INTERNATIONAL REAL ESTATE REVIEW

2019 Vol. 22 No. 4: pp. 535 – 570

Geographic Proximity and Competition for Scarce Capital: Evidence from U.S. REITs

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The question of whether REITs compete for scarce capital across geographic space is deserving of attention. In this study, we consider the issue of spatial competition among REITs across U.S. states in terms of the degree of interdependence in financial capital demand. First, we motivate the issue with a theoretical model of cost minimization by using a representative REIT in a given U.S. state and demonstrate that a priori, it is unclear whether the capital demand of a REIT depends on that of the REITs in other states. Then we use spatial econometrics techniques and find empirically that REITs compete for financial capital with REITs in other states. We also find evidence of feedback (or indirect) effects, thus implying amplified crowding out of financial capital when other REITs in nearby states increase financial capital demand. Our findings are aligned with the *predation hypothesis*, which suggests that REIT managers might exploit the financial distress of neighboring REITs and/or investors as an opportunity to steal their market share. Another key contribution of this study is that we focus on capital liquidity as opposed to stock liquidity.

Keywords

REITs, Financial Capital Scarcity, Geographic Spillovers

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1. Introduction

Is there competition for capital among REITs in different geographic regions (such as the U.S. states)? Also, do the macroeconomic variables of states affect state-level financial capital conditions? An in-depth understanding of these disaggregated aspects of financial capital determinants is important for understanding publicly traded assets.[1] While a large body of recent research has examined financial capital in several different contexts, much of that work has focused on the national level as opposed to the local level, without simultaneously considering a comprehensive set of asset classes (that is, REITs[2]). In the prior literature, REITs have been typically excluded because they are perceived as a highly regulated industry. However, REITs are especially strong candidates for potentially competing with each other for capital across geographic boundaries. Their exogenously determined payout ratio, high debt usage, and illiquid and locally segmented markets for their underlying assets (real estate) together imply possibly strong local competition for capital among REITs. We examine these issues in this paper. In other words, we test the following hypothesis: there is competition for capital among REITs across states. We find evidence that support this hypothesis.

Situating our study within the context of the literature, recent research has suggested that capital markets are in general locally segmented rather than integrated. Korniotis (2008) and Korniotis and Kumar (2013) argue that, due to heterogeneity and variation across the states, the U.S. economy is better described as a collection of 50 state-level investors than a representative U.S. investor.

An additional important reason for studying financial capital is that it has important implications for market liquidity due to liquidity spirals (Brunnermeier and Pedersen, 2009; Anthonisz and Putniņš, 2017) and segmentation (Agarwal and Hauswald, 2010). Glascock and Lu-Andrews (2014) are among the first to empirically test the relation between aggregated market and funding liquidity for REITs. They find a reinforcing relationship between the two liquidity measures at the national level. However, no known work has examined this liquidity issue for REITs at the state level. Other recent studies show that, at the state level, market liquidity is also positively affected by funding liquidity and local macroeconomic conditions due to market segmentation (Bernile et al., 2015; Luo et al., 2016). Evidently, an enhanced understanding of REIT financial capital conditions at the local level is important for a more complete comprehension of REIT market liquidity.[3]

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[1] Financial capital and funding liquidity are used interchangeably in this paper.
[2] Glascock and Lu-Andrews (2014); Riddiough and Steiner (2016, 2017); and Pavlov et al. (2016).
[3] Additionally, this work has implications for trading illiquidity when financing may be difficult for firms locally. See Ang, Papanikolaou and Westerfield (2014) for portfolio implications for illiquid assets.

Another key distinctive feature of our research is the focus on capital liquidity as opposed to stock liquidity. Given that REITs are one form of publicly listed companies, REITs can be considered a form of common stocks. Stock liquidity focuses on the ease of the trading activities of investors in secondary markets, while capital liquidity focuses on the primary market activities of firms (such as ease of raising capital). While other recent papers focus on stock liquidity, such as Bernile et al. (2015) and Wang et al. (2018), we study the capital liquidity for REITs.

An important determinant of the REIT capital structure is financial flexibility (Graham and Harvey (2001) describe this in more general terms for corporate capital structures). While financial flexibility is typically a firm-level phenomenon, we consider this issue in our state-level analyses by examining the financial flexibility of a "representative" REIT (as in the "representative agent" models of Hartley (1997)) in a state. Financial flexibility is crucial for REITs, given that financing frictions have been shown to lead to increased costs of capital and suboptimal levels of investment for other publicly listed companies (Kaplan and Zingales, 1997; Stein, 2001). These frictions are reduced with the availability of internal funds (Almeida et al., 2011), but there is a tradeoff between the lower cost of capital by building financial slack in the face of the high external cost of capital and higher agency cost. That is, there may be "empire building" during periods with poor growth opportunities (Jensen, 1986). In order to maintain financial flexibility, firms would also preserve access to low cost of capital through capital structure choices, i.e., maintain debt capacity (Denis and McKeon, 2012), and through equity repurchases and payouts (Brav et al., 2005; Bonaimé et al., 2013).[4] The issue of payouts is particularly relevant for REITs.

What are the consequences of a lack of financial flexibility for REITs? One potential answer to this question is that negative spillovers across REITs might be occurring when firms prey upon financially inflexible rivals.[5] In the present context, such spillovers might lead to inaccurate estimates of financial capital determinants (because the indirect effects are ignored) due to endogeneity/simultaneity issues that arise because some estimation techniques assume that spillovers, or indirect effects, across units (here, firms that are competing for financial capital) do not exist. We first assume each U.S. state consists of a "representative" REIT to examine potential differences in capital competition intensities. Our theoretical and empirical models allow for spillovers across units (i.e., states) and we also address the potential endogeneity of the capital decision of REITs in this particular context. In contrast, Nordlund (2016) develops a profit maximization model to explain why indirect effects might occur among firms within the same industry, but does not consider omitted geographic variables. Also, Nordlund (2016) considers different costs of capital, but does not directly address endogeneity. He assumes

[4] For a good review on financial flexibility, see Denis (2011).
[5] See Nordlund (2016).

that firms may enter into covenants with one another to coordinate their actions. Using covenant violations, he finds that non-violating firms benefit from violating peers by strategically preying on them. That is, non-violating firms are "treated" indirectly, which thus violates the estimation techniques in Nordlund (2016) who assumes that there are no indirect or spillover effects. Due to competition between violating and non-violating firms, the indirect treatment effect, or the spillover effect, is negative. Thus, a major shortcoming of Nordlund (2016) is that his firm-level analysis is subject to an important endogeneity issue, which is based on the argument in Garmaise and Natividad (2016). Specifically, Nordlund (2016) does not fully explain the source of the indirect effect. The indirect effect can either be an outcome of competition between geographic neighbors or across REITs within a particular industry. However, these implications can be important when financial capital conditions are affected by local economic conditions. In our model, we factor in the possibility that the optimum amount of capital for one REIT depends on the amount of capital for other REITs; and, our empirical tests of this model indicate that as other REITs use more capital, the amount of capital for a particular REIT decreases. We uncover evidence that support the hypothesis that there is competition for capital at the geographical and local scales.

More generally, spatial spillover effects are widely studied in the economics literature as an important source of externalities, in which some entities generate non-compensated benefits (or costs) from others. Moreover, spatial spillovers can highlight the role played by geographic proximity in the complex processes of local endogenous interactions and in different asset classes. For instance, empirical evidence of spatial interaction has been found in real estate markets (i.e., Anselin, 1988), the U.S. equity market (Pirinsky and Wang, 2006), and international stock markets (Asgharian et al., 2013). The asset pricing implications of spatial interactions have been examined in Kou et al. (2018) (hereinafter KPZ), where spatial econometrics techniques, such as spatial autoregressive models (SARs), are shown to be effective in eliminating cross-sectional correlations.

The theoretical model in our research is most closely related to the concept of growth spillovers. We consider a situation where capital utilized by REITs in some locations may crowd out the ability of REITs in another region to obtain and/or use capital. We consider the effects of state-level macroeconomic conditions on the financial capital of U.S. equity REITs and their spillovers across state borders. This model is more specific than that of the spillovers from financial flexibility considered in Nordlund (2016). In motivating the presence of potential spatial heterogeneity, we first develop a theoretical framework based on a representative REIT-level cost minimization model to develop comparative statics implications for our empirical analysis. We also motivate our model graphically by comparing the national capital markets with the local capital markets. Our model shows that either zero or negative spillovers are a possibility; however we empirically test for the sign and magnitude of the spillovers. We then use panel regression methods, with fixed effects along with spatial econometrics techniques, to estimate the sign and statistical significance of the cross-state financial capital spillover effects.[6]

The remainder of this paper is structured as follows. In the next section, we develop our theoretical model to describe the optimum capital demand of each representative REIT as a function of the capital of other REITs. Then we describe our empirical model. The subsequent section consists of an overview of the data (with a more detailed discussion of the data variables in Appendix 1). Finally, we describe our empirical results, followed by the conclusions where we summarize our key findings and possible directions for future research.

2. Theoretical Model

We consider a world in which each U.S. state has a representative REIT. In our cost minimization problem, we assume that K is the demand for the financial capital of a REIT (e.g., "REIT 1"), with price *r.* The "real" price of capital for REIT 1, r_1, also equals to the product of the nominal price of capital (determined in the national capital market), γ, and a local risk premium scalar, φ_1, or $r_1 = \gamma\varphi_1$[7]; where L is a composite of all of the other inputs (with price *w)*, including physical capital, labor, etc. Firm 1 will choose K_1, L_1 to minimize its operating costs, subject to a given level of "output". The REIT output is the space leased and managed, while the dividends paid to shareholders represent the value of the output.[8]

Figures 1 and 2 illustrate the national and local capital market conditions that determine the corresponding REIT capital prices. First we consider the national capital markets. The national supply of capital can be either upward sloping or flat. If the national supply is flat, as in Panel A of Figure 2, this implies perfect capital mobility between the international and domestic markets. Increased national demand for capital (which shifts the demand curve towards the right) has no impact on the national capital price, γ. An upward sloping curve for the

[6] Thus, we follow a recent trend in the literature of applying spatial econometrics techniques to better analyze local data (see for example Kelejian and Prucha, 1998; Cohen and Morrison Paul, 2004; Case et al., 2004; LeSage and Pace, 2009; and Cohen, 2010).

[7] We assume that the nominal price of capital, γ, is equal across the U.S. and allow variation in the "real" price of capital, r. The nominal price, γ, is assumed to be determined in the national capital market because stocks in developed markets are typically priced globally rather than locally (Hau, 2011).

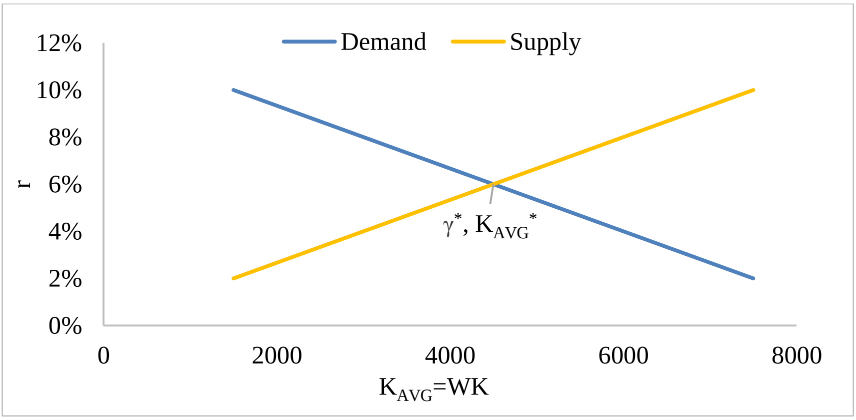
[8] According to the National Association of Real Estate Investment Trusts (Nareit), "Most REITs operate along a straightforward and easily understandable business model: by leasing space and collecting rent on its real estate, the company generates income which is then paid out to shareholders in the form of dividends…" (https://www.reit.com/what-reit , accessed 6/24/2018)

national capital supply as in Panel A of Figure 1, on the other hand, implies scarce capital at the national level. In other words, increased capital demand (which shifts the demand curve towards the right) leads to a higher national capital price, γ.

Figure 1 National and Local Economies with Scarce Capital

Figure 1 shows the scenario where capital is scarce at the national and local levels. In other words, the national capital supply slope is upward sloping. When national demand increases (i.e., when K_{AVG} increases), the capital demand curve in Panel A shifts to the right, which leads to a higher national capital price, γ^* (as well as higher local capital price, $\gamma^*\varphi_1$). Higher local capital price shifts the local capital supply curve upwards in Panel B, and therefore a local representative firm uses less capital in equilibrium, $\rho = \frac{\partial K_1^*}{\partial K_{AVG}} < 0$.

Panel A: National Capital Market



Panel B: Local Capital Market

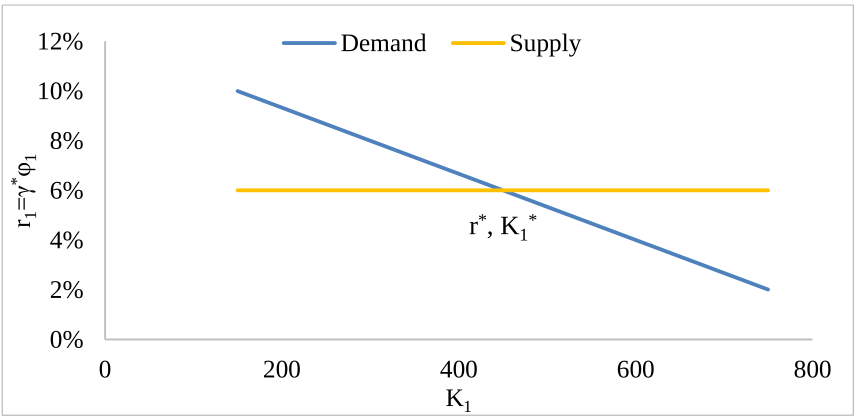
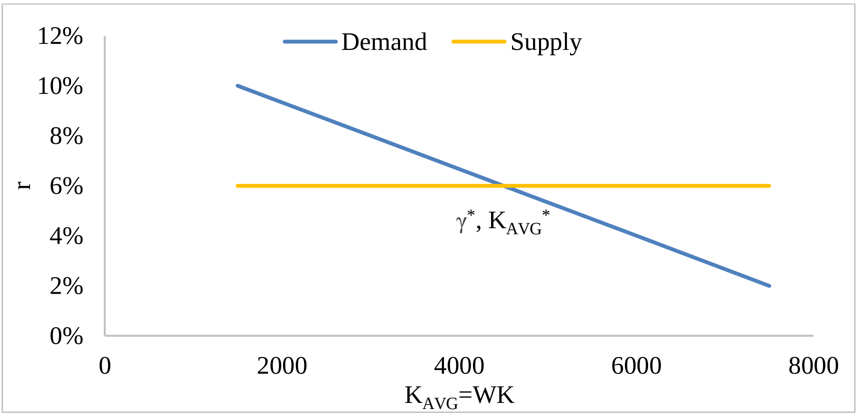


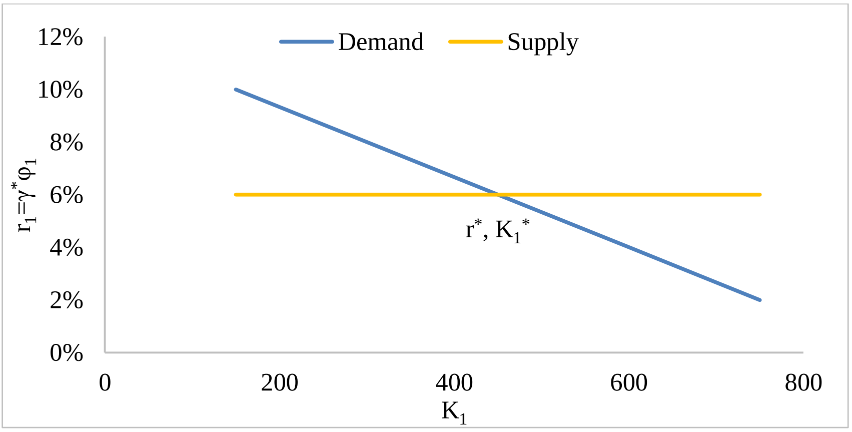
Figure 2 National and Local Economies with Perfect Capital Mobility

Figure 2 shows the scenario where capital is not scarce at the national level. In other words, national capital supply is flat. When national demand increases (i.e., when K_{AVG} increases), the national demand curve in Panel A shifts to the right, which has no impact on the national capital price, γ^* (as well as no impact on local capital price, $\gamma^*\varphi_1$). The local capital supply curve in Panel B remains unchanged, and therefore a local representative firm uses the same amount of capital in equilibrium, $\rho = \frac{\partial K_1^*}{\partial K_{AVG}} = 0$.

Panel A: National Capital Market



Panel B: Local Capital Market



We assume that this national price of financial capital, γ, is exogenous to representative REITs in each geographic region, thus implying that the supply of financial capital in each region is perfectly elastic (due to capital mobility). In Panel B of Figure 1, REIT 1 is too small to influence the national market price of capital; however, the total supply of capital in the nation is determined by the supply and demand in the entire market. The representative REIT takes the national level of capital as given when it chooses its financial capital because it realizes it is too small to influence the national price of capital. The price of capital differs across regions due to the local risk premium scalar. Therefore, we focus on the demand for capital through the representative REIT in each region, and all other REITs in the nation.

We discuss first the theory for the situation where the national supply of capital is upward sloping, which is typical in a large economy like the U.S. (Kiyotaki and West, 1996; Schaller, 2006). When the demand of other REITs increases outside of Region 1, the national demand curve shifts right as shown in Panel A of Figure 1, thus implying that the national price, γ, will rise. This leads to a higher local capital price (see Panel B of Figure 1) as well, since the local price is ϕ_1 , which implies an upward shift in the local capital supply curve. This leads to a lower amount of capital in equilibrium in the local region. In other words, the change in local capital with respect to a change in national capital is negative when the national capital supply curve slopes upward (i.e., when capital is scarce at the national level).

Alternatively, we consider the case where the national capital supply is flat (perfectly elastic), as shown in Panel A of Figure 2. When national demand rises due to other REITs, this shifts the national demand curve to the right, as shown in Panel A of Figure 2, but the price of capital does not change since there is no friction in the national capital market. There is no change in local capital in response to a change in national capital when the national capital supply curve is flat (i.e., when there is perfect international capital mobility) as shown in Panel B of Figure 2. Thus, a major objective of our empirical analysis is to test which of these two scenarios – scarce capital at the national level or no national capital friction – is supported by the data for REITs.

To motivate our empirical specification, we first develop a theoretical model to describe the choice of financial capital of the representative REIT. Specifically, the cost minimization problem for REIT 1 is:

$$\min_{K_1, L_1} wL_1 + r_1 K_1 \ \mathit{subject\ to}\ Y_1 = (S_1) f(K_1, L_1, K_{AVG}) \tag{1}$$

where S_1 is a set of shift factors that consist of other exogenous variables that affect output for REIT 1, and K_{AVG} is the average level of capital demanded by all other REITs in all of the other states (that is, it can be considered as the market level of capital, which REIT 1 takes as given).

This production function specification assumes that more financial capital used by other REITs may (or may not) affect the production technology of a particular REIT. REITs need financial capital to produce their outputs (which is the space leased and managed). However, we do not know, a priori, how the REIT capital usage of other regions affects the productivity of the representative REIT of Region 1, or whether there is any effect at all from the market level of capital on the capital of a particular REIT. Firm 1 takes K_{AVG} as given (that is, Firm 1 assumes it is small so that it has no "control" over the amount of capital used by REITs in other states, and in turn, over the market price, γ).

The optimization problem for REIT 1 is:

$$\min_{K_1,L_1}\{wL_1 + r_1K_1 + \lambda_1[Y_1 - (S_1)f(K_1, L_1, K_{AVG})]\} \tag{2}$$

First order conditions include:

$$r_1 - \lambda_1 S_1\left(\frac{\partial f}{\partial K_1}\right) = 0 \tag{3}$$

where λ_1 is the shadow value of output for REIT 1. In other words, this implies that in equilibrium, the "real" price of financial capital equals the value of its marginal product. In our empirical models, the local risk premium is captured through state-level fixed effects.

There is a similar first order condition for the composite input, L_1 and the shadow price, λ_1:

$$\begin{aligned} &w_1 - \lambda_1 S_1\left(\frac{\partial f}{\partial L_1}\right) = 0 \\ &Y_1 - (S_1)f(K_1, L_1, K_{AVG}) = 0 \end{aligned} \tag{4}$$

Consider a particular functional form for *f*, such as the Cobb-Douglas function:

$$Y_1 = S_1(K_1)^{a_1}(L_1)^{b_1}(K_{AVG})^{c_1} \tag{5}$$

where $0 < a_1 < 1$, $0 < b_1 < 1$, and $c_1 > 0$ or $c_1 < 0$ or $c_1 = 0$. Also, $a_1 + b_1 = 1$, so that there are constant returns to scale in the inputs of the region itself but potentially increasing or decreasing returns to scale overall (depending on whether the true value of c_1 is positive or negative). We do not know how (if at all) more capital demand at the national level impacts optimal local capital.

The first order conditions for REIT 1 imply:

$$r_1 = \gamma\varphi_1 = a_1\lambda_1 S_1[(K_1)^{a_1-1}(L_1)^{b_1}(K_{AVG})^{c_1}] \tag{6}$$

$$w_1 = b_1\lambda_1 S_1[(K_1)^{a_1}(L_1)^{b_1-1}(K_2)^{c_1}] \tag{7}$$

$$Y_1 - S_1(K_1)^{a_1}(L_1)^{b_1}(K_{AVG})^{c_1} = 0 \tag{8}$$

where γ is the nominal price of capital and *r* is the "real" cost of capital. Dividing Equation (6) by Equation (7) provides:

$$\left(\frac{\gamma\varphi_1}{w_1}\right) = \left(\frac{a_1}{b_1}\right)\left(\frac{L_1}{K_1}\right) \tag{9}$$

We can solve for K_1 as a function of K_{AVG}, by solving Equation (8) for L_1, substituting this value for L_1 into Equation (9), and solving Equation (9) for K_1. This yields:

$$K_1 = \left[\frac{(b_1)^{\frac{b_1}{b_1+a_1}}}{(a_1)^{\frac{b_1}{b_1+a_1}}}\right]\left[(Y_1)^{\frac{1}{b_1+a_1}}\right]\left[(K_{AVG})^{\frac{-c_1}{b_1+a_1}}\right]\left(\frac{\gamma\varphi_1}{w_1}\right)^{\frac{-b_1}{b_1+a_1}} \tag{10}$$

Equation (10) is the optimum demand for K_1, given K_{AVG} and the other exogenous variables and parameters. In other words, this is the reaction function of REIT 1 for financial capital.

If we take natural logs of this equation, we are left with:

$$\begin{aligned}\log(K_1) = {} & \frac{b_1}{b_1+a_1}\log\left(\frac{b_1}{a_1}\right) + \frac{1}{b_1+a_1}[\log(Y_1)] \\ & + \frac{-c_1}{b_1+a_1}\log(K_{AVG}) + \frac{b_1}{b_1+a_1}\log(w_1) \\ & + \frac{b_1}{b_1+a_1}\log(\gamma\varphi_1)\end{aligned} \tag{11}$$

Also,

$$\frac{\partial\log(K_1)}{\partial\log(K_{AVG})} = \frac{-c_1}{b_1+a_1}$$

Or equivalently,

$$\frac{\partial K_1}{\partial K_{AVG}} = \frac{-c_1 K_1}{(b_1+a_1)K_2} \tag{12}$$

Therefore, there is competition for capital at the national level when the reaction function for REIT 1 is downward sloping, or, equivalently, if the production function of REIT 1 shows increasing returns with respect to all 3 inputs. A sufficient condition for this capital scarcity at the national level is that $c_1 > 0$.

One way to empirically test for the sign of the reaction functions – and in turn, to understand how REITs in different U.S. states utilize capital differently, is to estimate the reaction functions econometrically with spatial econometrics. In other words, we can estimate $\frac{\partial\log(K_1)}{\partial\log(K_{AVG})}$ or $\frac{\partial K_1}{\partial K_{AVG}}$.

A negatively sloped reaction function implies that when the capital usage of everyone else increases, this leads to a fall in the capital demanded for a particular REIT. This hypothesis implies that while capital is not scarce locally, it is scarce nationally. This national scarcity leads to a higher national price of capital when national REITs increase their demand for capital, and this higher national price shifts the horizontal supply of capital curve for REIT 1 upward, leading to a movement along the demand curve to the left for REIT 1. While there is not an exact one to one correspondence between the national and the local prices due to the local risk premium, the local and national prices will clearly move in the same direction, given the positive local risk premium. We now describe our empirical estimations of the comparative statics implications of our model.

3. Spatial Predictive Regressions on Liquidity Variables

We present a spatial lag model in Equation (13) which can be used to test the hypothesis that there is competition for scarce capital. Modifying Equation (11) into a format that corresponds as closely as possible to the available data, we obtain (Appendix 1 provides details on the variable names, and Appendix 2 provides background on the spatial lag model):

$$\begin{aligned} COV_{s,t+1} = \alpha_0 + \rho W_t\left(COV_{s,t+1}\right) + \beta_{UNEMP} \cdot UNEMP_{s,t} \\ +\beta_{GSP} \cdot Delta\ GSP_{s,t} + \beta_{INC} \cdot Delta\ INC_{s,t} \\ +\beta_{NCREIF} \cdot NCREIF_{RET\,R_1,t} + \beta_{CPI} \cdot CPI_{R_2,t} \\ +\mu_s + \delta_t + \varepsilon_{s,t} \end{aligned} \tag{13}$$

where the logarithm of the quarterly regional consumer price index (*CPI*) corresponds to w_1 in the theoretical model in Equation (11); the local risk premiums, φ_1 , are captured by the percentage growth rate of gross state product (*Delta GSP*); and the unemployment rate (*UNEMP*) and commercial real estate index growth (*NCREIF_RET*) are assumed to be highly correlated with output, Y. Finally, W is a spatial weights matrix, and described in more detail below.

We examine the sign and significance of ρ in order to test the hypothesis that REITs in the U.S. states compete with each other for scarce capital. If we find that $\rho < 0$, then this would be evidence of negative spillover effects that imply capital is scarce nationally. However, if we find $\rho \geq 0$, the hypothesis of scarce capital would be rejected. The model in Equation (13) is a state-level generalization of the national level empirical model proposed by Glascock and Lu-Andrews (2014).

We begin by considering regression models with time and location fixed effects.[9] Since we are interested in predicting the demand for the financial capital of a representative local REIT, we aggregate the firm-level coverage ratio across all REITs headquartered in a particular state. All of the variables

[9] We do not include a control variable for risk since the state coverage ratio (*COV*) has been risk-adjusted. Here we use the state-level analysis as an example because most macroeconomic variables are available at the state level.

are defined in Section 4 and Appendix 1. We focus on state-level results for two reasons. First, most legislations associated with local capital markets are established at the state-level. Second, local economic data vendors typically span longer time horizons and are more populous at the state level than the finer geographic jurisdiction level.

We also adopt individual state macroeconomic factors instead of changes in composite indexes to unveil a broader picture. Specifically, we regress the state coverage ratio (COV) on date t+1 (*COV(t+1)*) on the state macroeconomic variables in date *t* with fixed effects.

The National Council of Real Estate Investment Fiduciaries (NCREIF) provides commercial real estate index returns on four regions (R_1) categorized based on local commercial property market dynamics, including the East, Midwest, South and West. Whereas the regional CPI data obtained from the U.S. Bureau of Labor Statistics (BLS) website is available for the four census regions (R_2), including the Northeast, Midwest, South and West, prior to 2017Q4 and nine census regions (R_2) since 2017Q4.

4. Data

In this paper, we use local (state-level and regional) economic activity data to examine how local economy can affect the capital accessibility of equity REITs. Our methods for calculating the capital accessibility of state representative firms are discussed below. A detailed explanation on the construction of the local macroeconomic variables can be found in the variable definitions in Appendix 1.

Since REITs represent a relatively homogeneous asset class with real estate as their underlying assets, we require a state to have at least one REIT in each quarter to be included in our sample (even though most states in our sample host more than one REIT in each quarter). Our sample ended up having 21 states with 419 REITs with non-missing information from 1994Q1-2018Q4. Over the entire sample period, California and New York have the most and second most REIT headquarters, respectively. There are 81 and 80 REITs currently or previously headquartered in California and New York, respectively. Missouri has only 5 REIT headquarters. The "average" state in our sample has approximately 7.6 REIT headquarters in a given quarter.

We use the state centroid as the location of the representative REIT of a state in order to mitigate the concern that the selection of headquarters location is endogenous to the REIT. Since state borders were determined far back during the 19th century (prior to when most listed securities were issued), it is less of a concern that our spatial weighting matrix might be endogenous by itself. However, geographic centroids might mask variations within a state in economic activity and labor markets (Ling et al., 2019). Therefore, we also download population centroids from the U.S. BLS website. The latitude and longitude coordinates of the geographic and population centroids for each state in our sample are reported in Table 1.

Table 1 States and Centroid Coordinates

This table reports the 21 U.S. states that hosted at least one equity REIT during each quarter. We follow common practice in spatial econometrics studies and exclude isolated islands. Four states or areas (Hawaii, HI; Alaska, AK; Virgin Islands, VI; and Puerto Rico, PR) that are not in the continental U.S. are deemed as isolated islands and dropped from the sample. We report Federal Information Processing Standard (FIPS) code, state name, state abbreviation, latitude and longitude of the geographic or population centroid of a state.

FIPS	State Name	State Abbrev.	Lat (GEO)	Lon (GEO)	Lat (POP2010)	Lon (POP2010)
04	Arizona	AZ	34.21	-111.60	33.37	-111.83
06	California	CA	37.15	-119.54	35.46	-119.36
08	Colorado	CO	38.99	-105.51	39.50	-105.20
09	Connecticut	CT	41.58	-72.75	41.49	-72.87
12	Florida	FL	28.46	-82.41	27.80	-81.63
13	Georgia	GA	32.63	-83.42	33.33	-83.87
17	Illinois	IL	40.10	-89.15	41.28	-88.38
18	Indiana	IN	39.90	-86.28	40.16	-86.26
24	Maryland	MD	38.95	-76.67	39.15	-76.80
25	Massachusetts	MA	42.16	-71.49	42.27	-71.36
26	Michigan	MI	44.84	-85.66	42.87	-84.17
29	Missouri	MO	38.35	-92.46	38.44	-92.15
34	New Jersey	NJ	40.11	-74.67	40.44	-74.43
36	New York	NY	42.91	-75.60	41.51	-74.65
37	North Carolina	NC	35.54	-79.13	35.55	-79.67
39	Ohio	OH	40.41	-82.71	40.48	-82.75
42	Pennsylvania	PA	40.90	-77.83	40.46	-77.08
47	Tennessee	TN	35.86	-86.35	35.80	-86.40
48	Texas	TX	31.43	-99.28	30.94	-97.39
51	Virginia	VA	37.52	-78.67	37.75	-77.84
53	Washington	WA	47.42	-120.60	47.34	-121.62

The summary statistics of the variables used in our analysis are reported in Table 2. We use the state COV one quarter ahead to proxy for the financial capital conditions of a state. The state COV is calculated as the average of the quarterly interest COV(s) for REIT(s) located in a particular state. Interest COV is widely adopted as a measure of financial solvency. As shown in Figure 3, states that host financial centers (i.e., California and Illinois) tend to be well-capitalized.

Table 2 Summary Statistics

All variables are defined in Appendix 1. We report the mean, median, standard deviation, and 25th and 75th percentiles for a sample of 2016 state-quarter observations from 1995Q1 to 2018Q4.

Variable	# Obs	Mean	Median	Std. Dev.	25 Pct.	75 Pct.
COV (t+1)	2,016	1.210	1.510	0.358	0.756	1.472
Test variable						
Delta SCI	2,016	0.297	0.408	0.116	0.281	0.437
PSEA	2,016	0.900	1.033	0.488	1.051	1.541
UNEMP	2,016	1.722	0.303	1.526	1.705	1.902
Delta GSP	2,016	3.734	2.711	1.739	3.872	5.568
Delta INC	2,016	1.106	1.059	0.634	1.122	1.629
CPI	2,016	0.928	2.003	0.001	0.003	0.005
Control variable						
APT	2,016	0.169	0.109	0.081	0.151	0.240
OFF	2,016	0.221	0.136	0.108	0.192	0.312
IND	2,016	0.065	0.038	0.037	0.058	0.092
RTL	2,016	0.309	0.107	0.218	0.307	0.390
SIZE	2,016	9.465	1.482	8.700	9.658	10.421
NCREIF_RET	2,016	1.022	0.021	1.017	1.024	1.033
CONSTRAINT	2,016	0.707	0.455	0	1	1
NUM_INV_GRD	2,016	0.883	0.630	0.693	1.099	1.386
HIGH LEV	2,016	0.873	0.333	1	1	1

For an individual REIT i headquartered in state s in quarter q,

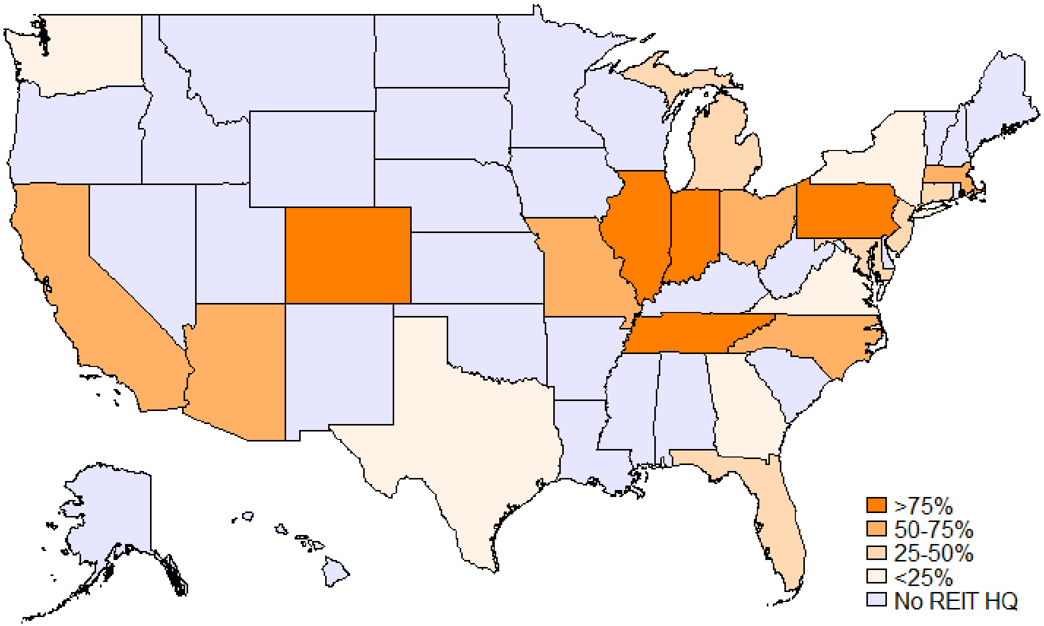
$$Interest\ Coverage\ Ratio_{i,s,q} = \frac{IBQ_{i,s,q}}{DVPQ_{i,s,q} + XINTQ_{i,s,q}} \tag{14}$$

where $IBQ_{i,s,q}$ is the income before extraordinary items, $DVPQ_{i,s,q}$ is the preferred dividends, and $XINTQ_{i,s,q}$ is the interest and related expenses. Then we aggregate the REIT-level interest COVs at the state level to obtain the COV. Suppose that there are a total of N REITs headquartered in state s in quarter q; we calculate the COV as follows:

$$COV_{s,q} = \frac{1}{N}\sum_{i=1}^{N} Interest\ Coverage\ Ratio_{i,s,q} \tag{15}$$

Figure 3 Heat Map of State COV of U.S. REITs

This figure plots the four quartiles of the state COVs of 21 U.S. states that hosted REIT headquarters in 2018Q4. Cut-off values correspond to the 25th, 50th, and 75th percentiles of the state COVs, respectively.



Quarterly financial statement data, obtained from Compustat, are used to calculate the state *COV* and state leverage (*LEV*). The latter is calculated as the average of the quarterly debt ratio(s) for REIT(s) located in a particular state. The dummy variable, *HIGH_LEV,* indicates that the *LEV* of one state is above the sample median. *SIZE* is the logarithm of the quarterly total book value of assets for REIT(s) located in a state. We follow Bernile et al. (2015) to construct a state funding constraint indicator (*CONSTRAINT*), which is based on the daily portfolio returns of NYSE-listed investment banks and securities brokers and dealers (i.e., SIC = 6211) headquartered in a particular state.[10] Data on daily portfolio returns are obtained from the Center for Research in Security Prices, LLC (CRSP), and the market excess return is downloaded from the website of Kenneth French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). To control for the effect of competition for financial capital within state borders, we include the logarithm of the number of REIT(s) with the investment-grade found in a state (*NUM_INV_GRD*). We manually adjust for headquarter relocations by using the Compustat Snapshot database.

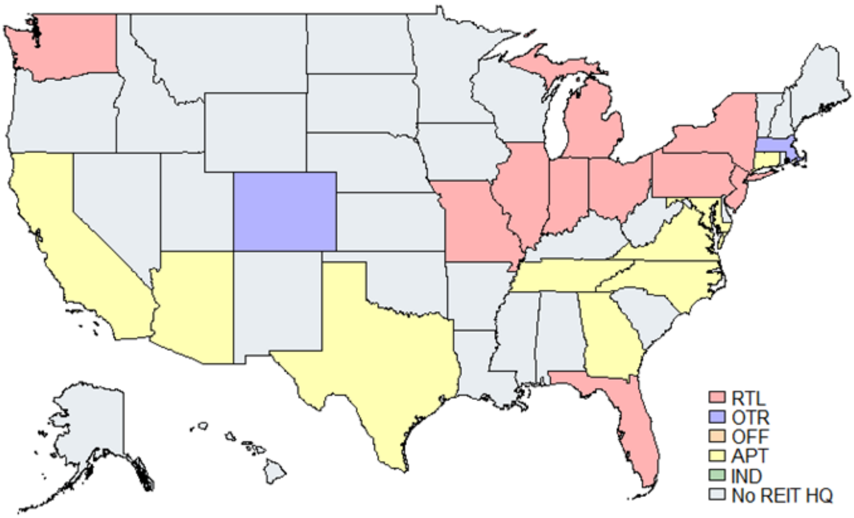
We obtain state and national coincident (leading) indexes from the Federal Reserve Bank of Philadelphia (FRED). Quarterly changes in the coincident indexes are calculated as the mean of monthly changes within a specific quarter. Quarterly predicted economic activity proxies are calculated as the means of the ratio of the State Leading Index, or the predicted six-month growth of the corresponding coincident index, to the corresponding coincident index. Data on the state unemployment rate and regional CPI (1987Q1 and onward) are obtained from the U.S. BLS; data on the gross state product and quarterly state income growth are obtained from the U.S. Bureau of Economic Analysis (BEA). Data on quarterly NCREIF property index returns (*NCREIF_RET*) are available for four U.S. regions including East, Midwest, South and West and obtained from the NCREIF website. We report pairwise correlation tables of the dependent and test variables used in our analysis for REITs in Table 3. Finally, we construct state-level property type weights by using the book value ("adjusted cost") of REIT-owned properties obtained from the S&P Global Real Estate Properties (formerly SNL Real Estate) database. We show the most dominant type of property of each state in Figure 4. Interestingly, at the beginning of our sample period (Panel A), most states were dominated by REIT holdings in core property types such as retail (*RTL*) and multifamily (*APT*). In 2018Q4 (Panel B), non-core property types (i.e., data centers) are the major types of property of most states in our sample except for the few in the Northeast region.

[10] We thank an anonymous referee for suggesting these control variables.

Figure 4 Major Property Type by State

This figure plots the major property types of 21 U.S. states that hosted REIT headquarters in 1995Q1 and 2018Q4. The major property type of a state is defined as the property sector that receives the largest amount of REIT allocations (i.e., office sector in New York).

Panel A: 1995Q1



Panel B: 2018Q4

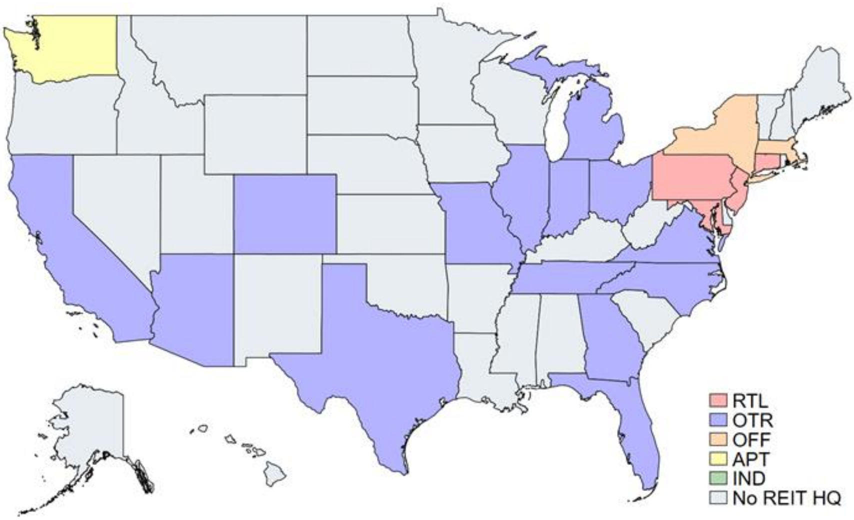


Table 3 Correlation Table

All variables are defined in Appendix 1. This table presents the pairwise correlations of variables defined in Appendix 1. In the first row, (1) – (7) represent *COV (t+1)*, *Delta SCI*, …, *CPI*, respectively. *** indicates statistical significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
COV (t+1)	1.000						
Delta SCI	0.572***	1.000					
PSEA	0.350***	0.859***	1.000				
UNEMP	-0.137***	-0.172***	-0.146***	1.000			
Delta GSP	-0.248***	0.096***	0.371***	-0.443***	1.000		
Delta INC	0.041	0.359***	0.458***	-0.275***	0.439***	1.000	
CPI	0.754***	0.669***	0.333***	-0.011	-0.470***	-0.018	1.000

5. Empirical Results

Our findings naturally fall into three categories. Before we present these results, Section 5.1 briefly discusses the predicted effects of the macroeconomic variables on state COV. Section 5.2 explains the interpretation of the spatial lag and spatial multiplier, and the difference between the SAR and spatial Durbin model (SDM). Section 5.3 describes the predictive panel and spatial analysis, and reports the regression results.

5.1 Macroeconomic Effects on Local Financial Capital

The predicted effects of each macroeconomic variable on *COV (t+1)* are reported in the variable definitions in Appendix 1. We include information on the local business cycle, i.e., unemployment rate (*UNEMP*), personal income growth (*Delta INC*), and gross state product growth (*Delta GSP*) into our analysis of local macroeconomic effects on local financial capital (*COV (t+1)*). *UNEMP* and *Delta INC* capture local labor market conditions and returns to human capital, respectively. Ceteris paribus, a lower local unemployment rate and higher personal income growth lead to higher financial capital in the next quarter. Our measure of commercial real estate value (*NCREIT_RET*) might reflect financial capital conditions to some extent because it measures the borrowing capacity of local investors conditional on their assets. Therefore, higher NCREIF property index returns positively predict future financial capital conditions.

We also include variables that capture local economic development (*Delta GSP*) and local inflation (*CPI*). Moreover, in order to examine the combined effect of local economic activity on financial capital conditions, we obtain state coincident and leading indices (*SCI* and *SLI*) from FRED. We also construct forward-looking proxies for local economic development (*PSEA*) as the ratio of *SLI* to *SCI*.[11] These forward-looking measures predict the 6-month growth of the corresponding coincident indexes with variables that lead the economy.[12] The theoretical model developed in Section 3 predicts that larger increases in economic development (*GSP growth*) and economic activities (*Delta SCI* and *PSEA*) and lower price levels (*CPI*) should lead to higher levels of financial capital in the next quarter. REITs hold real estate and are resistant to inflation.[13] They are attractive to investors particularly when local inflation rates are high (Glascock et al. 2002). Therefore, the relation between *CPI* and financial capital condition is equally likely to be positive, even though the effect of *CPI* on *COV* can be positive or negative.

5.2 Spatial Lag, Spatial Multiplier and Spatial Econometrics Models

In this section, we extend the panel regression analysis to estimate the SAR and SDM which are two of the most commonly used models in studies that apply spatial econometrics. As shown in Appendix 2, the main difference between the SAR and SDM is that the former (Equation 17a) assumes only the dependent variable has spatial dependence while the latter (Equation 17b) assumes that both the dependent and certain independent variables (i.e., *HIGH_LEV*) have spatial dependence.[14]

In all of the spatial models, an important consideration is how jurisdictions interact with each other. This is empirically modelled through a spatial weights matrix with dimensions *N* by *N*. We use a row-normalized inverse distance matrix (i.e., we allow the weights for a given observation to equal 1, as described below). Specifically, we first obtain data on the centroid location of each state (shown in Table 1) in the inverse distance matrix. Then we calculate the average distance between the centroids in states i and j as the *haversine* distance, d_{ij} (assuming that the surface of the earth is approximately spherical). The *haversine* formula is expressed as:

$$d_{ij} = 2 \cdot radius \cdot \arcsin\left(\sqrt{sin^2\left(\frac{lat_j - lat_i}{2}\right) + \cos(lat_i)\cos(lat_j)sin^2\left(\frac{lon_j - lon_i}{2}\right)}\right) \quad (16)$$

where d_{ij} is the geographic distance between the centroid of state I (with coordinates lat_i and lon_i) and centroid of state j (with coordinates lat_j and lon_j), and *radius* is the radius of the earth (*radius* = 6378 kilometers, or 3959

[11] *PESA* stands for predicted 6-month state economic activity growth.

[12] Such variables include state-level housing permits (1 to 4 units), state initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill.

[13] See for example the work of Glascock et al. (2002) and Darrat and Glascock (1989).

[14] The SDM is potentially more robust to cross-sectional heterogeneity than the SAR but subject to multicollinearity.

miles). Each element of the inverse distance matrix is expressed as $w_{i,j} = \frac{1/d_{i,j}}{\sum_{m=1}^{N-1} 1/d_{i,m}}$, where $d_{i,j}$ ($d_{i,m}$) is the distance between the centroids of states i and j/m (where we assume $d_{i,i} = 0$), and *N* is the total number of states.

5.3 Regression Results and Interpretation

In Table 4, we regress the state COV one quarter ahead (*COV (t+1)*) on the change in the state coincident index (*Delta SCI*) and predicted growth of state economic activity (*PSEA*), with state and time (year-quarter) fixed effects. Standard errors are clustered at the state level. We find that the coefficient estimates on *Delta SCI* and *PSEA* are positive and statistically and economically significant. These findings support our conjecture that the market for available funding is more likely to be segmented than integrated. Bernile et al. (2015) document a negative relation between *Delta SCI* and state Amihud illiquidity and state relative spread, both of which are negatively associated with stock market liquidity. Smajlbegovic (2019) shows that *PSEA* is positively correlated with future stock returns. This positive correlation is mainly explained by the cash flow news (i.e., earnings surprise). Our results in Table 4 are consistent with those in Smajlbegovic (2019) and might explain the positive relation between local economic activity and market liquidity documented in Bernile et al. (2015). However, due to the possibility of geographic spillovers, these coefficients should be interpreted with caution (since they might be over/under-estimated).

There is some evidence that regional commercial real estate returns (*NCREIF_RET*) predict state COV. However, the effect is significantly saturated with state and time fixed effects. The logarithm of the aggregated book value of assets (*SIZE*) and state capital constraint (*CONSTRAINT*) do not predict the state *COV*.

Based on our theoretical framework, one hypothesis is that the capital available to the representative REIT of each state is heterogeneous, and the impact of financial capital is likely to be asymmetrical among neighboring states. To put it differently, some states might compete with their neighbors by drawing scarce capital away from them, thus causing negative spillovers (externalities) on the financial capital conditions of their neighbors.

Empirically, we apply spatial econometrics to confirm this conjecture. We find that the impact of financial capital is asymmetrical, where some states are more dominant in the capital markets than their neighbors. We find a negative and statistically significant coefficient, ρ, on the spatially lagged financial capital measure, W_COV.[15]

[15] It is noteworthy that the financial capital conditions of state *i* itself always receives a spatial weight of 0; therefore, ρ only captures the effect of the financial capital conditions of neighboring states on the financial capital of state *i*. Moreover, neighboring states

Table 4 Regression Results with Changes in State Economic Activity Indices

In this table, we report the regression results of panel regressions and the SAR. The dependent variable is the state COV at quarter *t+1*, or *COV (t+1)*. The test variable is *Delta SCI* in Columns (1)-(3) and *PSEA* in Columns (4)-(6) at quarter *t*. All variables are defined in Appendix 1. The magnitude of the spatial spillover effect (feedback effect) is measured by the coefficient estimates of the spatial lagged outcome variable (*W_COV*). *W* is the row-normalized inverse-distance matrix based on either the geographic (GEO) or the population (POP) centroid. State and time (year-quarter) fixed effects are included. Standard errors are clustered at the state level. *t*-statistics are reported underneath the coefficient estimates in parentheses. ***, **, and * indicate significance for the coefficient at the 1%, 5%, and 10% levels.

COV (t+1)	(1) Panel	(2) SAR	(3) SAR	(4) Panel	(5) SAR	(6) SAR
W_COV		-0.691***	-0.695***		-0.688***	-0.693***
		(-4.22)	(-7.57)		(-4.21)	(-7.62)
Delta SCI	0.294*	0.307**	0.332**			
	(1.77)	(1.97)	(2.04)			
PSEA				0.115**	0.114***	0.126***
				(2.64)	(2.70)	(2.83)
NUM_INV_GRD	0.367***	0.369***	0.344***	0.363***	0.366***	0.340***
	(2.93)	(3.17)	(2.95)	(2.99)	(3.24)	(3.01)
NCREIF_RET	11.343*	11.078*	11.203*	11.216	10.975*	11.078*
	(1.64)	(1.71)	(1.68)	(1.62)	(1.68)	(1.65)
SIZE	-0.109	-0.112	-0.095	-0.109	-0.111	-0.095
	(-1.04)	(-1.10)	(-0.91)	(-1.03)	(-1.08)	(-0.90)
CONSTRAINT	-0.072	-0.065	-0.066	-0.071	-0.064	-0.065
	(-1.07)	(-1.08)	(-1.05)	(-1.06)	(-1.06)	(-1.03)
SPW	N/A	GEO	POP	N/A	GEO	POP
Clustering	State	State	State	State	State	State
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	2016	2016	2016	2016	2016	2016
R Squared	0.666	0.629	0.630	0.666	0.629	0.630

We find a negative spatial spillover effect, thus supporting the view that there is competition for financial capital among neighboring states. REITs largely resemble small-cap stocks and have payout restrictions (payout ratio > 90%). Therefore, they might have restricted sources of funding and more urgent demand for scarce capital than non-REIT firms.

A negative spillover effect also indicates overestimation of the effect of local economic activities on financial capital conditions with the use of panel regressions. When estimating the SAR, the coefficient estimates of the direct effect largely resemble those of the panel regressions. For instance, the direct

receive a larger weight because of the segmentation of the capital markets.

effect of *Delta SCI* is 0.30 in Column (2) and 0.33 in Column (3) when the geographic and population-based spatial weights matrixes are specified, respectively. The corresponding panel regression coefficient estimate in Column (1) is 0.29. In terms of economic significance, considering that the standard deviation of the *PSEA* is 0.49, one standard deviation increase in *Delta SCI* would increase the *COV (t+1)* by 0.06, or 5% relative to its mean of 1.21.

Spatial spillover effects provide a more comprehensive picture of the impact of local macroeconomic activities on state COV through the spatial multiplier effect. The spatial multiplier equals the inverse of one minus the coefficient estimate on W_COV, or $1/(1-\rho)$. Typically, for stability, ρ must be in the range of $-1 < \rho < 1$. Since ρ is negative in our application, the spatial multiplier is less than 1. This implies that the spatial multiplier effect may actually be a "spatial diminisher" due to the competition for capital among REITs headquartered in different states. Therefore, the direct effect (or the panel regression estimates) may be biased upward. For instance, in Column (6) of Table 4, the total effect of *PSEA* is 0.07 when allowing for competition for capital across space, which is considerably smaller than the corresponding direct effect of 0.13 and the panel regression coefficient estimate (0.12). These declining local economic effects are mainly due to the competition for capital among neighboring states.

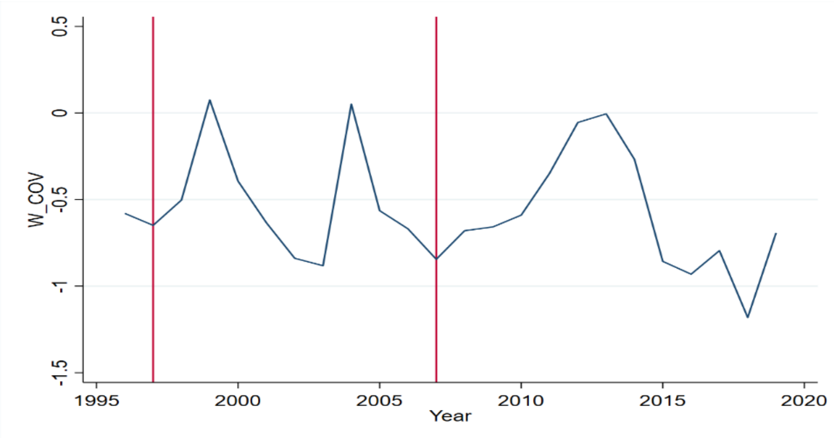
To further interpret the spatial spillover effect, we re-estimate the model in Table 4 separately for each year and plot the spatial coefficients in Figure 5. We find that our spatial coefficients are more negative one year *before* the economic downturns. For instance, the two vertical lines in Figure 5 highlight 1997 and 2007, which correspond to the beginning of the 1998 Asian financial crisis and 2008 global financial crisis, respectively.

Thus far we have discussed how changes in local economic activity indices (*Delta SCI*, *PSEA*) positively predict financial capital (state *COV*) in the next quarter. We also find a negative spatial spillover effect that is associated with financial capital. Such a negative spatial spillover effect has two implications: (i) REITs located in neighboring states are competing for scarce capital and, (ii) panel regression coefficient estimates and direct spatial effects overestimate the real impact of *Delta SCI* and *PSEA* on the state *COV*.

However, the economic meaning of local economic activity indices (i.e., *Delta SCI*) might be difficult to interpret (i.e., what does a 1% increase in *SCI* mean?). Moreover, these composite indices do not demonstrate the specifics of how state-level macroeconomic variables affect state financial capital. *Delta SCI* might affect state *COV* through local labor market conditions, local economic development, or collateral channels. Admittedly, with limitations imposed on a single index of local economic activities, we cannot restrict our analysis to existing composite indices. Therefore, we test Equation (13) by substituting the local economic activity indices with the state-level macroeconomic variables in Table 5.

Figure 5 Annual Spatial Coefficient

This figure plots the trend in the annual spatial coefficients (the coefficient estimates on *W_COV (t+1)*). A spatial autoregressive (SAR) analysis in Column (6) of Table 4 is conducted for each year to obtain the spatial coefficients.



In Columns (1)-(3) of Table 5, we adopt state macroeconomic variables that are likely to capture different aspects of state-level business cycles, including unemployment rate (*UNEMP*), change in gross state product (*Delta GSP*), and personal income growth (*Delta INC*). We find that *UNEMP* and *Delta GSP* significantly predict *COV (t+1)*. All coefficient estimates have the expected signs. A lower local unemployment rate (*UNEMP*)) and higher economic growth (*Delta GSP*) are associated with higher financial capital (state *COV*) in the next quarter. In terms of economic significance, one standard deviation increase in *Delta GSP* would increase the state *COV (t+1)* by 0.07, or 6% relative to its mean of 1.21. However, we do not find evidence that supports the personal income or collateral channels, since the coefficient estimates *Delta INC* and *NCREIF_RET* are statistically insignificant.

Negative spatial spillovers do not seem to be affected by the inclusion of individual state macroeconomic variables rather than the local economic activity indices. In other words, the financial capital of other states has a similar impact on that of a particular state. For instance, the coefficient on the spatial lagged financial capital (*W_COV*) is -0.69 in Column (3), which is comparable to -0.69 in Column (6) of Table 4. The corresponding spatial diminisher is 0.59. Therefore, the spatial spillover effects identified in our study are not subject to how we define the macroeconomic variables. However, using individual macroeconomic variables facilitates our interpretation of the mechanism of how local economic activities affect local financial capital conditions.

Table 5 Regression Results with State Economic Variables

In this table, we report the regression results of panel regressions and the SAR. The dependent variable is the state COV at quarter *t+1*, or *COV (t+1)*. State economic variables are *UNEMP, Delta GSP,* and *Delta INC* in Columns (1)-(3) and *UNEMP, Delta GSP, Delta INC,* and *CPI* in Columns (4)-(6) at quarter *t*. All variables are defined in Appendix 1. The magnitude of the spatial spillover effect (feedback effect) is measured by the coefficient estimates of the spatial lagged outcome variable (*W_COV*). *W* is the row-normalized inverse-distance matrix based on either the geographic (GEO) or the population (POP) centroid. State and time (year-quarter) fixed effects are included. Standard errors are clustered at the state level. *t*-statistics are reported underneath the coefficient estimates in parentheses. ***, **, and * indicate significance for the coefficient at the 1%, 5%, and 10% levels.

COV (t+1)	(1) Panel	(2) SAR	(3) SAR	(4) Panel	(5) SAR	(6) SAR
W_COV		-0.699***	-0.688***		-0.679***	-0.662***
		(-4.30)	(-7.67)		(-3.90)	(-6.46)
UNEMP	-0.570*	-0.618**	-0.549**	-0.590*	-0.632**	-0.564*
	(-1.68)	(-2.20)	(-1.90)	(-1.64)	(-2.14)	(-1.86)
Delta GSP	0.041**	0.034**	0.039**	0.039**	0.033**	0.038**
	(2.13)	(2.04)	(2.29)	(2.00)	(1.94)	(2.20)
Delta INC	-0.018	-0.014	-0.017	-0.015	-0.010	-0.014
	(-1.05)	(-0.85)	(-1.07)	(-0.81)	(-0.62)	(-0.83)
CPI				-6.815**	-5.802*	-5.808*
				(-2.05)	(-1.86)	(-1.84)
NUM_INV_GRD	0.329***	0.307***	0.278***	0.310***	0.291***	0.264***
	(2.73)	(3.08)	(2.79)	(2.75)	(3.08)	(2.82)
NCREIF_RET	10.116	9.528	9.673	7.786	7.744	7.884
	(1.53)	(1.57)	(1.54)	(1.24)	(1.34)	(1.31)
SIZE	-0.089	-0.101	-0.086	-0.063	-0.080	-0.066
	(-0.87)	(-1.00)	(-0.83)	(-0.66)	(-0.83)	(-0.66)
CONSTRAINT	-0.056	-0.053	-0.052	-0.057	-0.054	-0.053
	(-0.84)	(-0.90)	(-0.87)	(-0.90)	(-0.94)	(-0.92)
SPW	N/A	GEO	POP	N/A	GEO	POP
Clustering	State	State	State	State	State	State
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	2016	2016	2016	2016	2016	2016
R Squared	0.669	0.633	0.634	0.673	0.636	0.637

In the next three columns (Columns (4)-(6)) of Table 5, we include measures of regional price levels (*CPI*) and a test equation (13). All state macroeconomic variables (as well as fixed effects) remain in our sample.

We find a negative and significant relation between *CPI* and financial capital conditions (state *COV*). Local labor market conditions (*UNEMP*), local economic growth (*Delta GSP*), and the logarithm of the number of REITs with investment-grade ratings (*NUM_INV_GRD*) continue to be significant determinants of local financial capital conditions (state *COV*) in the following quarter. Spatial spillover effects are comparable to those reported in Columns (1)-(3).

Equity REITs specialize in alternative property types. Some REITs (i.e., REITs that specialize in core property types) might be more competitive in the capital markets than others. Moreover, some property types might be more dominant in certain geographic areas (i.e., office in New York). We address these issues by using the SDM. Specifically, we estimate Equation (17b), where *WX* refers to the spatial lags of a set of interaction terms between that state *COV* and property type weights. Property type weights are defined as the book value of a particular property type (i.e., office) divided by the total book value of REIT-owned properties in a particular state, varying by state-year.

In Table 6, we confirm that the competition effect is stronger among states which have neighbors dominated by REIT-owned industrial and multifamily properties. We find some evidence that the *COV* of a state is enhanced by the allocations of its neighbors to the office sector. Taken together, our findings in Table 6 suggest that the heterogeneity and dynamics of major property types across states explain for a significant portion of the competition effect.

Finally, we explore potential channels through which neighboring states compete for scarce capital. We predict that the competition effect is stronger for a state when its neighbors: 1) are highly leveraged, and/or 2) have a more constrained financial capital supply. We apply two variables to test these predictions. *HIGH_LEV* indicates that the debt ratio of an "average" REIT based in a particular state is larger than the sample median. *CONSTRAINT* captures the financial solvency of institutional investors headquartered in that state. The results are reported in Table 7.

Similar to Table 6, we use the SDM to estimate the interaction effects, where *WX* refers to the spatial lags of a set of interaction terms between the state *COV* and *HIGH_LEV* and/or *CONSTRAINT*. Our results show that the competition effect almost doubles when REITs and financial institutions in the neighboring states are in distress, thus supporting the *predation hypothesis*. Specifically, REIT managers might exploit the financial distress of neighboring REITs and/or investors as an opportunity to steal their market share.

Table 6 Spatial Analysis with Property Type Weights and Interactions

In this table, we report the regression results of panel regressions and the SDM. The dependent variable is the state COV at quarter *t+1*, or *COV (t+1)*. The test variable is *Delta SCI* in Columns (1)-(2) and *PSEA* in Columns (3)-(4) at quarter *t*. All variables are defined in Appendix 1. Property type weights and their interactions with the state COV are included in the analysis. *W* is the row-normalized inverse-distance matrix based on either the geographic (GEO) or the population (POP) centroid. State and time (year-quarter) fixed effects are included. Standard errors are clustered at the state level. *t*-statistics are reported underneath the coefficient estimates in parentheses. ***, **, and * indicate significance for the coefficient at the 1%, 5%, and 10% levels.

COV (t+1)	(1) SDM	(2) SDM	(3) SDM	(4) SDM
W_COV	-0.071*	-0.078	-0.072*	-0.076
	(-1.90)	(-1.32)	(-1.93)	(-1.29)
W_COV_APT	-6.099***	-3.238	-6.131***	-3.256
	(-3.07)	(-1.63)	(-3.07)	(-1.63)
W_COV_OFF	2.810*	-0.288	2.897*	-0.299
	(1.68)	(-0.19)	(1.72)	(-0.20)
W_COV_IND	-10.500***	-16.101***	-10.472***	-16.156***
	(-3.23)	(-3.84)	(-3.18)	(-3.88)
W_COV_RTL	-1.507	-2.100	-1.514	-2.089
	(-1.00)	(-0.88)	(-1.00)	(-0.88)
Delta SCI	0.264*	0.294*		
	(1.72)	(1.83)		
PSEA			0.067*	0.089**
			(1.78)	(2.30)
APT	-2.348***	-1.157	-2.272***	-1.070
	(-2.72)	(-1.06)	(-2.63)	(-0.98)
OFF	-0.469	0.151	-0.384	0.238
	(-0.51)	(0.19)	(-0.41)	(0.30)
IND	-3.852	-4.108	-3.691	-3.925
	(-1.49)	(-1.53)	(-1.44)	(-1.47)
RTL	-1.804*	-1.345	-1.706	-1.229
	(-1.69)	(-1.38)	(-1.57)	(-1.24)
NUM_INV_GRD	0.311***	0.216*	0.310***	0.215*
	(2.83)	(1.96)	(2.84)	(1.95)
NCREIF_RET	4.050	7.268	4.185	7.367
	(0.70)	(1.31)	(0.72)	(1.32)
SIZE	-0.100	-0.100	-0.098	-0.099
	(-1.15)	(-1.18)	(-1.11)	(-1.15)
CONSTRAINT	-0.024	-0.028	-0.024	-0.028
	(-0.50)	(-0.54)	(-0.50)	(-0.54)
SPW	GEO	POP	GEO	POP
Clustering	State	State	State	State
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
# Obs	2016	2016	2016	2016
R Squared	0.658	0.638	0.658	0.639

Table 7 Alternative Channels of the Competition Effect

In this table, we report the regression results of panel regressions and the SDM. The dependent variable is the state COV at quarter *t+1*, or *COV (t+1)*. The test variable is *Delta SCI* in Columns (1)-(2) and *PSEA* in Columns (3)-(4) at quarter *t*. All variables are defined in Appendix 1. *HIGH_LEV, CONSTRAINT,* and their interactions with the state COV are included in the analysis. *W* is the row-normalized inverse-distance matrix based on either the geographic (GEO) or the population (POP) centroid. State and time (year-quarter) fixed effects are included. Standard errors are clustered at the state level. *t*-statistics are reported underneath the coefficient estimates in parentheses. ***, **, and * indicate significance for the coefficient at the 1%, 5%, and 10% levels.

COV (t+1)	(1) SDM	(2) SDM	(3) SDM	(4) SDM
W_COV	-0.694***	-0.679***	-0.690***	-0.677***
	(-4.29)	(-7.50)	(-4.27)	(-7.53)
W_COV_HIGH_LEV	-0.610**		-0.594**	
	(-2.25)		(-2.23)	
W_COV_CONSTRAINT		-0.582**		-0.571**
		(-2.25)		(-2.23)
Delta SCI	0.382**	0.383**		
	(2.27)	(2.20)		
PSEA			0.136***	0.139***
			(3.03)	(2.92)
HIGH_LEV	-0.199*		-0.193*	
	(-1.82)		(-1.76)	
NUM_INV_GRD	0.333***	0.330***	0.329***	0.326***
	(2.96)	(2.88)	(3.03)	(2.95)
NCREIF_RET	11.536*	11.036	11.422*	10.922
	(1.72)	(1.61)	(1.70)	(1.59)
SIZE	-0.079	-0.080	-0.078	-0.079
	(-0.71)	(-0.73)	(-0.70)	(-0.72)
CONSTRAINT	-0.048	-0.095	-0.047	-0.093
	(-0.76)	(-1.48)	(-0.75)	(-1.44)
SPW	GEO	POP	GEO	POP
Clustering	State	State	State	State
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
# Obs	2016	2016	2016	2016
R Squared	0.646	0.642	0.646	0.641

6. Conclusion

Our study findings are aligned with the *predation hypothesis*, which suggests that REIT managers might exploit the financial distress of neighboring REITs and/or investors as an opportunity to steal their market share (Nordlund, 2016). There are several different specific aspects of the research that support our general findings.

First, we shed some light on the cross-sectional heterogeneity studied in this research. States that host financial centers (i.e., California, Illinois) tend to be well-capitalized (have higher state COV). In 1995Q1, most states were dominated by REIT holdings in core property types such as retail (*RTL*) and multifamily (*APT*). In 2018Q4, except for a few states in the Northeast region, non-core property (i.e., data centers) is the major property type of most states in our sample. This finding might be interesting to future researchers.

Next, we test the predictions from our theoretical model using by panel and spatial analysis. We find that state economic activity indices (*Delta SCI* and *PSEA*) significantly predict the financial capital conditions of a state (state *COV*). There are negative spatial spillovers among neighboring states, thus implying competition for scarce financial capital and a spatial "diminisher" effect. Our findings are not affected by heterogeneity across states and over time, as well as alternative specifications of spatial weights matrixes (based on either geographic or population centroids). Another interesting aspect of this part of the research is that spatial coefficients are more negative one year *before* economic downturns. Also, we find that the predictability of state-level composite indices on the state *COV* is mainly driven by labor market conditions (*UNEMP*) economic growth (*Delta GSP*) at the state-level, and regional price changes (*CPI*). We do not find evidence that supports personal income (*Delta INC*) or collateral (*NCREIF_RET*) channels, which affect stock liquidity (Bernile et al., 2015). The competition effect does not vary.

Finally, in order to facilitate a better understanding of the competition effect, we conduct a few more analyses. We find that the competition effect is higher among states which have neighbors dominated by REIT-owned industrial and multifamily properties. Collectively, our findings support the *predation hypothesis*.

Acknowledgement

We thank Rose Neng Lai (our editor), John Clapp, Xiaoying Deng, Zifeng Feng, Jian Zhou, two anonymous referees, and seminar participants at the University of Connecticut, the American Real Estate Society, and the Global Chinese Real Estate Congress for providing helpful comments. Any errors are our own.

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Appendices

Appendix 1: Variable Definitions

Variable	*Definition*
COV (t+1)	Quarterly state COV, which equals to the mean of the interest COVs of all firms headquartered in one state. Interest COV is calculated as income before extraordinary items (*IBQ*) divided by the sum of preferred dividends (*DVPQ*) and interest and related expenses (*XINTQ*). The data is obtained from the Compustat quarterly database.
Delta SCI Expected sign: (+)	The quarterly average of monthly change in the state coincident index (in percentage). state coincident index was developed by Crone and Clayton-Matthews (2005) based on the local labor market and local economic development conditions. The data are available from FRED at monthly frequency.
PSEA Expected sign: (+)	Quarterly average of the ratio of State Leading Index to state coincident index (in percentage). State Leading Index predicts the six-month growth rate of the coincident index of a state. In addition to the coincident index, the State Leading Index incorporates other variables that lead the economy, i.e., state-level housing permits (1 to 4 units), state initial unemployment insurance claims, delivery times from the ISM manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill. Data on the State Leading Index is available from FRED at monthly frequency.
UNEMP Expected sign: (–)	The logarithm of the quarterly average of the monthly unemployment rate within a specific quarter. Data on state-level unemployment rate is downloaded from the U.S. BLS.
Delta GSP Expected sign: (+)	Before 2005Q1, GSP growth is the annual growth rate of gross state product (in percentage). Since 2005Q1, GSP growth is the quarterly growth rate of gross state product. Data on annual and quarterly GSP growth is obtained from the U.S. BEA.
Delta INC Expected sign: (+)	State-level labor income quarterly growth (in percentage) obtained from the U.S. BLS.
CPI Expected sign: (+/–)	The logarithm of the quarterly regional CPI, beginning from 1987Q1. Before 2017Q4, data on CPI were available for 4 U.S. regions including Northeast, Midwest, South and West. Since 2017Q4, data on CPI are available for 9 regions including New England, Middle Atlantic, East North Central, West North Central, East South Central, West South Central, Mountain, and Pacific. Data on regional CPI is obtained from the U.S. BLS.

(***Continued…***)

(Appendix 1 Continued)

Variable	*Definition*
Adjusted Cost	Adjusted cost is defined as the maximum of (1) the reported book value, (2) the initial cost of the property, or (3) the historic cost of the property including capital expenditures and tax depreciation. The data are obtained from S&P Global Real Estate Properties database (formerly SNL Real Estate).
APT	The book value (adjusted cost) of multifamily properties divided by the total book value of REIT-owned properties in a particular state, varying by state-year.
OFF	The book value (adjusted cost) of office properties divided by the total book value of REIT-owned properties in a particular state, varying by state-year.
IND	The book value (adjusted cost) of industrial properties divided by the total book value of REIT-owned properties in a particular state, varying by state-year.
RTL	The book value (adjusted cost) of retail properties divided by the total book value of REIT-owned properties in a particular state, varying by state-year.
SIZE	The logarithm of the quarterly reported book value of total assets (*ATQ*) of all REITs headquartered in a particular state.
NCREIF_RET	Quarterly NCREIF property index returns (in percentage). Data on NCREIF property index returns are available for four U.S. regions including East, Midwest, South and West and obtained from NCREIF website.
CONSTRAINT	We regress value-weighted daily returns of portfolio of stocks headquartered in a particular state that have an SIC code equal to 6211 (investment banks, securities brokers, and dealers) against the market excess return to obtain the residuals. *CONSTRAINT* indicates that the average daily residual of a state is negative (capital constrained).
NUM_INV_GRD	The logarithm of the number of REITs headquartered in a particular state with an investment-grade credit rating.
HIGH_LEV	*HIGH_LEV* indicates that the average leverage ratios of all firms headquartered in one state is above sample median. Leverage ratio equals to the sum of total long-term debt (*DLTTQ*) and debt in current liabilities (*DLCQ*) divided by total assets (*ATQ*).

Appendix 2: Background on Spatial Lag and Spatial Multiplier

In order to examine the issue of cross-state spillovers and test for the sign and significance of $\frac{\partial K_1}{\partial K_2}$ in Equation (11), we need to adapt our state-level models as described above. A useful tool for this analysis is spatial econometrics, which typically includes an SAR and an SDM. As demonstrated in KPZ, the SAR is a formulation of the idea of spatial spillovers – in our applications, levels of the outcome variable y (i.e., state COV) depend on the levels of y in the neighboring geographic units.[16] On the other hand, the SDM says that, in addition to the levels of y in the neighboring geographic units, the levels of x (i.e., local macroeconomic variables) in the neighboring geographic units are also correlated with y. Within the context of liquidity spillovers, common forms of an SAR (Equation 17a) and an SDM combined with an SAR (Equation 17b) can be expressed as follows, respectively.[17]

$$Y = \rho WY + X\beta + u \tag{17a}$$

$$Y = \rho WY + X\beta + WX\theta + u \tag{17b}$$

where Y represents a vector of state COV and X represents a matrix of lagged state macroeconomic variables, and N is the number of states and T the number of time periods covered by the data. There are 21 states and the time periods range from the first quarter of 1994 to the fourth quarter of 2018. ρ, β, and $\theta$are parameters to be estimated. The parameter, ρ, represents the degree of spatial interaction, or the competition effect in our analysis, or $\frac{\partial K_1}{\partial K_2}$ in our theoretical model above. If $\rho < 0$, this implies that REITs are competing for scarce capital, as implied in Equation (11). β is a vector of the coefficient estimates of explanatory variables. When an SDM is used, θ is a vector of the coefficient estimates of spatially lagged explanatory variables. In our case, for instance, if $\theta > 0$, this implies that increases in GSP growth of the neighboring states lead to higher accessibility in a particular state. W is the spatial weighting matrix, with individual elements that consist of the inverse-distances (where the weight state j has on state i equals the inverse of the distance between states i and j, normalized by the sum of the weights between state i and all other states j). While the weights for the SAR can be different from the weights for the SDM, the same weights matrixes are often in practice used for both. WY is a matrix of spatial lags, and represents the weighted average of the endogenous variable of other jurisdictions, which is the financial capital measure – the state COV. Similarly, WX represents the spatial lags, or the weighted average, of the explanatory variables of other jurisdictions - the local macroeconomic variables. It has been shown (e.g., Kelejian and Prucha, 1998) that Equations (16a) and (16b) can be estimated by using instrumental variables techniques. For Equation (17a), X is the appropriate instrument for itself, and WX is the

[16] Also see Lesage and Pace (2009), Chapter 2.6.
[17] Cohen (2010)

instrument for WY. Similarly, for Equation (17b), X is the appropriate instrument for itself, WX is the instrument for itself, and W^2X is the instrument for WY.[18] The coefficient estimate, ρ, represents the effect on the state *COV* with a change in the weighted average of the *COV* of all other jurisdictions. Also, each element of the vector of coefficient estimates, θ, represents the effect on the financial capital conditions of a state with a change in the weighted average of the macroeconomic variables of the other states (and there may be several macroeconomic variables in *X*).

To illustrate the spatial multiplier effect, consider a simplified example with only two neighboring states (*j*=1); i.e., New York and Connecticut, in one quarter, *t*. Suppose *X* is the percentage change in the logarithm of unemployment rate (*UNEMP*) and Y is the state COV. Then the two rows of observations in Equation (16a) would be written as:

$$Y_{CT} = \rho Y_{NY} + X_{CT}\beta + u_{CT} \tag{18a}$$

$$Y_{NY} = \rho Y_{CT} + X_{NY}\beta + u_{NY} \tag{18b}$$

If X_{CT} increases by 1%, this leads to a $\beta\%$ increase or decline in Y_{CT}. However, this increase in Y_{CT} leads to a $\rho\beta\%$ change in Y_{NY}, which this leads to another $\rho^2\beta\%$ change in Y_{CT}, and so on and so forth. This spatial multiplier effect is just $\beta[1+\rho+\rho^2+\rho^3+\cdots]$ and can be expressed as $\beta\frac{1}{1-\rho}$. It is straightforward to generalize this to a case that involves multiple geographic units. Using the example from Column (3) of Table 5, if the direct effect on *Unemployment Rate*, $\beta_{unemp} = -0.55, \rho = -0.69$, then the total effect (including the spatial multiplier effect) is $-0.55 \times \frac{1}{1-(-0.69)} \approx -0.33$. Had we ignored the spatial spillover effect, this would have led to an overestimation of the impact by approximately 67%. The spatial spillover effects arise through the endogenous interactions between neighboring states, and with our spatial econometrics approach, we are able to identify the causal effects of the changes in the financial capital conditions of the states on that of a particular state.

[18] This is formally expressed as Gershgorin's theorem (Cohen, 2002).