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

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Abstract – Korniotis (2008) and Korniotis and Kumar (2013) argue that capital markets are locally segmented. Agarwal and Hauswald (2010) support this view by suggesting there are advantages to private information in lending. These studies suggest there may be regional competition for scarce capital. Thus, we use a theoretical model to analyze potential competition for scarce financial capital across U.S. state and Metropolitan Areas (MSA) borders. Kou, Peng and Zhong (2017) consider real estate securities in a spatial asset pricing context, but no previous work has considered competition for scarce capital among REITs. We separately test the hypothesis for REITs and other common stocks, based on our model's implications, that there is competition for financial capital across regions. Since REITs have high payout restrictions, they may have constrained funding sources and more urgent capital demand than traditionally-listed firms. Therefore, we also examine whether there is greater competition for capital among REITs than among other common stocks, across nearby regions. Our empirical findings confirm that REITs (stocks) in a particular geographic region compete for financial capital with REITs (stocks) in other regions. These competition effects are approximately 20 percent greater among REITs than among other publicly-listed firms. In addition to direct effects, we find evidence of feedback (or indirect) effects, implying amplified crowding out of financial capital when other REITs (stocks) in nearby regions increase financial capital usage. Our approach addresses endogeneity bias that may arise with an indirect treatment effect on geographic neighbors. Finally, state-level macroeconomic variables significantly impact firm liquidity.

Keywords: REITs, Common Stocks, Financial Capital Scarcity, Geographic Spillovers

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1. Introduction and Literature Review

Is there competition for scarce capital among firms in different geographic regions (such as U.S. states and also MSAs)? Also, do REITs, with their relatively high payout ratios, compete with each other for capital more strongly across regions than other listed companies? Do states' macroeconomic variables 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, having considered only common stocks[2] or REITs[3] , but not both in the same analysis). In the prior literature, REITs are typically excluded along with the other firms within the financial sector (SIC: 6000 – 6999) because they are perceived as a highly regulated industry. However, REITs are especially suited for the purpose of this study. Their exogenously determined payout ratio, high debt usage, and illiquid and locally segmented markets for their underlying assets (real estate) together imply a possibly stronger local competition for capital among REITs than the common stocks (if there is evidence of local competition for capital). We address these issues in this paper, and consider the relationship between market liquidity (ease of trading an asset) and funding liquidity (financial capital). Separately, we also examine the competition for scarce capital among entities in different states/MSAs, based on financial flexibility. Our key findings are that: 1) several macroeconomic variables are significant predictors of state-level financial capital conditions; 2) there

[1] Financial capital and funding liquidity are used interchangeably in this paper.

[2] De Jong, Verbeek, and Verwijmeren (2014); Li, Whited, and Wu (2016); Mclean and Palazzo (2017); Li and Tang (2016); Chen, Harford, and Lin (2017).

[3] Glascock and Lu-Andrews (2014); Riddiough and Steiner (2016); Pavlov, Steiner, and Wachter (2016); Riddiough and Steiner (2017).

is competition for scarce capital among stocks in different U.S. states (and in different MSAs); 3) there is also evidence of competition for scarce capital among REITs across states and MSAs; and 4) generally speaking, REITs compete for capital with other REITs in nearby states or MSAs more strongly than other publicly listed firms compete with each other, likely due to the high required payout ratios for REITs (i.e., a lack of financial flexibility).

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

Another 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, 2016) and segmentation (Agarwal and Hauswald, 2010).[4] 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, Korniotis, Kumar, and Wang, 2015; Luo, Xu, and Zurbruegg, 2016). An enhanced understanding of financial capital conditions at the local level is thus important for a more complete comprehension of market liquidity.[5]

An important determinant of corporate capital structure is financial flexibility (Graham and Harvey, 2001). While financial flexibility is typically a firm-level phenomenon, we consider this

[4] 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.

[5] Additionally, this work has implications for trading illiquidity when financing may be difficult for firms locally. See Aug, Papanikolaou and Westerfield (2014) for portfolio implications for illiquid assets.

issue in our state-level and MSA-level analyses by examining the financial flexibility of a "representative" firm (as in the "representative agent" models of Hartley, 1997) in the state or MSA. Financial flexibility is crucial because financing frictions could lead to increased costs of capital and suboptimal levels of investment (Kaplan and Zingales, 1997; Stein, 2001). These frictions diminish with the availability of internal funds (Almeida et al., 2011), but there is a tradeoff between lower cost of capital by building financial slack in the face of 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 the 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; Bonaime et al., 2013).[6]

What are the consequences of a lack of financial flexibility? One potential answer to this question is that negative spillovers across firms might be occurring when firms prey upon financially inflexible rivals.[7] Different types of spatial spillovers have been pinpointed more generally

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

in the economics literature, including, but not limited to, Knowledge Spillovers,[8] Industry Spillovers,[9] and Growth Spillovers[10] (Capello, 2009). In the present context, such spillovers might lead to inaccurate estimates of financial capital determinants (because of ignoring the indirect effects) due to endogeneity/simultaneity issues that arise because some estimation techniques assume that spillovers, or indirect effects, across units (here, firms competing for financial capital) do not exist. We first assume each geographic region consists of a "representative" firm, and then focus on REITs and stocks, to examine potential differences in capital competition intensities. Our theoretical and empirical models allow for spillovers across units (i.e., states and MSAs) and we also address the potential endogeneity of the capital decision of REITs and common stocks in this particular context. In contrast, Norlund (2016) develops a profit maximization model to explain why indirect effects might occur among firms within the same industry, but he does not consider omitted geographic variables. Also, Norlund (2016) considers different costs of capital, but does not directly address endogeneity. He assumes that firms may enter into covenants with one another to

[8] *Knowledge Spillovers* refer to the cases where knowledge created by one firm spreads to the other firms, thus creating value for those firms (Fischer, 2006). Knowledge or technology producers do not capture the complete knowledge value because knowledge spills over the firm and becomes available to other firms. Due to its value-enhancing nature, the expected effects of *Knowledge Spillovers* are always positive (Almenida and Kogut, 1999; Maier and Sedlacek, 2005; Fischer, 2006).

[9] *Industry Spillovers* are defined as the situation in which firms located in the same and/or nearby geographic area(s) experience productivity shocks at the presence of one productive and dynamic firm. The expected effects of *Industry Spillovers* could be positive as well as negative. One the one hand, exchange of knowledge and ideas, technological innovations and good managerial practice (Griliches, 1992), and labor market pooling effects could lead to positive externalities. On the other hand, due to the comparative advantage of new entry and higher costs of local inputs, market competitiveness may increase for local firms and thus lead to negative externalities (Capello, 2009; Alvarez, Arias, and Orea, 2006). *Industry Spillovers* are broader than *Knowledge Spillovers* and capture more interaction mechanisms among firms than information exchange. In other words, knowledge spillovers may be a subset of industry spillovers.

[10] *Growth Spillovers,* a situation in which one region's growth is affected by characteristics of neighboring regions, is the most general version of spatial spillovers. Similar to the *Industry Spillovers*, *Growth Spillovers* might have positive or negative effects. On the one hand, greater regional income generates greater internal savings and more job opportunities and neighboring regions can benefit from capital and labor accessibility (Harrod, 1939; Domar, 1957). On the other hand, the effects of *Growth Spillovers* can be negative since outflows of capital and/or talented labor to other regions may be detrimental to a particular region.

coordinate their actions. Using covenant violations, he finds that non-violating firms benefit from violating peers by preying strategically upon them. That is, non-violating firms are “treated” indirectly, which thus violates the assumption of Norland’s estimation techniques 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 Norlund (2016) is that his firm-level analysis is subject to an important endogeneity issue, which is based upon Garmaise and Batividad’s (2016) argument. Specifically, Nordlund’s thesis 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 firms within a particular industry. The former scenario is not addressed in Nordlund (2016). However, these implications can be important when financial capital conditions are affected by local economic conditions. In our model, we build in the possibility that the optimal amount of capital for one firm depends on the amount of capital for other firms; and, our empirical tests of this model indicate that as other firms use more capital, the amount of capital for a particular firm decreases. We uncover evidence in support for the hypothesis that there is competition for scarce capital on a geographical, and local, scale.

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) upon 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), in the U.S. equity market (Pirinsky and Wang, 2006), and in international stock markets (Asgharian, Hess, and Liu, 2013). The asset pricing implications of spatial interactions have been examined in Kou, Peng and Zhong (2017, hereby KPZ), where spatial econometrics techniques, such as spatial autoregressive model, are shown to be effective in eliminating cross-sectional correlations.

The theoretical model in our research is most closely related to the Growth Spillovers concept. We consider a situation where capital utilized by listed firms (stocks and/or REITs) in some locations may crowd out the ability of firms in another region to obtain and/or use capital. We consider the effects of state- (MSA)-level macroeconomic conditions on U.S. stocks' and equity REITs' financial capital conditions and its spillovers across state borders. This model is a more specific model than the financial flexibility spillovers considered by Nordlund (2016). In motivating the existence of potential spatial heterogeneity, we first rationalize our use of spatial econometrics tools with a theoretical framework based on a representative firm-level cost minimization model to develop comparative statics implications for our empirical analysis. Our model implies that either positive or negative spillovers are possibilities, however the actual sign of the spillovers is a question that we test empirically. We then employ panel regression methods, with fixed effects along with spatial econometrics tools, to estimate the sign and statistical significance of the cross-state/MSA financial capital spillover effects.[11] We also examine whether or not REITs exhibit different spillover patterns than stocks in the context of financial capital.

The remainder of this paper is structured as follows. In the next section we develop our theoretical model to describe the optimal capital to be used by each representative firm as a function of the capital used by other firms. Then we describe our empirical model, along with some

[11] 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 Paul, 2004; Case, Clapp, Dubin, and Rodriguez, 2004; Lesage and Pace, 2009; and Cohen, 2010).

general exposition on the spatial lag model. The subsequent section consists of an overview of the data (with a more detailed discussion of the data variables in the Appendix). Finally, we describe our empirical results, followed by a conclusions section where we summarize our key findings and possible directions for future research.

2. Theoretical Model

We consider a world where in each U.S. state/MSA there is a representative firm (for example, a common stock and/or a REIT; we could generalize this to a representative firm of other types). In this cost minimization problem, we assume *K* is financial capital with "real" price *r*; *L* is a composite of all other inputs with price *w*. Firm 1 will choose K_1, L_1 to minimize its operating costs. In other words, firm 1's problem is to:

$$\min_{K_1, L_1} wL_1 + r_1K_1 \ \ subject\ to\ Y_1 = (S_1)f(K_1, L_1, K_2), \tag{1}$$

where S_1 is a set of shift factors that consist of other exogenous variables that affect output for firm 1, and K_2 is the level of capital used by firm 2 in the other state/MSA.

This production function specification assumes that more financial capital used by other firms may affect the productivity of a particular firm. But we do not know, a priori, how other firms' capital usage affects productivity of a particular firm, or whether there is any effect at all of other firms' capital on a particular firm's capital. In other words, financial capital available to all states/MSAs may or may not be scarce. Firm 1 takes K_2 as given (that is, it has no "control" over the amount of capital used by other states/MSAs).

The optimization problem for firm 1 is:

$$\min\{wL_1 + r_1K_1 + \lambda_1[Y_1 - (S_1)f(K_1, L_1, K_2)]\}, \tag{2}$$

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 firm 1. In words, this implies that in equilibrium, the "real" price of capital equals the value of its marginal product. The "real" price of capital, r_1, also equals to the product of nominal price of capital, γ, and the risk premium scaler, φ_1, or $r_1 = \gamma\varphi_1$.[12]

Next suppose, for the moment, that there are only two state/MSA representative firms. This assumption simplifies the exposition that follows but does not affect the results of generalizing to *n* firms. Also, below we interchangeably use K_2 and K_{AVG} to refer to both firm 2 and all other firms. The results of firm 2's optimization problem is:

$$r_2 - \lambda_2 S_2 \left(\frac{\partial f}{\partial K_2}\right) = 0, \tag{4}$$

where λ_2 is the shadow price of output for firm 2.

Consider a particular functional form for *f*, such as:

$$Y_1 = S_1(K_1)^{a_1}(L_1)^{b_1}(K_2)^{c_1}, \tag{5}$$

where $0 < a_1 < 1$, $0 < b_1 < 1$, and $c_1 > 0$ or $c_1 < 0$ or $c_1 = 0$. This implies that a state's (MSA's) own capital is productive but it may or may not be scarce; more capital for firm 1 raises its output. But more capital demanded by firm 2 may raise or lower firm 1's output, or it may have no effect at all on firm 1's output. One objective of this paper is for us to determine whether or not capital is scarce. In other words, we can address the question: does the representative firm in a state (MSA) compete for capital with the representative firms in other states (MSAs)?

Then the first order condition of capital for firm 1 implies:

$$r_1 = \gamma\varphi_1 = \lambda_1 S_1[(K_1)^{a_1 - 1}(L_1)^{b_1}(K_2)^{c_1}], \tag{6}$$

[12] 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*.

and for firm 2:

$$r_2 = \gamma\varphi_2 = \lambda_2 S_2[(K_2)^{a_2-1}(L_2)^{b_2}(K_1)^{c_2}], \tag{7}$$

where γ is the nominal price of capital and r is the "real" cost of capital, and since γ is the same for both firms, this implies:

$$K_1^{a_1-c_2-1} = [\left(\frac{\varphi_1}{\varphi_2}\right)\left(\frac{\lambda_2}{\lambda_1}\right)\left(\frac{S_2}{S_1}\right)(K_2)^{a_2-c_1-1}][\frac{(L_2)^{b_2}}{(L_1)^{b_1}}], \tag{8}$$

We can solve for K_1 as a function of K_2, which basically is:

$$K_1 = [(K_2)^{(a_2-c_1-1)/(a_1-c_2-1)}]\{\left(\frac{\varphi_1}{\varphi_2}\right)\left(\frac{\lambda_2}{\lambda_1}\right)\left(\frac{S_2}{S_1}\right)\left[\frac{(L_2)^{b_2}}{(L_1)^{b_1}}\right]\}^{1/(a_1-c_2-1)}, \tag{9}$$

Equation (9) tells us the optimal amount of K_1, given K_2 and the other variables. In other words, this is firm 1's reaction function for their financial capital.

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

$$\log(K_1) = \frac{a_2-c_1-1}{a_1-c_2-1}\log(K_2) + \frac{1}{a_1-c_2-1}[\log(\lambda_2) - \log(\lambda_1) + \log(S_2) - \log(S_1) +$$

$$\log(\varphi_1) - \log(\varphi_2)] + \frac{b_2}{a_1-c_2-1}\log(L_2) - \frac{b_1}{a_1-c_2-1}\log(L_1), \tag{10}$$

Also,

$$\frac{\partial\log(K_1)}{\partial\log(K_2)} = \frac{a_2-c_1-1}{a_1-c_2-1},$$

Or equivalently, $\frac{\partial K_1}{\partial K_2} = \frac{K_1(a_2-c_1-1)}{K_2(a_1-c_2-1)}$ (11)

Therefore, there is competition for capital when the reaction function for firm 1 is downward sloping, i.e., if $\frac{a_2-c_1-1}{a_1-c_2-1} < 0$. A set of sufficient conditions for this are that $a_2 - c_1 > 1$ and $a_1 - c_2 < 1$. Another set of sufficient conditions is $a_2 - c_1 < 1$ and $a_1 - c_2 > 1$. Also, if $a_2 = c_1 + 1$, this implies no interdependences in optimal capital usage across states (MSAs).

This problem can be generalized to a setting with more than 2 firms. The optimization problem for firm 1 then becomes:

$$wL_1 + r_1K_1 \; subject \; to \; Y_1 = (S_1)f(K_1, L_1, K_{AVG}), \tag{12}$$

where K_{AVG} is the weighted average of all other firms' capital demand. We can derive reaction functions for each firm again.

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

If we find empirically that the reaction functions have a negative slope, then we can infer that the production "technologies" for the two firms are quite different. It is either the case that firm 1 may face a large negative spillover effect from firm 2's demand for capital (if c_1 is highly negative), or firm 2 may face a large negative spillover effect from firm 1's demand for capital (if c_2 is highly positive). It also may imply that capital is very productive for firm 1, along with a large negative spillover effect from firm 2's capital, while at the same time capital is not very productive for firm 2. In a more general setting with more than 2 firms, a negative reaction function implies that when everyone else's capital usage increases, this leads to a fall in the optimal amount of capital for one particular firm.

Below we test for which effect is present for REITs and stocks in U.S. states (MSAs). If we find a negative relation between the spatially lagged dependent variable (i.e., capital usage for other states/MSAs) and the capital usage in a particular state/MSA, then this would be evidence in favor of negative spillover effects that imply capital is scarce nationally. However, if we find the opposite, that is, if there is a positive relation between the spatially lagged dependent variable for all states and a particular state's (MSA's) capital usage, this would support the notion that there is no evidence of scarcity of capital.

3. Empirical Model

3.1. Panel Predictive Regression on Liquidity Variables

One major goal with the empirical model is to test the sign and significance of equation (11). Therefore, we need to estimate an equation where firm-level capital is the dependent variable. Ultimately, we also want to include as a regressor the average of all firms' capital usage, and the sign and significance on this term will enable us to test equation (11). Initially, we build up our empirical model by following Glascock and Lu-Andrews (2014), so we start by using the following panel regression models with time and location fixed effects. We extend the national-level analysis of Glascock and Lu-Andrews (2014), by using the *State/MSA Coverage Ratio* and *ln(EDF)* as our forward-looking measures of the representative firm's level of capital accessibility.[13] Both variables are as defined below in Section 4 and in the Appendix for variable definitions. We begin with state-level analysis, and then extend our study to MSA-level for robustness. We emphasize state-level results as our main findings for two reasons. First, most legislations associated with local capital markets are established at state-level. Second, local economic data vendors typically span longer time horizon and are more populous at the state-level than at the MSA-level. We regress *State Coverage Ratio* or *ln(EDF)* on the lagged change in state and national coincident indexes (*Change in SCI* and *Change in NCI*),

$$Capital\ Accessibility_{s,t+1} = \alpha_0 + \beta_{SCI} \cdot Change\ in\ SCI_{s,t} + \beta_{NCI} \cdot Change\ in\ NCI_t$$

$$+\delta_t + \varepsilon_{s,t}, \tag{13}$$

[13] We do not include a control variable for risk since *State Coverage Ratio* has been risk-adjusted. Here we use the state-level analysis as an example because most macroeconomic variables are available at state level.

where “Capital Accessibility” can be either State Coverage Ratio, or ln(EDF); we run these regressions for REITs and common stocks, separately; t = 1985Q1, 1994Q2, …, 2014Q4 for stocks and 1994Q1, 1994Q2, …, 2014Q3 for REITs, and s = 1, 2, …, N (where N is the total number of states with firm/REIT headquarters). In the first predictive regression, the dependent variable is *State Coverage Ratio* or *ln(EDF)* for predictive regressions.[14] It is calculated as the the mean of the interest coverage ratios or *ln(EDF)*s of all the firms (or REITs) headquartered within a particular state. The other variables are as defined in the Appendix. We include quarter fixed effects, δ_t, to control for unobservable general price changes over time.[15]

In our next set of regressions, we regress *State Coverage Ratio* (and separately, *ln(EDF))* on the lagged change in state coincident indexes (*Change in SCI*) with state and quarter fixed effects,

$$Capital\ Accessibility_{s,t+1} = \alpha_0 + \beta_{SCI} \cdot Change\ in\ SCI_{s,t} + \mu_s + \delta_t + \varepsilon_{s,t}, \quad (14)$$

State fixed effects, μ_s, effectively control for unobservable heterogeneity across U.S. states.[16]

Lastly, since the interpretation of composite indexes are limited, we adopt individual state and MSA macroeconomic factors instead of changes in composite indexes to unveil the full picture. Specifically, we regress *State Coverage Ratio* (and separately, *ln(EDF)*) on state macroeconomic variables with fixed effects in equation (15) and (16) (we also repeat this analysis at the MSA level):

[14] We also consider *State Mortgages* as an alternative measure of funding liquidity. For the benefit of space, we didn’t provide results on *State Mortgages* in the paper. The results are provided upon request.
[15] We also adopt leading variables such as *PSEA* and *PNEA* instead of coincident indexes.
[16] *Change in NCI* is excluded here because it does not vary cross-sectionally.

$$
\begin{aligned}
Capital\ Accessibility_{s,t+1} = {} & \alpha_0 + \beta_{unemp} \cdot Ln(unemployment\ rate)_{s,t} \\
& + \beta_{GSP} \cdot Gross\ State\ Product\ Growth_{s,t} + \\
& \beta_{stmort} \cdot Ln(State\ Mortgage\ Deduction)_{s,t} \\
& + \beta_{HPI} \cdot State\ House\ Price\ Growth_{s,t} + \mu_s \\
& + \delta_t + \varepsilon_{s,t},
\end{aligned} \tag{15}
$$

$$
\begin{aligned}
Capital\ Accessibility_{s,t+1} = {} & \alpha_0 + \beta_{unemp} \cdot Ln(unemployment\ rate)_{s,t} \\
& + \beta_{GSP} \cdot Gross\ State\ Product\ Growth_{s,t} + \\
& \beta_{stmort} \cdot Ln(State\ Mortgage\ Deduction)_{s,t} \\
& + \beta_{HPI} \cdot State\ House\ Price\ Growth_{s,t} + \\
& + Ln(Regional\ CPI)_{R,t} + \mu_s + \delta_t + \varepsilon_{s,t}
\end{aligned} \tag{16}
$$

R is the number of geographic regions for which CPI data are available; there are 4 such regions in the U.S., including Northeast, Midwest, South, and West regions.[17]

3.2. Spatial Lag and Spatial Multiplier

In order to examine the issue of cross-state (and separately, cross-MSA) 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 (and separately, MSA)-level models as described above. A useful tool for this analysis is spatial econometrics,

[17] We also estimate equation (16) using MSA-level data.

which typically includes a spatial autoregressive model (hereby SAR model) and sometimes a spatial Durbin model (hereby SDM model). As demonstrated in KPZ, the SAR model is a formulation of the idea of spatial spillovers – in our applications, levels of the outcome variable *y* (i.e., *State* or *MSA* Capital Accessibility) depend on the levels of *y* in neighboring geographic units.[18] On the other hand, the SDM model says that, in addition to the levels of *y* in neighboring geographic units, the levels of *x* (i.e., local macroeconomic variables) in neighboring geographic units are also correlated with y. Within the context of liquidity spillovers, common forms of a spatial autoregressive model (17a) and spatial Durbin's model combined with a spatial autoregressive model (17b) can be expressed as follows, respectively.[19]

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

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

Here *Y* represents a vector of *State*/*MSA Coverage Ratio* and *X* represents a matrix of lagged state macroeconomic variables, and *N* is the number of states/MSAs and *T* the number of time periods covered by the data.[20] For common stocks (REITs), there are 20 (21) states and the time periods range from the first quarter of 1985 (1994) to the fourth (third) quarter of 2014.[21] 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

[18] Also see Lesage and Pace (2009), Chapter 2.6.
[19] (Cohen, 2010)
[20] We create a balanced panel of state (MSA)-level liquidity measures and state (MSA)-level macroeconomic factors by keeping states/MSAs with more than 1 REIT headquarters throughout our sample period 1994-2014. A REIT does not necessarily have to exist through the whole sample period to be included in our computation of the state (MSA)-level centroid. The reasons are twofolds. First, all the measures are aggregated at the state (MSA)-level. Thus a single firm enter or exit the sample have very limited effect. Second, using the row-normalized contiguity matrix, which is not dependent on firms' geographic coordinates, yields similar evidence.
[21] At MSA-level, there are 38 (17) MSAs and the time periods range from the third quarter of 1991 (the first quarter of 1994) to the fourth quarter of 2014 for stocks (REITs).

implies stocks (REITs) are competing for scarce capital, as implied in equation (11) above. β is a vector of coefficient estimates of explanatory variables. When SDM Model is used, θ is a vector of coefficient estimates of spatially lagged explanatory variables. In our case, for instance, if $\theta > 0$, this implies that increases in other states' GSP lead to higher accessibility in a particular state. W is the spatial weighting matrix, with individual elements consisting of the inverse-distances (where the weight state or MSA *j* has on state or MSA *i* equals the inverse of the distance between states or MSAs *i* and *j*, normalized by the sum of the weights between state or MSA *i* and all other states or MSAs *j*). While the weights for the SAR model can be different from the weights for the SDM model, often in practice the same weights matrices are used for both. WY is a matrix of spatial lags, and it represents the weighted average of other jurisdictions' endogenous variable, which is the financial capital measure, *State* or *MSA Coverage Ratio*. Similarly, *WX* represents the spatial lags, or the weighted average, of other jurisdictions' explanatory variables, or local macro-economic variables. It has been shown (e.g., Kelejian and Prucha, 1998) that Equations (17a) and (17b) can be estimated by instrumental variables techniques. For Equation (17a), X is the appropriate instrument for itself, and WX is the 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.[22] The coefficient estimate, ρ, represents the effect on a state's *State*/*MSA Coverage Ratio* of a change in the weighted average of all other jurisdictions' *State*/*MSA Coverage Ratio*. Also, each element of the vector of coefficient estimates, θ, represents the effect on a state's (MSA's) financial capital conditions of a change in the weighted average of each of all other states' (MSAs') macroeconomic variables (and there may be several macroeconomic variables in *X*).

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

To illustrate the spatial multiplier effect, consider a simplified example with only two neighboring states (*j*=1), New York and Connecticut, in one quarter, t. Suppose X is the percentage change in the *State Unemployment Rate* (*Unemp*) and Y is the financial capital (*State Coverage Ratio*). Then the two rows of observations in Equation (17a) 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 β% rise or fall in Y_{CT}. But 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 the case involving multiple geographic units. Using the example from Panel A, Table 6, if the direct effect on *Unemployment Rate*, $\beta_{unemp} = -13.180, \rho = -0.535$, then the total effect (including the spatial multiplier effect) is $-13.180 \times \frac{1}{1-(-0.535)} \approx -8.59$. Had we ignored the spatial effects, this would have led to an overestimation of the impact by approximately 54%.[23] 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 states' changes in financial capital conditions on a particular state's financial capital.

[23] The overestimation of the effect of *Ln*(*Unemployment Rate*) on *State Coverage Ratio* is approximately 60.8% for REITs.

4. Data

In this paper, we use both national and local (MSA-level, state-level, and regional) data to examine how macroeconomic conditions can affect the financial capital (measured by *State* or *MSA coverage ratio*) of common equities (hereby stocks) and equity real estate investment trusts (hereby REITs). Our methods for calculating the state representative firm's capital accessibility are discussed below. A detailed explanation on the construction of the local macroeconomic variables can be found in the variable definitions Appendix.

We include states that have more than 15 headquartered stocks over the entire sample period.[24] 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 per quarter). Our sample ended up having 20 (21) states with 9598 (367) stocks (REITs) from 1985-2014 (1994-2014).[25] Over the entire sample period, California (California) and Texas (New York) are the states with the most and second most stock (REIT) headquarters. There are 1932 (81) and 1168 (43) stocks (REITs) currently or previously located in California (California) and Texas (New York), respectively. Missouri has only 164 (4) stock (REIT) headquarters. The "average" state in our sample has approximately 103 (17) stock (REIT) headquarters in a given quarter.

We use the state (or MSA) centroid as the location of a state's (or MSA's) representative stock and REIT in order to mitigate the concern that headquarter location choice is endogenous to the stock or REIT. Since state borders were determined far back during the 19th century (prior to

[24] We only include MSAs that have more than 5 headquartered stocks (Pirinsky and Wang, 2006) or at least one REIT in each quarter.

[25] Our MSA-level sample has 38 (17) MSAs with stocks (REITs) from 1991-2014 (1994-2014). We start from 1991 because data on MSA HPI growth is only available since then.

when most listed securities were issued), it is less of a concern that our spatial weighting matrix might be endogenous by itself.[26] The latitude and longitude coordinates of each state centroid in our sample are reported in Table 1.[27]

[Insert Table 1 about here]

Summary statistics of the variables used in our analysis are reported in Table 2 for stocks and REITs, respectively. We first use *State* (or *MSA) Coverage Ratio* to proxy for state (or MSA) financial capital conditions. *State Coverage Ratio* is computed as the arithmetic mean of quarterly interest coverage ratio for stocks or REIT(s) located in a particular state. Interest coverage ratio is widely adopted as a measure of financial solvency. Therefore, a higher *State Coverage Ratio* indicates higher financial capital available to a state representative stock (REIT).

[Insert Table 2 about here]

For an individual stock (REIT) *i* headquartered in state *s* in quarter *q*,

$$Interest\ Coverage\ Ratio_{i,s,q} = \frac{IBQ_{i,s,q}}{DVPQ_{i,s,q}+XINTQ_{i,s,q}}, \tag{19}$$

where $IBQ_{i,s,q}$ is the income before extraordinary items of the representative stock (or REIT) *i* headquartered in state *s* in quarter q. $DVPQ_{i,s,q}$ is the preferred dividends, and $XINTQ_{i,s,q}$ is the interest and related expenses. Then we aggregate the stock (or REIT)-level interest coverage ratio at the state level to obtain *State Coverage Ratio*. Suppose that there are a total of *N* stocks (or REITs) headquartered in state *s*, then for state *s* in quarter *q*, we compute *State Coverage Ratio* as,

[26] Similarly, there has been little or no change to most MSA boundaries over time.
[27] The latitude and longitude of each MSA centroid is reported in Table A-1 in a similar manner. MSAs are geographic entities defined by the U.S. Office of Management and Budget (OMB).

$$State\ Coverage\ Ratio_{s,q} = \frac{1}{N}\sum_{i=1}^{N} Interest\ Coverage\ Ratio_{i,s,q}, \tag{20}$$

Another proxy for capital accessibility that we use is Expected Default Probability, or *EDF*. *EDF* is derived from the Black-Scholes-Merton (BSM) model (Merton, 1974). When a firm's value falls beyond a certain threshold (i.e., its outstanding value of debt), a firm might have difficulty to meet its financial obligations, and thus find it harder to access the external financial markets. Bharath and Shumway (2008) use a z-score functional form implied by the Merton model and construct a naïve measure that improves forecasting ability. The naïve default probability measure can also be implemented more easily than the original Merton EDF. Shumway EDF is widely adopted in a series of recent studies (e.g., Chang, Hayes, and Hillegeist, 2016). Following Bharath and Shumway (2008), we construct the naïve default probability estimates by first calculating distance to default as,

$$naive\ DD = \frac{ln[(E+F)/F]+(r_{it-1}-0.5\cdot naive\ \sigma_V^2)T}{naive\ \sigma_V\sqrt{T}} \tag{21}$$

where *E* is the market value of equity; *F* is the market value of debt, which is assumed to be equal to the face value of debt; r_{it-1} is the expected return on firm's assets, which is assumed to be equal to the firm's stock return over the previous year; $naive\ \sigma_V^2$ is the total volatility of a firm; *T* is the forecasting horizon of 1 year. Then, we estimate the naïve probability estimate for each individual firm-month as,

$$\pi_{naive} = \aleph(-\text{naive DD}) \tag{22}$$

Finally, at the state-quarter level, we aggregate the naïve probability estimates for all the firms located within a particular state by taking the average, then we take the natural logarithm to normalize our probability measure, *ln(EDF)*.

Daily security return and quarterly financial statement data, obtained from the CRSP and Compustat quarterly databases, are used to compute the *State(and MSA) Coverage Ratio* and *ln(EDF)*.[28] We manually adjust for headquarter relocations using a combined dataset of headquarter relocation announcements.[29] We use *State (and MSA) Coverage Ratio* as the proxy for state (and MSA) financial capital because it captures (to some extent) the ease with which a stock (or REIT) can gain access to capital.

Data on the state unemployment rate and regional consumer price index (1987Q1 and onward) are obtained from the U.S. Bureau of Labor Statistics (BLS); data on gross state product and quarterly state income growth are obtained from the U.S. Bureau of Economic Analysis (BEA). Marginal tax rates and state mortgage deduction are acquired from the Feenberg Taxism database on NBER's website. State housing price index (HPI) growth is obtained from the Federal Housing Finance Agency (FHFA) website. National macroeconomic data are acquired from the Federal Reserve Bank of St. Louis Database (available on FRED). We also obtain State and National Coincident (Leading) Indexes from the Federal Reserve Bank of Philadelphia (available on FRED). Quarterly change 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 State and National Leading Index, or the predicted six-month growth of the corresponding coincident indexes, to the corresponding coincident indexes. We also report pairwise correlation tables of all variables used in our analysis for stocks and REITs in Table 3.[30]

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[28] We calculate *MSA Coverage Ratio* in a similar manner.
[29] For the years 1988 – 2005, these were collected by Dr. Joseph Engelberg. For 2006 onward, this information was obtained from news articles from Factiva search.
[30] Data on the MSA unemployment rate, gross MSA product, MSA income growth, and MSA HPI growth is obtained from the same data sources.

[Insert Table 3 about here]

5. Empirical Results

Our findings naturally fall into three categories. Before we present these results, section 5.1 below briefly discusses the predicted effects of macroeconomic variables on *State* (and *MSA) coverage ratio* for stocks and REITs. Section 5.2 explains the interpretation of the spatial lag and spatial multiplier, and the distinction between the Spatial Autoregressive Model and Spatial Durbin's Model. Section 5.3 describes the predictive panel regressions and Spatial Autoregressive (SAR) Model and reports regression results.

5.1. Macroeconomic effects on local financial capital

The predicted effects of each macroeconomic variable on *State Coverage Ratio* are reported in the variable definitions Appendix. We include information on the local business cycle, i.e., unemployment rate (*Ln*(*state unemployment rate*) or *Ln*(*MSA unemployment rate*)), and housing price index growth (*State HPI growth* or *MSA HPI growth*) into our analysis of local macroeconomic effects on local financial capital (*State coverage ratio* or *MSA coverage ratio*). The unemployment rate (*Ln*(*state unemployment rate*) or *Ln*(*MSA unemployment rate*)) and personal income growth (*State income growth* or *MSA income growth*) capture local (state-level or MSA-level) labor market conditions and return to human capital, respectively. Ceteris paribus, a lower local unemployment rate leads to higher financial capital in the next quarter. Our measure of housing price index growth (*State HPI growth* or *MSA HPI growth*) reflects financial capital conditions to some extent because it measures local households' borrowing capacity conditional on their housing equity. Therefore, higher local housing price index growth positively predicts future financial capital conditions. Similarly, one would argue that a higher level of return to human capital (*State income growth* or *MSA income growth*) leads to higher financial capital in the next quarter.

We also include variables that capture local economic development (*GSP growth* or *GMP growth*), local borrowing flexibility (*Ln*(*state mortgage deduction*)), and local inflation (*Regional CPI*). Moreover, in order to examine the combined effect of economic activity on financial capital conditions, we obtain state and national coincident indexes (*Change in SCI*, *Change in NCI*) from the Federal Reserve Bank of Philadelphia (FRED). We also adopt forward-looking proxies for economic development (*PSEA*, *PNEA*) in addition to the coincident indexes.[31] These forward-looking measures predict the 6-month growth of the corresponding coincident indexes with variables that lead the economy.[32] The theoretical model developed in Section 3 predicts that larger increases in economic development (*GSP growth* or *GMP growth*) and economic activities (*Change in SCI*, *Change in NCI*, *PSEA*, and *PNEA*), higher levels of borrowing flexibilities (*Ln*(*state mortgage deduction*)), and lower price levels (*Regional CPI*) should lead to higher level of financial capital (i.e., *State coverage ratio*) for stocks in the next quarter. REITs hold real estate and are resistant to inflation.[33] They are attractive to investors particularly when local inflation rates are high (Glascock, Lu and So, 2002). Therefore, we expect a positive relation between regional inflation and financial capital conditions of REITs. Also, since the market for available funding is more likely to be segmented than integrated, local economic activities (*Change in SCI*, *PSEA*) should be more influential than national ones (*Change in NCI*, *PNEA*).

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[31] *PESA* and *PNEA* stand for predicted 6-month state and national economic activities, respectively.
[32] 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.
[33] See for example the work of Glascock, Lu and So (2002) and Darrat and Glascock (1989).

5.2. Spatial lag, and spatial multiplier, and spatial econometrics models

In this section, we extend panel regression analysis in estimating the spatial autoregressive model (Hereafter SAR) and the spatial Durbin's model (Hereafter SDM). SAR and SDM are two of the most commonly used models in studies applying Spatial Econometrics. The main difference between SAR and SDM is that SAR (equation 17a) assumes only the dependent variable has spatial dependence while SDM (equation 17b) assumes both the dependent variable and certain independent variables (i.e., in our example, state or MSA macroeconomic variables) have spatial dependence.[34]

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

$$d_{ij} = 2 \cdot radius \cdot \arcsin\left(\sqrt{sin^2\left(\frac{lat_j - lat_i}{2}\right) + \cos(lat_i)\cos(lat_j) sin^2 (\frac{lon_j - lon_i}{2})}\right) \quad (23)$$

where d_{ij} is the geographic distance between state (MSA) *i*'s centroid (with coordinates lat_i and lon_i) and state (MSA) *j*'s centroid (with coordinates are lat_j and lon_j), and *radius* is the earth's radius (*radius* = 6,378 kilometers, or 3,959 miles). The centroid of each state (MSA) is

[34] In our study, the SDM is potentially more robust to cross-sectional heterogeneity than the SAR model but is subject to multicollinearity. Therefore, we present only SAR results in the next subsection.

exogenously determined and not subject to selection bias. 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 (MSAs) *i* and *j*/*m* (where we assume $d_{i,i} = 0$), and *N* is the total number of states (MSAs).

We report results for both stocks (excluding highly regulated industries, i.e., financial and utility firms) and REITs, each in different tables. For instance, while Panel A, Table 4 reports regression results for stocks, Panel B, Table 4 reports regression results for REITs. The rest of the tables are arranged in a similar manner. In order to show how the coefficient estimates can vary across panel regressions and the spatial autoregressive (SAR) model, we report panel regression results, *direct effects*, and *total effects.* The latter equals the sum of *direct effects* and *indirect effects* caused by the spatial multiplier, which captures the feedback effects of dependent variables between neighboring states (MSAs). We also report the spatial multiplier next to the SAR parameter, ρ. As we describe in the model section, the spatial multiplier is $\frac{1}{1-\rho}$. We estimate the spatial multiplier utilizing this formula.

5.3. Regression results and interpretation

In Table 4, we test equation (13) by regressing the measure of state financial capital – aggregate measure of *State coverage ratio* – on the change in state and national coincident indexes (*Change in SCI*, *Change in NCI*), with quarterly fixed effects.[35] We find that in general, *State coverage ratio* is more influenced by state-level economic activities (*Change in SCI*) than national ones (*Change in NCI*). The coefficient estimate on the *Change in SCI* is statistically significant and economically meaningful, for both stocks and REITs, while the coefficient estimate on the

[35] We also use forward-looking measures of economic activities, i.e., predicted economic activity indexes, instead of the coincident indexes. The results, which largely resemble Table 4 and 5, are reported in Table A-2 and Table A-3.

Change in NCI is insignificant. This finding is consistent with our prediction given the evidence that the market for available funding is more likely to be segmented than integrated. But due to the possibility of geographic spillovers, these coefficients should be interpreted with caution (since they might be over/under-estimated).

[Insert Table 4 about here]

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

Empirically, we apply the spatial autoregressive (SAR) model to confirm this conjecture. We find that the impact of financial capital is asymmetric, where some states are more competitive in the local capital markets than their neighbors. We find a negative and statistically significant coefficient, ρ, on the spatially lagged financial capital measure, $W \times State\ coverage\ ratio$ for both common equities (stocks) and REITs.[36]

The magnitude of spatial spillover effects is comparable but more negative for REITs (-0.596) than stocks (-0.497). Since REITs largely resemble small-cap stocks and have payout re-

[36] It is noteworthy that financial capital conditions of state i itself always receives a spatial weight of 0; therefore, ρ only captures the effect of neighboring states' financial capital conditions on state i's financial capital. And neighboring states receive larger weights because of the segmentation of market for funding liquidity.

strictions (payout ratio > 90%), they may have restricted sources of funding and more urgent demand for scarce capital (explained by the lower coverage ratio). Therefore, it is likely that there is stronger competition for capital among REITs than among stocks.

Moreover, a negative spillover effect indicates overestimation of the effect of local economic activities on financial capital conditions for both stocks and REITs. When estimating the spatial autoregressive (SAR) model, the coefficient estimates of the direct effect largely resemble those of the panel regressions. For instance, the direct effect of *Change in SCI* is 3.104 (0.556) for stocks (REITs). The corresponding panel regression coefficient estimates in Table 4 are 3.477 and 0.545 for stocks and REITs, respectively. In terms of economic significance, considering that the standard deviation of the *Change in SCI* is 0.28 (0.29) for stocks (REITs), one standard deviation rise in the *Change in SCI* would increase the *State Coverage Ratio* by 0.97 (0.16), or 19% (23%) relative to its mean of 5.06(0.70). As REITs are more constrained borrowers than issuers of common stocks, alongside with their locally segmented asset markets dominated by private information, these results confirm our expectation that local economic development would have a stronger effect on REITs than stocks.

Spatial spillover effects unveil a more comprehensive picture of the impact of *Change in SCI* on *State coverage ratio*, through the spatial multiplier effect. The spatial multiplier equals the inverse of one minus the coefficient estimate on the spatial lagged financial capital measure, 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 stocks (REITs) in different geographic states. Therefore, the direct effect (and the panel regression estimates) may be biased upward. When allowing for competition for capital across space, the total effect of

Change in SCI is 2.075 (0.353) for common equities (REITs), which is considerably smaller than the corresponding direct effect of 3.171 (0.577) and the panel regression coefficient estimates (3.544 and 0.569 for stocks and REITs, respectively). These changes in coefficient estimates are not only statistically significant, but also economically meaningful. The relative economic effect of local economic activities on capital accessibility of stocks (REITs) decreases from 19% (23%) to 11% (15%), or a 42% (35%) decrease relative to the panel regression estimates. These declining local economic development benefits are mainly due to the competition for capital among geographically proximate stocks (REITs).

Since national economic activities do not seem to predict *State coverage ratio* in the next quarter, we exclude *Change in NCI* and include state and quarter fixed effects. By including state fixed effects, we control for the possibility that the spatial spillovers may be driven by unknown state-level characteristics. Any regional or national macroeconomic variables must be excluded before state fixed effects are adopted. Results with state fixed effects for stocks and REITs are reported in Table 5, Panels A and B, respectively.

[Insert Table 5 about here]

The results in Table 5 largely resemble those reported in Table 4. The coefficient estimates of the spatial lagged *State coverage ratio* and the *Change in SCI* are statistically significant and economically meaningful, for both stocks and REITs. Therefore, our results are not likely to be driven by state-level omitted variables.

Thus far we have discussed how changes in economic activities (*Change in SCI*, *Change in NCI*) predict financial capital (*State coverage ratio*) in the next quarter. In general, changes in state economic activities are positively correlated with future financial capital of stocks and REITs headquartered in a particular state. We also find a negative spatial spillover effect that is associated with financial capital, for both stocks and REITs. Such a negative spatial spillover effect has two implications: (i) stocks and REITs located in neighboring states are competing for scarce capital; such competition is stronger for REITs and, (ii) panel regression coefficient estimates and direct spatial effects overestimate the real impact of *Change in SCI* on *State coverage ratio*. The true impact is the total effect, which is the product of the direct effect and spatial multiplier.

However, one may question the usage of changes in state (national) coincident indexes (*Change in SCI, Change in NCI*) since these measures do not demonstrate the specifics of how state-level macroeconomic variables affect state financial capital. For instance, whether *Change in SCI* has an effect on future *State coverage ratio* through local labor market conditions, local economic development, or collateral channel is not clear at this moment. Relatedly, one may argue that interpretation of composite indexes is not as intuitive as individual macroeconomic variables. Admittedly, with limitations imposed on a single index of local economic activities, we cannot restrict our analysis to existing composite indexes. Therefore, we test equation (15) by substituting the *Change in SCI* with the state-level macroeconomic variables in Table 6.

[Insert Table 6 about here]

Based on our theoretical framework, we adopt state macroeconomic variables that are likely to capture different aspects of state-level business cycles, including unemployment rate (*Ln*(*state unemployment rate*)), housing price index growth (*FHFA HPI growth*), local economic development (*GSP growth*), and local borrowing flexibility (*Ln*(*state mortgage deduction*)). Evidence from both panel regressions and the spatial autoregressive (SAR) model seems to suggest that there are subtle differences in state macroeconomic variables that affect the financial capital of common equities (stocks) and REITs. Specifically, for stocks, we find that unemployment rate (*Ln*(*state unemployment rate*)), local economic development (*GSP growth*), and local borrowing flexibility (*Ln*(*state mortgage deduction*)) significantly predict *State coverage ratio* in the next quarter. All coefficient estimates have the expected signs. Lower local unemployment rate (*Ln*(*state unemployment rate*)), higher economic growth (*GSP growth*), and higher local borrowing flexibility (*Ln*(*state mortgage deduction*)) are associated with higher financial capital (*State coverage ratio*) in the next quarter. However, we do not find evidence that supports a housing collateral channel, since the coefficient estimate on housing price index growth (*FHFA HPI growth*) is statistically insignificant.

On the other hand, local labor market conditions (*Ln*(*state unemployment rate*)) and local economic growth (*GSP growth*) are significant determinants of local financial capital (*State coverage ratio*) of REITs. The coefficient estimates on local borrowing flexibility (*Ln*(*state mortgage deduction*)), and housing price index growth (*FHFA HPI growth*) are statistically insignificant.

Negative spatial spillovers do not seem to be affected by the inclusion of state macroeconomic variables rather than the local economic activity index, for both common equities (stocks) and REITs. In other words, for both REITs and stocks, other states' financial capital have a similar impact on a particular state's financial capital. The coefficient estimates on the spatial lagged financial capital ($W \times$ *State coverage ratio*) is -0.537 (-0.608) for stocks (REITs). The corresponding spatial multiplier is 0.65 (0.62) for stocks (REITs), which is comparable to 0.67(0.63) reported in Table 4 and 5. Therefore, the spatial spillover effects identified in our study are not subject to how we define the macroeconomic variables. That is, using individual state macroeconomic variables results in a similar degree of spatial spillovers as using index measures. However, using individual macroeconomic variables facilitates our interpretation of the mechanism of how local economic activities affect local financial capital conditions.

Finally, we include measures of regional price levels (*Ln*(*Regional CPI*)) and test equation (16). All state macroeconomic variables (as well as state and quarter fixed effects) remain in our sample. The results are reported in Table 7.

[Insert Table 7 about here]

For stocks, the effect *Ln*(*unemployment rate*) on *State Coverage Ratio* is not affected by the inclusion of *Ln(Regional CPI*). However, the coefficient estimate on *Ln*(*State Mortgage Deduction*) becomes insignificant once we include *Ln*(*Regional CPI*). Also, *Ln*(*regional CPI*) has a negative and significant impact on *State coverage ratio* in the next quarter. Some of the unexpected results here may be in part due to the lack of variation in CPI data across states that are within the same region.[37]

On the other hand, local labor market conditions (*Ln*(*state unemployment rate*)) and local economic growth (*GSP growth*) continue to be significant determinants of local financial capital conditions (*State coverage ratio*) of REITs while the other local macroeconomic variables are less relevant. Interestingly, the relation between *Ln*(*regional CPI*) and *State coverage ratio* is positive but statistically insignificant for REITs. We expect this positive relation because equity real estate investment trusts (REITs) hold real estate as their underlying assets and are relatively resistant to changes in the general level of prices (Glascock, Lu and So, 2002). Their inflation-hedging char-

[37] State-level CPI estimates are not published by the Bureau of Labor Statistics, or any other known source.

acteristic is especially attractive to investors when local inflation is high. Therefore, REITs distinguish themselves from stocks in that their financial capital condition is positively, not negatively, correlated with local price changes.

It is also worthwhile to note that the spatial spillover effects of stocks and REITs converge with the inclusion of regional and national macroeconomic variables. The coefficient estimate on the spatially lagged financial capital conditions (*W* × *State coverage ratio*), ρ, further decreases from -0.535 in Table 6, Panel A to -0.577 in Table 7, Panel A for stocks, and is about constant (from -0.608 in Table 6, Panel B to -0.606 in in Table 7, Panel B) for REITs. In terms of spatial multipliers, they are 0.63 for stocks and 0.62 for REITs, respectively.

To further explore the effect of local macroeconomic variables on capital accessibility, we use the logarithm of state-level naïve default probabilities, *ln(EDF)*, instead of *State/MSA Coverage Ratio* as the dependent variable and re-estimate Table 4, 5, A2 and A3. The results are reported in Tables 8 and 9, respectively.

In Table 8, we present results in panels A and B for stocks. We exclude REITs because of an insufficient number of observations available. In Panel A, we include lagged *Change in SCI* and *Change in NCI* as test variables. Here, *ln(EDF)* negatively predicts a firm's capital accessibility – the higher a firm's default likelihood, the less its capital accessibility. Therefore, we predict that coefficients of var1 and var2 bear opposite sign to those reported in Table 4. Consistent with our prediction, the coefficient is negative for *Change in SCI*, and positive for *Change in NCI*, both coefficients are statistically significant. In general, improvement in local macroeconomic activities significantly reduces the likelihood of local firms' financial insolvency, thus increases their capital accessibility. When only the *Change in SCI* is included, the coefficient is comparable to estimate in Table 5.

[Insert Table 8 about here]

Importantly, using SAR model, we confirm that there is a competition effect across neighboring states – the coefficient on the spatial lag of *ln(EDF)* is about -0.68 (larger in magnitude than -0.50 in Table 4), and is significant at 1% level. This competition effect translates into an overestimation of coefficients of macroeconomic variables, which are to be 40% smaller than the panel regression estimates.

Again, capital markets are likely to reflect future economic activities rather than current ones. In Table 9, we use forward-looking proxies for macroeconomic variables, *PSEA* and *PNEA*, as test variables. Our results largely resemble those in Table 8.

[Insert Table 9 about here]

We mainly focus on state-level analysis because most local macroeconomic data is available only at state level. However, it does not imply that the competition effects identified in our analysis only occurs at the state-level. In the U.S., large MSAs could span multiple states, and based on the summary statistics, personal income growth appears to be quite different at the MSA-level than at the state-level. It is likely that MSA-level data is able to capture different aspects of local economic activities than state-level data. Therefore, we re-estimate the state-level regressions from Table 6 with MSA-level data. The results are reported in Table 10.

[Insert Table 10 about here]

The results in Table 10 are divided into four panels due to the availability of gross MSA product growth (from 2003Q1). The competition effect for scarce capital still exists at MSA level. And the magnitude of the competition effect largely resembles state-level results. Personal income growth appears to be an important determinant of *MSA Coverage Ratio* at least when spatial econometrics is applied, indicating that MSA-level data captures different features of local human capital than state-level data.

6. Conclusion

In this research, we develop a theoretical model to describe the capital usage of stocks and REITs. We empirically test the comparative statics implications of the model, in order to answer the questions: Is there competition for scarce capital among firms in different geographic regions (such as U.S. states and also MSAs)? And how, if at all, do REITs compete differently with each other than other publicly listed companies? Finally, do state-level macroeconomic variables impact state-level financial capital conditions?

Overall, our findings are fourfold. First, we find evidence of competition for scarce capital across state (and MSA) borders for REITs, and second, we also find competition among other publicly listed firms across space. This evidence is mitigated by the spatial multiplier effects (which in this case, these are actually spatial “diminisher” effects because they are smaller than 1.0). Additional capital usage by some states (or MSAs) leads to less capital usage by a particular state (or MSA), which feeds back to the other states (or MSAs) and causes them to use even less capital, and so forth.

Third, when comparing the degree of competition for scarce capital among REITs, against the competition among other listed companies, we find that REITs in different regions compete more strongly with each other by approximately 20%. These results reflect the characteristic of REITs that they have relatively high payout ratios of at least 90%, which implies less financial flexibility for REITs than other listed firms.

Our fourth set of findings pertain to state and MSA macroeconomic variables and capital usage. State and MSA macroeconomic variables, especially local labor market conditions, economic development, and changes in the general level of prices, significantly predict capital usage in the next quarter. In addition, the spatial "diminisher" effects that impact the degree of interdependency among regions in their competition for capital also impact the other explanatory variables. For instance, the effects of changes in the general level of prices on capital usage are somewhat dampened due to the spatial "diminisher" effects. For example, with stocks, an increase in the general level of prices has a negative impact on capital usage in a particular state (or MSA) and this negative impact affects other states by decreasing the amount of capital that those other states (or MSAs) use. In turn, this impact feeds back to decrease capital usage in the particular state (or MSA) even further, and so forth. Therefore, the spatial "diminisher" effects impact capital usage through this additional channel of the regional macroeconomic variables.

There are several potential extensions and areas for future work that may be worthwhile pursuing. Since market liquidity is affected by local economic conditions and financial capital conditions, one could examine the existence of spatial spillovers of market liquidity across geographic neighbors. Our study also has implications for asset pricing. For instance, it has been documented that investors have a strong preference for local assets, and local equity returns have been shown to exhibit co-movement. Investor proximity effects, or local bias, might be explained by knowledge spillovers between investors, or common shocks to productivity. Our theoretical model and applications of spatial econometrics tools provide an ideal setting for studying the local bias phenomenon. Finally, as another extension to our work, one could also look at the locality of a firm's assets instead of firm headquarters. We use firm headquarters to define firm location because most information transmission and decision-making occurs at firm headquarters. However, for some companies, this assumption may not hold. Specifically, for REITs, the majority of general and administration (G&A) expenses occur at the property-level.

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Appendix: Variable Definitions

State-level	
State coverage ratio	Quarterly state interest coverage ratio, which equals to the mean of interest coverage ratios of all firms headquartered in one state. Interest coverage ratio 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 Compustat quarterly database.
Ln(EDF)	Quarterly average of the logarithm of state naïve default probability, which equals to the mean of ln(EDF)s of all firms headquartered in one state. Ln(EDF) is calculated as Bharath and Shumway (2008). The data is obtained from CRSP daily and Compustat quarterly databases.
Change in SCI (in percentage) Expected sign: (+)	Quarterly average of the change in State Coincident Index, calculated as the mean of monthly change in State Coincident Index. State Coincident Index is constructed based on the local labor market and local economic development conditions. The data is available from Federal Reserve Bank of Philadelphia (FRED) at monthly frequency.
PSEA (in pct.) Expected sign: (+)	Quarterly average of the ratio of State Leading Index to State Coincident Index. State Leading Index predicts the six-month growth rate of the state's coincident index. In addition to the coincident index, 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 Institute for Supply Management (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 Federal Reserve Bank of Philadelphia (FRED) at monthly frequency.
Ln(state unemployment rate) Expected sign: (–)	Natural logarithm of quarterly state-level unemployment rate (in percentage), which equals to the mean of the monthly state unemployment rate within a specific quarter. Data on unemployment rate is downloaded from the U.S. Bureau of Labor Statistics (BLS).
FHFA HPI growth (in percentage) Expected sign: (+)	Quarterly change in the all-transactions price index of residential real estate in the state, obtained from Federal Housing Finance Agency (FHFA).
GSP growth (in percentage) Expected sign: (+)	Before 2005Q1, GSP growth is the annual growth rate of gross state product. From 2005Q1 and after, GSP growth is the quarterly growth rate of gross state product. Data on personal income is obtained from the U.S. Bureau of Economic Analysis (BEA).
Ln(state mortgage deduction) Expected sign: (+)	Feenberg state marginal tax rate on mortgage, obtained from NBER website.
State income growth	State-level labor income quarterly growth, obtained from the U.S. Bureau of Labor Statistics (BLS).
MSA-level	
MSA coverage ratio	Quarterly MSA interest coverage ratio, which equals to the

	mean of interest coverage ratios of all firms headquartered in one MSA. The data is obtained from Compustat quarterly database.
Ln(MSA unemployment rate) Expected sign: (-)	Natural logarithm of quarterly MSA-level unemployment rate (in percentage), which equals to the mean of the monthly state unemployment rate within a specific quarter. Data on unemployment rate is downloaded from the U.S. Bureau of Labor Statistics (BLS).
GMP growth (in pct.) Expected sign: (+)	Annual growth rate of gross domestic product by metropolitan area, obtained from the U.S. Bureau of Economic Analysis (BEA). Data on GMP is available from 2003Q1.
MSA income growth (in pct.) Expected sign: (+)	MSA-level labor income annual growth, obtained from the U.S. Bureau of Economic Analysis (BEA).
MSA HPI growth (in pct.) Expected sign: (+)	Quarterly change in the all-transactions price index of residential real estate in the metropolitan area, obtained from Federal Housing Finance Agency (FHFA).
Regional	
Ln(regional CPI) Expected sign: (+/–)	Natural logarithm of the quarterly regional consumer price index, beginning from 1987Q1. 4 U.S. regions include Northeast, Midwest, South and West. Data on regional CPI is obtained from the U.S. Bureau of Labor Statistics (BLS).
National	
Change in NCI (in percentage) Expected sign: (+)	Quarterly average of the change in National Coincident Index, calculated as the mean of monthly change in National Coincident Index. National Coincident Index is constructed based on the national labor market and national economic development conditions. The data is available from Federal Reserve Bank of Philadelphia (FRED) at monthly frequency.
PNEA (in pct.) Expected sign: (+)	Quarterly average of the ratio of National Leading Index to National Coincident Index. National Leading Index predicts the six-month growth rate of the U.S.'s coincident index. Data on the State Leading Index is available from Federal Reserve Bank of Philadelphia (FRED) at monthly frequency.

Table 1: States and Centroid coordinates

This table reports the 23 states that host at least 15 common equities (stocks) or at least 1 equity real estate investment trusts (REITs) 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; Puerto Rico, PR) that are not in main U.S. are deemed as isolated islands and thus are dropped from the sample. Financial (firms with SIC codes 6000 – 6999) and utility (firms with SIC code 4000 – 4999) firms are excluded from the common equities (stocks). A comprehensive list of U.S. equity REITs defined by NAREIT can be downloaded from Dr. S. McKay Price's website. Sample period for common equities (stocks) is from 1985Q1 to 2014Q4. Sample period for REITs is from 1994Q1 to 2014Q3. Difference sample periods are adopted for stocks and REITs because of the structural change in REIT industry in the early 1990s (modern REIT era started from 1993, Feng, Price, and Sirmans, 2011). We exclude states with fewer than 15 firms to minimize potential measurement error (Korniotis and Kumar, 2013). We don't have the same requirement for REITs because (i) REITs represent a relatively homogeneous asset class and, (ii) the sample size restriction – we have on average less than 200 REITs in each quarter. However, we do require a particular state to have at least one REIT in each quarter in order to maintain a balanced panel. We report state name, state abbreviation, latitude, longitude, stocks and REITs identifiers. Latitude and longitude are the geographic coordinates of a state's centroid. Two identifiers equal to 1 if a state hosts at 15 stocks or at least 1 REIT, and missing ("-") otherwise.

State Name	State Abbrev.	Latitude	Longitude	Stocks	REITs
Arizona	AZ	34.21	-111.60	-	1
California	CA	37.15	-119.54	1	1
Colorado	CO	38.99	-105.51	1	1
Connecticut	CT	41.58	-72.75	1	1
Florida	FL	28.46	-82.41	1	1
Georgia	GA	32.63	-83.42	1	1
Illinois	IL	40.10	-89.15	1	1
Indiana	IN	39.90	-86.28	-	1
Massachusetts	MA	42.16	-71.49	1	1
Maryland	MD	38.95	-76.67	1	1
Michigan	MI	44.84	-85.66	1	1
Minnesota	MN	46.32	-94.20	1	-
Missouri	MO	38.35	-92.46	1	1
North Carolina	NC	35.54	-79.13	1	1
New Jersey	NJ	40.11	-74.67	1	1
New York	NY	42.91	-75.60	1	1
Ohio	OH	40.41	-82.71	1	1
Pennsylvania	PA	40.90	-77.83	1	1
Tennessee	TN	35.86	-86.35	1	1
Texas	TX	31.43	-99.28	1	1
Virginia	VA	37.52	-78.67	1	1
Washington	WA	47.42	-120.60	1	1

Table 2: Summary Statistics (Update this table with balanced panel information)

All variables are defined in Appendix. Summary statistics of the variables are reported for common equities (stocks) and equity real estate investment trusts (REITs). Financial (firms with SIC codes 6000 – 6999) and utility (firms with SIC code 4000 – 4999) firms are excluded from the common equities (stocks). A comprehensive list of U.S. equity REITs defined by NAREIT can be downloaded from Dr. S. McKay Price's website. Sample period for common equities (stocks) is from 1985Q1 to 2014Q4. Sample period for REITs is from 1994Q1 to 2014Q3. Difference sample periods are adopted for stocks and REITs because of the structural change in REIT industry in the early 1990s (modern REIT era started from 1993, Feng, Price, and Sirmans, 2011). We exclude states with fewer than 15 firms (Korniotis and Kumar, 2013) and MSAs with fewer than 5 firms (Pirinsky and Wang, 2006) to minimize potential measurement error. We don't have the same requirement for REITs because (i) REITs represent a relatively homogeneous asset class and, (ii) the sample size restriction – we have on average less than 200 REITs in each quarter. However, we do require a specific state (MSA) to have at least one REIT in each quarter in order to maintain a balanced panel. We report mean, median, standard deviation, 25 percentile and 75 percentile in Column 1 to 5, respectively.

Variable	# Obs	Mean	Median	Std. Dev.	25 Pct.	75 Pct.
Stocks (financial and utility firms are excluded), 1985Q1 – 2014Q4						
State coverage ratio	2,400	5.06	5.17	16.73	-0.78	11.93
Ln(EDF)	2,400	-2.26	-2.15	0.90	-2.78	-1.63
MSA coverage ratio	3,572	6.53	5.66	16.63	-0.25	14.34
Change in SCI (in pct.)	2,400	0.21	0.27	0.28	0.10	0.40
Change in NCI (in pct.)	2,400	0.21	0.25	0.15	0.17	0.31
PSEA (in pct.)	2,400	1.14	1.15	1.36	0.48	1.87
PNEA (in pct.)	2,400	1.10	1.06	0.78	0.76	1.63
Ln(state unemployment rate)	2,400	1.74	1.73	0.31	1.53	1.95
Ln(MSA unemployment rate)	3,572	1.62	1.62	0.36	1.38	1.86
FHFA HPI growth (in pct.)	2,400	0.91	0.97	1.66	0.19	1.70
MSA HPI growth (in pct.)	3,572	0.86	0.95	2.32	-0.15	2.02
GSP growth (in pct.)	2,400	4.27	4.46	3.15	1.41	6.73
GMP growth (in pct.)	1,824	4.04	4.06	3.45	2.50	5.98
State income growth (in pct.)	2,400	1.27	1.30	1.13	0.77	1.85
MSA income growth (in pct.)	3,572	5.21	5.22	3.61	3.49	7.37
Ln(state mortgage deduction)	2,400	0.80	0	0.91	0	1.69
Ln(regional CPI)	2,240	5.13	5.14	0.23	4.96	5.33
REITs, 1994Q1 – 2014Q3						
State coverage ratio	1,764	0.70	0.65	0.96	0.30	1.04
MSA coverage ratio	1,428	1.33	0.71	2.44	0.31	1.46
Change in SCI (in pct.)	1,764	0.19	0.25	0.29	0.08	0.37
Change in NCI (in pct.)	1,764	0.20	0.24	0.16	0.15	0.29
PSEA (in pct.)	1,764	0.82	0.98	1.07	0.38	1.45
PNEA (in pct.)	1,764	0.87	0.99	0.69	0.64	1.24
Ln(state unemployment rate)	1,764	1.73	1.69	0.32	1.50	1.93
Ln(MSA unemployment rate)	1,428	1.64	1.62	0.39	1.36	1.90
FHFA HPI growth (in pct.)	1,764	0.82	0.95	1.78	0.13	1.70
MSA HPI growth (in pct.)	1,428	0.85	1.00	2.40	-0.11	2.05
GSP growth (in pct.)	1,764	4.45	4.58	2.65	3.10	6.00
GMP growth (in pct.)	816	3.97	4.08	3.38	2.41	5.79

State income growth (in pct.)	1,764	1.13	1.16	1.12	0.65	1.68
MSA income growth (in pct.)	1,428	5.17	5.34	3.59	3.31	7.42
Ln(state mortgage deduction)	1,764	0.67	0	0.86	0	1.58
Ln(regional CPI)	1,764	5.24	5.24	0.15	5.12	5.38

Table 3: Correlation Table

All variables are defined in Appendix. Pairwise correlation tables of the variables are reported for common equities (stocks) and equity real estate investment trusts (REITs) in Panel A and B, respectively. Financial (firms with SIC codes 6000 – 6999) and utility (firms with SIC code 4000 – 4999) firms are excluded from the common equities. In the first row, number 1 – 11 represents State coverage ratio, Change in SCI, …, State income growth, respectively. * indicates the statistical significance at 1% level.

Panel A – Stocks (financial and utility firms are excluded)

	1	2	3	4	5	6	7	8	9	10	11	12
State coverage ratio	1											
Ln(EDF)	-0.27*	1										
Change in SCI	0.10*	-0.33*	1									
Change in NCI	0.12*	-0.35*	0.84*	1								
PSEA	0.10*	-0.26*	0.91*	0.72*	1							
PNEA	0.13*	-0.24*	0.77*	0.89*	0.81*	1						
Ln(unemp)	0.08*	-0.20*	-0.19*	-0.18*	-0.05	-0.05	1					
FHFA HPI growth	-0.00	-0.07*	0.35*	0.28*	0.32*	0.28*	-0.36*	1				
GSP growth	-0.05	0.18*	0.45*	0.40*	0.54*	0.54*	-0.37*	0.41*	1			
Ln(stmort)	0.01	0.07*	0.05*	0.00	0.05	-0.00	-0.14*	0.01	0.05	1		
Ln(regional CPI)	0.00	-0.31*	-0.26*	-0.29*	-0.43*	-0.54*	0.22*	-0.24*	-0.72*	-0.02	1	
State income growth	0.10*	-0.11*	0.50*	0.46*	0.44*	0.42*	-0.23*	0.20*	0.33*	0.04	-0.26*	1

Panel B – REITs

	1	2	3	4	5	6	7	8	9	10	11
State coverage ratio	1										
Change in SCI	0.17*	1									
Change in NCI	0.16*	0.87*	1								
PSEA	0.17*	0.95*	0.83*	1							
PNEA	0.18*	0.83*	0.93*	0.86*	1						
Ln(unemp)	-0.21*	-0.26*	-0.25*	-0.16*	-0.17*	1					
FHFA HPI growth	0.10*	0.38*	0.30*	0.36*	0.30*	-0.34*	1				
GSP growth	0.19*	0.71*	0.61*	0.68*	0.57*	-0.51*	0.44*	1			
Ln(stmort)	-0.08*	0.02	-0.05	0.03	-0.02	-0.09*	-0.01	0.13*	1		
Ln(regional CPI)	0.25*	-0.26*	-0.28*	-0.34*	-0.42*	0.52*	-0.22*	-0.48*	-0.14*	1	
State income growth	0.12*	0.54*	0.49*	0.50*	0.46*	-0.29*	0.20*	0.49*	0.10*	-0.24*	1

Table 4: Spatial Autoregressive Model with the Change in State and National Coincident Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the Change in State and National Coincident Indexes (*Change in SCI, Change in NCI*) at quarter t. All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *State Coverage Ratio*). *W* is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. Quarter fixed effect is included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio (ρ)	–	–	–		**-0.497**	***	Multiplier ≈	
(t statistics)	–	–			**(-7.75)**		0.67	
Change in SCI	3.477	*	–	–	3.104	*	2.033	*
(t statistics)	(1.86)		–	–	(1.67)		(1.65)	
Change in NCI	-38.755		–	–	-34.765		-54.485	
(t statistics)	(-0.07)		–	–	(-0.07)		(-0.17)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	28%				33%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Panel B – REITs

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.596**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.14)**		0.63	
Change in SCI	0.545	***	–	–	0.556	***	0.340	***
(t statistics)	(3.54)		–	–	(3.63)		(3.53)	
Change in NCI	5.704		–	–	-28.447		-17.369	
(t statistics)	(1.54)		–	–	(-1.26)		(-1.26)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	19%				19%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Table 5: Spatial Autoregressive Model with the Change in State Coincident Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the Change in State Coincident Indexes (*Change in SCI*) at quarter t. Change in National Coincident Index (*Change in NCI*) is excluded because of the inclusion of state fixed effects. All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable ($W \times$ *State Coverage Ratio*). *W* is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. State and quarter fixed effects are included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio		SAR – State Coverage Ratio	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × State Coverage Ratio (ρ)	– –	–	**-0.502** ***	Multiplier ≈
(t statistics)	– –		**(-7.83)**	0.67
Change in SCI	3.544 *	– –	3.171 *	2.075 *
(t statistics)	(1.89)	– –	(1.71)	(1.69)
Number of Obs	2400		2400	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	28%		33%	
State Fixed Effects	Yes		Yes	
Quarter Fixed Effects	Yes		Yes	

Panel B – REITs

Model	GLS – State Coverage Ratio		SAR – State Coverage Ratio	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × State Coverage Ratio	– –	–	**-0.597** ***	Multiplier ≈
(t statistics)	– –		**(-8.16)**	0.63
Change in SCI	0.569 ***	– –	0.577 ***	0.353 ***
(t statistics)	(3.68)	– –	(3.78)	(3.70)
Number of Obs	1743		1743	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	19%		19%	
State Fixed Effects	Yes		Yes	
Quarter Fixed Effects	Yes		Yes	

Table 6: Spatial Autoregressive Model with the Change in State Macroeconomic Variables

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the state macroeconomic variables at quarter t. State macroeconomic variables include *Log(Unemployment rate)*, *Gross State Product Growth*, *Log(State Mortgage Deduction)*, *State House Price Index Growth*, and *State Income Growth*. All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (W × *State Coverage Ratio*). W is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. State and quarter fixed effects are included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.535**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.34)**		0.65	
Ln(unemployment rate)	-12.168	***	–	–	-13.180	***	-8.393	***
(t statistics)	(-5.58)		–	–	(-6.08)		(-5.98)	
Gross State Product Growth	0.155		–	–	0.116		0.074	
(t statistics)	(0.79)		–	–	(0.63)		(0.63)	
Ln(State Mortgage Deduction)	7.680	**	–	–	9.320	***	5.929	***
(t statistics)	(2.18)		–	–	(2.86)		(2.88)	
State House Price Index Growth	0.154		–	–	0.102		0.065	
(t statistics)	(0.58)		–	–	(0.41)		(0.41)	
State Income Growth	0.281		–	–	0.257		0.163	
(t statistics)	(0.70)		–	–	(0.69)		(0.69)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	35%				35%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – REITs

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.608**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.30)**		0.62	
Ln(Unemployment rate)	-0.469	**	–	–	-0.568	***	-0.344	***
(t statistics)	(-2.49)		–	–	(-3.04)		(-3.04)	
Gross State Product Growth	0.051	***	–	–	0.045	***	0.027	***
(t statistics)	(3.48)		–	–	(3.34)		(3.25)	
Ln(State Mortgage Deduction)	-0.036		–	–	-0.020		-0.012	
(t statistics)	(-0.44)		–	–	(-0.26)		(-0.26)	
State House Price Index Growth	0.023		–	–	0.024		0.015	
(t statistics)	(1.25)		–	–	(1.43)		(1.43)	
State Income Growth	-0.013		–	–	-0.007		-0.004	
(t statistics)	(-0.42)		–	–	(-0.23)		(-0.23)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	20%				20%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table 7 – Regional Inflation and Local Liquidity Spillover Effects

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the state, regional, and national macroeconomic variables at quarter t. State macroeconomic variables include *Log(Unemployment rate)*, *Gross State Product Growth*, *Log(State Mortgage Deduction)*, *State House Price Index Growth*, and *State Income Growth*. Regional macroeconomic variable is *Log(Regional CPI)*, which is a proxy for local inflation. (Since we couldn't find inflation measure at state level, regional CPI is by far the most accurate measure of local inflation; due to data availability of *Log(Regional CPI)*, our analysis of common equities in Panel A and B starts from 1987Q1 and has 2,240 observations). All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (W × *State Coverage Ratio*). W is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. State and quarter fixed effect is included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.577**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.59)**		0.63	
Ln(Unemployment rate)	-11.831	***	–	–	-12.742	***	-7.890	***
(t statistics)	(-5.07)		–	–	(-5.50)		(-5.42)	
Gross State Product Growth	0.138		–	–	0.088		0.055	
(t statistics)	(0.66)		–	–	(0.45)		(0.46)	
Ln(State Mortgage Deduction)	5.915		–	–	6.858	*	4.250	*
(t statistics)	(1.46)		–	–	(1.83)		(1.83)	
State House Price Index Growth	0.185		–	–	0.076		0.047	
(t statistics)	(0.62)		–	–	(0.27)		(0.27)	
State Income Growth	0.234		–	–	0.215		0.133	
(t statistics)	(0.54)		–	–	(0.54)		(0.53)	
Ln(Regional CPI)	-22.837	***	–	–	-34.954	***	-21.610	***
(t statistics)	(-4.15)		–	–	(-6.44)		(-6.83)	
Number of Obs	2240				2240			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	35%				35%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – REITs

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.606**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.28)**		0.62	
Ln(Unemployment rate)	-0.417	**	–	–	-0.521	***	-0.317	***
(t statistics)	(-2.15)		–	–	(-2.72)		(-2.72)	
Gross State Product Growth	0.052	***	–	–	0.046	***	0.028	***
(t statistics)	(3.56)		–	–	(3.40)		(3.37)	
Ln(State Mortgage Deduction)	-0.035		–	–	-0.020		-0.012	
(t statistics)	(-0.44)		–	–	(-0.26)		(-0.26)	
State House Price Index Growth	0.026		–	–	0.027		0.016	
(t statistics)	(1.38)		–	–	(1.55)		(1.55)	
State Income Growth	-0.013		–	–	-0.006		-0.004	
(t statistics)	(-0.39)		–	–	(-0.21)		(-0.21)	
Ln(Regional CPI)	2.816		–	–	2.567		1.562	
(t statistics)	(1.18)		–	–	(1.11)		(1.11)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	20%				20%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table 8: Spatial Autoregressive Model with the Change in State and National Coincident Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the natural logarithm of *Expected Default Frequency*, or *EDF*, at quarter t+1. *Expected Default Frequency* is calculated following Bharath and Shumway (2008). Independent variables are the Change in State and National Coincident Indexes (*Change in SCI*, *Change in NCI*) at quarter t. All variables are defined in Appendix. REITs do not have sufficient number of observations, and are thus excluded. Panel A exhibits the results when *Change in SCI* and *Change in NCI* are both included as independent variables. Panel B exhibits the results when only *Change in SCI* is included as independent variable. Only quarter fixed effect is included in Panel A. Panel B includes both state and quarter fixed effects. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable ($W \times Ln(EDF)$). W is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – *Ln*(*EDF*)		SAR – *Ln*(*EDF*)	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × *Ln*(*EDF*) (ρ)	– –	–	**-0.678** ***	Multiplier ≈
(t statistics)	– –		**(-7.75)**	0.60
Change in SCI	-0.543 ***	– –	-0.533 ***	-0.307 ***
(t statistics)	(-8.88)	– –	(-8.76)	(-8.11)
Change in NCI	59.979 ***	– –	104.89 ***	60.352 ***
(t statistics)	(4.72)	– –	(8.17)	(8.73)
Number of Obs	2400		2400	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	77%		77%	
State Fixed Effects	No		No	
Quarter Fixed Effects	Yes		Yes	

Panel B – Stocks (financial and utility firms are excluded)

Model	GLS – *Ln*(*EDF*)		SAR – *Ln*(*EDF*)	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × *Ln*(*EDF*) (ρ)	– –	–	**-0.680** ***	Multiplier ≈
(t statistics)	– –		**(-9.77)**	0.60
Change in SCI	-0.544 ***	– –	-0.534 ***	-0.309 ***
(t statistics)	(-8.89)	– –	(-8.81)	(-8.36)
Number of Obs	2400		2400	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	77%		77%	
State Fixed Effects	Yes		Yes	
Quarter Fixed Effects	Yes		Yes	

Table 9: Spatial Autoregressive Model with the Predicted Change in State and National Coincident Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is *Ln*(*EDF*), at quarter t+1. Independent variables are the Predicted 6-month Change in State and National Coincident Indexes (*PSEA*, *PNEA*) at quarter t. All variables are defined in Appendix. REITs do not have sufficient number of observations, and are thus excluded. Panel A exhibits the results when *PSEA* and *PNEA* are both included as independent variables. Panel B exhibits the results when only *PSEA* is included as independent variable. Only quarter fixed effect is included in Panel A. Panel B includes both state and quarter fixed effects. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable ($W \times Ln(EDF)$). W is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. Quarter fixed effect is included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – *Ln*(*EDF*)				SAR – *Ln*(*EDF*)			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × *Ln*(*EDF*) (ρ)	–	–	_		**--0.672**	***	Multiplier ≈	
(t statistics)	–	–			**(-9.69)**		0.60	
PSEA	-0.134	***	–	–	-0.132	***	-0.076	***
(t statistics)	(-11.1)		–	–	(-11.0)		(-9.76)	
PNEA	7.294	***	–	–	12.632	***	7.299	***
(t statistics)	(4.82)		–	–	(8.27)		(8.83)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	78%				78%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Panel B – Stocks (financial and utility firms are excluded)

Model	GLS – *Ln*(*EDF*)				SAR – *Ln*(*EDF*)			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × *Ln*(*EDF*) (ρ)	–	–	_		**-0.674**	***	Multiplier ≈	
(t statistics)	–	–			**(-9.72)**		0.60	
PSEA	-0.134	***	–	–	-0.132	***	-0.076	***
(t statistics)	(-11.1)		–	–	(-11.1)		(-10.1)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	78%				78%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table 10 – MSA Level Analysis for Stocks (38 MSAs) and REITs (17 MSAs)

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *MSA Coverage Ratio* at quarter t+1. Independent variables are the MSA macroeconomic variables at quarter t. MSA macroeconomic variables include *Log(MSA Unemployment rate)*, *MSA Income Growth*, and *MSA House Price Index Growth*. *Gross MSA Product Growth* is available from 2003Q1 and is included in Panel C and D. All variables are defined in Appendix. Panel A (C) exhibits the results for common equities (stocks). Panel B (D) reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *State Coverage Ratio*). *W* is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. State and quarter fixed effects are included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded) 1991Q3 – 2014Q4

Model	GLS - MSA Coverage Ratio				SAR - MSA Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × MSA Coverage Ratio	–	–	–		**-0.379**	***	Multiplier ≈	
(t statistics)	–	–			**(-5.99)**		0.73	
Log(MSA Unemployment rate)	-7.241	***	–	–	-7.085	***	-5.120	***
(t statistics)	(-4.12)		–	–	(-4.01)		(-3.95)	
Gross MSA Product Growth	–	–	–	–	–	–	–	–
(t statistics)	–	–	–	–	–	–	–	–
MSA Income Growth	0.191		–	–	0.231	**	0.167	**
(t statistics)	(1.64)		–	–	(2.10)		(2.09)	
MSA House Price Index Growth	0.168		–	–	0.174		0.126	
(t statistics)	(1.18)		–	–	(1.31)		(1.30)	
Number of Obs	3572				3572			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	14%				14%			
MSA Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – Stocks (financial and utility firms are excluded) 2003Q1 – 2014Q4

Model	GLS - MSA Coverage Ratio				SAR - MSA Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × MSA Coverage Ratio	–	–	_		**-0.410**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.63)**		0.71	
Log(MSA Unemployment rate)	-4.611		–	–	-4.672		-3.312	
(t statistics)	(-1.46)		–	–	(-1.57)		(-1.56)	
Gross MSA Product Growth	0.492	***	–	–	0.512	***	0.362	***
(t statistics)	(2.73)		–	–	(2.85)		(2.79)	
MSA Personal Income Growth	0.207		–	–	0.245		0.174	
(t statistics)	(1.22)		–	–	(1.51)		(1.50)	
MSA House Price Index Growth	0.258		–	–	0.259	*	0.183	*
(t statistics)	(1.60)		–	–	(1.73)		(1.71)	
Number of Obs	1824				1824			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	11%				11%			
MSA Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel C – U.S. Equity REITs 1994Q1 – 2014Q4

Model	GLS - MSA Coverage Ratio				SAR - MSA Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × MSA Coverage Ratio	–	–	_		**-0.736**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.85)**		0.58	
Log(MSA Unemployment rate)	-0.887		–	–	-0.743	**	-0.412	**
(t statistics)	(-1.22)		–	–	(-2.04)		(-2.02)	
Gross MSA Product Growth	–	–	–	–	-	-	-	-
(t statistics)	–	–	–	–	-	-	-	-
MSA Personal Income Growth	0.080	*	–	–	0.086	***	0.047	***
(t statistics)	(1.87)		–	–	(3.23)		(3.23)	
MSA House Price Index Growth	-0.027		–	–	-0.024		-0.013	
(t statistics)	(0.94)		–	–	(-0.83)		(-0.83)	
Number of Obs	1428				1428			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	17%				17%			
MSA Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel D – U.S. Equity REITs 2003Q1 – 2014Q4

Model	GLS - MSA Coverage Ratio				SAR - MSA Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × MSA Coverage Ratio	–	–	_		**-0.736**	***	Multiplier ≈	
(t statistics)	–	–			**(-6.42)**		0.58	
Log(MSA Unemployment rate)	-1.526	**	–	–	-1.589	***	-0.884	**
(t statistics)	(-2.27)		–	–	(-2.58)		(-2.54)	
Gross MSA Product Growth	-0.031		–	–	-0.035		-0.020	
(t statistics)	(-0.89)		–	–	(-1.04)		(-1.03)	
MSA Personal Income Growth	0.055	*	–	–	0.067	**	0.037	**
(t statistics)	(1.72)		–	–	(2.26)		(2.23)	
MSA House Price Index Growth	-0.045		–	–	-0.047	*	-0.026	
(t statistics)	(-1.46)		–	–	(-1.65)		(-1.63)	
Number of Obs	816				816			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	8%				8%			
MSA Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table A-1: MSAs and Centroid coordinates

This table reports the 40 states that host at least 5 common equities (stocks) or at least 1 equity real estate investment trusts (REITs) 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; Puerto Rico, PR) that are not in main U.S. are deemed as isolated islands and thus are dropped from the sample. Financial (firms with SIC codes 6000 – 6999) and utility (firms with SIC code 4000 – 4999) firms are excluded from the common equities (stocks). A comprehensive list of U.S. equity REITs defined by NAREIT can be downloaded from Dr. S. McKay Price's website. Sample period for common equities (stocks) is from 1991Q1 to 2014Q4. Sample period for REITs is from 1994Q1 to 2014Q3. Difference sample periods are adopted for stocks and REITs because of the structural change in REIT industry in the early 1990s (modern REIT era started from 1993, Feng, Price, and Sirmans, 2011). We exclude MSAs with fewer than 5 firms to minimize potential measurement error (Pirinsky and Wang, 2006). We don't have the same requirement for REITs because (i) REITs represent a relatively homogeneous asset class and, (ii) the sample size restriction – we have on average less than 200 REITs in each quarter. However, we do require a particular MSA to have at least one REIT in each quarter in order to maintain a balanced panel. We report Core-based statistical area (CBSA) code, MSA name, latitude, longitude, stocks and REITs identifiers. Latitude and longitude are the geographic coordinates of a MSA's centroid. Two identifiers equal to 1 if a state hosts at 5 stocks or at least 1 REIT, and missing ("-") otherwise.

CBSA Code	MSA Name	Latitude	Longitude	Stocks	REITs
10420	Akron, OH	41.148687	-81.349463	1	-
12060	Atlanta-Sandy Springs-Roswell, GA	33.692817	-84.399584	1	1
12420	Austin-Round Rock, TX	30.26263	-97.65444	1	-
12580	Baltimore-Columbia-Towson, MD	39.38291	-76.67397	1	1
13820	Birmingham-Hoover, AL	33.463808	-86.813922	1	1
15380	Buffalo-Cheektowaga-Niagara Falls, NY	42.910628	-78.736284	1	-
16740	Charlotte-Concord-Gastonia, NC-SC	35.188911	-80.867193	1	1
17140	Cincinnati, OH-KY-IN	39.071527	-84.427435	1	-
17460	Cleveland-Elyria, OH	41.252857	-82.011552	1	1
18140	Columbus, OH	39.968129	-82.836654	1	-
19740	Denver-Aurora-Lakewood, CO	39.565082	-104.95793	1	1
24660	Greensboro-High Point, NC	36.025838	-79.791694	-	1
26420	Houston-The Woodlands-Sugar Land, TX	29.77094	-95.36936	1	1
26900	Indianapolis-Carmel-Anderson, IN	39.747438	-86.206134	1	1
27260	Jacksonville, FL	30.236739	-81.791904	1	1
28140	Kansas City, MO-KS	38.937168	-94.444393	1	1
29820	Las Vegas-Henderson-Paradise, NV	36.215107	-115.01474	1	-
31140	Louisville/Jefferson County, KY-IN	38.336708	-85.670868	1	-
32820	Memphis, TN-MS-AR	35.007684	-89.815236	-	1

33340	Milwaukee-Waukesha-West Allis, WI	43.176649	-88.172225	1	-
33460	Minneapolis-St. Paul-Bloomington, MN-WI	45.064989	-93.345578	1	-
34980	Nashville-Davidson--Murfreesboro--Franklin, TN	36.089099	-86.724429	1	1
36420	Oklahoma City, OK	35.429871	-97.503839	1	-
36540	Omaha-Council Bluffs, NE-IA	41.290028	-95.999126	1	-
36740	Orlando-Kissimmee-Sanford, FL	28.434477	-81.363084	1	1
37100	Oxnard-Thousand Oaks-Ventura, CA	34.471498	-119.07831	1	1
38060	Phoenix-Mesa-Scottsdale, AZ	33.185712	-112.07047	1	-
38300	Pittsburgh, PA	40.439032	-79.830876	1	-
38900	Portland-Vancouver-Hillsboro, OR-WA	45.598479	-122.47884	1	-
39580	Raleigh, NC	35.719731	-78.500937	1	1
40060	Richmond, VA	37.462382	-77.474738	1	-
40380	Rochester, NY	42.913265	-77.584367	1	-
41180	St. Louis, MO-IL	38.735246	-90.350178	1	-
41620	Salt Lake City, UT	40.451241	-113.0348	1	-
41700	San Antonio-New Braunfels, TX	29.428709	-98.602203	1	-
41740	San Diego-Carlsbad, CA	33.033927	-116.73521	1	1
41940	San Jose-Sunnyvale-Santa Clara, CA	36.910326	-121.37691	1	-
45300	Tampa-St. Petersburg-Clearwater, FL	28.153512	-82.40742	1	-
46140	Tulsa, OK	36.250412	-96.166232	1	-
47260	Virginia Beach-Norfolk-Newport News, VA-NC	36.718108	-76.356805	1	-

Table A-2: Spatial Autoregressive Model with the Predicted Economic Activity Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the Predicted State and National Economic Activities (*PSEA*, *PNEA*) at quarter t. All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *State Coverage Ratio*). *W* is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. Quarter fixed effect is included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio (ρ)	–	–	_		**-0.498**	***	Multiplier ≈	
(t statistics)	–	–			**(-7.77)**		0.67	
PSEA	0.797	**	–	–	0.764	**	0.500	**
(t statistics)	(2.15)		–	–	(2.07)		(2.04)	
PNEA	3.520		–	–	3.638		2.339	
(t statistics)	(0.08)		–	–	(0.08)		(0.08)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	33%				33%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Panel B – REITs

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	-		**-0.592**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.08)**		0.63	
PSEA	0.122	***	–	–	0.119	***	0.073	***
(t statistics)	(2.97)		–	–	(2.91)		(2.84)	
PNEA	0.277		–	–	-3.506		-2.147	
(t statistics)	(1.16)		–	–	(-1.29)		(-1.29)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	19%				19%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Table A-3: Spatial Autoregressive Model with the Predicted Economic Activity Indexes

In this table, we report regression results of panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *State Coverage Ratio* at quarter t+1. Independent variables are the Predicted State Economic Activities (*PSEA*) at quarter t. Predicted National Economic Activities (*PNEA*) proxy is excluded because of the inclusion of state fixed effects. All variables are defined in Appendix. Panel A exhibits the results for common equities (stocks). Panel B reports the results for equity real estate investment trusts (REITs). The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *State Coverage Ratio*). *W* is the row-normalized inverse-distance matrix. The impact of spatial spillover effect (feedback effect) on macroeconomic effects is captured by the spatial multiplier, which equals to $1/(1-\rho)$. Direct effect largely resembles the coefficient estimates of the panel regressions. Total effect, which approximately equals to the product of direct effect and spatial multiplier, is reported in parallel to the direct effect. State and quarter fixed effects are included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A – Stocks (financial and utility firms are excluded)

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio (ρ)	–	–	–		**-0.504**	***	Multiplier ≈	
(t statistics)	–	–			**(-7.86)**		0.67	
PSEA	0.803	**	–	–	0.770	**	0.503	**
(t statistics)	(2.16)		–	–	(2.09)		(2.06)	
Number of Obs	2400				2400			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	33%				33%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – REITs

Model	GLS – State Coverage Ratio				SAR – State Coverage Ratio			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × State Coverage Ratio	–	–	–		**-0.593**	***	Multiplier ≈	
(t statistics)	–	–			**(-8.09)**		0.63	
PSEA	0.128	***	–	–	0.124	***	0.076	***
(t statistics)	(3.09)		–	–	(3.04)		(2.98)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	19%				19%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			