Asset Pricing, Spatial Linkages and Contagion in Real Estate Stocks

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Abstract

Although spatial techniques have been used to capture the spillovers in asset returns across different regions, they have not yet been applied in an asset pricing context. Combining asset pricing models and equilibrium spatial models can be a good way to disentangle spillover effects across assets thereby accounting for systemic risks. We use an innovative approach and estimate a four-factor Spatial Capital Asset Pricing Model (SCAPM) which allows us to account for correlations in the error terms. We can account for direct or indirect spillover effects in the presence of increased spillovers through the idiosyncratic component or of increased spillovers through the market respectively. We find that contagion dramatically increases during the global financial crisis and the spillover effect can explain up to 40% of total asset variation. In the rest of the time, idiosyncratic risks have been the predominant type of risk in real estate stocks. Our results have implications for investors showing that the market can channel asset volatility leading to contagion during crisis periods and therefore residual linkages between country indices need to be accounted for as a means of assessing the diversification benefits of a global portfolio.

Keywords: Spatial CAPM, systemic risk, idiosyncratic risk, contagion, listed property returns.

JEL Classifications: C23, G15, F36, R3

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1 Introduction

In the aftermath of the global financial crisis global investors have been trying to reassess the diversification benefits from investing internationally. Whereas international stock markets have been considered as highly volatile and interconnected, real estate is regarded as a more heterogeneous asset class with high idiosyncratic risk and low market risk exposure. The recent global financial crisis (GFC) has changed this notion. Albeit originating in the US subprime mortgage market, the GFC led to strong spillover effects spreading across developed and emerging countries. The globalisation of the financial markets and the emergence of securitisation have enabled the transmission of shocks on the underlying real estate markets through liquid vehicles, such as mortgage backed securities (MBSs) and stocks of listed real estate companies such as Real Estate Investment Trusts (REITs). The risk stemming from an exposure to the US real estate market was not anymore seen as a stand-alone risk which as the traditional asset pricing theories imply can be diversified away if holding enough assets in the portfolio. It presented a systemic risk affecting asset prices across the world undermining the diversification benefits of a global asset portfolio.

There is a variety of studies which estimate the contagion effects during crises and assess the channels through which contagion has been transmitted (see Kodres and Pritsker (2002), Baele (2005), Bekaert et al. (2014)). Kodres and Pritsker (2002) develop a model of asset prices to explain contagion which is associated with the spillover effects of idiosyncratic shocks. They focus on contagion caused by cross-market rebalancing when investors respond to shocks in one country by adjusting their portfolios in the remaining markets. Acemoglu et al. (2015) model financial contagion as a function of the structure of interbank liabilities. Contagion effects can be associated with runs on collateral and with liquidity spirals when asset prices fall and lead to a decrease in the equity value of financial institutions or volatility increases leading to a rise in the haircuts and a fall in the leverage of financial institutions.[1] Bekaert et al. (2014) assess six different ways how contagion can occur in an asset pricing context identifying channels such as globalisation, information asymmetries, herding, etc. Systemic risks are not only associated with contagion but can also stem from market-wide shocks such as global financial imbalances (see Obstfeld and Rogoff (2009), Reinhart and Rogoff (2009), Borio and Disyatat (2011), Shin (2012)). Although the definition of contagion is arbitrary, the idea is that contagion emerges from changes in a single asset that become widespread in the cross-sectional dimension.[2] Therefore, we refer to contagion as the increased spillover effects through the market and the idiosyncratic component triggered by an asset specific event.

[1] Such effects have been observed in the asset-backed commercial paper market in 2007 (see Acharya et al. (2012)) and in the repo market in 2008 (see Gorton and Metrick (2011), Krishnamurthy et al. (2011)).

[2] De Bandt and Hartmann (2000) discuss the literature on systemic risks and conclude that contagion is at their heart defining it as "a particularly strong propagation of failures from one institution, market or system to another". Bekaert et al. (2014) refer to contagion as to "unexpected increases in factor loadings and residual correlations".

Only a few studies assess the contagion effect with an asset pricing context (Bekaert et al. (2014) and Anton and Polk (2014)). Billio et al. (2012) argue that in order to measure systemic risk one must capture the degree of connectivity across the market participants. Anton and Polk (2014) measure the connectivity between stocks based on the common active mutual fund owners. They show that the higher the degree of shared ownership, the stronger the co-movements in those stock returns. We use an innovative approach to account for the role of connectivity across assets in an asset pricing context by using techniques from spatial econometrics. We extend the four-factor CAPM in Fama and French (2012) to incorporate a spatial component and estimate a spatial CAPM (SCAPM). While equilibrium spatial models can explain how real estate markets are connected using measures of spatial proximity, such as geographic distance, they abstract from the stochastic nature of real estate returns, the demand for real estate stemming from investors and the associated risk premiums included in the real estate prices. In turn, in the investment literature asset pricing models have been widely used to theoretically determine the required rate of return given the asset's non-diversifiable risk but does not take into account the spatial dynamics. Returns have therefore been modelled either in a purely spatial context in order to capture the co-movement across regions or in a purely asset pricing context to account for the asset's systematic risk. We follow Milcheva and Zhu (2016) and estimate a SCAPM in order to disentangle spillover effects across assets which we associate with systemic risks. In order to capture the cross-country return co-movements we use a variety of bilateral linkages, such as trade flows, geographic distance, cultural similarities, cross-border bank exposure, foreign direct investment (FDI), portfolio investment, interest rate convergence and inflation convergence. Cashman et al. (2016) estimate the role of the intra-firm cultural and geographic dispersion on firm's financial market liquidity and capital costs. They find that the dispersion of the properties in a real estate firm in terms of distance and cultural differences affects the informational environment of the organisation and hence its liquidity. In a similar vein, we use those two measures along other proximity indicators to assess how portfolio risk spills over across countries.

Looking at direct real estate asset returns may be suboptimal when estimating the SCAPM as real estate has different properties compared to the traditional investment assets such as stocks and bonds. Real estate is characterised by high transaction costs, little liquidity, indivisibility, inability of short sales, etc. Therefore, the conventional asset pricing models may not be suitable to fully capture those risks. In order to overcome some of the above problems, we use stock indices of listed real estate companies since those returns are known to capture the underlying real estate market fluctuations but also provide more liquidity, reduce transaction costs and mitigate indivisibility and short-selling issues. The SCAPM is estimated at a global level for real estate stock indices from 14 developed countries using the global market factors as in Fama and French (2012). The model is estimated as a panel at a rolling window basis using Bayesian techniques.

We find that the SCAPM is not rejected and the spatial parameters are significant throughout the sample period. Systemic risks associated with contagion dramatically increase during the GFC and explain up to 40% of total real estate asset risk. In the rest of the time, idiosyncratic risks have

been the predominant type of risk for real estate stocks. Our results have implications for investors showing that the market can channel asset volatility leading to contagion during crisis periods and therefore residual linkages between country indices need to be accounted for as a means of assessing the diversification benefits of a global portfolio.

2. Literature review

This paper is related to three different strands of literature. First, as we are using real estate stocks and national index returns – we address research about the application of conventional asset pricing models on real estate as well as the asset pricing models in an international context which include global factors rather than country-level factors. Second, by incorporating a spatial element into the CAPM, the paper relates to the vast literature on spatial economics which explains asset prices by measures of market proximity such as geographic or economic distance. Third, as co-movements across assets are associated with systemic risks which stem from the interconnectedness across markets, the paper relates to the literature on global financial imbalances and contagion.

Whether assets are priced locally in segmented markets or globally on a single market has been the focus in the asset pricing literature since the globalisation on the financial markets. There is a vast body of literature that tries to predict asset prices using international asset pricing models including foreign components (Merton (1973), Solnik (1974), Grauer, Litzenberger, and Stehle (1976), Sercu (1980), Stulz (1981), and Errunza and Losq (1985), Liow (2006)). The rapid pace of financial market liberalisation has highlighted the role of global factors for the pricing of local assets since foreign investors can access the market more easily. Global asset pricing models have been presented by Merton (1973), Karolyi and Stulz (2003), Bekaert et al. (2009), Hou et al. (2011), Fama and French (2012) among others. Merton (1973) develops an International CAPM under the premise that the premiums capture the pervasive extra-market risk factors. Karolyi and Stulz (2003) show that limiting the asset pricing to account only for domestic market variations would underestimate the return of assets whose market model residual is positively correlated with the global market portfolio. However, Griffin (2002) argues that only country-specific factors based on firm-level characteristics can explain the co-movements in global stock returns. Hou et al. (2011) examine how firm-level characteristics can explain cross-sectional and time-series variation in stock returns internationally compared to global and foreign components using various multifactor models on cross-country level. They find that the local and local plus foreign factor models produce lower pricing errors than their purely global counterparts. Fernandez (2011) proposes an S-CAPM model with one single factor and applies it to 126 stocks in Latin American. Instead of the Fama and French factors, she constructs weight matrices to capture the returns of BMS, HML and WML portfolios. In our paper, we construct the weight matrix according to the linkages between each pair of countries, while controlling for firm characteristics using the Fama-French factors. We show that after we control for those factors, there is additional correlation across the international real estate stock markets driven by financial or economic linkages between the countries.

With regards to the application of traditional asset pricing models, previous research has looked into explaining how risk should be managed in real estate portfolios (Blundell (2007), Crosby et al. (2016)) separately looking at systematic risks (Liow (2006), MacGregor and Schwann (2011)) and idiosyncratic risks (Chiang (2010), Akinsomi et al. (2013)). Crosby et al. (2016) look in addition to macro risks also at asset level risks by accounting for information contained in individual property transactions such as submarket quality and tenant covenants. Blundell et al. (2005) also look at risk in property portfolios splitting it into fundamental drivers of risk and modulators that lower or increase the variance triggered by the fundamentals. In terms of the idiosyncratic risk, Chiang (2010) finds that it is related to the vintage of the REIT and excess returns. Akinsomi (2014) show that idiosyncratic risk needs to be considered when pricing Shariah compliant REIT returns.

With regards to spatial econometrics, the concept developed is to capture the effect of a shock at a specific point in space on another place (see Haining (2003)). The most common spatial dependence widely studied in the literature is through geographic proximity (see Fingleton (2001, 2008)). We add to the ongoing research on spatial linkages across property returns by assessing a wide set of measures of financial and economic integration next to economic proximity. Zhu et al. (2013) argue that geographic closeness is important for explaining housing return and volatility co-movements. However, economic proximity presents an additional source of property co-variations. Bekaert et al. (2014) explore how the global crisis led to an equity market contagion. They distinguish between domestic, US and global contagion implying an increase in the co-movement of the domestic asset portfolio with domestic, US-specific or global factors. The authors explore six different channels assessing the banking system, the globalisation effect, the change in financial policies, the information asymmetry, the wake-up call hypothesis or global risk and liquidity. They find contagion effects from the US stock market through trade exposure with US return fluctuations affecting the stock market performance of its trade partners. We also adopt some of the above channels of return interdependence through bilateral country exposures captured by the spatial linkages. We use the bilateral bank exposure, interest rate, exchange rate and inflation convergence to account for the increased shock transmission through the balance sheets of globally operating banks. Countries with high levels of bank balance-sheet foreign exposure would show higher interdependence in their asset markets. We also account for the globalisation hypothesis, according to which countries that are more integrated globally through trade and financial linkages will experience stronger co-movements, especially during crises periods.

There is vast literature on the global financial crisis and the spillover effects associated with contagion and financial imbalances. The problem with detection contagion is that estimates of the correlations across assets or markets may be associated with volatility spillovers rather than contagion.[3] Forbes and Rigobon (2002) argue that it is important to differentiate between

[3] Claessens and Forbes (2001) summarise the literature on contagion and volatility spillovers. Bisias et al. (2012) present a good overview of more than 30 systemic risk measures. The standard way used to account for systemic risk is by looking at the Value at Risk (VaR). Hartmann et al. (2004) develop a contagion measure in the vein of the extreme

interdependence and contagion. They use the term interdependence instead of contagion to measure the co-movement of returns across countries as they show that once they account for market volatility of correlation coefficients there is almost no increase in the correlation coefficients. Research by Diebold and Yilmaz (2010), Rose and Spiegel (2010, 2011), Tong and Wei (2011) and Eichengreen et al. (2012) assesses the drivers of the transmission of the crisis adopting either a microeconomic or a macroeconomic approach. Tong and Wei (2011) show that the stock prices of firms which depend stronger on external finance such as bank lending would decline proportionally stronger. Beltratti and Stulz (2012) explain the cross-sectional variation of stock returns of global banks. Banks that have performed badly had higher leverage, more shareholder-friendly boards and were mainly financed through short-term capital market funding. Recently, a vast empirical literature has tried to quantify systemic risks. Anton and Polk (2014) refer to contagion as a sudden increase in correlations across assets not explained by fundamentals. They look at firm level stock returns and show that contagion results from ownership-based connections across stocks and increases during crisis periods.

3 Theoretical underpinnings

The majority of the asset pricing models consider only the universe of stocks and bonds since these assets are more liquid and more easily tradable. A rationale to incorporate direct real estate in an asset pricing framework is found in the spatial allocation of households. Wieand (1999) develops a spatial equilibrium model under uncertainty where the decision about the price and quantity of housing consumed is determined in a two-period asset-pricing context. He explains the bid price of a house by the homeowner's portfolio risk, including the total risk to the site, and the market price of risk. Bid prices for housing should reflect the total riskiness of the wealth portfolio, including locational payoffs, and the market price of risk. The author proposes that empirical studies should try to measure expected values, variances and covariances of locational payoffs with household wealth. More recently, Ortalo-Magne and Prat (2010) model a standard spatial equilibrium with a portfolio choice in an asset pricing context arguing that “in equilibrium, the spatial allocation of households is determined together with local rents and the volatility of rents”. One way to account for property assets in the market portfolio is to incorporate spatial allocation choices of households. They argue that the market portfolio should account for all assets in the economy including real estate because the demand for housing in a given region is assumed to drive the prices of all assets. The authors state that “the spatial allocation of households also determines the weights of each location-specific real estate asset in the market portfolio that is relevant for the pricing of systematic risk”. The idea is that the spatial allocation needs to be

value theory. Recently, Adrian and Brunnermeier (2008) propose a conditional VaR to measure spillover effects from an individual institution on the entire financial system using current institutional characteristics. Acharya et al. (2010) propose the systemic expected shortfall (SES) measure which reports the expected amount of undercapitalisation of a financial institution. The measure is derived from the expected shortfall measure and leverage.

considered in the CAPM as it contributes to the systematic risk because some real estate assets also form part of the market portfolio. The household chooses a certain location when he or she is indifferent between the benefits of a location associated with access to local amenities and income perspectives and the costs of the house price or the rest. As the agent is exposed to local productivity shocks, the location choice will depend on their income less the rent – as is the case in spatial equilibrium models – but also on the correlation of their income with that of the other residents in the same location. The decision how to allocate funds across different assets determines the expected returns everywhere, their volatility and covariance with the other assets, and the weight of assets from each country in the global market portfolio that is relevant for the pricing of all assets in the economy. Ortalo-Magne and Prat (2010) argue that the country REIT index is a suitable measure to track the housing demand in the model, which is the same for all agents, as it does not include the properties which are owned by local residents for hedging purposes.

4 Methodology

4.1 CAPM and SCAPM

In finance, the CAPM is widely used to determine a theoretically appropriate required excess rate of return of an asset from the risk-free rate, if that asset is to be added to an already well-diversified portfolio, given the asset's sensitivity to the market risk, represented by $\bar{\beta}_i$ and the expected excess return of the market. The CAPM is given by:

$$\tilde{r}_{t,i} = \bar{\alpha}_i + \bar{\beta}_i \tilde{r}_t^M + u_{t,i} \tag{1}$$

with $\tilde{r}_{t,i}$, the excess return of asset *i* in period *t* calculated as $\tilde{r}_{t,i} = r_{t,i} - r_t^{rf}$, r_t^{rf}, the risk-free rate in period *t*, $\tilde{r}_t^M$, the excess market return given by $\tilde{r}_t^M = r_t^M - r_t^{rf}$, and $u_{i,t}$, the error term with $u_{i,t} \sim N(0, \upsilon_i^2)$.

Under the assumption of $\text{cov}(\tilde{r}_t^M, u_t) = 0$, we have for the variance of the asset vector:

$$\Sigma = \bar{\beta} \Psi \bar{\beta}' + \Omega, \tag{2}$$

where Σ is the covariance matrix of the returns, Ω is the covariance matrix of error terms. Ψ is the covariance matrix of the common factors with $\Psi = E[(\tilde{r}_t^M - E(\tilde{r}_t^M))(\tilde{r}_t^M - E(\tilde{r}_t^M)')]$. From (4) we can see that the asset variance can be decomposed into a systematic part ($\bar{\beta}\Psi\bar{\beta}'$) which depends on the asset sensitivity to the market and the market variance, and an idiosyncratic part (Ω) which depends on the variance of the residuals.

The traditional CAPM accounts for co-movements between each two assets indirectly through the

relationship of each asset with the market. Moreover, the CAPM assumes that the residuals are not correlated across time and across the assets. However, we have seen that during crisis periods a shock which is assumed to be idiosyncratic in nature and to have no systematic implications in a well-diversified portfolio can actually trigger systemic risks. This can happen through different channels due to illiquidity, portfolio rebalancing, herding behavior, etc. To capture the spillovers of asset's idiosyncratic risk we incorporate a spatial term which explicitly accounts for the linkages across the assets. The SCAPM is given by:

$$\tilde{r}_{t,i} = \alpha_i + \rho \sum_{j=1,\, j\neq i}^{N} w_{t,j,i}\tilde{r}_{t,j} + \beta_i \tilde{r}_t^M + e_{t,i}\,, \tag{3}$$

where $w_{t,j,i}$ captures the 'distance' between each two countries in period *t*, and $w_{t,j,i} = 0$ for $i = j$ for country *i* and *j*. We use time-varying weights since shifts in the weights can have implications on the estimated coefficients. $\sum_{j=1,\, j\neq i}^{N} w_{t,j,i}\tilde{r}_{t,j}$ is the weighted sum of the contemporaneous excess returns between each two country portfolios in period *t*. ρ is the spatial autoregressive parameter capturing the comovement effects between the portfolio returns. We allow for heteroskedastic error terms with $e_{i,t} \sim N(0, \sigma_{i,t}^2)$. Kou et al. (2015) derive asset pricing models including a spatial component which characterize how spatial linkages affect expected portfolio returns under market equilibrium. They show that if each investor holds a mean-variance efficient portfolio, in equilibrium, the market return in the SCAPM will be mean-variance efficient and every investor will hold a combination of the market portfolio and the risk-free asset. Milcheva and Zhu (2016) show that estimating a spatial factor model improves the model fit of a four-factor model and can capture remaining correlation among the residuals.

4.2 SCAPM in a matrix form

In order to account for spillover effects across returns, we estimate the SCAPM as a panel model linking the individual country index returns using a spatial matrix. Given *N* country-level portfolios, Equation (2) can be expressed in a matrix form such as:

$$\begin{bmatrix} \tilde{r}_{t,1} \\ \tilde{r}_{t,2} \\ \vdots \\ \tilde{r}_{t,N} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} + \rho \begin{bmatrix} 0 & w_{t,1,2} & \cdots w_{t,1,N} \\ w_{t,2,1} & 0 & \cdots w_{t,2,N} \\ \vdots & \vdots & \ddots \vdots \\ w_{t,N,1} & w_{t,N,2} & \cdots \quad 0 \end{bmatrix} \begin{bmatrix} \tilde{r}_{t,1} \\ \tilde{r}_{t,2} \\ \vdots \\ \tilde{r}_{t,N} \end{bmatrix} + \tilde{r}_t^M \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{bmatrix} + \begin{bmatrix} e_{t,1} \\ e_{t,2} \\ \vdots \\ e_{t,N} \end{bmatrix} \tag{4}$$

with $w_{t,1,2}$ being the weight calculated from the distance between country 1 and 2 in period *t*.

Because of the standardization of the weight matrix described in Section 4.3, $w_{t,1,2}$ is not necessarily equal to $w_{t,2,1}$, so that the weight matrix can be asymmetric. Equation (4) can be expressed as:

$$\tilde{r}_t = \alpha + \rho W_t \tilde{r}_t + \tilde{r}_t^M \beta + e_t . \quad (5)$$

$\tilde{r}_t$ denotes the vector of excess returns of the N portfolios in period t and $\tilde{r}_t^M$ is the value of the global market return, which is the same for each dependent variable. W_t is the standardized $N \times N$ non-stochastic spatial dependence weight matrix with zeros in the diagonal terms and non-zeros in the off-diagonal terms. α is an $N \times 1$ coefficient vector of the individual portfolio alphas. β is a $N \times 1$vector, with elements representing the portfolio betas, and $\beta = (\beta_1, \beta_2, ..., \beta_N)'$ e_t is an $N \times 1$ vector of error terms. Since the SCAPM in Equation (5) has the dependent variable both on the left and right hand side, in order to estimate it we need to use its reduced form. The reduced form is given as:

$$\tilde{r}_t = (I_N - \rho W_t)^{-1} \left[\alpha + \tilde{r}_t^M \beta + e_t \right]. \quad (6)$$

We define $(I_N - \rho W_t)^{-1} = V_t$ so that Equation (5) can be rewritten as:

$$\tilde{r}_t = V_t \alpha + V_t \tilde{r}_t^M \beta + V_t e_t . \quad (7)$$

Since $V_t = (I_N - \rho W_t)^{-1} = I_N + \rho W_t + \rho^2 W_t^2 + \rho^3 W_t^3 + ...$, Equation (9) implies a spatial multiplier effect on the asset excess returns (see Anselin (2006) and LeSage and Pace (2009)). Any changes in the returns in one country will also affect the remaining countries through the spatial linkages among the countries. Not only the 'first order neighbours', ρW_t, get affected, but also 'neighbour's neighbours' are impacted through the spatial multiplier effect, $\rho^2 W_t^2$, $\rho^3 W_t^3$, etc. In the end, the shock can have a feedback effect on the country of origin of the shock.

Kou et al., (2015) show that, in equilibrium, under the assumption of $\text{cov}(\tilde{r}_t^M, e_t) = 0$,

$$\beta_t = (I_N - \rho W_t) \frac{Cov\left(\tilde{r}_t, \tilde{r}_t^M\right)}{Var\left(\tilde{r}_t^M\right)} = (I_N - \rho W_t)\bar{\beta} , \quad (8)$$

which implies the sensitivity between the asset return and the market also depends on the degree of spatial interaction V:

$$\bar{\beta} = E\left[\frac{Cov\left(\tilde{r}_t, \tilde{r}_t^M\right)}{Var\left(\tilde{r}_t^M\right)}\right] = E\left(V_t\beta\right) = \bar{V}\beta = \beta + \rho\bar{W}\beta + \rho^2\bar{W}^2\beta + \rho^3\bar{W}^3\beta + \cdots \quad (9)$$

where $\bar{V} = \frac{1}{T}\sum_{t=1}^{T} V_t$ and $\bar{W} = \frac{1}{T}\sum_{t=1}^{T} W_t$. As in the factor model, the variance of the returns in the spatial factor model can be decomposed into the market risk of the asset and the idiosyncratic risk:

$$\Sigma = \bar{V}\beta\Psi\beta'\bar{V}' + \bar{V}\Xi\bar{V}', \quad (10)$$

where Σ is the covariance matrix of the returns which is the same as the covariance in the factor model. Ξ is the covariance matrix of the error terms in the spatial factor model. The spillover risk is the part of the total asset risk in (10) which is associated with the spatial term $\bar{V}$ and is given by:

$$\Theta = \Sigma - \beta\Psi\beta' - \Xi \quad (11)$$

The spillovers are larger for assets which are closer to each other as captured by the weight matrix. The part of the spillover risk which is diversifiable is[4]:

$$\Theta_D = \bar{V}\Xi\bar{V}' - \Xi. \quad (12)$$

The part of the spillover risk that cannot be diversified away is given by:

$$\Theta_{ND} = \bar{V}\beta\Psi\beta'\bar{V}' - \beta\Psi\beta'. \quad (13)$$

In Appendix 2 we show a proof that the risk in (12) can be diversified away whereas the risk in (13) is non-diversifiable even if we hold a large portfolio of assets. We can see that investors can diversify the spillover part of the idiosyncratic risk by holding the assets in proportions to their spatial weights.

We estimate the SCAPM including three other factors next to the market return as in Fama and French (2012) accounting for the size, value and momentum in stock returns. In order to account for changes in the coefficients across time, we estimate Equation (6) using a rolling window of 36 months. In doing so, we obtain an alpha and beta for each portfolio and each month as well as a spatial coefficient for each month. With regards to the estimation, we use Bayesian estimation with heteroskedastic error terms following LeSage (1997 and 2003).[5]

4.3 The spatial weight matrix

[4] See Appendix 2 for the proof of diversifiability of the spillover risk.

[5] We prefer Bayesian estimation over Maximum Likelihood (ML) estimation due to problems resulting from the low degrees of freedom associated with the heteroscedastic error terms when using ML estimation.

The spatial weight matrix plays a crucial role in spatial econometric models because the estimated spatial correlation depends on the specification of the weight matrix. In our empirical estimation, we try a variety of financial and economic channels, including geographic distance, cultural proximity, openness proximity, trade, FDI, bank balance-sheet exposure as well as interest rate, inflation and exchange rate convergence (Milcheva and Zhu (2015)).[6] The weight matrix is constructed in two steps. First, we calculate the distance or proximity between each two markets. Then we transform the measure of proximity to a weight which is standardized. Taking FDI linkages for example, we first calculate the importance of country *j* for country *i* by taking the FDI between the two countries as a proportion of total FDI of country *i* with all other countries:

$$F_{i,j,t}^{FDI} = \frac{Outward_{i,j,t} + Outward_{i,j,t}}{\sum_k Outward_{i,k,t} + \sum_k Outward_{k,i,t}}. \tag{10}$$

where $Outward_{i,j,t}$ stands for the outward foreign direct investment from country *i* to country *j*, and $k = 1,\ldots, N$. $F_{i,j,t}^{FDI}$ measures the importance of country *j* for country *i* in terms of their interconnectedness through FDI.

Alternatively, the proximity can also be measured based on a certain distance between two countries. For example, the difference in the culture of the two countries could be defined as:

$$F_{i,j}^{Culture} = \left| Culture_i - Culture_j \right|, \tag{11}$$

where $Culture_i$ is the average value of the six Hofstede scores for country *i*. In this case, $F_{i,j}^{Culture}$ is a measure of distance or dis-similarity.

In the second step, we convert the *F* matrix to a corresponding continuity matrix *C* whose elements $c_{i,j,t}$ are defined as:

$$c_{i,j,t} = 1 - \frac{\max_{j,t} F_{i,j,t} - F_{i,j,t}}{\max_{j,t} F_{i,j,t} - \min_{j,t} F_{i,j,t}}, \tag{12}$$

when $F_{i,j,t}$ is a measure of linkage / similarity, or

[6] The description and calculation of the alternative weight matrices is enclosed in the Appendix.

$$c_{i,j,t} = 1 - \frac{F_{i,j,t} - \min_{j,t} F_{i,j,t}}{\max_{j,t} F_{i,j,t} - \min_{j,t} F_{i,j,t}} \ , \qquad (13)$$

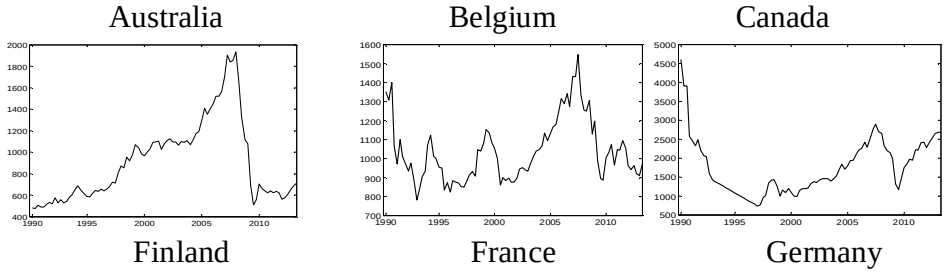
when $F_{i,j,t}$ is a measure of distance / dissimilarity.

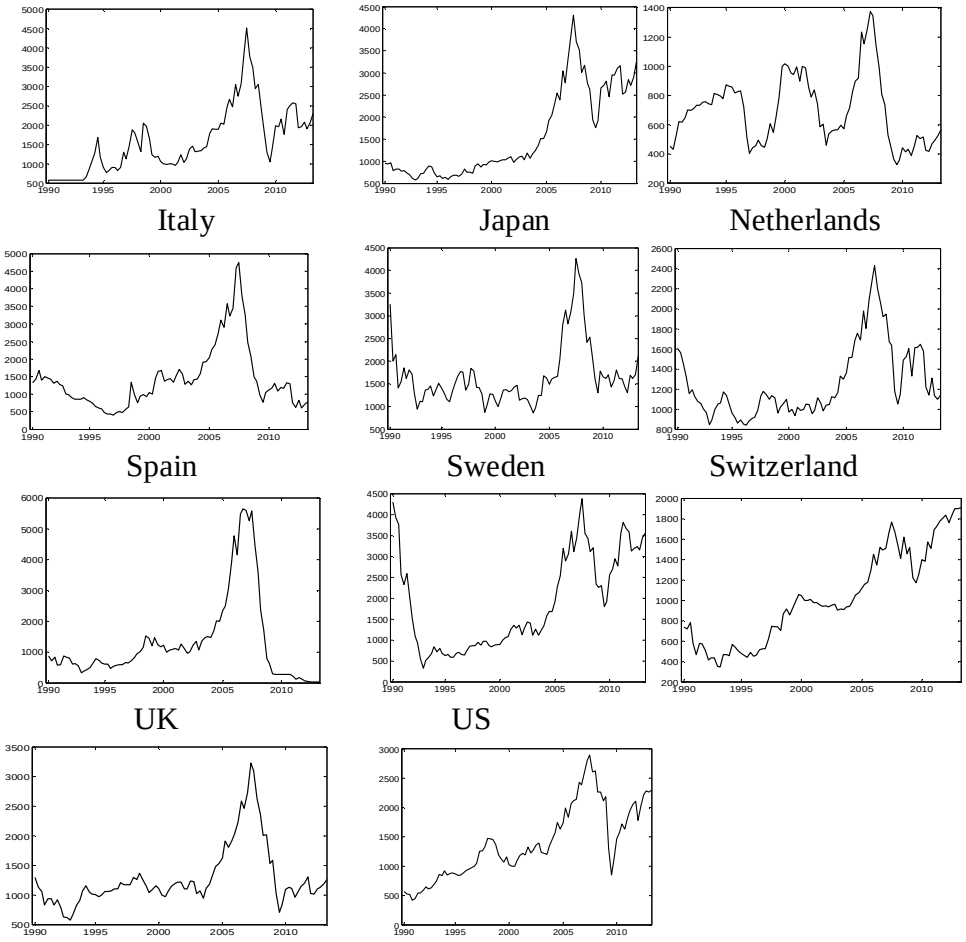
The weight matrix *W* is then obtained from *C* through row standardisation, such that for each *i*, $\sum_{j,t} w_{i,j,t} = 1$. If the weight matrix is constructed skipping this second step, it will remain symmetric. The second step assures that the matrix is not necessarily symmetric, so that even if country *i* is an important neighbour for country *j* (i.e., $c_{j,i,t}$ is close to one), country *j* may be not important for country *i* (i.e., $c_{i,j,t}$ is close to zero).

4.4 Data

Our estimation sample includes the following 14 countries – Australia, Belgium, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, Switzerland, UK and the US – since they have sufficiently long time series data for listed real estate company returns. The estimation uses monthly data and the estimation period ranges from 1991M1 to 2012M12. The dependent variable is the monthly log-difference of the FTSE EPRA/NAREIT index capturing the performance of listed real estate companies in each country. The national indices are taken from the European Public Real Estate Association (EPRA) representing Europe's publicly listed property companies and tracking the performance of companies engaged in the ownership, trading and development of income-producing real estate. The fundamental business of those listed real estate companies is investing in and operating real estate assets, with income being generated from renting these assets to other organizations. Figure 1 shows the indices of the listed property companies in each country. We can see that the price indices in the majority of the countries soared up in 2007 and then dropped dramatically in the outbreak of the crisis in 2008-09.

Figure 1: FTSE NAREIT/EPRA index of listed property companies in 14 countries





The explanatory variables are the four factors used in Fama and French (2012) and are obtained from Ken French's website[7]. The four factors include a global market return index, the difference between the returns on diversified portfolios of small stocks and big stocks (SMB), the difference between the returns on diversified portfolios of high book-to-market (value) stocks low book-to-market (growth) stocks (HML), and the difference between the month *t* returns on diversified portfolios of the winners and losers of the past year (WML). As we are dealing with country-level data, we use the global factors for developed markets. The descriptive statistics for all variables are reported in Table A1. The average monthly return of the market index over the sample period is 0.4% compared to a risk-free rate of 0.3%. The return of the global listed real estate index is also 0.4% which is considerably lower than the return of the underlying market – the global direct commercial real estate index of 6.7% based on valuations. The risk of investing in direct real estate is highest with a standard deviation of 6.1% followed by listed real estate, 5.5%, and the risk of the market of 4.4%. Regarding the listed real estate index, we observe some variation across the selected countries with the lowest average returns in Spain with -1.2% and the highest in US with 0.6%. The highest correlation in returns is observed between the Netherlands and France (74.6%)

[7] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

followed by the UK and France (61.7%), and the lowest is between Sweden and Canada (4%).

Data for the trade matrix comes from the Trade Statistics of the OECD. Bilateral FDI flows are from the Foreign Direct Investment Statistics of the OECD. For bank balance-sheet exposure we use bilateral bank claims based on the consolidated bank statistics of the BIS using Table 9B. For the cultural similarity we use the Hofstede's cultural dimensions from his website https://geert-hofstede.com/.[8]

5 Results

5.1 The SCAPM versus the CAPM

Table 1 shows the results using different weight matrices. The spatial coefficient ranges between 0.443 and 0.515, which is smaller to what has been reported in previous studies regarding stock comovement using a spatial econometrics model as well as different types of weight matrices (Fernandez (2011), Asgharian et al. (2013)). Asgharian et al. (2013) use different weight matrices and report coefficients between 0.81 and 0.83. However, their study and the majority of the articles on spatial linkages estimate a spatial model and not a spatial factor model. Fernandez (2011) estimates what she calls an S-CAPM, however, she uses a different methodology. Instead of the Fama and French factors, she constructs weight matrices to capture the returns of BMS, HML and WML portfolios. She reports spatial coefficients between 0.77 and 0.86 based on a sample of 126 firms in Latin America. The smaller spatial coefficient reported in our study can be due to the nature of underlying direct real estate assets which those listed firms hold, which are less liquid and more heterogeneous.

The significance of our coefficients means that it is important to account for spatial linkages across real estate firms as it affect the performance of individual companies through different channels. By adding the spatial component, the R-squared increases by 28 percent, from 0.21 to 0.27. We can see from the Bayesian Information Criterion (BIC) that the SCAPM using any of the weight matrices is preferred to the CAPM which has a BIC of -1.754. Table 1 also reports the average absolute value of the intercept, or the 'alpha', which is the average of the absolute alphas of the 14 country indices. In addition to the alpha, we include its average standard error and a GRS F-test by Gibbons et al. (1989) for the joint significance of the individual alphas. As expected, the average absolute value of alpha decreases in the SCAPM due to the inclusion of an additional variable that can explain part of the return variations. The standard error of the intercept is also smaller in the SCAPM. In the SCAPM, the GRS test value is smaller in both economic and statistic magnitude.

Table 1: SCAPM with alternative weight matrices

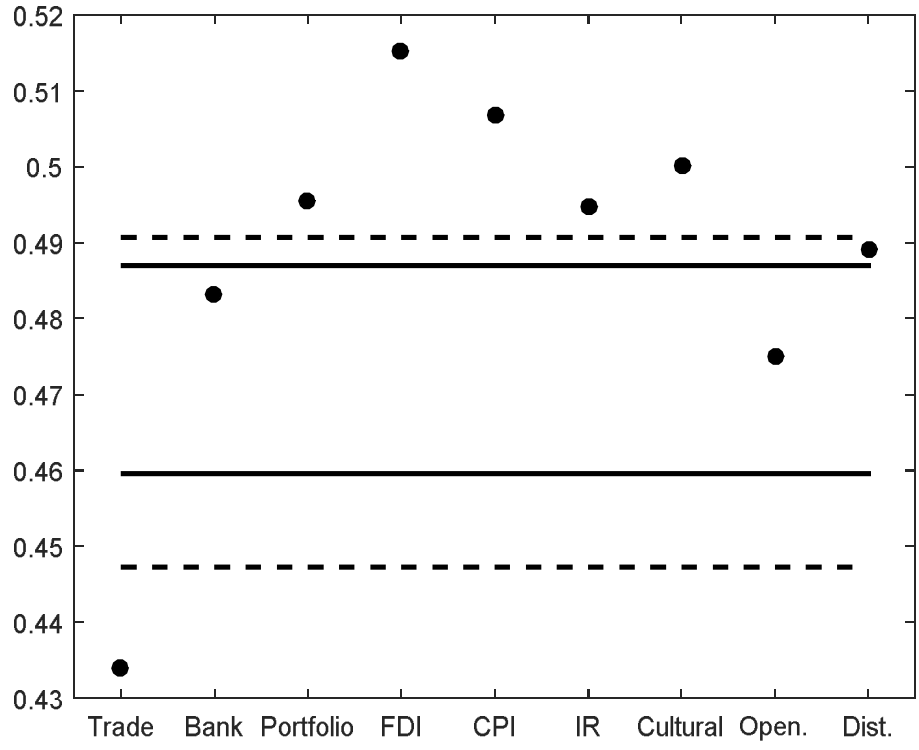
[8] See the Appendix for the exact definitions of the distance measures and theory behind their usage.

Note: The model is estimated from 1991M1 to 2012M12. The dependent variable is the log difference of the excess listed property index for each country in each month. ρ is the coefficient for spatial dependence. Std(ρ) is the standard deviation of ρ. R2 is the average coefficient of determination in the panel model. BIC stands for the Bayesian Information Criteria. |α| stands for the absolute mean of the individual alphas. Std(α) stands for the average standard deviation of alpha. The GRS is a test for the joint significance of the portfolio alphas. With 14 portfolios and 264 monthly returns, the critical values for the GRS test for all models are 1.53, 1.73 and 2.15 for 10%, 5% and 1% significance level, respectively.

	ρ	Std(ρ)	R2	BIC	| α|	Std(α)	GRS
SCAPM							
Trade	0.443***	0.016	0.272	-2.737	0.004	0.003	1.555*
Bank Flow	0.483***	0.018	0.270	-2.735	0.004	0.003	1.610*
Portfolio investment	0.495***	0.018	0.276	-2.751	0.004	0.003	1.592*
FDI	0.515***	0.017	0.280	-2.749	0.004	0.003	1.549*
Interest rate convergence	0.495***	0.018	0.269	-2.732	0.004	0.003	1.643*
Inflation convergence	0.507***	0.017	0.275	-2.750	0.004	0.003	1.497
Cultural Similarity	0.500***	0.020	0.267	-2.744	0.004	0.003	1.469
Openness Similarity	0.475***	0.017	0.266	-2.734	0.004	0.003	1.530
Geographic distance	0.489***	0.017	0.279	-2.760	0.004	0.003	1.554*
CAPM			0.211	-1.754	0.007	0.004	2.374***

The results in Table 1 show that most weight matrices using measures of financial integration, geographic distance or cultural proximity do a good job in capturing the spatial correlation across the country returns. One reason could be that the global shocks are the dominant factors for the co-movements of the returns, so the cross sectional correlation between market returns is predominantly caused by strong global co-movements of the returns. If this is the case, the estimated values of ρ should be large, no matter how the relative weights in W are chosen. We follow Asgharian et al., (2013) and perform a simulation analysis to check whether the estimated value of ρ is also economically significant. We randomly generate 200 spatial weights matrices and estimate the model for each matrix separately. This results in 200 different estimates of ρ. Figure 2 shows the 99% and 90% inter-percentile ranges of the empirical distribution of these estimates together with the estimated ρ-values obtained when using our eight distance measures. As shown in Figure 2, ρ-values lying in the interval [0.447; 0.491] at 99% confidence interval. Our distance measures generally outperform the vast majority of randomly defined distance measures with trade, bank flows, openness and distance being below the 95% confidence interval line and hence are economically insignificant. Therefore, for the further analysis we will only focus on the weight matrices which are economically significant, such as portfolio investment flows, FDI, CPI convergence, interest rate convergence and cultural similarity.

Figure 2: Comparison of the estimated spatial dependent coefficient (*ρ*) from the neighbourhood measures (Appendix 2) compared with the empirical distribution of the (*ρ*) from random matrices.



Note: this figure compares the estimated values of the spatial coefficients (ρ) from our selected neighbourhood measures (the dots) with those from randomly generated neighbourhood matrices. The estimated spatial dependence coefficient is based on SCAPM model (Equation 4). The lines show the 99% and 90% inter-percentile ranges for the empirical distribution of the estimated spatial dependent coefficient (ρ) from 200 randomly generated spatial weights matrices.

We further conduct a robustness test to account for global market factors specifically associated with the real estate market. We include either the global FTSE NAREIT/EPRA index representing the listed real estate sector in above countries or the global IPD index representing the direct commercial real estate sector which is the underlying asset in which listed real estate companies are invested. The results are presented in Table 2. When the factor associated with the direct real estate market is added, the spatial dependence coefficient slightly decreases to between 0.426 and 0.457. When the indirect listed real estate index is included the spatial coefficients remain similar to the baseline case in Table 1. The R-squared slightly increases by around 1 percentage point. Overall however, there is no noticeable difference in the models with and without the real estate market index. The models are not sensitive to the inclusion of further factors as demonstrated by the stability of the adjusted R-squared.

Table 2: Additional market indices for SCAPM and CAPM

Note: The model is estimated from 1991M1 to 2012M12. The dependent variable is the log difference of the excess listed property index for each country in each month. The global market factors are the global IPD index return (Models 3 and 4) and the global EPRA index return (Models 5 and 6). SML R^2 reports the R^2 in the security market

line regression – regressing excess returns on beta coefficients. The spatial weight matrix is based on bilateral trades of the two countries. ρ is the coefficient for spatial dependence. Std(ρ) is the standard deviation of ρ. R2 is the average coefficient of determination in the panel model. BIC stands for the Bayesian Information Criteria. |α| stands for the absolute mean of the individual alphas. Std(α) stands for the average standard deviation of alpha. The GRS is a test for the joint significance of the portfolio alphas. With 14 portfolios and 264 monthly returns, the critical values for the GRS test for all models are 1.53, 1.73 and 2.15 for 10%, 5% and 1% significance level, respectively.

	ρ	Std(ρ)	R2	BIC	| α|	Std(α)	GRS
Global direct property returns							
SCAPM							
Portfolio investment	0.435***	0.018	0.286	-2.748	0.004	0.003	1.490
FDI	0.457***	0.020	0.288	-2.744	0.004	0.003	1.457
Interest rate convergence	0.426***	0.019	0.285	-2.751	0.004	0.003	1.370
Inflation convergence	0.430***	0.019	0.284	-2.752	0.004	0.003	1.376
Cultural Similarity	0.439***	0.024	0.278	-2.750	0.004	0.003	1.352
CAPM			0.240	-1.755	0.006	0.004	2.165***
Global listed property returns							
SCAPM							
Portfolio investment	0.491***	0.016	0.283	-2.718	0.008	0.004	2.595***
FDI	0.513***	0.018	0.287	-2.717	0.008	0.004	2.589***
Interest rate convergence	0.479***	0.015	0.277	-2.713	0.007	0.004	2.677***
Inflation convergence	0.484***	0.017	0.277	-2.714	0.007	0.004	2.765***
Cultural Similarity	0.498***	0.023	0.272	-2.715	0.007	0.004	2.646***
CAPM			0.220	-1.727	0.012	0.006	3.813***

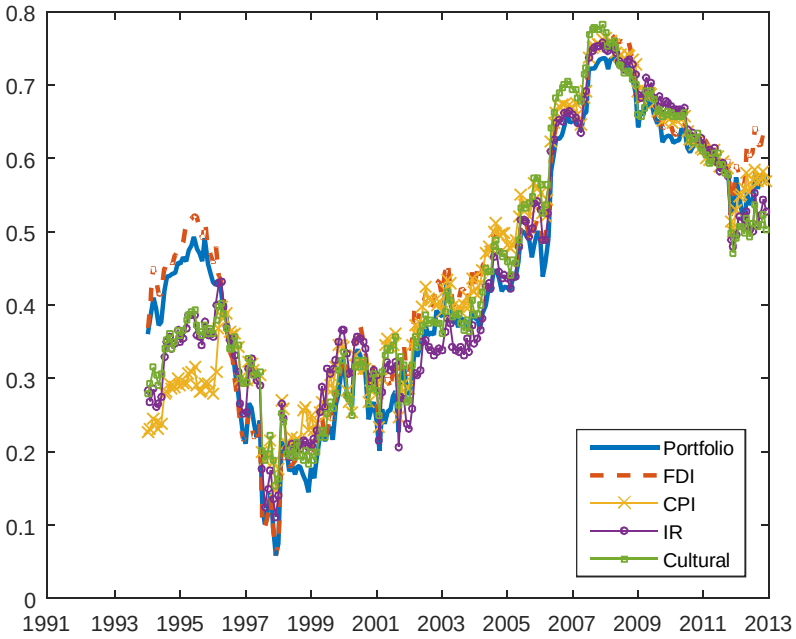
5.2 Time-varying spatial coefficients

In order to look how the interdependence across the markets changes over time, we estimate the SCAPM using a rolling window of 36 months. The spatial coefficient ρ is the same for each asset return but varies over time. The results for the different weight matrices are presented in Figure 3. The spatial coefficient is significantly positive throughout the entire period starting in 1998 although for reasons of more clear representation we leave out the confidence bands[9]. The value of the spatial coefficient maters for the calculation of the asset variance capturing the spillover effects. We can see that the coefficient shows strong variation over time ranging from nearly zero in 1997 to up to nearly 0.8 in 2008. It means that the co-movement between the country portfolios rises sharply to 70-80% in 2007 and stays high during the crisis period. Until the end of 2012 it hasn't returned to its pre-crisis value yet. In a similar fashion, Lizieri (2013) estimates a three-factor CAPM using a rolling window with equity, small cap and bonds to assess the returns of

[9]Figure A2 in the appendix provides the results with 95% confidence interval based on an FDI matrix. Other measures of distance yields similar results.

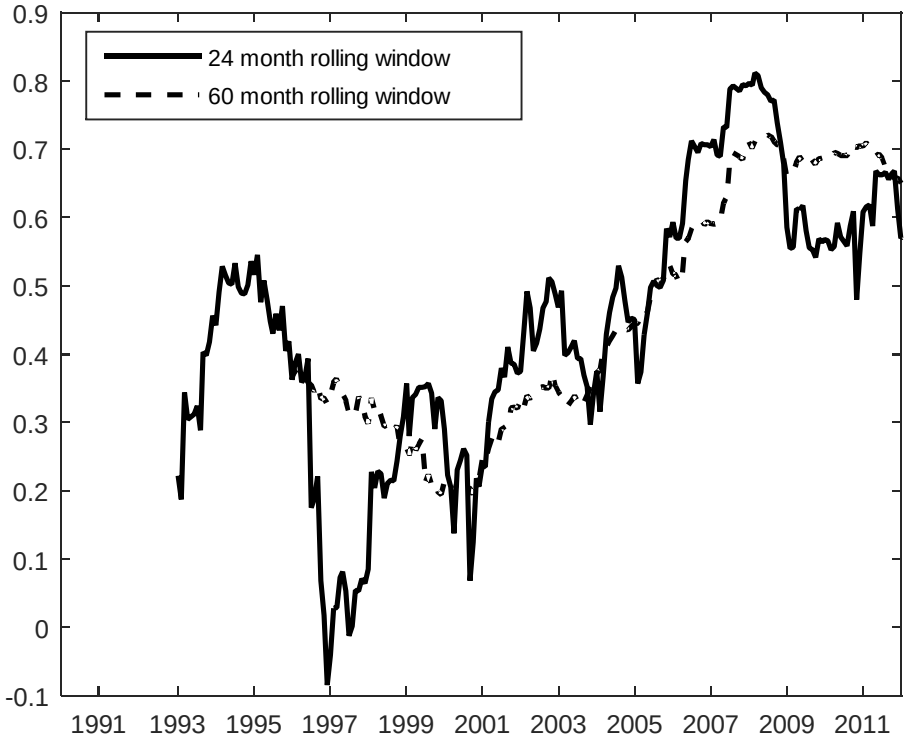
direct property in UK. They show that the parameters of the CAPM model are time-varying and the variation has increased during the global financial crisis and has not recovered by the end of 2011. Another observation from Figure 3 while using a different weight matrix leads to more heterogeneous results in the late Nineties, the time-varying spatial coefficients converge across the different spillover channels over time and during the peak of the GFC, there would be almost no difference in the value of the coefficients. In 2012 we again observe some divergence with FDI providing the upper bound and cultural similarity – the lower bound of the value of the spatial coefficient.

Figure 3: Estimated spatial coefficients (ρ) based on a 36-month rolling window using alternative weight matrices



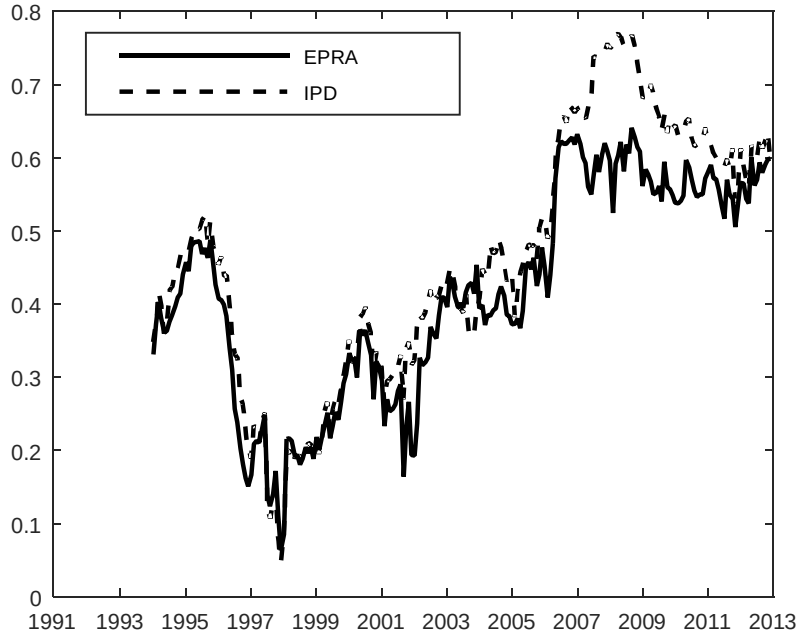
Using a different rolling window of either 24 months or 60 months, estimating here only a model with FDI weights for brevety, yields similar conclusions (see Figure 4). Using a short rolling window can capture even more volatility in the estimates in particular during the first half of the century. Starting in 2001 with the dotcom crisis we can see an increase in the interconnectedness on the real estate markets up until 2009. The sample period can capture one full cycle with the coefficient first falling (1995-2001), then gradually increasing (2001-2009) and then falling again (2009-2013). Hence, the comovement across the real estate returns follows a cyclical pattern and assuming constant parameters in a standard CAPM may bias the risk assessment.

Figure 4: Estimated spatial coefficients (ρ) based on 24-month and 60-month rolling windows using an FDI matrix



Adding further factors directly associated with the real estate market such as the IPD global direct property index or the EPRA/NAREIT global listed real estate stock index produces similar conclusions (see Figure 5). The only noticable difference across the spatial coefficients is during the crisis period from 2007 to 2010 when they is slight misallignment. The spatial coefficient estimated in an SCAPM along with the EPRA/NAREIT index is 10 percentge point lower that a model including the IPD index or no real estate index at all (see Figure 3). However, on the whole, we do not see any systematicly different value of the coeffients across the models.

Figure 5: Estimated spatial coefficients (ρ) with FDI linkages and an additional real estate market factor based on 36-month rolling windows



5.3 Contagion effects

Our main goal by estimating the SCAPM is to disentangle from the total asset risk, the risk that is due to contagion. We calculate the total asset risk, the idiosyncratic risk and the market risk using the variances of the returns, the residuals and the market factors, respectively. The total asset risk as estimated under the spatial factor model should be equivalent to the total asset risk as estimated under the factor model. However, a part of this risk as modelled in the SCAPM will be attributed to spillover effects across the portfolio returns and can hence be associated with contagion. The spillovers are larger for companies whose underlying assets are spatially 'closer' to each other in the broader sense as captured by the different weight matrices. An increase in those spillover effects is associated with contagion.

Figure 6 shows the average results for the FDI weight matrix across all 14 country portfolios. The results for the remaining matrices are presented in Figure A1 in the Appendix as we observe similar outcomes. Prior to the GFC, the idiosyncratic and the market risks reach their lowest values. With the onset of the crisis, we see a sharp jump in both risks with the market risk reaching its highest levels during the entire observation period. The idiosyncratic risk is also increasing substantially but is not as high as in previous periods, such as in mid 1990s. This risk dynamics reflects the uncertainties associated with the underling direct real estate market. Studies have shown that real estate stocks behave more like stocks in the short term and like real estate in the long term. When the idiosyncratic risk falls at such low levels, as has happened in the first half of the last decade,

before it rises again in the onset of the GFC, real estate stocks may reflect the dynamics on the equity market and also be associated with increased transparency and liquidity on the real estate market. Starting in 2008 the idiosyncratic risk has increased again along with the market risk suggesting that during distressed periods the dynamics in the real estate stock returns is not only driven by general economic conditions but also by asset-specific risks which we argue are transmitted to other stocks leading to contagion. We can see that spillover risk (the red line) in Figure 6a makes up for almost half of the total asset risk. Up until 2007, spillovers were hardly observed across the assets. With the onset of the GFC spillovers have increased dramatically. The increase in the spillover effects is seen as evidence of contagion effects. In Figure 6b, we split the spillover risk into the diversifiable part (in red) and the undiversifiable part (in yellow). The undiversifiable is the spillover through the market risk. It is the part of the contagion that is triggered by common risks in the market to which all assets are exposed: a shock originating in one asset (country) has an indirect effect on the other assets (countries) through the market. This part of the spillover risk cannot be diversified by portfolio managers. The spillovers of idiosyncratic risk can be diversified, and they are associated with direct contagion effects: a shock originating in one asset (country) has a direct effect of the other assets (countries). The spillovers are larger for assets (countries) which are more closely related to each other. We can see from Figure 6b, that a large proportion of the spillover effect is channelled through the market rather than the individual assets, and as the prove in the Appendix shows, it cannot be diversified away. This is in line with our observation that the market risk increases dramatically during the GFC and a large chunk is associated with contagion effects to other assets. As a result, a global asset portfolio may not provide the necessary diversification benefits during a crisis period because, first, the sensitivity to market fluctuations increases and, second, those asset-specific fluctuations are spread to other asset through the market leading to contagion.

Figure 6: Variance decomposition based on a SCAPM with FDI weights – average across countries

Figure 6a: Spillover risk, market risk and idiosyncratic risk

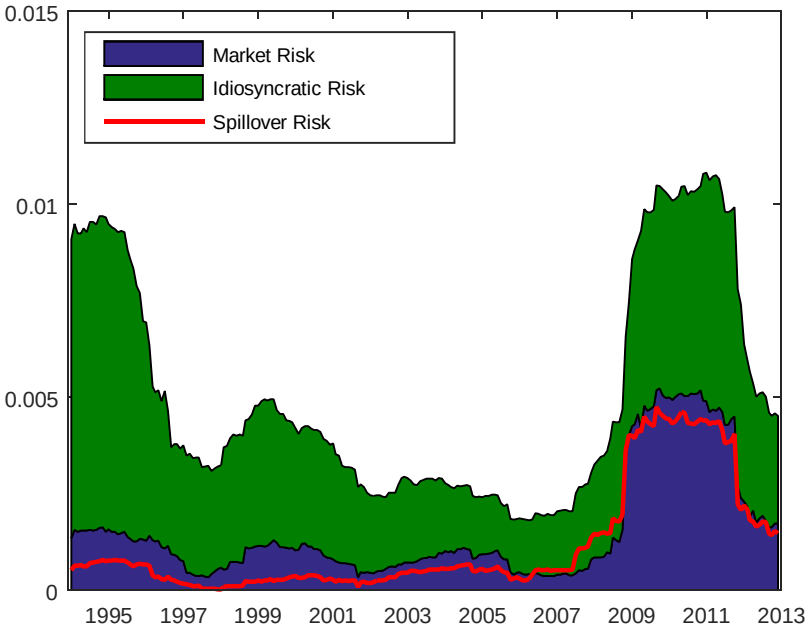
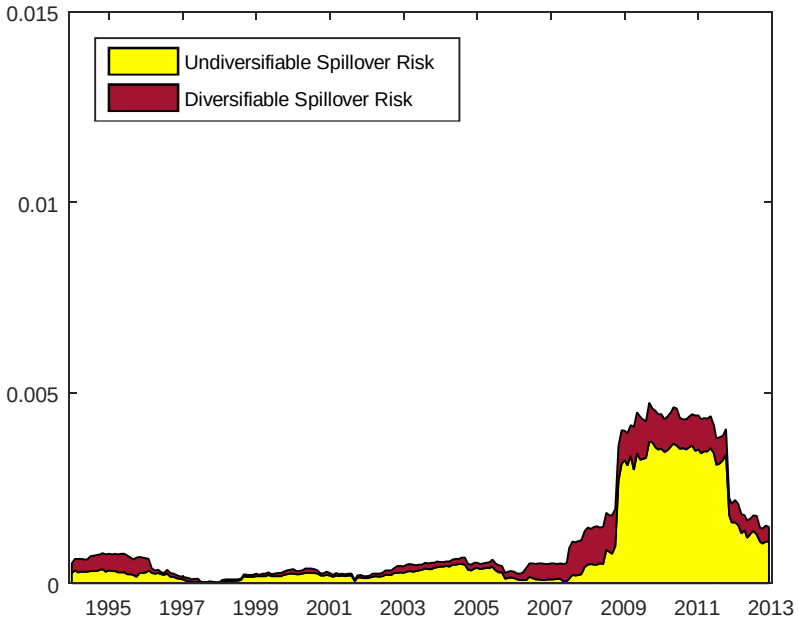


Figure 6b: Diversifiable and non-diversifiable spillover risk



6 Conclusion

This paper presents an alternative way for global asset pricing incorporating spatial linkages across portfolio returns. For this purpose we use performance data of listed property company indices in 14 countries. We extend the four-factor CAPM by Fama and French (2012) to incorporate spatial linkages as a means to account for contagion. We follow the extensive literature of spatial econometrics and use different measures of spatial proximity such as bilateral trade flows, geographic distance, cultural proximity and financial integration. We account for an increase in the interdependence between the country returns during normal and distressed periods by estimating time-varying coefficients. We disentangle the spillover effects associated with both market and country-specific risks by decomposing the asset variance into a spatial and non-spatial part. Contagion is captured by changes in the spillover effects.

Our results show that during the GFC, the spatial interdependence remarkably increases, and triggers strong contagion effect through the idiosyncratic component. The spillover can explain up to 40% of total asset risk during the GFC, and a large proportion of is associated with the spillover of idiosyncratic risks. Our results have implications for investors showing that the market can channel asset volatility leading to contagion during crisis periods and therefore residual linkages between country indices need to be accounted for as a means of assessing the diversification benefits of a global portfolio.

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Zhu, B., R. Fuess and N. Rottke. 2013. Spatial linkages in returns and volatilities among US regional housing markets. Real Estate Economics 41 (1), 29–64. **Appendix 1: Definition of Spatial Linkages**

Distance measures

Geographic distance

The standard measure to capture the business cycle synchronisation across countries widely used in the spatial literature is geographic distance. The reason is that neighbouring countries often keep close economic relationships. Therefore, as Fazio (2007) and Orlov (2009) argue, geographically close countries would have as a result stronger trade and financial linkages. Miao et al. (2011) explore correlations among real estate returns in 16 US metropolitan areas and find that the strongest correlation appears to be in geographically adjacent regions. A similar result has been found for stock returns by Flavin et al. (2002). Portes and Rey (2005) show that geographic distance presents a barrier to international equity flows. We measure geographic proximity ($F_{i,j}^{D}$) based on the distance ($D_{i,j}$) between the capital cities of each pair of countries *i* and *j*:

$$F_{i,j}^{D} = D_{i,j}\,. \tag{A1}$$

Cultural similarity

Cultural similarity assesses a range of indicators such as the degree of the society to embrace entrepreneurial risk; if the decision-making process is affected by a short-term or long-term investment horizon; the power distribion across members of the group; the degree of tolerance of inequality; if goals are driven by a pursuit of individualistic goals or collectivistic aspirations. We use the Hofstede scores from the Hofstede website[10]. These authors divide cultural similarities into six different dimensions of a society's attitudes and responses: 1) Power Distance, 2) Individualism versus Collectivism, 3) Masculinity versus Femininity, 4) Uncertainty Avoidance, 5) Long Term versus Short Term Orientation, and 6) Indulgence versus Restraint. It is important to include cultural similarity as culture influences can affect a nation's economic performance, as well as the economic exchange between countries (Guiso et al. (2006 and 2009)). Moreover, Chui, Titman, and Wei (2010) find that national culture influences the performance of momentum strategies. Beracha et al. (2014) find that institutional investors trade less frequently in culturally distant countries. We estimate cultural similarity hence as follows:

$$F_{i,j}^{Culture} = \left| Culture_i - Culture_j \right|. \tag{A2}$$

[10] https://www.geert-hofstede.com/

where $Culture_i$ is the average value of the six Hofstede scores for country *i*.

Openness Similarity

Instead of using cultural or geographic distance, we use a measure of openness from the Heritage Foundation, accounting for both trade and investment openness. For this purpose we take the average of the trade and the investment openness, which are sub-indices of the Index of Economic Freedom constructed by the Heritage Foundation. Trade freedom is defined as "the absence of tariff and non-tariff barriers that affect imports and exports of goods and services" (The Heritage Foundation, 2014). Investment freedom is determined by the number of restrictions on foreign investment, such as restrictions on real estate purchases, foreign exchange and capital controls, different national treatment of foreign investment, bureaucracy, expropriation of investment, etc. We calculate the openness proximity between two countries *i* and *j* as:

$$F_{i,j,t}^{open} = | Open_{i,t} - Open_{j,t} |, \quad \text{(A3)}$$

where $Open_{i,t}$ is the openness score in country *i* at period *t*.

Bank foreign exposure

It is important to account for financial integration since the international banking system is becoming a more important conduit for the transfer of capital across countries as has been shown by the dramatic increase in international bank foreign claims in the last 20 years prior to the crisis (see McGuire and Tarashev (2008)). The increase in cross-border bank flows can be explained by the global banking channel recently modelled in Bruno and Shin (2014). The main idea is that banks in advanced economies rely heavily on wholesale funding – much of which may have come from abroad. International banks may grow their foreign claims portfolio through two channels. They can establish affiliates in different countries and extend claims locally through their branches and subsidiaries in these countries or they can extend cross-border flows by booking the claims and liabilities from outside the recipient or host countries.

On the asset side, an increase in foreign bank assets exposure is associated with higher credit risk reflecting also an increase in leverage. For example, a liquidity problem of the borrowers (e.g, foreclosure and bankruptcy) increases the credit risk of the lender. The latter can respond to that by decreasing his balance sheet exposure and reducing both foreign and domestic credit supply. Moreover, since large banks borrow from the wholesale market most liabilities are short-term positions in foreign currency while most assets are long-term positions in local currency increasing the maturity mismatch and the currency risk.

On the liability side, in turn, there is a funding risk since banks not only lend to foreign borrowers but they also rely heavily on funding from abroad, especially from other banks. The growth of foreign bank inflows can lead to an increase in asset prices either directly by pushing up demand for domestic assets or by facilitating more rapid credit growth in addition to domestic deposits and other domestic sources. The strong credit growth in many developed countries prior to the crisis could have been driven by the increasing dominance of capital flows from foreign banks, meaning that these countries were more prone to international developments in credit markets (see also Allen et al (2011)).

We calculate the ratio of the bank claims between each two countries to the sum of total bank claims of each of the two countries:

$$F_{i,j,t}^{bank} = \frac{Claim_{i,j,t} + Claim_{j,i,t}}{\sum_k Claim_{i,k,t} + \sum_k Claim_{k,i,t}}, \tag{A4}$$

where $Claim_{i,j,t}$ stands for the bank claim from country i to country j. $F_{i,j,t}^{bank}$ measures the importance of country j for country i in terms of bank integration and $k = 1,\ldots, N$.

Interest rate convergence

Previous research uses the degree of interest rate convergence across countries as a measure of financial integration (see Marston (1997) and Asgharian et al. (2013)) because it could capture the degree of financial liberalisation. The co-movement across returns in countries with high interest rate convergence can be explained by arbitrage-free conditions leading to more efficient capital relocation.

We use the difference in the 3-month money market rate (*IR*) between country *i* and country *j* and also account for fluctuations in exchanges rate by subtracting the purchasing power parity (PPP) between the two countries:

$$F_{i,j,t}^{IR} = \left| IR_{i,t} - IR_{j,t} - E_{t-1}\left(\frac{FX_{ij,t}}{FX_{ij,t-1}} - 1 \right) \right|, \tag{A5}$$

where $FX_{i,j}$ is the expected growth of the price of one unit of currency in country *j* in terms of the currency in country *i* and *IR* is the interest rate.

Foreign direct investment

Foreign direct investment can foster business cycle synchronisation across countries through demand and supply side channels so that countries with stronger FDI linkages can be more heavily exposed to co-movements in asset returns than countries with little investment exposure.

We calculate the importance of country *j* for country *i* by taking the FDI between the two countries

as a proportion of the total FDI[11] of country *i* with all other countries:

$$F_{i,j,t}^{FDI} = \frac{Outward_{i,j,t} + Outward_{i,j,t}}{\sum_k Outward_{i,k,t} + \sum_k Outward_{k,i,t}}. \quad \text{(A6)}$$

where $Outward_{i,j,t}$ stands for the outward foreign direct investment from country *i* to country *j*, and $k = 1,\ldots, N$.

Inflation convergence

It is also important to account for inflation convergence across countries as a measure of proximity since real estate provides a good hedge against inflation (see, e.g., Ely and Robinson (1997), Hoesli et al. (2008)). Transmission occurs when the existence of purchasing power parity (PPP) induces investors to try to hedge domestic assets with foreign real estate since inflation differences among those countries do not exist (see Cooper and Kaplanis (1994)). Previous research shows that inflation convergence has a positive impact on stock market co-movement. Hardouvelis et al. (2006) find a positive relationship between inflation proximity and stock market integration among euro area countries while Johnson and Soenen (2002) reach a similar conclusion for Asian economies. More recently, Asgharian et al. (2013) find that inflation convergence increases the co-movement across stock market returns using a sample of 41 countries.

The inflation proximity between two countries is calculated as:

$$F_{i,j,t}^{cpi} = \left| INFL_{i,t} - INFL_{j,t} - E_{t-1}\left(\frac{FX_{ij,t}}{FX_{ij,t-1}} - 1 \right) \right|, \quad \text{(A7)}$$

where $FX_{i,j}$ is the expected growth of the price of one unit of currency in country *j* in terms of the currency in country *i* and *INFL* is the inflation rate.

[11] The FDI linkage can also be defined based on the outward and inward FDI separately, e.g. $F_{i,j,t}^{Out} = \frac{Outward_{i,j,t}}{\sum_k Outward_{i,j,t}}$, and $F_{i,j,t}^{In} = \frac{Inward_{i,j,t}}{\sum_k Inward_{i,j,t}}$, but both weights generate very similar results, and also similar results with the weight based on total inward and outward FDI. The reason may be in the small difference between the outward FDI flow and the inward FDI flow. Therefore, we only report the results based on total FDI.

Appendix 2: Proof of diversifiable and non-diversifiable spillover risk

The spatial CAPM model with a single factor is given as:

$$r_{i,t} = \alpha_i + \rho \sum_{j=1, j\neq i}^{N-1} w_{i,j,t} r_{j,t} + f_t \beta_i + e_{i,t} \quad \text{(B1)}$$

with $r_{t,i}$ is the excess return of asset i (i = 1,2.., N) in period t (t = 1,2.., T). f_t denotes a common factor such as the excess market return and $f_t \sim N(\bar{r}_m, \sigma_m^2)$. $e_{i,t}$ is the error term with $e_{i,t} \sim N(0, \sigma_{e_i}^2)$. $w_{i,j,t}$ is the element of the $N \times N$ matrix W_t, which has zero in the diagonal terms and standardized rows so that $\sum_{j=1, j\neq i}^{N} w_{i,j,t} = 1$. W_t is assumed to have bounded row and column norms, which implies that each unit has a finite number of neighbors that does not increase with N. ρ is the spatial autoregressive coefficient capturing the degree of comovement across the returns. β_i is the sensitivity of asset i to factor f.

In a matrix form, Equation (B1) can be written as:

$$r_t = \alpha + \rho W_{N,t} r_t + f_t \beta + e_t . \quad \text{(B2)}$$

The reduced form of Equation (B2) is given as:

$$\tilde{r}_t = (I - \rho W_{N,t})^{-1} \alpha + (I - \rho W_{N,t})^{-1} f_t \beta + (I - \rho W_{N,t})^{-1} e_t \quad \text{(B3)}$$

We define $v_{i,j,t}$ as the elements of an $N \times N$ matrix V_t and $V_t = (I - \rho W_t)^{-1} = I + \rho W_t + \rho^2 W_t^2 + \ldots$, so going back to the non-matrix representation for simplicity, Equation (B1) can be re-written as:

$$\begin{aligned} r_{i,t} = & \left[\alpha_i + (v_{i,i,t} - 1)\alpha_i + \sum_{k=1, k\neq i}^{N} v_{i,k,t} \alpha_k \right] + \left[\beta_i + (v_{i,i,t} - 1)\beta_i + \sum_{k=1, k\neq i}^{N} v_{i,k,t} \beta_k \right] f_t \\ & + \left[e_{i,t} + (v_{i,i,t} - 1) e_{i,t} + \sum_{k=1, k\neq i}^{N} v_{i,k,t} e_{k,t} \right] \end{aligned} . \quad \text{(B4)}$$

Let $s_{i,t}$ be the pre-determined weights used for the construction of portfolios based on the assets i = 1, …, N and assuming that the following granularity conditions hold for all $t \in \mathrm{T}$, we construct a portfolio $\sum_{i=1}^{N} s_{i,t-1} r_{it}$. Assuming that $\mathrm{cov}(f_t, e_{i,t}) = 0$, the total risk of the portfolio (Σ) can be calculated as:

$$\Sigma = \mathrm{var}(\sum_{i=1}^{N} s_{i,t-1} r_{it}) = \mathrm{var}\left\{ \sum_{i=1}^{N} s_{i,t-1} \left[\beta_i + (v_{i,i,t} - 1)\beta_i + \sum_{k=1,k\neq i}^{N} v_{i,k,t}\beta_k \right] f_t \right\}$$
$$+ \mathrm{var}\left[\sum_{i=1}^{N} s_{i,t-1} \left(e_{i,t} + (v_{i,i,t} - 1)e_{i,t} + \sum_{k=1,k\neq i}^{N} v_{i,k,t} e_{k,t} \right) \right] \quad \text{(B5)}$$

Equation (B5) decomposes the total variance of the portfolio into two parts, market risk related variance (Z) and idiosyncratic risk related variance (Ω):

$$\Sigma = \mathrm{Z} + \Omega. \quad \text{(B6)}$$

For idiosyncratic risk related variance, Ω, in Equation (B6) we have:

$$\Omega = \sum_{i=1}^{N} s_{i,t-1}^2 \left\{ \sigma_{e_i}^2 + (v_{i,i,t} - 1)\sigma_{e_i}^2 + \sum_{k=1,k\neq i}^{N} v_{i,k,t}\sigma_{e_k}^2 \right\}$$
$$= \sum_{i=1}^{N} s_{i,t-1}^2 \sigma_{e_i}^2 + \sum_{i=1}^{N} s_{i,t-1}^2 (v_{i,i,t} - 1)\sigma_{e_i}^2 + \sum_{i=1}^{N} \sum_{k=1,k\neq i}^{N} s_{i,t-1}^2 v_{i,k,t}\sigma_{e_k}^2 \quad \text{(B7)}$$

B7 decomposes the idiosyncratic related variance also into two parts Ω_t^E and Ω_t^{ES}:

$$\Omega_t^E = \sum_{i=1}^{N} s_{i,.t-1}^2 \sigma_{e_i}^2 \quad \text{(B8)}$$

is the part of risk due to orthogonal idiosyncratic risks, and the rest:

$$\Omega_t^{ES} = \sum_{i=1}^{N} s_{i,t-1}^2 (v_{i,i,t} - 1)\sigma_i^2 + \sum_{i=1}^{N} \sum_{k=1,k\neq i}^{N} s_{i,t-1}^2 v_{i,k,t}\sigma_k^2 \quad \text{(B9)}$$

is the spillover of idiosyncratic risk.

In an equally-weighted portfolio we have $s_{i,.t-1} = \frac{1}{N}$ so that:

$$\Omega_t^E = \sum_{i=1}^{N} s_{i,.t-1}^2 \sigma_i^2 = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2 = \frac{1}{N} \bar{\sigma}^2; \quad \text{(B10)}$$

with $\bar{\sigma}^2 = \frac{1}{N} \sum_{i=1}^{N} \sigma_i^2$. For the spillover part we have:

$$\Omega_t^{ES} = \sum_{i=1}^{N} s_{i,t-1}^2 (v_{i,i,t} - 1)\sigma_i^2 + \sum_{i=1}^{N} s_{i,t-1}^2 \sum_{k=1,k\neq i}^{N} v_{i,k,t}\sigma_k^2 = \frac{1}{N^2}\sum_{i=1}^{N}(v_{i,i,t} - 1)\sigma_i^2 + \frac{1}{N^2}\sum_{k=1,k\neq i}^{N} v_{i,k,t}\sigma_k^2$$
$$= \frac{1}{N}(\bar{v}_t - 1)\bar{\sigma}^2 + \frac{1}{N}\bar{\sigma}^{*2} \quad . \qquad \text{(B11)}$$

with $\bar{\sigma}^{*2} = \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1,k\neq i}^{N} v_{i,k,t}\sigma_i^2$.

Taking the limit for (B10) when the number of assets in the portfolio goes to infinity, we have:

$$\lim_{N\to\infty} \Omega_t^E = 0 \qquad \text{(B12)}$$

which implies that when the number of assets goes to infinity, the risk due to the orthogonal idiosyncratic risk can be fully diversified.

Taking the limit for (B11) when the number of assets in the portfolio goes to infinity, we have:

$$\lim_{N\to\infty} \Omega_t^{ES} = 0 . \qquad \text{(B13)}$$

which implies that when the number of assets goes to infinity, the risk due to the spillover of idiosyncratic risk can be fully diversified. Hence for the total residual variance we have:

$$\lim_{N\to\infty} \Omega_t = \lim_{N\to\infty} \Omega_t^{ES} + \lim_{N\to\infty} \Omega_t^{S} = 0 . \qquad \text{(B14)}$$

which implies that when the number of assets goes to infinity, the total risks that come from idiosyncratic risk can be fully diversified.

For the market risk related variance, Z, in Equation (B6) we have:

$$Z = \sum_{i=1}^{N}\left\{ s_{i,t-1}^2 \left[\beta_i^2 + (v_{i,i,t} - 1)^2 \beta_i^2 + \sum_{k=1,k\neq i}^{N} v_{i,k,t}^2 \beta_k^2 \right]\sigma_f^2 \right\}$$
$$+ \sum_{i=1}^{N}\sum_{j=1}^{N-1}\left\{ s_{i,t-1}s_{j,t-1}\left[\beta_i + (v_{i,i,t} - 1)\beta_i + \sum_{k=1,k\neq i}^{N} v_{i,k,t}\beta_k \right]\left[\beta_j + (v_{j,j,t} - 1)\beta_j + \sum_{k=1,k\neq j}^{N} v_{j,k,t}\beta_k \right]\sigma_f^2 \right\} . \qquad \text{(B15)}$$

Similar to the above, we can decompose Equation (B15) into a strictly market component and the spillover component. The first one is given as:

$$Z_t^M = \sum_{i=1}^{N} s_{i,t-1}^2 \beta_i^2 \sigma_f^2 + \sum_{i=1}^{N}\sum_{j=1}^{N-1} s_{i,t-1}s_{j,t-1}\beta_i\beta_j\sigma_f^2 . \qquad \text{(B16)}$$

The spillover component is given as:

$$Z_t^{MS} = \sum_{i=1}^{N}\left\{ s_{i,t-1}^2 \left[(v_{i,i,t}-1)^2 \beta_i^2 + \sum_{k=1,k\neq i}^{N} v_{i,k,t}^2 \beta_k^2 \right] \sigma_f^2 \right\}$$
$$+\sum_{i=1}^{N}\sum_{j=1}^{N-1}\left\{ s_{i,t-1}s_{j,t-1} \left[(v_{i,i,t}v_{j,j,t}-1)\beta_i\beta_j + v_{j,j,t}\beta_i \sum_{k=1,k\neq i}^{N} v_{i,k,t}\beta_k + v_{i,i,t}\beta_j \sum_{k=1,k\neq j}^{N} v_{j,k,t}\beta_k + \sum_{k=1,k\neq i}^{N}\sum_{k=1,k\neq j}^{N} v_{i,k,t}v_{j,k,t}\beta_k^2 \right] \sigma_f^2 \right\} \quad \text{(B17)}$$

Define $\beta_{i,t}^* = \sum_{k=1,k\neq i}^{N} v_{i,k,t}\beta_k$, B17 can be represented as:

$$Z_t^{MS} = \sum_{i=1}^{N}\left\{ s_{i,t-1}^2 \left[(v_{i,i,t}-1)^2 \beta_i^2 + \beta_{i,t}^{*2} \right] \sigma_f^2 \right\}$$
$$+\sum_{i=1}^{N}\sum_{j=1}^{N-1}\left\{ s_{i,t-1}s_{j,t-1} \left[(v_{i,i,t}v_{j,j,t}-1)\beta_i\beta_j + v_{j,j,t}\beta_i\beta_{i,t}^* + v_{i,i,t}\beta_j\beta_{j,t}^* + \beta_{i,t}^*\beta_{j,t}^* \right] \sigma_f^2 \right\} . \quad \text{(B18)}$$

In the case of $s_{i,.t-1} = \frac{1}{N}$ for all *i*-s, we obtain $\bar{\beta} = \frac{1}{N}\sum_{i=1}^{N}\beta_i$, $\bar{\beta}_t^* = \frac{1}{N}\sum_{i=1}^{N}\beta_{i,t}^*$ and $\bar{v}_t = \frac{1}{N}\sum_{i=1}^{N} v_{i,i,t}$ And rewrite Equations (16) and (18) as follows:

$$Z_t^M = \frac{N}{N^2}\bar{\beta}^2\sigma_f^2 + \frac{N(N-1)}{N^2}\bar{\beta}^2\sigma_f^2 \text{ and} \quad \text{(B19)}$$

$$Z_t^{MS} = \frac{1}{N}[(\bar{v}_t-1)^2\bar{\beta}^2 + \bar{\beta}_t^{*2}]\sigma_f^2 + \frac{N(N-1)}{N^2}[(\bar{v}_t-1)^2\bar{\beta}^2 + 2\bar{v}_t\bar{\beta}\bar{\beta}_t^* + \bar{\beta}_t^{*2}]\sigma_f^2 . \quad \text{(B20)}$$

For the limit of B(19) and B(20) we obtain:

$$\lim_{N\to\infty} Z_t^M = \bar{\beta}^2\sigma_f^2 ; \quad \text{(B21)}$$

which indicates that the strictly market risk cannot be fully diversified by holding enough assets. Regarding the spillover component of market risk, we have:

$$\lim_{N\to\infty} Z_t^{MS} = [(\bar{v}_t-1)^2\bar{\beta}^2 + 2\bar{v}_t\bar{\beta}\bar{\beta}_t^* + \bar{\beta}_t^{*2}]\sigma_f^2 . \quad \text{(B22)}$$

The total market risk is the sum of the strictly market risk and the spillover component of the market risk:

$$\lim_{N\to\infty} Z_t = \lim_{N\to\infty} Z_t^M + \lim_{N\to\infty} Z_t^{MS} = \bar{\beta}^2\sigma_f^2 + [(\bar{v}_t - 1)^2\bar{\beta}^2 + 2\bar{v}_t\bar{\beta}\bar{\beta}_t^* + \bar{\beta}_t^{*2}]\sigma_f^2 = \left(\bar{v}_t\bar{\beta} + \bar{\beta}_t^*\right)^2\sigma_f^2 . \quad \text{(B23)}$$

If we only consider neighbors of the first order: $V_t = (I - \rho W_t)^{-1} \approx I + \rho W_t$, then $v_{i,i,t} = 1$ and $\beta_{i,t}^* = \sum_{k=1,k\neq i}^{N} \rho w_{i,k,t}\beta_k$, for i=1,2,…N, and for $t \in \mathrm{T}$.

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \beta_{i,t}^* = \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1,k\neq i}^{N} \rho w_{i,k,t}\beta_k = \rho\bar{\beta} . \quad \text{(B24)}$$

Hence, we have the limit of the spillover of market risk as:

$$\lim_{N\to\infty} Z_t^{MS} = \rho[2\bar{\beta} + \rho\bar{\beta}^2]\sigma_f^2 . \quad \text{(B25)}$$

When $-1 < \rho < 1$ and $\rho \neq 0$, the part of the spillovers triggered by market risk cannot be diversified.

The total market risk is:

$$\lim_{N\to\infty} Z_t = (\bar{\beta}^2 + 2\rho\bar{\beta} + \rho^2\bar{\beta}^2)\sigma_f^2 = \bar{\beta}^2(1+\rho)^2\sigma_f^2 . \quad \text{(B26)}$$

Table A1: Descriptive Statistics

Dependent variable: listed real estate index returns on country level

Real estate return	**AU**	**BE**	**CA**	**FI**	**FR**	**DE**	**IT**	**JP**	**NL**	**ES**	**SE**	**CH**	**UK**
Mean	0.001	0.000	0.000	0.005	0.005	0.000	-0.002	0.001	0.000	-0.012	0.002	0.005	0.001
Std	0.044	0.037	0.061	0.113	0.050	0.072	0.090	0.085	0.045	0.110	0.092	0.045	0.060
Max	0.121	0.146	0.173	0.692	0.144	0.338	0.342	0.230	0.128	0.228	0.398	0.195	0.222
Min	-0.27	-0.20	-0.44	-0.51	-0.24	-0.34	-0.37	-0.24	-0.18	-0.58	-0.40	-0.21	-0.25
Correlation													
AU													
BE	0.348												
CA	0.351	0.195											
FI	0.216	0.316	0.164										
FR	0.409	0.525	0.280	0.476									
DE	0.267	0.259	0.220	0.269	0.474								
IT	0.332	0.461	0.258	0.328	0.510	0.403							
JP	0.281	0.173	0.264	0.197	0.333	0.209	0.245						
NL	0.416	0.509	0.323	0.448	0.746	0.452	0.534	0.321					
ES	0.348	0.387	0.179	0.193	0.385	0.154	0.386	0.125	0.369				
SE	0.258	0.405	0.040	0.338	0.483	0.257	0.317	0.209	0.416	0.173			
CH	0.283	0.356	0.250	0.186	0.498	0.311	0.365	0.194	0.468	0.321	0.262		
UK	0.416	0.391	0.294	0.375	0.617	0.455	0.357	0.283	0.552	0.295	0.405	0.419	
US	0.514	0.325	0.451	0.306	0.498	0.431	0.343	0.335	0.515	0.104	0.292	0.325	0.594

Explanatory variables

	Global market return	**SMB**	**HML**	**WML**	**Risk-free rate**	**Global listed real estate return**	**Global direct real estate return**
Mean	0.004	0.001	0.004	0.006	0.003	0.004	0.067
Std	0.044	0.021	0.024	0.041	0.002	0.055	0.061
Max	0.114	0.103	0.112	0.179	0.006	0.182	0.132
Min	-0.195	-0.097	-0.096	-0.239	0.000	-0.330	-0.085
Correlation	**with**	**dependent**	**variable**				
AU	0.511	-0.107	0.060	-0.092	0.511	0.580	0.181
BE	0.310	0.012	0.122	-0.143	0.310	0.365	0.081
CA	0.357	0.010	0.225	-0.136	0.357	0.444	0.178
FI	0.317	0.125	0.104	-0.137	0.317	0.398	0.044
FR	0.523	0.068	0.161	-0.237	0.523	0.611	0.114
DE	0.426	0.077	0.088	-0.207	0.426	0.426	0.089
IT	0.420	0.147	-0.020	-0.124	0.420	0.389	0.108
JP	0.476	0.036	0.155	-0.161	0.476	0.489	0.120
NL	0.526	0.005	0.162	-0.206	0.526	0.610	0.097
ES	0.267	0.054	0.105	-0.043	0.267	0.257	0.173
SE	0.333	0.023	0.085	-0.117	0.333	0.381	0.173
CH	0.329	0.045	0.150	-0.100	0.329	0.423	0.121
UK	0.485	0.039	0.251	-0.317	0.485	0.641	0.157
US	0.588	0.029	0.240	-0.288	0.588	0.794	0.018

Table A2: Coefficients of common factors for excess real estate returns in individual countries based on the CAPM using FDI weights

Note: The model is estimated from 1991M1 to 2012M12. The dependent variable is the log difference of the excess listed property index for each country in each month. The coefficients reported are based on equation $r_{i,t} - r_t^{rf} = \alpha_i + \beta_{1i}(r_t^M - r_t^{rf}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}WML_t + u_{i,t}$. *95% Bayesian credible interval is in parentheses.* [a] *denotes significance at the 5% level. SMB – returns of small minus big portfolios, HML – returns of high minus low book-to-market portfolios, WML – returns of winners minus losers portfolios capturing the momentum effects.*

	α	$r_t^M - r_t^{rf}$	SMB	HML	WML
AU	-0.003	0.435 [a]	-0.222	0.181	0.085
	[-0.008;0.003]	[0.302;0.565]	[-0.470;0.038]	[-0.062;0.430]	[-0.047;0.221]
BE	-0.004	0.258 [a]	-0.006	0.260 [a]	-0.021
	[-0.009;0.002]	[0.129;0.383]	[-0.262;0.249]	[0.030;0.488]	[-0.162;0.121]
CA	-0.001	0.412 [a]	0.140	0.558 [a]	-0.012
	[-0.007;0.004]	[0.271;0.559]	[-0.129;0.416]	[0.315;0.806]	[-0.158;0.133]
FI	-0.007 [a]	0.740 [a]	0.755 [a]	0.534 [a]	-0.085
	[-0.014;-0.001]	[0.589;0.892]	[0.453;1.070]	[0.251;0.831]	[-0.252;0.088]
FR	-0.001	0.601 [a]	0.359 [a]	0.501 [a]	-0.066
	[-0.007;0.004]	[0.461;0.732]	[0.108;0.611]	[0.261;0.740]	[-0.204;0.069]
DE	-0.005	0.512 [a]	0.342 [a]	0.396 [a]	-0.096
	[-0.011;0.002]	[0.357;0.665]	[0.041;0.641]	[0.123;0.681]	[-0.251;0.055]
IT	-0.011 [a]	0.789 [a]	0.641 [a]	0.482 [a]	-0.132
	[-0.019;-0.004]	[0.607;0.978]	[0.326;0.969]	[0.206;0.794]	[-0.298;0.035]
JP	-0.011 [a]	1.012 [a]	0.253	0.860 [a]	-0.053
	[-0.018;-0.004]	[0.863;1.163]	[-0.086;0.612]	[0.520;1.207]	[-0.262;0.156]
NL	-0.006 [a]	0.533 [a]	0.117	0.428 [a]	-0.005
	[-0.012;-0.001]	[0.409;0.658]	[-0.133;0.393]	[0.191;0.662]	[-0.146;0.142]
ES	-0.012 [a]	0.731 [a]	0.437 [a]	0.614 [a]	0.072
	[-0.020;-0.004]	[0.534;0.928]	[0.069;0.791]	[0.264;0.967]	[-0.158;0.286]
SE	-0.003	0.675 [a]	0.202	0.451 [a]	-0.072
	[-0.009;0.004]	[0.517;0.834]	[-0.083;0.490]	[0.166;0.746]	[-0.234;0.099]
CH	-0.001	0.327 [a]	0.100	0.293 [a]	0.017
	[-0.006;0.005]	[0.195;0.467]	[-0.157;0.360]	[0.064;0.520]	[-0.110;0.153]
UK	-0.005	0.637 [a]	0.357 [a]	0.697 [a]	-0.244 [a]
	[-0.011;0.001]	[0.500;0.776]	[0.087;0.634]	[0.454;0.958]	[-0.391;-0.077]
US	0.000	0.672 [a]	0.203	0.672 [a]	-0.057
	[-0.006;0.006]	[0.531;0.823]	[-0.048;0.462]	[0.428;0.927]	[-0.201;0.101]

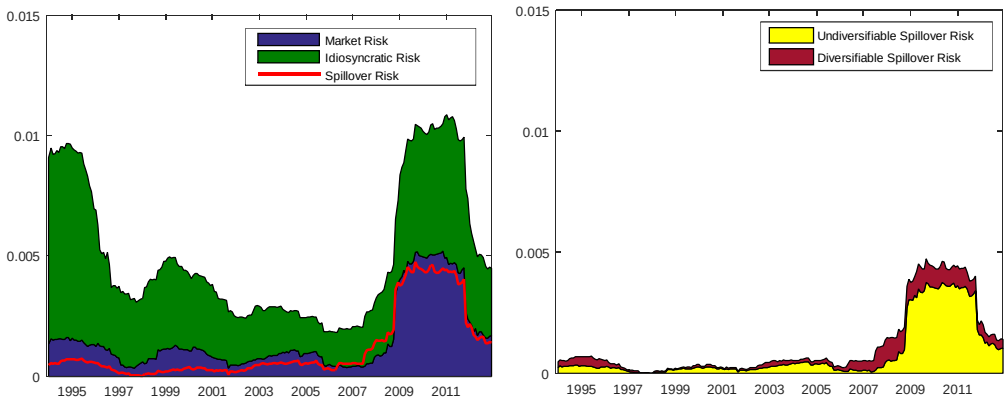
Table A3: Coefficients of common factors for excess real estate returns in individual countries based on the SCAPM using FDI weights

Note: The model is estimated from 1991M1 to 2012M12. The dependent variable is the log difference of the excess listed property index for each country in each month. The reported coefficients are based on equation $r_{i,t} - r_t^{rf} = \rho \sum_{j=1, j\neq i}^{N} w_{j,i,t}(r_{i,t} - r_t^{rf}) + \alpha_i + \beta_{1i}(r_t^M - r_t^{rf}) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} WML_t + u_{i,t}$ *. 95% Bayesian credible interval is in parentheses.* [a] *denotes significance at the 5% level. SMB – returns of small minus big portfolios, HML – returns of high minus low book-to-market portfolios, WML – returns of winners minus losers portfolios capturing the momentum effects.*

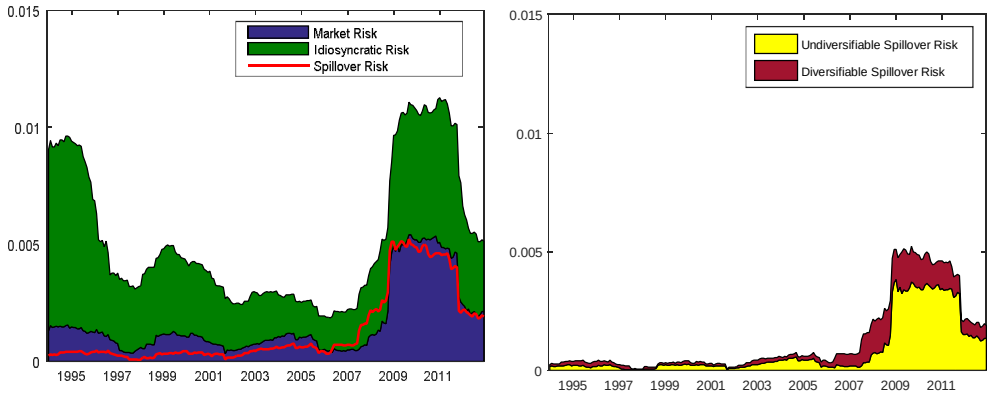
	α	$r_t^M - r_t^{rf}$	SMB	HML	WML
AU	-0.001	0.103	-0.353 [a]	-0.138	0.128 [a]
	[-0.006;0.004]	[-0.027;0.227]	[-0.598;-0.123]	[-0.352;0.071]	[0.006;0.252]
BE	-0.002	-0.052	-0.124	0.016	0.025
	[-0.007;0.003]	[-0.174;0.073]	[-0.362;0.120]	[-0.193;0.222]	[-0.090;0.147]
CA	-0.001	0.065 [a]	0.019	0.227 [a]	0.069
	[-0.007;0.004]	[-0.067;0.194]	[-0.226;0.264]	[0.006;0.449]	[-0.070;0.202]
FI	-0.003	0.490 [a]	0.666 [a]	0.416 [a]	-0.052
	[-0.008;0.003]	[0.357;0.620]	[0.413;0.927]	[0.160;0.672]	[-0.200;0.097]
FR	0.002	0.281 [a]	0.177	0.211	-0.034
	[-0.004;0.007]	[0.159;0.401]	[-0.065;0.409]	[-0.002;0.422]	[-0.160;0.093]
DE	-0.004	0.273 [a]	0.204	0.105	-0.073
	[-0.009;0.002]	[0.136;0.407]	[-0.058;0.470]	[-0.155;0.361]	[-0.214;0.064]
IT	-0.008 [a]	0.490 [a]	0.505 [a]	0.103	-0.083
	[-0.014;-0.002]	[0.335;0.643]	[0.218;0.785]	[-0.147;0.369]	[-0.232;0.072]
JP	-0.008 [a]	0.602 [a]	0.190	0.503 [a]	0.011
	[-0.014;-0.002]	[0.454;0.753]	[-0.114;0.487]	[0.195;0.801]	[-0.172;0.198]
NL	-0.004	0.195 [a]	-0.054	0.133	0.025
	[-0.009;0.001]	[0.075;0.313]	[-0.281;0.193]	[-0.084;0.351]	[-0.109;0.151]
ES	-0.015 [a]	0.447 [a]	0.349 [a]	0.487 [a]	0.171 [a]
	[-0.022;-0.008]	[0.288;0.602]	[0.049;0.652]	[0.219;0.769]	[0.001;0.342]
SE	-0.001	0.331 [a]	0.012	0.155	0.010
	[-0.007;0.005]	[0.192;0.470]	[-0.240;0.261]	[-0.114;0.406]	[-0.138;0.155]
CH	0.001	-0.008	-0.023	-0.000	0.074
	[-0.004;0.007]	[-0.131;0.114]	[-0.248;0.198]	[-0.210;0.217]	[-0.059;0.202]
UK	-0.003	0.300 [a]	0.217	0.401 [a]	-0.202 [a]
	[-0.008;0.003]	[0.176;0.424]	[-0.032;0.479]	[0.186;0.615]	[-0.337;-0.066]
US	0.002	0.414 [a]	0.118	0.431 [a]	-0.053
	[-0.003;0.007]	[0.284;0.550]	[-0.128;0.361]	[0.206;0.649]	[-0.192;0.082]

Figure A1: Variance decomposition based on a SCAPM with different weights – average across countries

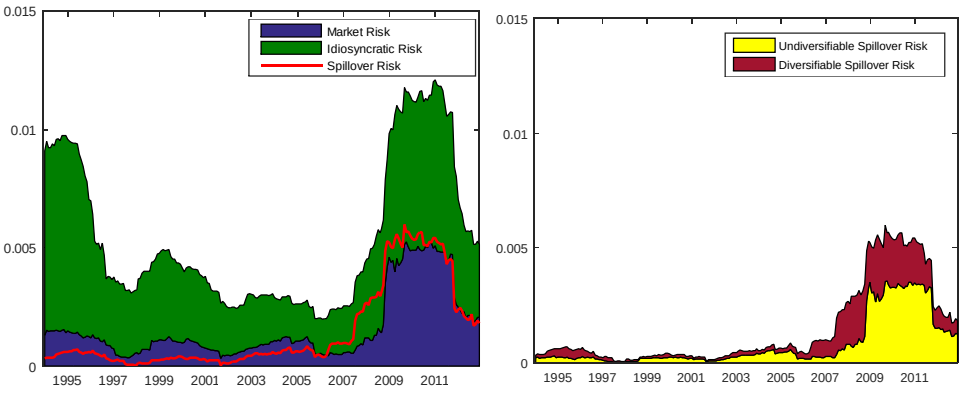
Portfolio



CPI Convergence



Interest Rate Convergence



Cultural Similarity

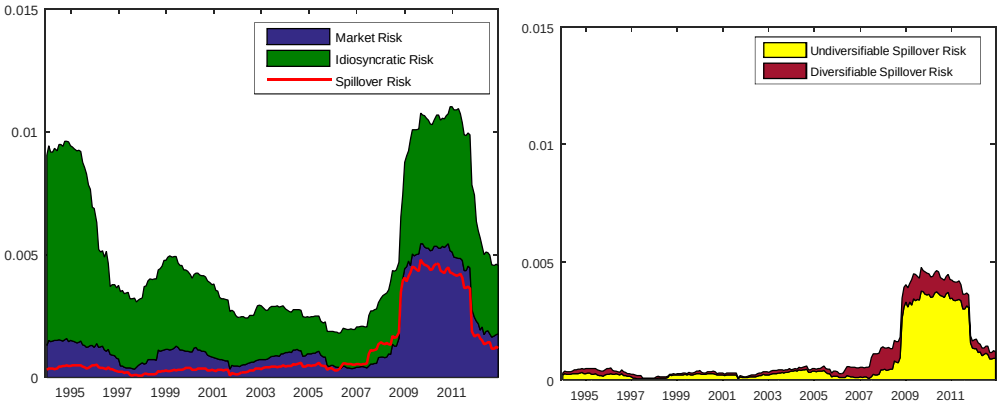
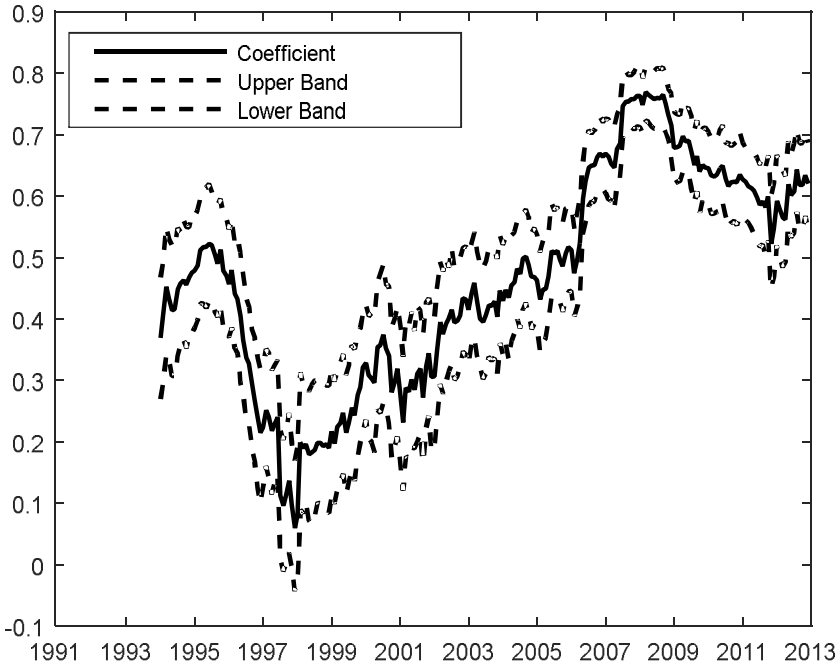



Figure A2: Estimated spatial coefficients (ρ) with FDI linkages based on 36-month rolling windows