The Pricing of Spatial Linkages in Companies' Underlying Assets

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Abstract

Spatial linkages in returns have not yet received much attention in an asset pricing context, however, they can capture important information about returns in a lemons market with heterogeneous assets such as real estate. We explain abnormal returns of real estate companies by modelling the spatial comovement across their underlying assets. We connect stocks using the location of their underlying assets, the properties. We show that the degree of spatial comovement across the underlying assets explains the variation in abnormal returns, controlling for exposure to systematic return factors. We propose a trading strategy which exploits the information contained in the spatial linkages of the underlying assets. We show that a long-short hedge strategy exacerbates this excess comovement in returns. An investment strategy which buys the stocks that experience an increase in their price if their connected stocks have also gone up and sells the stocks that experience a drop if their connected stocks have also gone down can earn a non-market return of an annual 12%.

Keywords: Asset pricing, Factor Models, Spatial Linkages, Real Estate, Hedging Strategies.

JEL classification: G11, G12, C21, C23.

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I. Introduction

This paper investigates how information contained in spatial linkages of companies' underlying assets can be accounted for in an asset pricing context. In particular we use stocks of listed real estate companies such as Real Estate Investment Trusts (REITs) to show the pricing of spatial linkages. The REITs can be seen as portfolios of direct real estate assets and their performance is thus highly dependent of the performance of their properties. Given that the real estate market is highly heterogeneous with assets being of different quality and with buyers and sellers having heterogeneous information about the traded assets, we argue that information about the REITs can be extracted from the spatial linkages across the properties. In such markets, spatial linkages in the underlying assets can cause comovements in the returns of the REITs beyond the comovement implied through their fundamentals. Fu and Gupta-Mukherejee (2014) argue that in financial markets which are characterised with large frictions in dissemination of information, market participants can acquire information through informal channels such as the links between funds and the links between funds and companies. Coval and Moskowitz (2001) argue that geographic proximity matters as local fund manager can access local information more easily and monitor the operations of the local companies. Hong et al. (2005) discuss the word-of-mouth channel through fund managers in the same location have correlated strategies. One way comovement can happen between the underlying assets of companies is through the price pressure channel. Price pressure effects on asset pricing have predominantly been studied in the context of stock markets dating back to Scholes (1972). He argues that stock prices can diverge from their information-efficient value following uninformed demand shocks by the capital providers. There have been a number of models developed ever since to explain pricing in markets with impatient sellers which leads to fire sales. Fire sales refer to situations in which market participants face urgency for funds and sell assets at prices that are below the usual price (Kurlat (2016)). Starting from Akerlof (1970)'s lemons market problem in which sellers are informed but buyers are uninformed, information theories have evolved to show how heterogeneous market information about the traded assets can affect their pricing. Shleifer and Vishny (1992, 1997) and Kiyotaki and Moore (1997) present models of fire sales that are well suited for markets for real assets such as real estate as those assets can be given alternative uses. The models in Fostel and Geanakoplos (2008) and Geanakoplos (2009) can also be used to explain the pricing of real estate following fire sales. Even though the actual payoffs from holding the real estate are the same for all market participants, the authors show that the changes in prices of assets during a fire sale can be explained if buyers have different opinions about the true value of the asset and face borrowing constraints. Kurlat (2016) presents a model in which differences among buyers stem from the quality of their information. Such a setting can also be applied to housing markets where buyers in general possess different information about the quality of the property and the neighbourhood. In terms of the empirical applications, Coval and Stafford (2007) show that a fire sale in equity markets in the context of common open-end mutual funds is associated with large liquidity premiums and prices below fundamental values. Although stock markets are considered to be highly liquid, Anton and Polk (2014) show that a fire-sale premium exists and it can be explained by institutional ownership of stocks. There is however little research on the connectedness of companies through their underlying assets. We would expect that as the real estate market is much less liquid than the stock market, the fire-sale liquidity premium would be more pronounced. Within the context of the commercial real estate market, the price pressure channel can be set into force in several ways which are explained in more detail in the next section.

When analyzing asset prices in isolation, the classic asset pricing models only account for the time-series variation of the asset with the factors. However, valuable information would be lost if additional cross-sectional dependence exists across the assets. Milcheva and Zhu (2016) show that incorporating a spatial term into a four-factor Fama-French-Carhart model improves the model performance. Spatial equilibrium theories argue that spatial interdependence across agents can explain economic behaviour (Anselin (2003)). In general, the concept developed in spatial econometrics is to capture the effect of a shock at a specific point in space to another place (Haining (2003)). Such models are often used to explain housing transactions, as the prices of the physical assets can depend on the prices of the surrounding buildings (DiPasquale and Wheaton (1995), Fujita and Thisse (2003)). The most common spatial dependence widely studied in the literature is through geographic proximity (Fingleton (2001, 2008)).[3] The reason is that neighbouring regions often keep close economic relationships. Therefore, as Fazio (2007) and Orlov (2009) argue, geographically closer regions would have as a result stronger economic linkages too. 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).

This paper contributes to the existing literature by combining two by now independent approaches – empirical asset price modelling and spatial econometrics – to investigate the information contained in the relationships between companies which result from the proximity in their underlying assets. We conjecture that if a share price increases (falls) following a shock to the company's underlying assets, an increase (drop) in the price of another stock can follow if that firm owns buildings in a close proximity. In addition, we provide a trading strategy for real estate stocks which can achieve significant non-market returns by using the information contained in the spatial linkages of the underlying assets.

Our paper is methodologically related to the works of Barberis and Shleifer (2003), Barberis et al. (2005) and Anton and Polk (2014) who use a factor model to show how stocks comove depending on the degree of common ownership by active mutual funds. In particular, they use the residuals from a five-factor model and look at drivers of residual correlation using a measure of common institutional ownership, controlling for other pair characteristics.[4] In this paper, we adopt a two stage approach. First, we obtain the abnormal returns using a five factor model. In a second step, the variation in the residuals is explained in a spatial panel model using a spatial weight matrix and controlling for a range of company specific characteristics.

[3] More recent literature explores the use of other measures of proximity such as financial and economic integration (Zhu et al. (2013) and Milcheva and Zhu (2015)).

[4] Lou (2012) also shows that looking at the momentum effects in returns, stocks with high expected flows from mutual funds commove.

We model the spatial linkages using a measure of physical distance between the underlying assets. Using locational variables in an asset pricing model is rare but there are a few studies who account for locational factors in addition to the four standard factors. One way to account for the location of the company is to use the location of its headquarters (Pirinsky and Wang (2006)[5]). More recently, Bernile et al. (2015) include a locational dispersion factor which is constructed using locations mentioned in the company's financial reports.[6] Becker et al. (2011) use the location of the large shareholders of a company to relate to the firm's performance. Hong et al. (2008) explain the difference in stock prices of companies located in different areas by the aggregate book value of the firms located and the aggregate risk tolerance of investors in that region. The above measures are, however, an incomplete estimate of the link between firm performance and location. We propose instead a different approach to location by assessing the effect of location relative to the other companies. For this purpose, we use companies whose performance is strongly related to the physical location of their assets as is the case for property companies.[7] Such companies can function as

[5] Pirinsky and Wang (2006) look at the role of the location of the headquarters of the company for its stock returns in an asset pricing context. They find strong comovement across returns of companies located in the same geographic area.

[6] Bernile et al. (2015) construct the measure of firm location by using the number of times a state is mentioned in a given report. They find that including a local market factor explains more of the time-series variation of the returns as compared to only using national market factors. The authors show that international portfolio decision and performance are affected by the information asymmetries created through spatially distributed information. Therefore investors prefer to invest in companies with greater local economic exposure and, overall, such assets perform better.

[7] Looking at direct real estate asset returns may be suboptimal when estimating an asset pricing model as real estate has different properties compared to the traditional investment assets, such as stocks and bonds. Real estate is characterized 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 listed real estate companies since their returns are known to capture the underlying real estate market fluctuations but also provide more liquidity, reduce transaction costs and mitigate indivisibility and short-

funds who invest in income-producing real estate or can be run as operating companies. Most of the real estate companies in the US are real estate investment trusts (REITs) which must derive almost the entire income from the operation of real estate assets and should pay out at least 90% of their taxable income to shareholders, and in exchange benefit from tax reductions. Since most of the performance is driven by the income and the capital growth from the underlying assets, the location of the properties is regarded as one of the most important factors in determining the value of the companies.

Our results show that the degree of locational proximity of the underlying assets of different companies explains the cross-sectional variation in return correlation, controlling for exposure to systematic return factors, sectoral and regional similarity, and range of other individual characteristics. We find that spatial linkages across the companies' underlying assets can serve as an indicator for misvaluation of stocks. We demonstrate that a long-short trading strategy exacerbates the excess comovement. An investment strategy which buys the stocks that experience an increase in their price if their connected stock returns have also gone up and sells the stocks that experience a drop if their connected stock returns have also gone down can earn an average abnormal return of about 12% per year. This is in line with previous findings which find abnormal returns of a long-short strategy extracting information from the institutional ownership of 9% (Anton and Polk (2014)) and 10% (Coval and Stafford (2007)) per year.

II. The price pressure channel

Most of the research on the real estate price pressure channel assesses externalities of housing transaction prices on nearby buildings. Campbell et al. (2011) look at forced sales by analysing prices of foreclosed houses and their effects on neighbouring property prices. The authors show that the price of a house close to a foreclosed property is lower than house prices in an area without foreclosures due to negative

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selling issues.

externalities reflecting things like physical damage to the neighbourhood in which the foreclosed house is located. Similar results have been reported by Harding et al. (2008) and Rossi-Hansberg et al. (2010). Andersen and Nielsen (2016) use a natural experiment to investigate when forced sales turn into fire sales of houses resulting from a sudden death of the owner and is thus independent from demand and supply market shocks. They find that forced sales of house prices trade at a discount which depends on the urgency of the fire sale. The price pressure channel can also be related to the illiquidity concerns when trading illiquid assets. Ang et al. (2014) show that investors in illiquid assets pay an illiquidity premium of 2% of their wealth when they are not able to trade an asset for an uncertain period of time. Within the context of the commercial real estate market, the price pressure channel can be set into force in several ways. First, similar to the idea of shared institutional ownership, real estate funds can face a forced sale. Due to the low liquidity of the asset class, in case of investors willing to withdraw money from the fund, in order for the fund to quickly sell some assets, it needs to do this at a large discount. In such cases, funds can chose to sell buildings in attractive and busy locations in which many other commercial buildings are located as well. This can negatively affect the prices of nearby buildings owned by other real estate companies. Fire sales have been the driver of the bad performance in open-end real estate funds during the GFC and other unexpected market shocks such as the Brexit vote in the UK in June 2016.

Second, price pressure can also result from other drivers such as a major tenant leaving a building and that having negative externalities on the property prices in the area. This can happen if large global corporations employing a lot of people in one area move their operations to a different location. This can then have an impact of the revenue of the smaller businesses located in that area. Also, it could lead to lower rental income for the real estate companies owning properties nearby, negatively affecting their performance. The opposite effect can be observed as well. Positive price externalities can be created if a large tenant moves to a new area attracting smaller tenants, leading to a fall in the vacancy rate of surrounding buildings and an increase in rental income for real estate companies with buildings in that location.

Third, price pressures can also be associated with irrational exuberance (Akerlof and Shiller (2009)) such as overconfidence or overly pessimistic behaviour. Investors in the commercial real estate market can purchase trophy buildings or newly constructed buildings at a price higher that the price of the surrounding buildings. This can put an upward pressure on prices of surrounding buildings.

Fourth, another reason for price pressures on the real estate markets could be associated with positive externalities from urban revitalization, as argued by Rossi-Hansberg et al. (2010). Within the commercial real estate market context, the sale of a property for a price above the expected price for that area can be seen as a signal of an area with high real estate liquidity.

III. Methodology

In finance, asset pricing models are widely used to determine a theoretically appropriate required excess rate of return of an asset. Fama and French (1992) estimate a factor model accounting for systematic differences of size and style across stocks. Carhart (1997) extends the Fama-French three-factor model accounting for momentum. Pastor and Stambaugh (2003) argue the case for adding a market liquidity factor in addition. We include all of the above factors and estimate, in a first stage, a five-factor model, which is given as follows:

$$r_{t,i} = \alpha_i + \beta_{1,i} r_{t,i}^M + \beta_{2,i} SMB_{t,i} + \beta_{3,i} HML_{t,i} + \beta_{4,i} WML_{t,i} + \beta_{5,i} LIQ_{t,i} + \varepsilon_{t,i} \tag{1}$$

with $r_{t,i}$, the excess return of asset *i* (*i* = 1,2.., *N*) in period *t* (*t* = 1,2.., *T*) calculated as $r_{t,i} = \tilde{r}_{t,i} - r_t^{rf}$ with r_t^{rf}, the risk-free rate in period *t* and $\tilde{r}_{t,i}$ the stock return of stock *i* in period *t*. $r_{t,i}^M$ is the excess return on the market. $SMB_{t,i}$ (small minus big) is the average return of a portfolio of small capitalization stocks minus the average return of a portfolio of large capitalization stocks; $HML_{t,i}$ (high minus low) is the difference in returns of a portfolio consisting of high book-to-market stocks and a portfolio of low book-to-market stocks; $WML_{t,i}$ (winners minus losers) is the difference in returns between a portfolio of stocks which have shown positive momentum over the last 12 months a portfolio of stocks which have shown negative momentum over the last 12 months; $LIQ_{t,i}$ is the liquidity factor which is an equally-weighted average of the liquidity measures of individual stocks associated with temporary price fluctuations induced by order flows. α_i represents the average abnormal return for stock *i* and $\beta_{k,i}$ is the sensitivity of the *i*-th asset to the *k*-th factor. $\varepsilon_{t,i}$ is the residual with $\varepsilon_{t,i} \sim N(0, \upsilon_i^2)$.

In a second stage, we estimate an unbalanced spatial panel model which has as a dependent variable the monthly abnormal returns from the individual asset regressions in Equation (1). The explanatory variables consist of a spatial term, the lagged monthly abnormal returns and a host of firm characteristics. The spatial panel model is given as:

$$r_t^{ab} = a + b_0 r_{t-1}^{ab} + \rho \mathbf{W}_t r_t^{ab} + \sum_{k=1}^{K} b_k controls_t + u_{t,i} \tag{2}$$

where r_t^{ab} is the vector of abnormal returns at time *t*. We combine the asset residuals from Equation (1) in each period in a panel setting[8]. $\mathbf{W}_t$ is a time-varying spatial weight matrix. It is based on the distance between the underlying assets of each pair of stocks. The matrix is time-varying, as the property portfolio composition of each firm changes over time. ρ is the spatial dependence coefficient. We also consider a set of company-specific variables to control for sector and regional similarity, age, size, debt-to-equity (D/E) ratio, trading volume, return on equity, and etc. We consider two types of diversification strategies – sector diversification and regional diversification. To account for sector diversification, we include a dummy variable which equals one if a firm holds properties in different real estate sectors, and zero

[8] An alternative way of calculating abnormal returns could be based on a 24-month rolling window estimation (Ferreira, et al., 2012). This means that in the first stage Equation (1) is estimated using the last 24 months of observations. Tthe abnormal return is then calculated as the sum of the intercept of the model and the residual. These results are shown in Appendix 2. The estimated spatial comovement is around two times larger than in the baseline model.

otherwise. To account for regional diversification, we create a dummy variable which take the value of one if a firm owns properties in more than one state and zero otherwise. We also include year and firm dummies. The unbalanced spatial panel regression is solved by a maximum likelihood (Baltagi, et al., 2013).

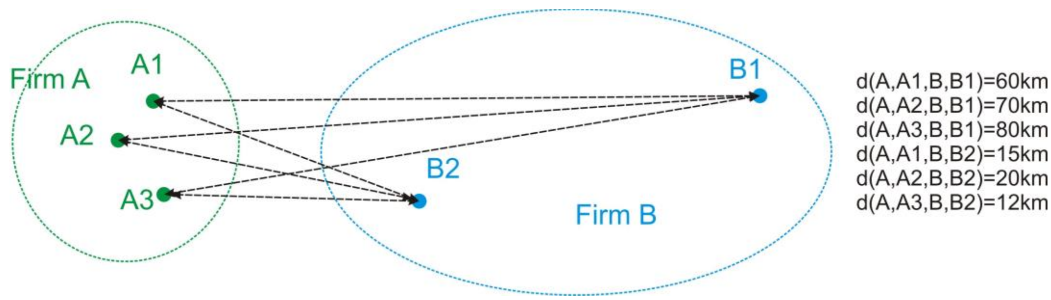
The spatial weight matrix

Real estate companies provide a suitable setting for the spatial factor model as such companies extract a large proportion of their income (80–90%) operating direct real estate assets, mostly through rents. This enables us to use the locations of the underlying assets of the company and to construct spatial weights for each pair of firms.

One shortcoming of previous papers explaining the comovement across returns by the common fund ownership is that fund ownership is an endogenous variable. Funds can focus their investments in stocks that have common fundamentals due to funds' correlated trading needs and thus naturally commove (Greenwood and Thesmar (2011)). Our location-based measure of comovement is less striking because it is based on the location of properties. Although the choice of the property location alone can be endogenous, the bulk of property linkages between each two firms can be seen as exogenous. The reason being is that, on the whole, across the entire property portfolio, a pair of firms will end up having an independent asset allocation. The choice of the location of the underlying asset of one company can be explained by similar unobservables as the location strategy of another firm. However, due to the nature of the real estate market, most real estate companies albeit following certain investment strategy, take more ad-hoc approach due to the illiquidity of the market and the nature of the asset class.

The locations of the properties of each company are identified using SNL Financial. Figure 1 shows an example of how the distance between firm A and firm B is calculated based on the individual distances between a pair of properties from the distinct firms. Let us assume that company A is invested in three properties, A1, A2 and A3, and company B is invested in two properties, B1 and B2. The dashed lines show the distance between each pair of properties.

Figure 1: Construction of the spatial weights between each pair of real estate companies



To generalise the above, we can assume that $d_{i,l,j,k,t}$ is the distance between property *l* of firm *i* in period *t* and property *k* of firm *j* in period *t*. In that case $d_{i,l,j,k,t}$ will be equal to $d_{j,k,i,l,t}$. As we end up having several distances between each two firms, we need to find an approach how to average across the distances. For this purpose, we construct two distances. The distance, $D_{i,l,j,t}$, between a property *l* of firm *i* to all properties of firm *j* in period *t* and the distance, $D_{j,k,i,t}$, between a property *k* of firm *j* to all properties of firm *i* in period *t*. The distances are calculated as the minimum distance across the distances each two properties *l* and *k* first for firm *i* and then for firm *j*:

$$D_{i,l,j,t} = \min(d_{i,l,j,k,t}) \text{ and } D_{j,k,i,t} = \min(d_{j,k,i,l,t}) \tag{3}$$

with $l = 1, 2, .., L_t$, and L_t as the total number of properties held by firm *i* in period *t* (e.g., L_t=3 in Figure 1) and $k = 1, 2, .., K_t$ with K_t the total number of properties held by firm *j* in period *t* (e.g., K_t=2 in Figure 1). We end up with L_t distances for firm *i* and K_t distances for firm *j* in period *t*. Those numbers can change if the firms rebalance their portfolios in the next period. We then calculate the weight for each pair of companies in two steps. First, we calculate two weights for each pair of companies. We convert the distances $D_{i,l,j,t}$ and $D_{j,k,i,t}$ to corresponding measures of contiguity. We calculate the proportion of properties of firm *i* that can be regarded as 'neighbours' to firm *j* and the proportion of properties of firm *j* that can be regarded as 'neighbours' to firm *i*:

$$w_{i,l,j,t} = \frac{1}{L_t} \sum_{l=1}^{L_t} q_{i,l,j,t} \text{ and } w_{j,k,i,t} = \frac{1}{K_t} \sum_{k=1}^{K_t} q_{j,k,i,t} \tag{4}$$

with $q_{i,l,j,t}$ and $q_{j,k,i,t}$ defined as:

$$q_{i,l,j,t} = \begin{cases} 1 & \text{if } D_{i,l,j,t} \leq 25\text{km} \quad \text{and } i \neq j \\ 0 & \text{otherwise} \end{cases} \text{ and } q_{j,k,i,t} = \begin{cases} 1 & \text{if } D_{j,k,i,t} \leq 25\text{km} \quad \text{and } i \neq j \\ 0 & \text{otherwise} \end{cases} .(5)$$

This implies that if a property l in firm i has a distance of less than 25km to any other property of firm j, property l of firm i is 'adjacent' to firm j, and can be regarded as a 'neighbour' of firm j. The same is true for property k in firm j. In the second step, we use the minimum of these two proportions to calculate the linkage between each pair of firms:

$$w_{i,j,t} = w_{j,i,t} = \min\left(w_{i,l,j,t}, w_{j,k,i,t}\right). \tag{6}$$

In Equation (6) we define the weight between each two firms using their minimum of the individual firm weights in order to account for the case in which firms have different levels of geographic asset concentration. We assume that the pair of firms would not as strong of a relationship as indicated by the average weight if the two individual weights are far apart from each other. In that case, we prefer to assume overall weak relationship but we are aware that there could be alternative ways of averaging. In the last step, we combine each element of Equation (6) in a W_t matrix with the pairwise proportions for each period. We then row-standardize matrix W_t so that for each i so that $\sum_j w_{i,j,t} = 1$.

To get a better understanding of the way the weights are constructed, we can use the example in Figure 1. The distance from A1, A2 and A3 to firm B is 15km, 20km and 12km respectively (from Equation 3). The distance from B1 and B2 to firm A is 60km and 12km respectively. For firm A, three out of three properties locate within the threshold distance of 25km which leaves us with a proportion of 1 (from Equation 4). For firm B, one out of two properties locates within the 25km distance which leaves us with a weight of 0.5. The spatial weight between firm A and B is then defined as the minimum of 1 and 0.5, and is thus 0.5 (from Equation 6). If the weight is 0, it implies that none of the properties between the two firms is located within 25km. If the weight is 1, it implies that all properties of a firm locate within 25km from the corresponding counterparty.

IV. Data

The data regarding the individual company characteristics is collected from SNL Financial. The returns and the market capitalization data are from Thomson Reuters Datastream. We collect data for all available US listed property companies between 1996 and 2015. In total we collect data for 223 firms. However, not all of them report the location of their properties, therefore we only use those which provide locational data and end up with 202 companies. We also exclude those firms holding international portfolios restricting our data sample to firms only invested within the US. This reduces the sample size to 115 firms. After removing companies with missing observations for the control variables (e.g., debt to equity ratio, and etc), 74 distinct companies remain in our sample.

Figure 2 shows the number of firms with complete observations in our sample over the study period as well as the market capitalization in each year. Up until 2007, the number of listed real estate companies in our sample has steadily increased from 29 to 70 and the average firm size increased by over 10 times, from $0.4 billion to over $4.1 billion. During the GFC, real estate companies experienced a large drop in size and shrunk to $1.2 billion as of 2009. Starting in 2009, real estate stocks have recovered to their pre-crisis value. Between 2010 and 2015, real estate companies showed the highest increase in market capitalization in the entire sample period.

Figure 2: Number of firms with complete observations over time and their market capitalization

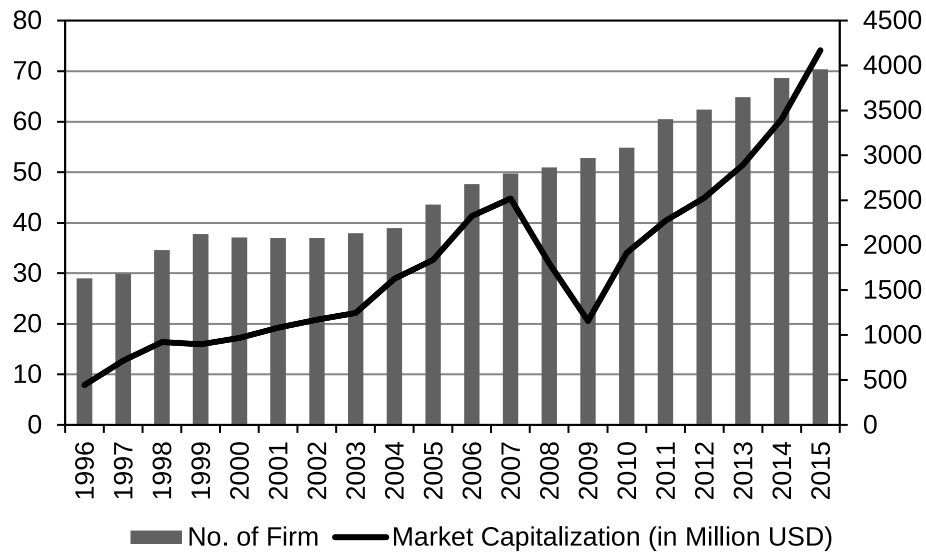
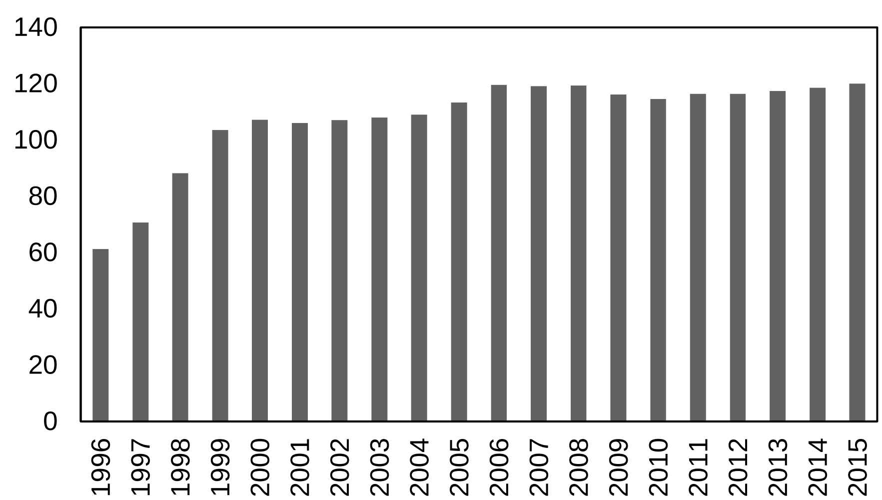


Figure 3 shows the average number of properties held by these firms over time. As shown in Figure 3, the number of underlying properties doubled, increasing rapidly from 1996 to 2000. Figure A1 in the Appendix shows the locations of the properties of each of the 74 companies.

Figure 3: Average number of underlying assets for each firm over time



We use two sets of explanatory variables to estimate the abnormal return in the first stage. The first set are the three Fama-French factors, the Carhart momentum factor and the Pastor and Stambaugh liquidity factor.

The data is obtained from Ken French's website (French (2016))[9] for the first four factors and from Pastor's website[10] (Pastor and Stambaugh, 2008) for the liquidity factor. The four factors include a US market return index (MR), 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 and 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). The liquidity factor (LIQ) measures the aggregate liquidity shock in the financial markets. [11]

Table 1: Descriptive statistics for the factors (averages 1998–2015)

Note:The existing factors are the five factors that are frequently used in asset price models. The first three factors (MR, SMB, HML) are the Fama and French factors accounting for market return, size and type; the fourth factor (WML) is the Carhart momentum factor, and the fifth factor (LIQ) is the Pastor and Stambaugh liquidity factor. The constructed factors are the same as above but constructed using 223 US real estate companies instead in order to better capture to cross-sectional and time-series variation in the returns.

	Mean	Std. Dev.	Max	Min
Existing factors (Fama and French, Carhart, Pastor and Stambaugh)				
MR	0.006	0.046	0.114	-0.172
SMB	0.003	0.033	0.192	-0.154
HML	0.002	0.033	0.139	-0.131
WML	0.004	0.029	0.122	-0.176
LIQ	0.006	0.040	0.215	-0.108
Constructed factors (using 223 US real estate companies)				
MR	0.008	0.059	0.252	-0.329
SMB	0.004	0.023	0.115	-0.083
HML	0.002	0.042	0.131	-0.214
WML	0.003	0.062	0.197	-0.291
LIQ	0.001	0.004	0.021	-0.045

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

[10] See http://faculty.chicagobooth.edu/lubos.pastor/research/

[11] Anthonisz and Putnins (2016) construct a downside measure of liquidity as the sensitivity of the stock liquidity to negative market returns. They find that this measure provides a 10-times larger stock return that its symmetric counterparty.

The second set of factors is constructed by us only using real estate companies instead. We call those factors the constructed factors. We follow the finding in the real estate literature which shows that REITs may not perfectly move together with general financial markets reflecting information specific to them or the underlying real estate market. We construct the five factors using the 223 real estate firms instead. As shown in Table 1, the average excess return of the market index over the sample period is 0.6%. This is slightly less that the 0.8% return of the 223 real estate companies. We also see that the variation in the constructed factors is larger for the return, type and momentum and smaller for size and liquidity. In fact, it seems that the constructed liquidity factor shows very little variation over time as compared to existing one. Apart from this factor, the remaining factors seem to have similar average returns in both sets of variables.

As we explain the abnormal returns from the factor model by the spatial linkages of the firms' underlying assets and other firm-specific characteristics, we collect additional explanatory variables. Following Chen et al. (2012) and Anton and Polk (2014), we control for the profitability using the return on average equity (ROAE) and the turnover ratio. In addition, we also account for the real estate investment growth following Alcock and Steiner (2016). We also include the market-to-book (M/B) ratio, the age of each company, its size as measured by the market capitalization and the debt-to-equity (D/E) ratio.

Table 2 summarizes the firm characteristics of the real estate companies. We show data averaged across time, from 1996 to 2015, and across the 74 companies. All variables except the dummy variables are windsorised at the 1st and 99th percentiles to mitigate the effects of large outliers. In addition, we show descriptive statistics of the characteristics of firms with high and low total returns which are connected through their underlying assets to similarly performing companies. In particular, we sort firms according to their total returns and according to the performance of their 'connected' firms.[12] Panel B shows descriptive statistics only for firms with high average returns that are connected to high-return firms (HH portfolio of firms)[13]. High-return firms include firms with 33% highest average annual returns across all firms in the

[12] By 'connected' firms we mean the companies which own properties in a proximity on less than 25km to each other.
[13] These are the HH portfolios in Table 9.

previous year which all fall in the category of firms whose connected counterparties have on average the 33% highest returns.[14] Panel C summarizes firms with low returns that are connected to low-return firms (LL portfolio)[15].

Table 2: Descriptive statistics for the real estate companies (averages across 1998–2015)

*Note: this table reports the descriptive statistics for a sample of real estate companies over the period from 1998 to 2015. Panel A shows descriptive statistics for all 74 firms. Panel B shows descriptive statistics only for firms with high returns that are connected to high-return companies (HH firms). Panel C shows the firms with low returns that are connected to low-return companies (LL firms). The monthly abnormal return is the average residual from Equation (1). The age is reported in months accumulated up to the second month of 2015. M/B ratio is the market-to-book ratio. ROAE is the return on average equity in percent, RE Investment Growth is the real estate investment growth in percent. The turnover ratio is annual terms and is calculated as the trading volume divided by common shares outstanding. D/E ratio is the debt- to-equity ratio. ***, ** and * denotes that the difference in mean is significantly different from the average of all firms at 1%, 5% and 10% levels, respectively, based on t-statistics.*

	Mean	Std. dev.	Max	Min	Difference in Mean
Panel A: All Firms					
Monthly Abnormal Return	0.000	0.099	2.858	-4.694	
Monthly Total Return	0.006	0.125	2.996	-5.392	
Age (months)	215	149	642	6	
Market Capitalization ($m)	1856	2712	26068	0.350	
M/B Ratio	0.815	0.946	7.692	-5.263	
ROAE (%)	6.763	11.839	57.410	-40.720	
RE Investment Growth (%)	16.645	35.649	205.830	-31.820	
Turnover Ratio	2.765	4.297	36.561	0	
D/E Ratio	1.672	2.368	20.785	-11.024	
Panel B: HH Firms					
Monthly Abnormal Return	0.000	0.071	0.444	-0.557	-0.0001

[14] The grouping of firms into HH and LL categories in explained in more detail in the Results Section.
[15] These are the LL portfolios in Table 9.

Monthly Total Return	0.007	0.090	0.451	-0.823	0.0005
Age (months)	210	152	627	6	-5
Market Capitalization ($m)	2488	3706	26068	1.78	631***
M/B Ratio	0.874	1.213	7.692	-5.263	0.060
ROAE (%)	7.265	12.616	57.410	-40.720	0.502
RE Investment Growth (%)	14.282	35.775	205.830	-29.480	-2.363***
Turnover Ratio	2.805	5.145	36.561	0	0.040
D/E Ratio	1.375	2.085	11.689	-11.024	-0.297***
Panel C: LL Firms					
Monthly Abnormal Return	-0.006	0.139	1.916	-2.320	-0.006**
Monthly Total Return	-0.0017	0.165	1.984	-2.413	-0.009***
Age (months)	278	171	533	47	63***
Market Capitalization ($m)	1497	2822	17512	2.25	-359.199***
M/B Ratio	1.020	1.042	7.692	-5.263	0.205***
ROAE (%)	2.885	14.729	56.050	-40.720	-3.878***
RE Investment Growth (%)	8.999	32.688	205.830	-31.820	-7.646***
Turnover Ratio	2.484	4.543	36.561	0	-0.281*
D/E Ratio	2.199	3.902	20.785	-11.024	0.527***

The average return across all companies is 0.6% per month. The HH firms do not yield significantly higher returns than the average of the 74 firms. The LL firms on the other side yield significantly lower returns than the baseline, -0.17% per month. The average age of the companies is 18 years (or 215 months), with the oldest company being 53 years old and the youngest just 6 months. LL firms are on average almost 5 years older than HH firms. We also see a large variation across the size of the companies in terms of market capitalization with the highest being $26,068 million and the lowest, $0.35 million. On average a company has a market capitalization of $1,856 million. The HH firms are significantly larger with a capitalization 34% higher than the average. The LL firms are significantly smaller than the average. This implies that larger firms perform on average better than smaller firms. The average M/B ratio is 0.81, the highest, 7.6, and the lowest, -5.2. It is similar to the average ratio of 0.8 across all types of industries which suggests that REITs can be seen as value stocks. In particular, the M/B ratio is a good indicator of the valuation of a real estate company as the book value should accurately measure the true value of the firm given that real estate firms have mostly tangible assets on their books as compared to i.e. IT companies. There are little differences across the M/B ratios of the different sub-portfolios. The average ROAE is 6.7% but it goes down to -40% in the worst case for some of the companies. The ROAE of the companies in our sample is lower than the average for all types of industries which is nearly 11%. However, it is higher than the average ROE for the real estate industry of 1.7%. HH firms do not exhibit significantly higher ROAE. However, we see that LL firms have on average significantly lower ROAE of 2.8%.

We also include the turnover ratio as a measure of liquidity. Barinov (2014) shows that the turnover ratio is negatively related to liquidity and that relationship is stronger for firms with option-like equity due to bad credit ratings. We calculate the turnover ratio as the total value of the trading volume of a company for a whole year divided by the end-of-year outstanding value of common stocks. It is a measure of the liquidity of the company. The higher the turnover ratio the more liquid the company is. On average each common share is traded 2.76 times a year. The LL firms have significantly lower trading ratio than the average of 2.48. The HH firms on the other side are more liquid that the baseline. Real estate investment growth is 16% consistent with findings in Bond and Xue (2014) and Alcock and Steiner (2016). The growth for the LL firms is significantly smaller, taking a value of about 10%. The D/E ratio is on average 1.67 but some companies have very high D/E ratio of more than 20. This is consistent with previous findings that demonstrate that REITs carry significant leverage (Barclay et al. (2013)). The leverage is significantly higher for LL companies and significantly lower for HH firms.

V. Results

A. Baseline Model Results

We first estimate a five-factor model using the existing factors as described above. We run firm-by-firm regressions using monthly data. We can see that the performance of the model is poor as the R-square is low, at only 2.5% on average, and none of the factors is significant on average (see Model 1 in Table 3). This is compared with R-squares of above 60% for stock regressions by Fama and French (2012) using the four Fama and French factors. The reason for the low explanatory power is that the general stock market factors do not include enough real estate companies and a large part of the risk is idiosyncratic. Real estate companies invest predominantly in real estate and can be driven by factors specific to certain buildings such as location, sector, etc. This is reflected in the low and insignificant beta of 0.17. One of the reasons for the low synchronicity between real estate companies and the market, as argued by Chung et al (2011), can be due to spatial uniqueness of the underlying assets. In order to capture the comovement in the real estate equity market, we construct the five factors using the 232 US real estate firms. The results are reported in Model 2 in Table 3. The R-square of Model 2 is now much higher with a value of 58%. However, this value is still not as high as the one observed for stocks. This can point again to remaining idiosyncratic price variations as we account for the REIT market. We can see that the variations in the returns are explained purely by the market index (RM) as it is the only significant factor. The average beta across the 74 companies is 1.13 which is very close to the beta of the market of 1. That means that the 74 companies in our sample which we regress individually on a factor constructed using 232 real estate companies commove very closely with the rest of the real estate firm universe.

Table 3 Estimation of factor models

Note: Model 1 is using the existing factors. Model 2 is using constructed factors. We construct the factors in the same way as Fama and French however we only use real estate companies. A total of 232 US REITs are included in the factor calculations. Alpha is the constant in the factor model. RM stays for the coefficient associated with the index return; SMB is the average coefficient of the return differential of small-minus-big portfolios; HML is the average coefficient of a return differential of high-minus-low portfolios; MOM is the average coefficient of the momentum return index. LIQ stands for the average coefficient of the Pastor and Stambaugh liquidity factor. We run a time-series regression for each of the 74 REITs for which locational data is available. Average t-statistics are provided in brackets.

	Alpha	RM	SMB	HML	MOM	LIQ	Adjusted R2
				Model 1 (existing factors)			
Coefficient	0.0084	0.0171	-0.0480	0.1670	-0.2120	-0.1343	0.0259
T-stats.	(1.32)	(0.15)	(0.10)	(0.65)	(-0.20)	(-0.55)	
				Model 2 (constructed factors)			
Coefficient	-0.0009	1.1328	-0.0336	0.0301	-0.0114	0.4111	0.5834

T-stats.	(-0.01)	(14.08)	(-1.05)	(0.38)	(0.26)	(0.20)

In a second stage, we use the abnormal returns from the factor model (Model 2) to estimate an unbalanced spatial panel model with 10,140 observations. We regress the residuals on the spatially weighted lagged residuals and a set of control variables discussed in Section IV. We weight the lagged residuals using a spatial weight matrix. The weights capture the spatial linkages between each pair of residuals using the locations of the underlying property holdings of each company. We control for profitability, liquidity, size, sector, as well as house price growth in addition to using a set of dummy variables. We see that the spatial coefficient is significantly positive and takes the value of 0.11.[16] It means that spatial linkages across the underlying assets of firms significantly drive the comovements across the residuals, controlling for systematic factors as well as company-specific characteristics. The spatial panel model explains 53% of the variations in the residuals. The control variables have the expected signs but not all of them are significant. There is a significantly positive relationship between the size of the company and its abnormal return even after controlling for size as a systematic risk factor. The relationship is not linear as we see that the square of the size has a significant negative effect on the residuals. It means that event though size in general is associated with high abnormal returns, with increasing company size, the effect becomes smaller and smaller. This is not abnormal as we would expect that when the firm becomes too big, the increase in the abnormal returns slows down. We can see that the lagged abnormal returns have a significant effect on current abnormal returns, however the sign is negative. A 10 percentage point increase in the abnormal return would lead to a drop of the abnormal returns in the next period by 0.7 percentage points. Although the effect is small, it is significant and shows that there is some systematic correction over time in abnormal performance of REITs. This is in line with our assumptions of mean-convergence of residuals.

Companies which assure higher returns on equity (ROEA) to their investors also have significantly higher

[16] The results based on the residuals from the Fama and French index model specifications are robust. They are shown in the Appendix 2. As shown in Appendix 2, the estimated co-movement is much higher than using the constructed factors, implying that using real estate firms to construct the common factors can eliminate the co-movement in the abnormal returns of real estate firms due to the co-movement in the real estate market.

abnormal returns. This is in line with funds who have managed to outperform the market over a continued period of time by investing in high ROE stocks. We also find that high abnormal returns significantly comove with high debt-to-equity (D/E) ratios. This can also be related to above positive relationship. We would expect that more leveraged companies are performing better due to cheaper funding costs. We can see that another important company characteristics, the real estate investment growth has a significantly negative effect on abnormal returns, which is also in line with expectations. Small stocks should compensate for the risk exposure. The more the company grows its business, the lower the chances for any additional abnormal returns. We see that the turnover ratio is not significant. It means that abnormal returns are not explained by the trading volume of shares of the respective company. An interesting finding which is easy to test within the context of REITs is how the properties of the underlying asset portfolio affect company's abnormal returns. We can see that if the company invests in properties in more than one US state, this would negatively impact on the performance. Our finding implies that REITs diversifying across MSAs tend to be valued lower than REITs with tighter geographic focus, consistent with the documented negative geographic allocation valuation effects in Hartzell et al. (2014) and Ling, et al. (2016). We do not find that the sector (apartments, offices, retail, industrial, etc.) which the properties represent explains abnormal returns. These results contribute to the ongoing discussion in real estate literature of whether geographic or sectoral diversification is more important. Overall, we show that the residuals of a five-factor model can be explained by spatial linkages between the underlying assets of the companies. Location seems to be a key explanatory variable, as locational dummy variables are also significant. Other features of the underlying assets seem not to matter. In terms of the company characteristics, we only find evidence for significant effects due to size, ROE, D/E ratio and investment growth.

Table 4: Unbalanced spatial panel regression

Note: This table reports the estimates of an unbalanced spatial panel regression. The dependent variable is the residuals from Model 2 in Table 3 – the residuals from a five-factor model using constructed factors. Independent variables include the lagged abnormal return, age, size, market-to-book ratio, return on *average equity (ROAE), real estate investment growth, turnover ratio, debt-to-equity ratio, a dummy if the company is investing only in one state, a dummy if the company is diversified across real estate sectors and the house price growth. The weight matrix is constructed based on Equation (3)-(6) using 25km as the bandwidth. We also include year dummies, and firm dummies. LR denotes the Likelihood ratio statistic for the null hypothesis "including spatial coefficient cannot improve model's fit". We report the associated t-statistics in brackets.* ***, ** and * denotes 1%, 5% and 10% significance level, respectively.

Model 3: Spatial panel model for abnormal returns	
Spatial coefficient ρ	0.1116***
	(4.20)
Lagged abnormal return	-0.0793***
	(-9.61)
Age	-0.0043
	(-1.28)
Age squared	0.0005
	(0.85)
Size	0.3366***
	(78.58)
Size squared	-0.0999***
	(-57.24)
M/B ratio	0.0007
	(0.83)
ROAE	0.0001
	(1.59)
RE inv. growth	-0.0001***
	(-4.04)
Turnover ratio	0.0002
	(1.04)
D/E ratio	0.0005*
	(1.89)
State dummy	-0.0183***
	(-2.44)
Sector dummy	-0.0009
	(-0.24)
House price growth	-0.1724
	(-1.48)
Year dummies	Yes
Firm dummies	Yes
No. of Observations	10140
Adj. R2	0.533
LL	18039
LR	20***

B. Robustness analysis

In Table 5 we estimate the spatial panel model using different distance bandwidths between the underlying assets. We see that the results are similar to the ones reported in Table 4. The distance bandwidths we use are 10 km, 50 km, 75 km and 100 km. The models perform very similarly in terms of log likelihood and R-squared. The spatial coefficient takes values between 0.089 and 0.102 which is slightly less that the value in the baseline model of 0.11, however, all of spatial coefficients are significant.

Table 5: Spatial panel regressions using different distance bandwidth

Note: This table reports the estimates of unbalanced spatial panel regressions using different weight matrices. In each model the weight matrix is constructed using a different distance bandwidth between the properties of a pair of companies. The dependent variable are the residuals from Model 2 in Table 3 – the residuals from a five-factor model using constructed factors. Independent variables include the lagged abnormal return, age, size, market-to-book ratio, return on average equity, real estate investment growth, turnover ratio, debt-to-equity ratio, two dummies for diversification and the house price growth. We also include year dummies, and firm dummies. We report the associated t-statistics in brackets. ***, ** and * denotes 1%, 5% and 10% significance level, respectively.

	Model 4: 10 KM	Model 5: 50 KM	Model 6: 75 KM	Model 7: 100 KM
Spatial coefficient ρ	0.0904***	0.1024***	0.0897***	0.1002***
	(3.91)	(3.90)	(3.59)	(3.89)
Control variables	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes
No. of Observations	10140	10140	10140	10140
Adj. R2	0.533	0.532	0.532	0.533
LL	18037	18038	18036	18037

In order to make sure that the physical distance is the best way to capture the relationships in the companies and that the spatial weight matrix does not capture some other linkages or global comovements, we add into our spatial panel model an alternative weight matrix. We construct additional weight matrices based on the similarity of size, the similarity in their M/B ratio and the similarity in their momentum.[17] As Bernile et al. (2015) show, the geographic proximity of firm's headquarter can also explain the correlation in the abnormal returns. Therefore, we also construct a weight matrix which is defined based on whether the headquarters of each two companies are located in the same city.[18] Because the real estate markets can perform quite different in each MSAs due to variations in local legislations and economic conditions, concerns may arise that the estimated comovement is not due to the closeness of the underlying assets, but because these properties locate in the same MSAs.[19] In order to address this issue, we also add a matrix which only has positive weights if the underlying assets are located within the same MSA. If the comovement is purely triggered by common factors within one MSA rather than geographic distance, the coefficient for the distance based matrix would be insignificant if the MSA based weight matrix is added. The results are reported in Table 6. In all cases, the spatial dependence triggered by the geographic proximity of the underlying assets remains significant, ranging from 0.074 to 0.108. The spatial coefficient of the additional weight matrix ranges from 0.009 to 0.069 but is insignificant for each of them. This shows that the geographic distance is not capturing other linkages between the companies such as similarities due to size, performance or actual company location. It seems that adding additional weight matrices which are not based on the linkages between the underlying assets do not change the model fit as they are insignificant. This is to show that our measure of company linkages does a good job in capturing comovements as compared to more commonly used spatial measures. Also, it is a call to using spatial distance between underlying assets rather than the spatial linkages between the actual companies.

Table 6: Spatial panel regressions with an additional weight matrix

Note: This table reports the estimates of unbalanced spatial panel regressions using an additional weight

[17] Detailed information about the construction of these alternative weight matrices is in the Appendix 3.
[18] Detailed information about the construction of these alternative weight matrices is in the Appendix 3.
[19] Detailed information about the construction of these alternative weight matrices is in the Appendix 3.

matrix. Each regression consists of two weight matrices – the geographic distance between the underlying assets (ρ) and an additional weight matrix which can be the similarity in size between the real estate companies (ρ_SIZE), the similarity in their market-to-book ratio (ρ_M/B), the similarity in their lagged returns looking at the last two to 12 months (ρ_MOM), the proximity of their headquarters (ρ_HQ), the similarity in location of the underlying assets in terms of MSAs (ρ_MSA). The dependent variable are the residuals from Model 2 in Table 3 – the residuals from a five-factor model using constructed factors. Independent variables include the lagged abnormal return, age, size, market-to-book ratio, return on average equity, real estate investment growth, turnover ratio, debt-to-equity ratio, two dummies for diversification and the house price growth. The weight matrix is constructed based on Equations (3) - (6) using 25km as the bandwidth. We also include year dummies and firm dummies. We report the associated t-statistics in brackets. ***, ** and * denotes 1%, 5% and 10% significance level, respectively.

	Model 8: Size	Model 9: M/B ratio	Model 10: MOM	Model 11: Headquarter	Model 12: MSA
ρ	0.1071***	0.0987***	0.0843***	0.1083***	0.0741**
	(2.85)	(2.59)	(2.44)	(4.02)	(2.09)
ρ_SIZE	0.0093				
	(0.19)				
ρ_M/B		0.0245			
		(0.50)			
ρ_MOM			0.0691		
			(1.25)		
ρ_HQ				0.0098	
				(0.78)	
ρ_MSA					0.0401
					(1.62)
Control variables	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes
No. of observations	10140	10140	10140	10140	10140
Adj. R2	0.533	0.533	0.533	0.533	0.533
LL	18039	18039	18040	18038	18040

In Table 7 we add to the baseline model a set of weight matrices which capture the sectoral proximity in each of the sectors. So, in addition to the geographic location between the underlying assets we have weight matrices for the similarity of those assets in terms of the sector they represent. We include a weight matrix using the properties only in one of the six sectors – office, industrial, retail, residential, hotel – separately. For the weight matrix within each sector, the weight is again defined using their geographic distance, as shown in Equations (4) and (5). We can see that the spatial coefficient capturing the geographic distance remains significant but decreases in value down to 0.0430. As expected, spatial dependence seems to be stronger for properties within the same sector. The highest spatial coefficient is observed for the residential properties, 0.10 followed by industrial, 0.06. This means that each pain of companies would show higher comovement if they are invested more in residential. The transmission hence why occurred through the sector of the underlying asset in addition to the distance between the assets. The high comovement in the residential market is understandable as it is much more homogenous that the commercial real estate market where even though buildings can belong to one type of sector, e.g. office, they can be large differences among the office buildings and their performance.

Table 7: Spatial panel regressions accounting for geographic distance and sectoral proximity of the underlying assets

Note: This table reports the estimates of unbalanced spatial panel regressions using an additional weight matrix. Each regression consists of two weight matrices – the geographic distance between the underlying assets (ρ) and five additional weight matrices which are related to the similarity of the sector which the properties represent: retail (ρ_Retail), residential (ρ_Residential), office (ρ_Office), industrial (ρ_Industrial), or hotel (ρ_Hotel). The dependent variable are the residuals from Model 2 in Table 3 – the residuals from a five-factor model using constructed factors. Independent variables include the lagged abnormal return, age, size, market-to-book ratio, return on average equity (ROAE), real estate investment growth, turnover ratio, debt-to-equity ratio, two dummies for diversification and the house price growth. The weight matrix is constructed based on Equation (3), (4) and (5) using 25 km as the bandwidth. We also include year dummies, and firm dummies. We report the associated t-statistics in brackets. ***, ** and

* denotes 1%, 5% and 10% significance level, respectively.

	Model 13: Within Sector correlation
ρ	0.0430***
	(14.12)
ρ_Retail	0.0297***
	(6.72)
ρ_Residential	0.1005***
	(29.52)
ρ_Office	0.0050*
	(1.74)
ρ_Industrial	0.0608***
	(16.89)
ρ_Hotel	0.0313***
	(13.83)
Control variables	Yes
Year Dummy	Yes
Firm Dummy	Yes
No. of observations	10140
Adj. R2	0.535
LL	188477

In addition to above robustness test, we also control for global drivers by using the distance decay model (Asgharian et al. (2013)). For each individual firm, we split the connected firms into three groups. The first group consists of firms that hold properties with a minimum distance within 25 km. Group two consists of firms that hold properties with a distance between 25 km and 50 km of the properties held by the firm of interest. Group three includes firms whose underlying assets have a minimum distance longer than 50 km from the connected firm. Once the firms for the three groups are identified, we construct three weight matrices. Each matrix includes only the firms that belong to each group and the weight for the rest of the other firms is set to zero. For example, for the weight matrix based on the firms with underlying assets within a distance between 25 km and 50 km, the weight is defined as the proportion of the underlying properties within this distance; for the rest of the firms, the weights are set to zero. The results are presented in Table 8. The spatial coefficients of the three matrices are different and the confidence bands do not overlap. The coefficient of the 25-km matrix is significantly higher than the other two matrices, indicating that the comovement effect is not driven by global common factors. Overall, when the minimum distance of the underlying assets is longer than 25 km, the spatial dependence becomes insignificant.

We further perform a simulation analysis to control for unobserved global factors which might be captured by our measure of spatial comovement. To rule this out, we add a randomly generated weight matrix into the regression to see if a randomly general matrix is doing a similar job than a matrix constructed using the distance between the properties. The simulation runs 200 times. The results are presented in Table 8. We report the 95% inner-percentile range of the distribution of the estimates. We can see that the coefficient for the random weight matrix is insignificant and the confidence intervals for the spatial coefficient do not overlap with those for the randomly generated weight matrix. Hence the variations in the abnormal returns can be indeed driven by the geographic proximity of the underlying assets and not by strong global comovements of the abnormal returns. This result also shows that the spatial weight matrix using geographic distance between the underlying assets outperforms the majority of randomly generated weight matrices thus best capturing the spatial comovement among the firms.

Table 8: Spatial panel regressions with alternative distance measures

Note: This table reports the estimates of unbalanced spatial panel regressions using an alternative way to construct the spatial weight matrix. First, we construct three weight matrices – a matrix with properties in proximity of less than 25 km (ρ_25), the properties in proximity of between 25 km and 50 km (ρ_25_50) from each other, and the properties with distance larger than 50 km (ρ _50). Second, we construct a random weight matrix (ρ_Random) and compare the spatial coefficient against that of our baseline spatial matrix. The dependent variable are the residuals from a five-factor model using constructed factors (Model 2 in Table 3). Independent variables include the lagged abnormal return, age, size, market-to-book ratio, return on average equity, real estate investment growth, turnover ratio, dividend yield, debt-to-equity ratio, dummies for diversification and the house price growth. The weight matrix is constructed based on

Equations (3) - (6) using 25km as the bandwidth. We also include year dummies, and firm dummies. We report the associated t-statistics in brackets. ***, ** and * denotes 1%, 5% and 10% significance level, respectively.

	Model 14: Neighbors vs non-neighbors	Model 15: Random matrix
ρ_25	0.1209***	
	[0.0161;0.2257]	
ρ_25_50	0.0034	
	[-0.0058;0.0104]	
ρ _50	0.0093	
	[-0.0051;0.0201]	
ρ		0.1426***
		[0.1196;0.1657]
ρ_Random		-0.0331
		[-0.0813;0.0087]

C. Trading strategies

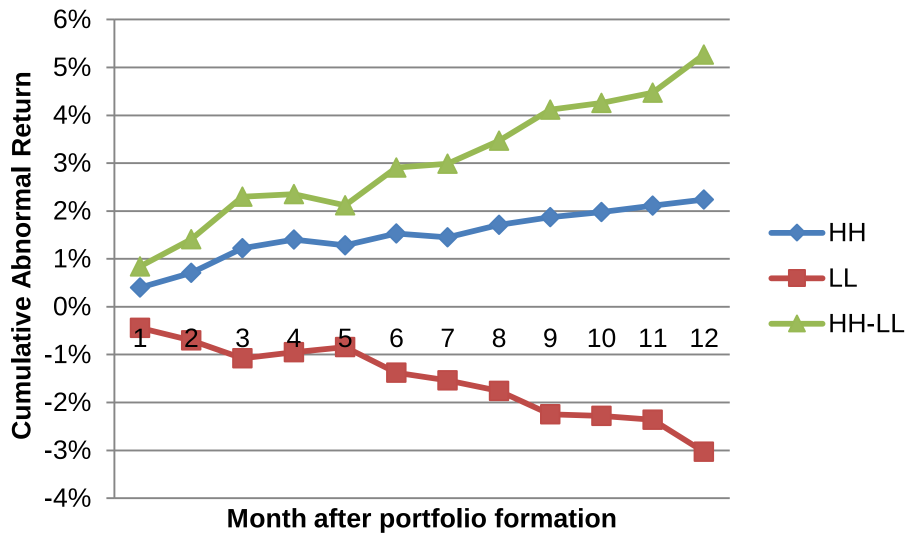
Given above findings, we propose a trading strategy that exploits the information in the locational comovements across the abnormal returns. Similar trading strategies have been used previously to exploit information contained in linkages between companies resulting from fire sales of stocks with common institutional ownership. Chen et al. (2012) develop a trading strategy that benefits from the divergence in the prices of a pair of similar stocks. Anton and Polk (2014) present an investment strategy that identifies stocks that temporarily move together and profits from their eventual divergence in price. Our trading strategy is similar to the one in Anton and Polk (2014), however, we use the proximity in the location of companies' underlying assets to measure how similar or different stocks are. If geographic proximity between properties can cause comovement in the returns of the companies that own those assets, our trading strategy would use the return of the connected stock portfolio to benchmark against. The difference in the returns would be used as a signal of the mispricing of the respective company. Similar to Anton and Polk (2014), our strategy exploits upward and downward real estate price pressures channelled through the spatial proximity of the companies' underlying assets. We would expect that the best signals of mispricing would come when a company is facing a fire sale of its assets, driving pricing of surrounding properties down, as fire sales are more common than forced buys.

We examine the buy-and-hold abnormal returns on two portfolios. The first portfolio consists of an equally-weighted portfolio of the worst performing (low-return) companies (33% lowest returns in the past 12 months). In addition, these companies also invest in properties which locate close to those properties which also yield low returns (33% lowest returns in the past 12-months). We call this the LL portfolio, for low own return and low connected portfolio return. Similarly, the second portfolio consists of an equally-weighted portfolio of companies with high returns (33% highest returns in the last 12 months) that invest in properties located close to properties of other good performing firms (33% highest returns in the past 12 months). We call this the HH portfolio, for high own return and high connected portfolio return. We then show in Figure 4 how those two abnormal buy-and-hold portfolio returns change over a period of 12 months. The cumulative abnormal returns of the 12 buy-and-hold alphas are calculated by regressing the returns of the two portfolios on the common factors extending the sample period by one period each time (Anton and Polk, 2014). We then look at the difference between the alphas of the HH portfolio as against the LL portfolio (HH-LL).

Figure 4 shows the cumulative abnormal returns of the different portfolios. The cumulative alpha of the LL portfolio is negative and increasing in absolute value over time. The HH portfolio is able to generate a positive and growing buy-and-hold alpha over the course of one year. On the other hand, the LL portfolio is consistently underperforming the benchmark, delivering lower alphas in every next period. These findings suggest that stock prices of real estate companies are pushed away from fundamentals by the locational dynamics of the underlying asset portfolio and those patterns last for at least one year. We can see that the return of the connected stock portfolio is a useful measure of the extent of the misvaluation of that stock. Similar to the findings in Anton and Polk (2014), we show that the misvaluation seems to be much larger in value and more prolonged in time than the standard short-term reversal effect. Similar to previous findings (Coval and Stafford (2007), Anton and Polk (2014)), we find that the medium-term effect is stronger for the LL portfolio which is consistent with the forced selling hypothesis.

Figure 4: Cumulative alphas for a connected-stock strategy

Note: This figure graphs the abnormal buy-and-hold performance of a cross-stock-reversal trading strategy that exploits information about the location of the underlying assets of real estate companies. These stocks are sorted into 9 portfolios based on independent quintile sorts on their own 12-month return and the 12-month return on their connected stock portfolio. We first measure the degree of connections by the distance of the underlying properties based on Equation (4) and (5). We then define the connected return as $\sum_{j=1}^{N} w_{i,j,t}\tilde{r}_{j,t}$ *. Following Antón and Polk (2014), each composite portfolio below is an equal-weighted average of the corresponding simple strategies. The figure plots the buy-and-hold abnormal returns on stocks that are in the high own-return and high connected-return portfolio (HH), stocks that are in the low own-return and low connected-return portfolio (LL), and the difference between the above – the high and low abnormal returns (HH-LL). Returns are benchmarked against the five constructed factors as explained in the text***.***



Given above findings, we construct composite portfolios which take into account the predictability of cross-sectional variation using the spatial linkages across the underlying assets. We construct 12-month buy-and-hold portfolios. We independently sort stocks according to their returns (own return) and the returns of a portfolio of companies which are connected to the stock of interest through their underlying assets (connected portfolio return) over the past year. The connected portfolio return is calculated as $\sum_{j=1}^{N} w_{i,j,t}\tilde{r}_{j,t}$. In total we construct nine portfolios. The breakpoints for each grouping are the 33th and 67th percentiles. We have the following composite portfolios which consist of the own return and the connected portfolio return as follows: HH, HM, HL, MH, MM, ML, LH, LM, and LL. H, M and L stay for high, median, or low returns in the own or the connected portfolio domain. We construct the high (low) quantile using the 33% highest (lowest) returns of each category. HL for example means a portfolio consisting of the companies with the 33% of the highest own return stocks and 33% of the lowest connected portfolio return stocks. We then use the time series of the returns of each of those nine composite portfolios to estimate the composite portfolio alphas in a five-factor model using the constructed factors. Table 9 shows the results. We can see that locational proximity of underlying assets pushes the returns of portfolios of connected companies away from their fundamental values on the both end of the performance. The connected portfolio return is a good measure of the extent of mispricing. Similar to the observations in Figure 4, the alphas on the nine composite portfolios decrease as we move from high to low connected portfolio returns within the own-return quantile and as we move from high to low own-return portfolios within the connected-return quantile. This is to show that the information contained in the connected portfolio returns is a useful predictor of the own return. Those results remain robust when we use different return quantiles and different factor model specifications. Therefore, we propose a long-short trading strategy (HH-LL strategy) which exploits the information in the connected returns. This HH-LL strategy buys the composite HH portfolio and sells the composite LL portfolio yielding a significantly positive alpha of approximately 1% per month. We can use this long-short hedge strategy to exacerbate excess comovement stemming from the spatial linkages across the underlying assets. An investment strategy which buys the stocks that experience an increase in their price if their connected stocks have also gone up and sells the stocks that experience a drop in their price if their connected stocks have also gone down can earn an average non-market return of 12% per year. This is in line with previous findings who find non-market returns of a long-short strategy extracting information from institutional ownership of 9% (Anton and Polk (2014)) and 10% (Coval and Stafford (2007)) per year. The difference of our results as compared to previous findings is that we generate positive alphas through the HH composite portfolio rather than through the LL portfolio, which provides evidence on some momentum in the public equity real estate market and calls for adding value through a growth strategy.

Similarly to previous findings, we show that about 80% of the alpha of the long-short strategy comes from the LL composite portfolio, in line with our expectations that forced sales can be the driver of the comovements. We compare the HH-LL strategy against a strategy that ignores the information in the spatial linkages (MH-ML strategy). The MH-ML strategy buys a composite portfolio of the median own return quantile and the high connected return quantile (MH) and sells a composite portfolio of the median own return quantile and the low connected return quantile (ML). This strategy yields an insignificant alpha. These results confirm that the long-short strategy can successfully make use of information about misvaluation in stocks contained in the spatial linkages among their underlying assets.

Table 9: Alphas on connected-stock trading strategies

This table presents the profitability of a trading strategy exploiting the connectedness across the underlying assets of real estate companies. We independently sort stocks into quantiles based on their own return over the last year and the return on their connected portfolio over the last year. We first measure the degree of connections by the distance of the underlying properties based on Equation (4) and (5). We then calculate the connected return as $\sum_{j=1}^{N} w_{i,j,t}\tilde{r}_{j,t}$ *. Following Anton and Polk (2014), each composite portfolio below is an equal-weighted average of the corresponding simple strategies. The table reports the five-factor alphas on these 9 composite portfolios. The five factors include the constructed four factors and the liquidity factor. We also report the average returns on a HH-LL trading strategy that buys the high own-return and high connected-return composite portfolio (HH) and sells the low own-return and low connected-return composite portfolio (LL).*

Five factor alphas						
		Connected portfolio return				
		High	**Median**	**Low**	**H-L**	**MH-ML**
Own Return	**High**	0.0019	0.0015	0.0000	0.0019	
		(0.96)	(1.04)	(0.01)	(0.95)	
	Median	-0.0000	-0.0006	-0.0004	0.0004	0.0031
		(-0.01)	(-0.34)	(-0.33)	(0.32)	(1.23)
	Low	-0.0008	-0.0024	-0.0079***	0.0069	
		(-0.21)	(-1.09)	(-2.43)	(2.42)	
	H-L	0.0027	0.0039	0.0079	0.0098	**HH-LL**
		(1.25)	(2.13)	(2.53)	(3.39)	

VI. Conclusion

We model spatial comovement across returns of real estate companies using a factor model in order to cross-sectional correlation across returns. We connect the stocks through the location of their underlying assets – the properties. We show that the degree of spatial comovement of their properties explains the variation in abnormal returns, controlling for exposure to systematic return factors, style and sector similarity, and range of other individual and pair characteristics. These results imply a trading strategy which exploits information contained in the spatial linkages across the companies' properties. We show that a long-short hedge strategy exacerbates this excess comovement by exploiting information contained in the spatial linkages of underlying assets. An investment strategy which buys the stocks that experience an increase in their price if their connected stocks have also gone up and sells the stocks that experience a drop if their connected stocks have also gone down can earn an annual abnormal return of nearly 12%.

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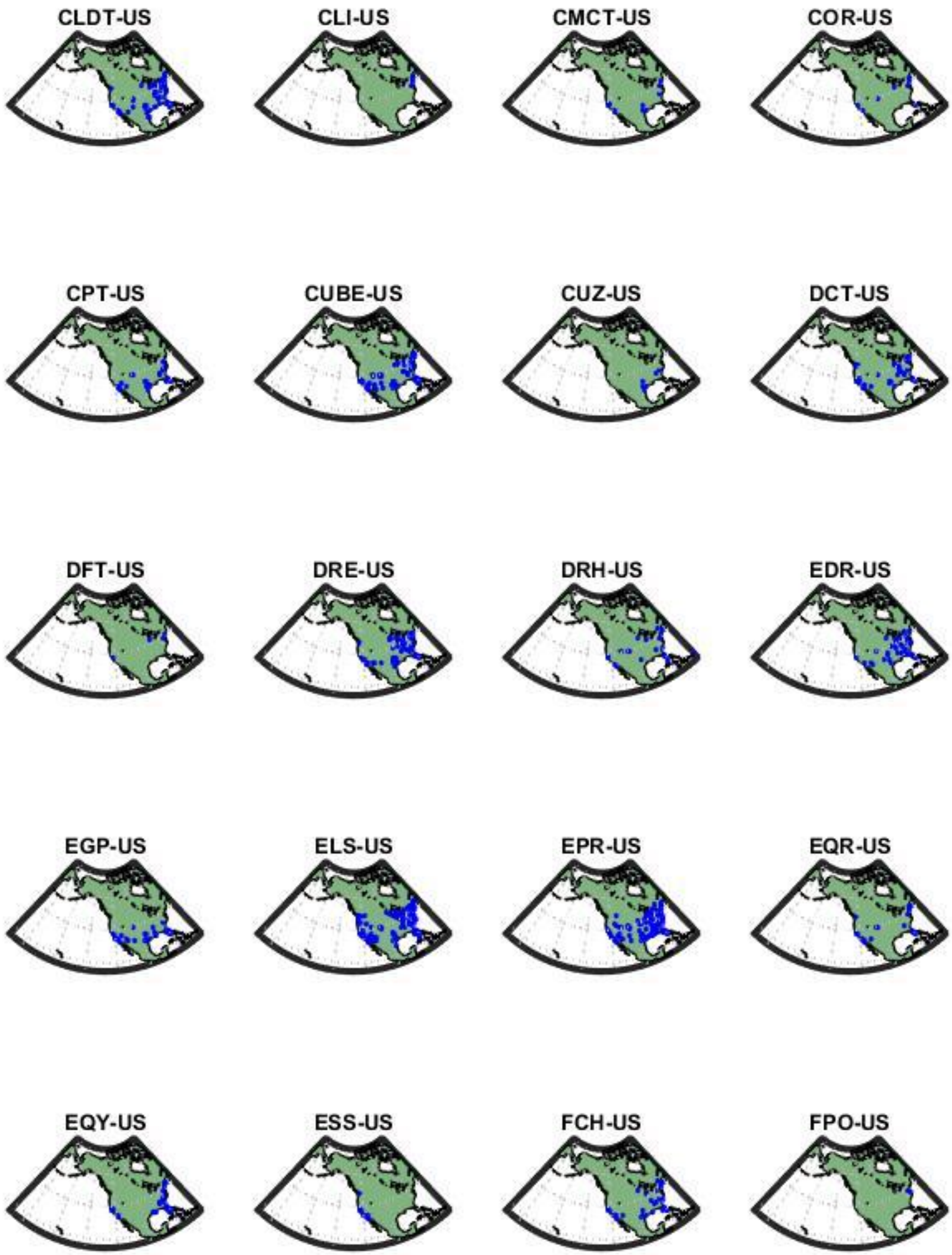
Appendix

Figure A1: The locations of the properties owned by individual listed real estate firms in US as of 2015 (Ticker code of the company used as the heading of each graph)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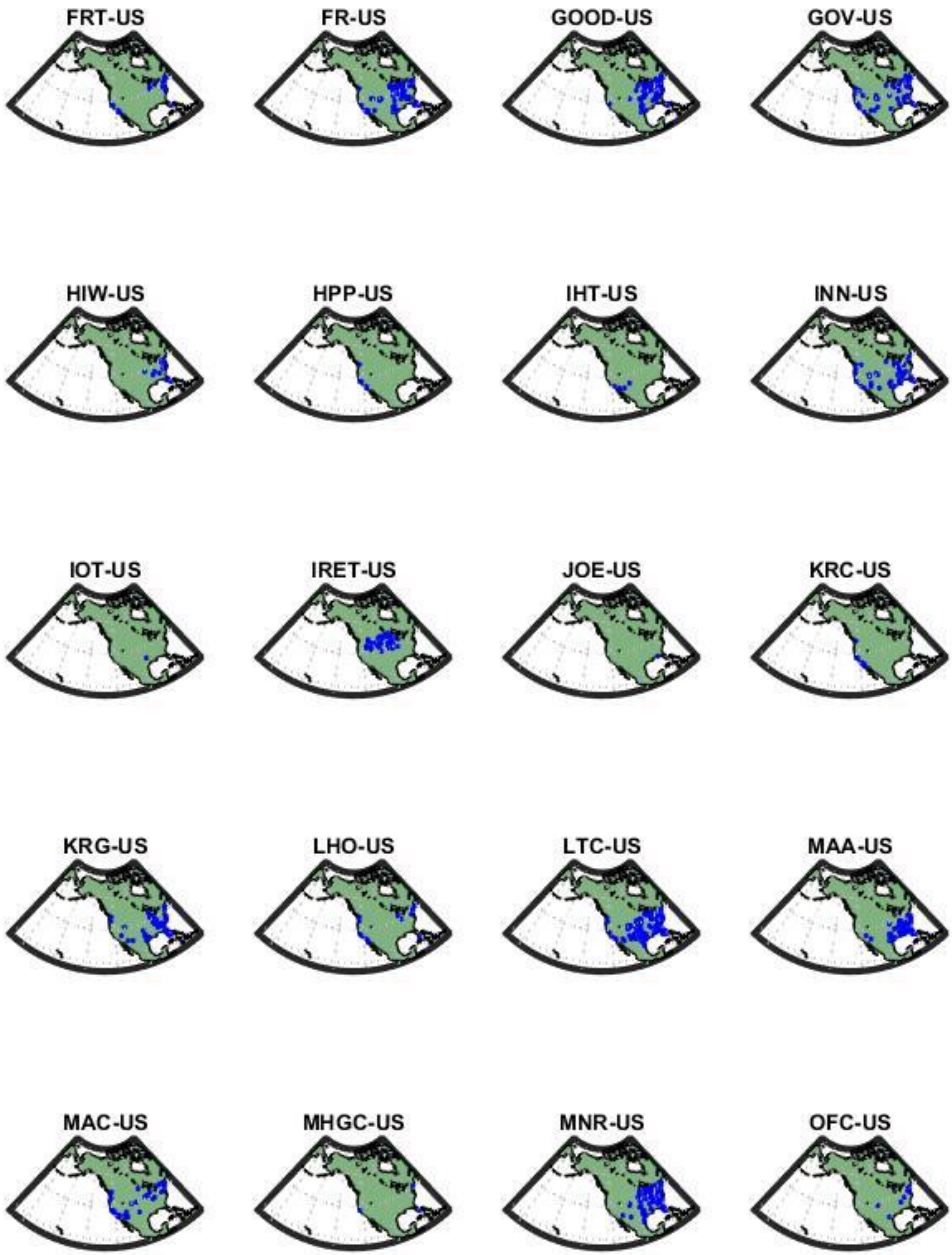
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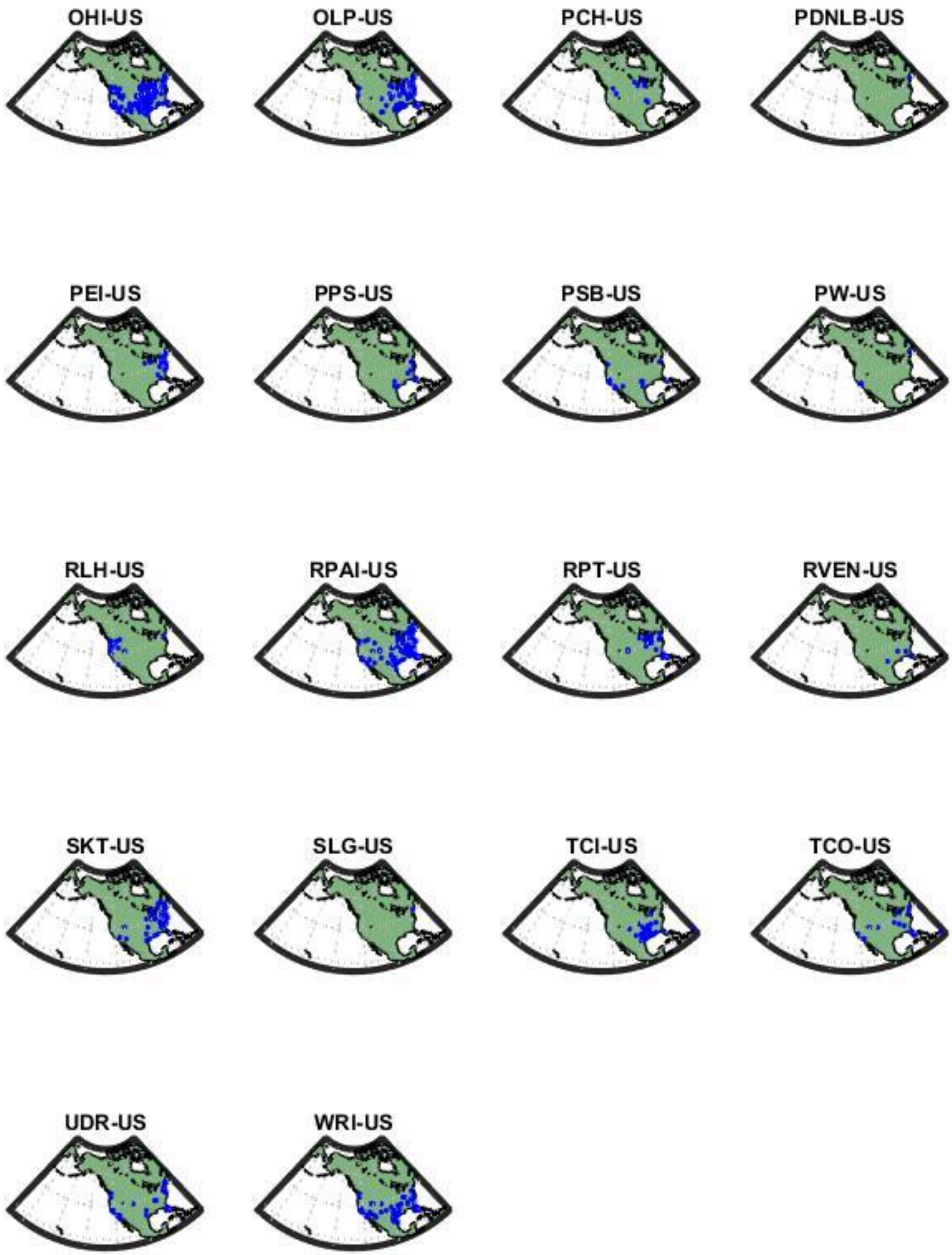
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PCH-US
PDNLB-US
PEI-US
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PSB-US
PW-US
RLH-US
RPAI-US
RPT-US
RVEN-US
SKT-US
SLG-US
TCI-US
TCO-US
UDR-US
WRI-US

Appendix 2

Table A1: Unbalanced spatial panel models of abnormal returns obtained through alternative ways

Note: This table reports the estimates of unbalanced spatial panel regressions for the monthly abnormal returns obtained through alternative ways in the first stage. We report abnormal returns obtained from a standard five-factor Fama-French model; abnormal returns obtained from a six factor model including a liquidity factor; from a model similar to the one defined in Ferreira et al (2012). ρ is the spatial dependent coefficient. We report the associated t-statistics in parentheses.

	Model using abnormal returns from a standard Fama-French five factor model	Model using abnormal returns from a standard Fama-French five factor with a liquidity factor	Model using abnormal returns defined by Ferreira et. al. (2012), using the constructed Fama-French factors and a liquidity factor
Spatial coefficient ρ	0.3748***	0.3857***	0.2033***
	(51.92)	(52.15)	(7.37)
Lagged abnormal return	-0.0399***	-0.0562***	-0.1147***
	(-8.48)	(-11.63)	(-12.28)
Age	-0.0031	-0.0039	0.0106
	(-0.39)	(-0.71)	(1.56)
Age squared	0.0003	0.0004	-0.0012
	(0.25)	(0.40)	(-1.49)
Size	0.5564***	0.5407***	0.3359***
	(130.54)	(124.53)	(59.12)
Size squared	-0.0796***	-0.0765***	-0.1111***
	(-53.22)	(-50.11)	(-50.11)
M/B ratio	-0.0012	-0.0013	0.0009
	(-1.19)	(-1.52)	(0.88)
ROAE	0.0001***	0.0002***	0.0001
	(2.43)	(2.99)	(1.32)
RE inv. growth	-0.0002***	-0.0001***	-0.0000
	(-5.44)	(-5.91)	(-1.14)
Turnover ratio	-0.0005***	-0.0005***	0.0002
	(-3.57)	(-3.80)	(0.80)
D/E ratio	0.0003	0.0003	0.0001
	(1.26)	(1.16)	(0.23)
State dummy	-0.0033	-0.0028	-0.0307***
	(-0.51)	(-0.43)	(-3.18)
Sector dummy	0.0038	0.0052	0.0030
	(1.11)	(1.54)	(0.59)
House price growth	0.1161	0.1422	-0.2486
	(1.11)	(1.37)	(-1.62)
Year dummy	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes

No. of Observation	10140	10140	8945
Ad R-squared	0.812	0.800	0.482
LL	19541	19327	13951

Appendix 3: Definition of Alternative Spatial Linkages

Similarity in size

In addition to geographic closeness of the underlying assets, comovement can also arise due to the similarity of the characterstics of the firms. We follow Ashigariah et al., (2012) and construct the matrix according to the similarity in size:

$$F_{i,j,t}^{size} = | Size_{i,t} - Size_{j,t} |, \tag{A1}$$

where $Size_{i,t}$ is the market capitalization of firm i in period t. $F_{i,j,t}^{size}$ measures the proximity of the size between two firms i and j.

Similarity in M/B ratio

We also construct the matrix according to the similarity in Market to Book ratio of the two firms:

$$F_{i,j,t}^{MB} = | MB_{i,t} - MB_{j,t} |, \tag{A2}$$

where $MB_{i,t}$ is the market to book ratio of firm i in period t. $F_{i,j,t}^{MB}$ measures the proximity of the size between two firms i and j.

Similarity in Momentum

We also construct the matrix according to the similarity in previous return of the two firms:

$$F_{i,j,t}^{MOM} = | R_{i,t} - R_{j,t} |, \tag{A3}$$

where $R_{i,t}$ is the average return of firm i in the past year.

The above three kinds of F matrix is then converted to a continguity matrix C as:

$$C_{i,j,t} = 1 - \frac{F_{i,j,t} - \min_{j,t} F_{i,j,t}}{\max_{j,t} F_{i,j,t} - \min_{j,t} F_{i,j,t}}, \tag{A4}$$

C matrix is then standardized to matrix W so that for each i, $\sum_{j,t} w_{i,j,t} = 1$.

Closeness of Headquarters

We also construct weight matrix according to the headquarter location, which is defined as

$$F_{i,j,t}^{HQ} = \begin{cases} 1 & \text{if HQ is in same city} \\ 0 & \text{otherise} \end{cases}. \tag{A5}$$

Then F matrix is then standardized to matrix W so that for each i, $\sum_{j,t} w_{i,j,t} = 1$. This headquarter location matrix can also be defined according to the criteria of whether the headquarters are within the same MSAs, the results are similar.

Continuity definition using MSA

We also use alternative ways to define the location of the underlying assets. For example, in equation (4), instead of using a bandwidth of 25 KM, we use a dummy variable for whether the two properties are in the same MSAs:

$$c_{i,l,j,k} = \begin{cases} 1 & \text{if property l in firm i and property k in firm j are in same MSA} \quad \text{for } i \neq j \\ 0 & \text{otherwise} \end{cases} \tag{A6}$$

and then we use the minimum proportion of the underlying properties in the same MSA for the two firms:

$$c_{i,j} = c_{j,i} = \min\left(\frac{1}{L_i}\sum_{l=1}^{L_i} c_{i,l,j}, \frac{1}{L_j}\sum_{k=1}^{L_i} c_{j,k,i}\right). \tag{A7}$$