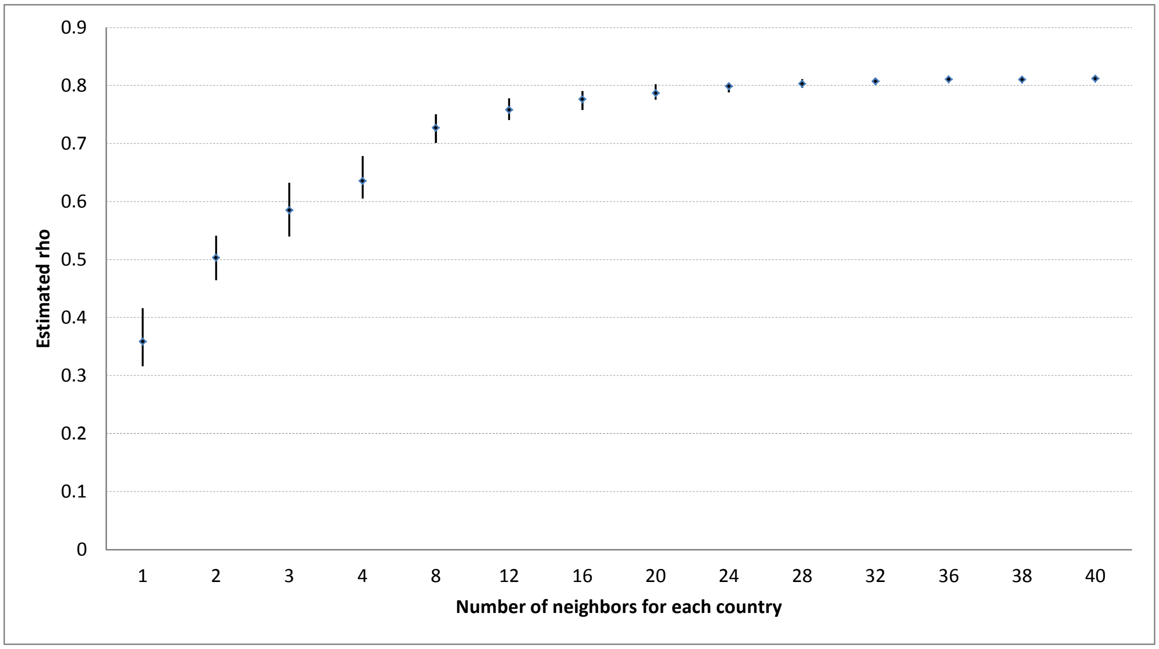
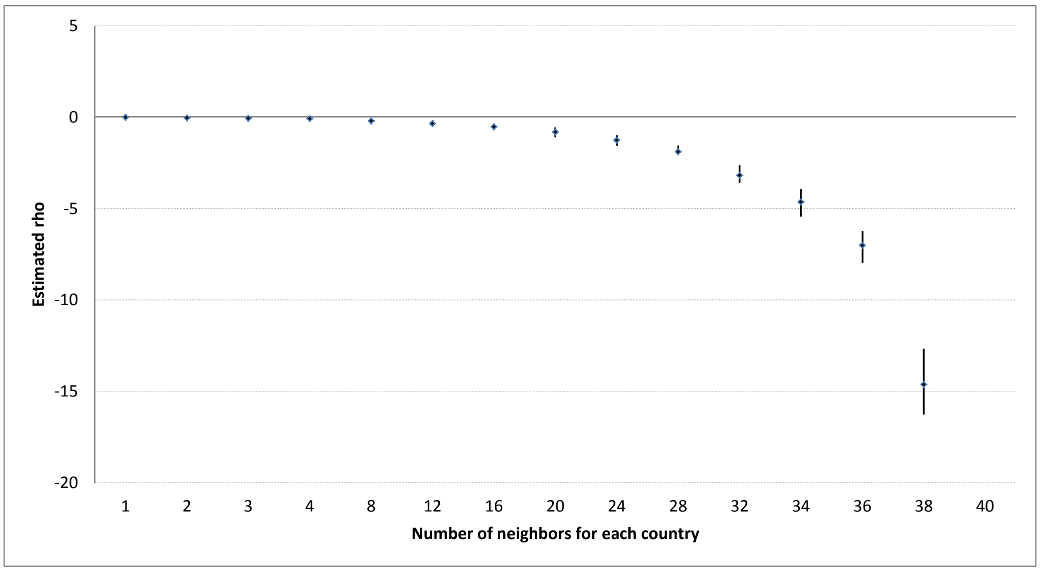


Figure 2. Estimated spatial autocorrelation coefficients for demeaned returns with randomly generated neighborhood matrices

The first graph of this figure shows the average estimated values of ρ obtained from an SAR(1) model (see equation 11) 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. 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.



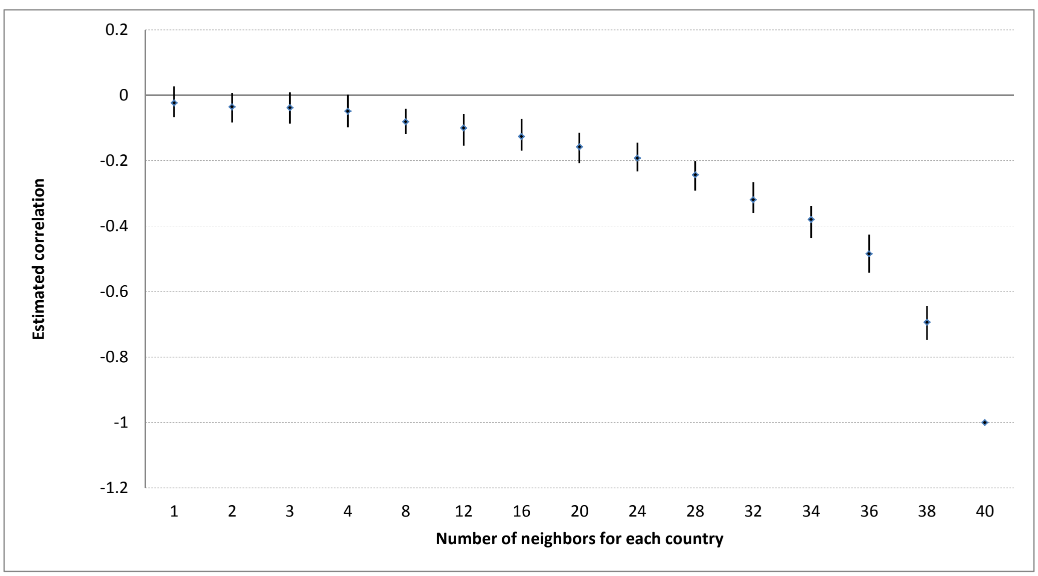


Figure 3. The world map depicting return correlation with the US market

This figure presents a world map depicting the monthly return correlations of the 40 equity markets with the US market over the period from January 1995 to December 2010. We divide the correlations into four intervals: less than 0.5, between 0.5 and 0.6, between 0.6 and 0.7, and between 0.7 and 1. There are approximately 10 countries in each interval.

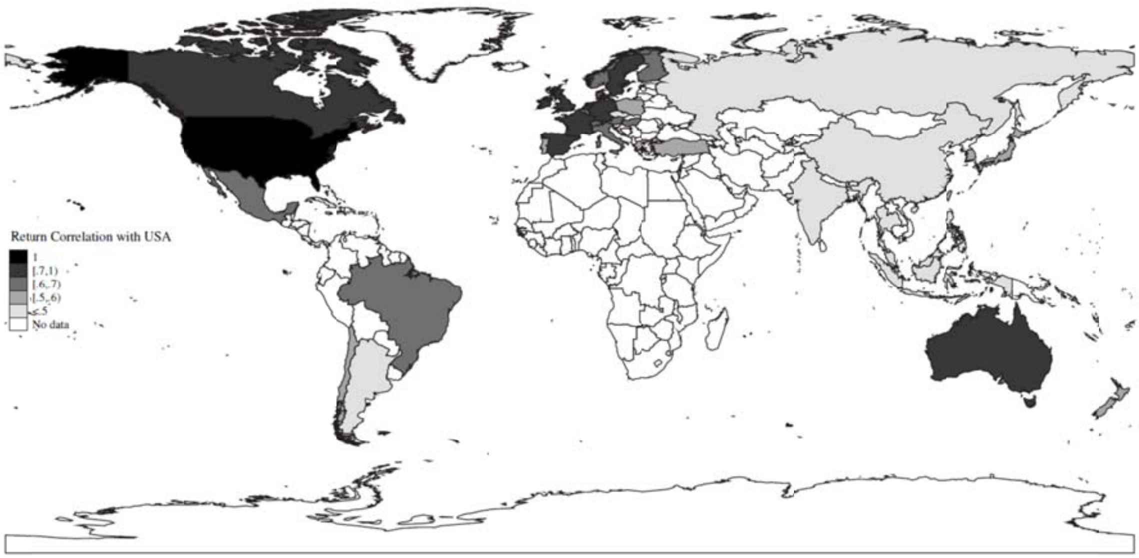
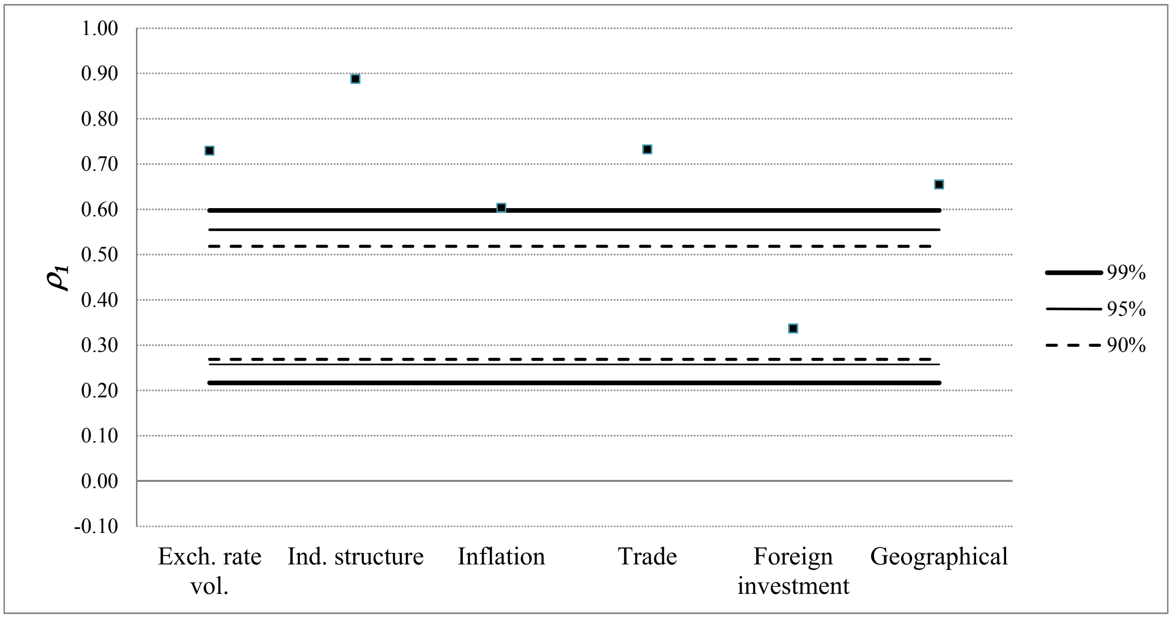


Figure 4. The estimated ρ_1 and ρ_2 for returns compared with the lower and upper quantiles of the empirical distribution of the estimated ρs

This figure compares the estimated values of ρ_1 and ρ_2 from six selected neighborhood factors (the dots) with those from randomly generated neighborhood matrices. The lines show the 99%, 95%, and 90% intervals for the empirical distributions of the estimated ρs from 200 randomly generated contiguity matrices. The data cover 41 equity markets over the period from January 1995 to December 2010.



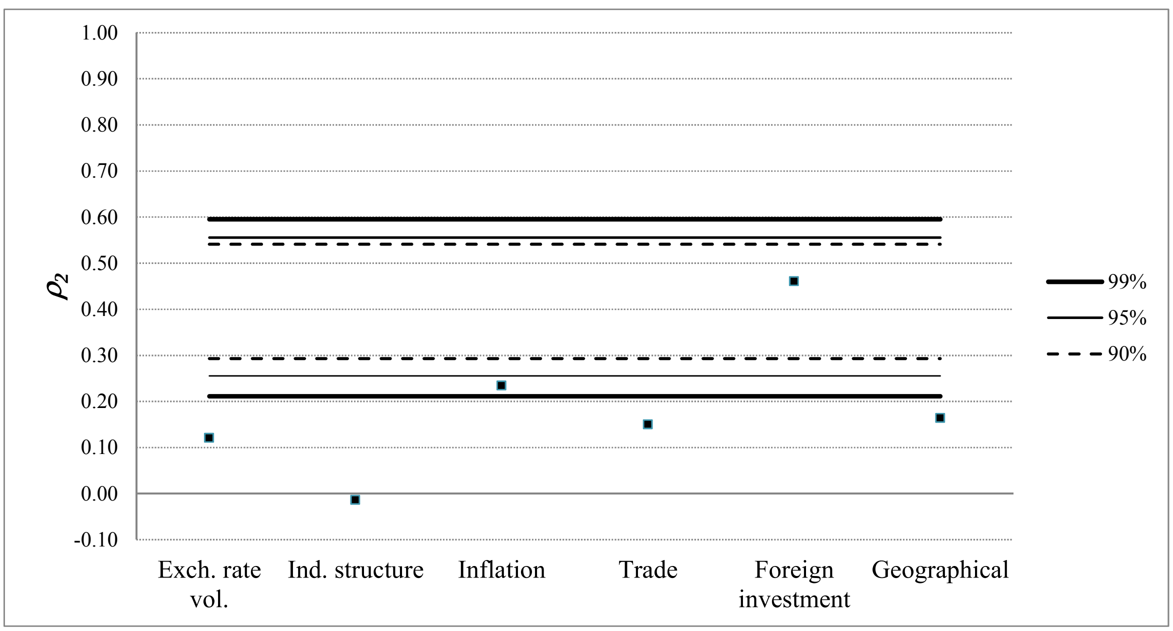


Figure 5. Out-of-sample standard deviations of the minimum variance portfolios

This figure shows the out-of-sample standard deviations of the minimum variance portfolios obtained by using alternative covariance matrices as well as that of an equally weighted portfolio. We use three windows (four, five, and six years, respectively) to estimate the sample covariance matrix. We also construct spatial covariance matrices using our neighborhood matrices and the sample variances from a one-year estimation window. The data cover 41 equity markets over the period from January 1995 to December 2010.