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Three Essays on the Geography of Finance

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Abstract

This dissertation consists of three essays on the geography of finance. In the first essay, we study the relation between geographic dispersion and firm value. In the context of asset-sells, information asymmetry hypothesis and managerial alignment hypothesis offer opposite predictions on the market reaction to asset-sell announcements. Real estate investment trusts (REIT) firms provide an ideal setting to investigate these two competing but not mutually exclusive effects. We construct a unique panel data of more than 800,000 property-year observations and apply a two-stage sequential decision-making method to mitigate selection bias at both firm level and property level. We find that REIT firms tend to dispose of distant properties and there is a negative relation between distance and cumulative abnormal returns (CARs, also known as cumulative prediction errors), consistent with managerial alignment hypothesis. Further, informational and social factors explain corporate decisions on asset sell-offs and the effect of social interactions only exists in less-populated areas. Together, these findings suggest a dominant role of managerial alignment effect.

In the second essay, we analyze cross-state/MSA spillover effects of local capital scarcity. We propose a theoretical framework to capture the competition for scarce capital across state/MSA borders and calibrate its implications with spatial autoregressive (SAR) and spatial Durbin's (SDM) models. Our application of spatial econometrics tools mitigates potential bias in estimation that arises due to the violation of Stable Unit Treatment Value Assumption (SUTVA), which leads to indirect treatment effect (competition effect) on geographic neighbors. Overall, our findings suggest that negative spatial spillovers may arise due to competition for scarce capital, and the competition effect is amplified during local and national economic downturns.

In the third essay, we introduce geographic variables and implement a novel econometric method.

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We test the hypothesis that geographic (state-level) macroeconomic factors and funding liquidity affect market liquidity. We find cross-state spillover effects for market liquidity. These spatial spillover effects have two implications. First, higher REIT market liquidity in neighboring states leads to decreased REIT market liquidity in a particular state. Second, there is also a spatial multiplier effect (less than 1) that diminishes the magnitudes of the total effect of state macroeconomic effects on funding liquidity. These results indicate that neighboring states compete for scarce capital, leading to negative effects on the growth trajectories across state borders. Such negative effects are more extreme during market downturns.

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Essay 1

Geographic Proximity and Managerial Alignment:

Evidence from Asset Sell-offs by Real Estate Investment Trusts

1. Introduction

The relation between geographic dispersion and firm value has been extensively studied. However, two key hypotheses predict different outcomes. On the one hand, geographic proximity mitigates information asymmetry and improves firm performance (*information asymmetry hypothesis*; see John and Ofek, 1995; Lerner, 1995; Coval and Moskowitz, 1999, 2001; Grinblatt and Keloharju, 2001; Peterson and Rajan, 2002; Giroud, 2013). On the other hand, Landier, Nair and Wulf (2009) suggest that social concerns could affect the conflict with shareholder wealth maximization when firms are more concerned about nearby operating assets due to reputational concern and the management of geographically dispersed firms align their interests better with nearby employees rather than with shareholders (*managerial alignment hypothesis*).

Asset sales are considered as effective channels to examine the relation between geographic dispersion and corporate decision making (Jovanovic and Rousseau, 2002; Yang, 2008; Warusawitharana, 2008; Boot, 1992; Lang, Poulsen and Stulz, 1995; Kose, Sodjahin 2010). In the context of asset sales, information asymmetry effect predicts a *positive* relation between distant sales and post sell-off stock market reaction (measured by cumulative abnormal return, or CAR) while managerial alignment effect suggests a *negative* relation between distant sales and post sell-off stock market reaction.[1] In this study, we examine the asset sell-offs by equity real estate investment trusts (REITs), which provides an ideal setting to investigate the two competing but *not* mutually exclusive effects. REITs operate within a single asset class (because REITs must have at least 75%, of assets and income from real estate related assets), have similar dividend

[1] Cumulative abnormal return (CAR) is also known as the cumulative prediction error (CPE) used in Glascock, Davidson and Sirmans (1991). It is noted that although the two hypotheses generate opposite predictions, they are not necessarily mutually exclusive. All else equal, if information asymmetry effect (managerial alignment effect) dominates, we should observe a positive (negative) reaction to distant sell-offs.

payout policies (because they are required to pay out 90% of taxable income as dividends), have high institutional ownership (see Chan, Erickson, and Wang, 2003), and have similar antitakeover provisions (because 5-50 rule and excess share provision). These features help mitigate the likelihood of alternative explanations to asset sell-offs such as changes in corporate strategy (Kaplan and Weisbach, 1992), financing needs (Lang, Poulsen, and Stulz, 1995) and corporate governance (John and Sodjahin, 2010; John, Knyazeva and Knyazeva, 2011).

Real estate is heterogeneous and illiquid with slow market mechanism (Ling and Archer, 2013; Levitt and Syverson, 2008). Based on the link between distance and information flows, soft information might play an important role in the real estate market as information on potential rental growth and local market conditions cannot be cheaply hardened.[2] Managers might tend to dispose of distant properties and to keep the nearby properties because information in the real estate market is more costly to communicate to distant agents.

Landier, Nair and Wulf (2009) suggest that distance creates a potential distortion between managerial incentives and shareholder interests because managers react differently to economic shocks to underlying operating assets and business divisions through social interactions.[3] For example, managers of geographically concentrated firms are more concerned about nearby operating assets due to reputational concern and about employees with whom they interact more frequently. When information is soft, personal interactions are important. More frequent social

[2] This argument has its root in Petersen (2004), in which soft information is defined as information that is difficult to quantify. This implies that the cost of soft information, compared with that of hard information, is much higher for operating assets that are distant from the management (usually measured by firm headquarters). Bank lending related studies provide extensive discussions on the link between distance and information flows (Petersen and Rajan, 2002; Liberti, 2005; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012). As a result, small banks are found to have information advantage in lending to less transparent firms using soft information.

[3] In a different context of individual decisions, Glaeser, Sacerdote and Scheinkman (1996) find a relation between proximity and social interactions.

interactions with nearby employees and reputational concerns would likely affect a firm's decision on asset allocation and disposition.

The sources of uncertainty in the real estate sector mainly come from property type and location, both are considered as highly rigid and relatively permanent. This relative simplicity makes it a plausible benchmark to evaluate information asymmetry through geographic dispersion.[4] To mitigate information asymmetry, market participants tend to purchase nearby properties (Garmaise and Moskowitz, 2004) and REITs tend to be geographically focused (Cronquist, Hogfeldt, and Nilsson, 2001; Hartzell, Sun, and Titman, 2014). While this may be expected, our sample shows that REITs have a large dispersion of properties that are not close by conventional measurement. For example, the top-ten MSAs in our disposition sample were over 860 miles (1,388 kilometers) from their REITs' headquarters (HQs).

We manually collect a sample of property sell-offs by REITs from 2003 to 2013 based on an extensive search of news articles. We are able to construct a panel sample of underlying properties with detailed information on type and location, taking sales, purchases, mergers and acquisitions into consideration. Constructing these data sets is not a trivial task as there are about 36,528 underlying properties held by REITs and non-REIT firms in each year, adding to 840,150 during the entire sample period and much of the information has to be hand collected and verified due to missing data, renovations and changes of usage.[5] The sample of property-year observations

[4] Some studies examine manufacturing industries (Edmans and Mann, 2015; Arnold, Hackbarth, and Puhan, 2015). We argue that real estate might be better suited in testing the information asymmetry effect because the production at plant locations could be quite dynamic, depending on firm's strategy which is less observable.
[5] We include both to account for the property transactions and M&As between REITs and non-REIT firms. The total number of properties held by REITs from 2003-2013 is 344,010.

is merged with a comprehensive list of U.S. public equity REITs from 1993-2015 identified by NAREIT.[6]

We start our analysis by investigating the impact of property-headquarter distance on investor reactions to property sell-offs by REITs. As a cluster of properties was sold in most of sell-off transactions, our distance proxies include mean and median distances from the properties being sold to the sell-off firm's headquarter. By defining nearby (distant) sell-offs as distance below (above) median, our univariate analysis suggests that CARs of distant sell-offs are significantly lower. By controlling for firm-level characteristics, including fundamentals, sources of fund and use of fund, as well as deal-level characteristics in multivariate analyses, we find that positive reactions are associated with nearer property sales.[7]

The sell-off decisions at *firm-level* are endogenous and subject to selection bias as firms are self-selected to be sellers. One commonly used approach to mitigate this concern is to construct a matched sample of non-sell-off firms by using propensity score matching to control for firm characteristics. However, selection bias may also occur at *property-level* because assets being sold might be fundamentally different than those being held. We address this problem with a two-stage *sequential* decision making process. In the first stage, we estimate the likelihood of firm-level asset sell-offs. In the second stage we estimate the likelihood of property-level sell-offs, conditional on firm-level sell-off decision. Our matched sample is constructed based on joint probabilities, which is the product of the firm-level sell-off probability and the property-level conditional probability.

[6] A comprehensive list of U.S. equity REITs identified by NAREIT can be downloaded from Dr. S. McKay Price's website: http://www.mckayprice.com/research.html. We construct our dataset in a similar manner to Feng, Price and Sirmans (2011).
[7] To be sure that this is not driven by outliers, we sort the data by quartiles: the positive reactions uniformly declined as distance increases.

This research design could help mitigate the double selection bias at both firm-level and property-level.

The univariate investigation of firm and property characteristics confirm that there is a large heterogeneity between sell-off firms and control firms. Within sell-off firms, the properties that being sold are quite different than those being held. We find consistent results with Landier et al (2009) that firms adopt a "pecking order" and are more likely to sell distant properties than nearby properties. Based on a matched sample controlling for both firm-level and property-level heterogeneity, we conclude that investors react more negatively to distant sales and managerial alignment effect dominates. Our results are robust to different discrete choice models (logit and probit), different matched samples (i.e. based on firm-level, and both firm-level and property-level only), different weights (by number of sell-off and by holding properties), and different model specifications.

Population size might contain valuable information regarding the managerial alignment effect because of managerial visibility or scale of monitoring effect. Therefore, to further examine the role of social factors, we divide our matched sample into subsamples of large- and small-population. Consistent with Landier et al. (2009), we find that social factors only affect post sell-off stock performance of firms headquartered in less populated counties, where managers are more visible.[8] We also employ local (city or state-level) union power as a proxy for employee friendliness and find that REITs located in areas with high union power ex ante are more likely to adopt geographically focused strategy.

[8] This confirms our prediction that *managerial alignment effect* and *information asymmetry effect* are not mutually exclusive. In less populated areas, *managerial alignment effect* dominates *information asymmetry effect*.

Lastly, market participants could be confident with negotiating deals from further distance because more observable settled deals are available to the market participants mitigate information concern. This possible link between market depth and distance would be driven by information asymmetry but could also predict a negative relation between market reaction to property sale and sell-off distance to HQs. We take advantage of our property-level dataset and find that there is virtually no relation between selloff distance and market depth.

This study makes several important contributions. First, although the effects of information asymmetry have been extensively examined, the effects of managerial alignment have not. Information asymmetry hypothesis and managerial alignment hypothesis offer opposite predictions on the relation between geographic dispersion and firm value. The setting of REIT sell-offs is uniquely suited in testing these two competing effects as real estate is a sector subject to high information asymmetry and soft information plays an important role when cash flows are driven by local market with high idiosyncratic risks and when information about the true value cannot be cheaply hardened. Although these two hypotheses are not mutually exclusive, our findings favor managerial alignment effect, and complement Landier et al (2009)'s finding suggesting that the managerial decisions are crucial in determining the balance between shareholders and social concerns on reputation and employees.

Second, our unique sample of asset sell-offs by REITs with detailed information on more than 800,000 property-year observations spanning a ten-year sample period provides us an opportunity to investigate the *double* endogeneity and selection bias problems at both firm-level and property-level using a sequential choice model. We believe this is the first study to address this issue in the literature of asset sales and the REIT literature.

Third, although prior studies in real estate suggest that REITs tend to be more property-type focused and location-focused, and many find that more property-type focused REITs value more than property-type diversified firms, they fail to find that it is the case in location-focused firms (see, for example, Cronqvist, Hogfeldt, and Nilsson, 2001). Our findings propose a new perspective and suggest that one should take into consideration managerial alignment with shareholders' benefit.

The reminder of the paper is organized as follows. In section 2, we briefly discuss the relevant literature. In section 3, sample construction and variable measurement are described. In Section 4, empirical results that test the two effects' implications are reported. Section 5 concludes the paper.

2. Literature Review

This study is related to several strands of literature. First, information concern has long been recognized as an important driving force of individual and corporate decisions. The effect of information asymmetry have received much attention since Peterson (2004), which classified information sources into hard vis-a-vis soft information. He argues that information concern arises when soft information, which cannot be easily quantified and is personal, dominates in a particular market. For example, in the banking industry, credit decisions are made based upon information collected over time through frequent and personal contacts with the borrower (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012). Since the term, "soft information", is innovated by Petersen (2004), its existence and effect have been noticed and discussed in many prior studies. For instance, issues such as "Home Bias" and "Local Bias" have received a lot of attention in the finance literature (French and Poterba, 1991; Huberman, 2001;

Bodnaruk, 2009). A central argument of these studies is that investors tend to ignore diversification benefits and invest in the familiar.

One may doubt if such facts still exist as technologies that facilitate information transmission become more mature nowadays. Based on the recent literature such as Bernile, Kumar and Sulaeman (2015), however, the hardening of information doesn't fully resolve the "Home Bias" and "Local Bias".[9] One potential explanation is that certain components of soft information are heavily dependent on social interactions, which is personal and hard to quantify. This is especially true for the real estate industry, where assets are highly illiquid and information consideration is significant (Garmaise and Moskowitz, 2004).

Eichholtz, Holtermans and Yonder (2015, hereby *EHY*) and Liu, Gallimore and Wiley (2015, hereby *LGW*) are among the first to examine the role of investor proximity, or investors' preference for local assets, in commercial real estate markets.[10] *EHY*'s thesis argues that geographic diversification presents no free lunch for office investors. That is, there is a tradeoff between risk reduction associated with diversification and lower rent in the presence of market frictions, i.e., information asymmetry. And office investors are segmented by geographic distance because they have difference preference for risk taking.

LGW examine the same research question, but from a different perspective. To be specific, LGW examine the *change*, instead of the *level*, of office investors' property holdings. That is, they look at acquisitions and dispositions of offices by local and nonlocal investors. Contrary to *EHY*, *LGW* document that nonlocal investors overpay (by about 14%) because of both *information*

[9] Hardening of information refers to the question of whether information can be interpreted and coded into a numeric score (or scores) (Petersen, 2004, pp. 6). For a comprehensive review of possible consequences of the hardening of information on both financial markets and institutions, one can refer to Petersen (2004).
[10] Lambson (2004) examines buyer proximity in residential real estate markets.

asymmetry (measured by investor-property distance) and *anchoring* (measured by rent difference), and sell at a (7%) discount because of *information asymmetry*. The selloff discount is more severe when nonlocals sell to locals.[11]

Second, our evidence suggests that social factors are important and shape corporate decisions (Wang, 2012; John, Knyazeva, and Knyazeva, 2011). Introduced by geographical locations, these social factors affect firms' operation and thus shareholder wealth. For instance, Landier, Nair and Wulf (2009) argue that proximity to employees leads to misalignment of managerial incentives with shareholder objectives because managers interact more frequently with nearby employees. They find that in-state divestitures of a firm's entities lead to positive and significant *ex post* stock performance when the firm's headquarter is located in a less populated county. They give rise to the conflict of interest between stakeholders and shareholders, which is further explored in John, Knyazeva, and Knyazeva (2011). In addition, the amount of population affects firm's corporate governance through proximity to the firm's headquarter because of larger pools of director talent. Knyazeva, Knyazeva, and Masulis (2013) find that population is positively correlated with local director pool and thus the monitoring effect on firm's management. A recent paper by Ang, Jong, and Poel (2014) find that CEOs' divestments of familiar segments generate 1.2% higher abnormal returns and the greater returns are particularly pronounced for divestments of direct-experience segments by more entrenched CEOs.

Finally, our study contributes to the mixed evidence found on diversification discount of listed firms. "Diversification discount" attracts a lot of attentions in the finance and real estate literature. It is defined as "the fact that the average diversified firm has been worth less than a

[11] We don't find a significant discount for REITs.

portfolio of comparable single-segment firms" (Lang and Stulz, 1994, pp. 36). Several explanations to diversification discount are proposed. First, firm-level diversification may provide more benefits to managers than it does to shareholders (Amihud and Lev, 1981). Second, internal capital markets in conglomerates transfer funds across divisions in a suboptimal manner (Lamont, 1997; Whited, 2001). Third, diversified firms are less transparent and more difficult to analyze. Therefore, their underlying stocks are less liquid and have lower value.

REITs provide a suitable laboratory to study the "diversification discount" issue because REITs are less heterogeneous than conventional firms and the underlying assets, real estate, are less opaque than other revenue generating assets. Capozza and Seguin (1999) note that a focused strategy is likely to be a "double-edged sword". On the one hand, firms adopt focused strategy see their value increases due to the increased liquidity provided by increase in focus. On the other hand, focused strategy might cause variability in income stream of a focused firm and thus higher interest rates. And this phenomenon could be severe when a firm is highly levered or invested in illiquid assets such as real estate.

The "diversification discount" on property type has been found in several recent studies such as Cronquist, Hogfeldt, and Nilsson (2001) and Ro and Ziobrowski (2012). However, evidence on the "diversification discount" on geographic dispersion of REITs' underlying properties is mixed (Hartzell, Sun, and Titman, 2014). Moreover, failure to notice endogeneity issue and could potentially bias the results found in previous studies.[12]

[12] For instance, Lamont and Polk (2001) argue that poor performers may be more likely to diversify in an attempt to increase value. Similarly, Campbell, Petrova and Sirmans (2003) also notice that a weakness of the diversification literature in Real Estate is that there are few studies that examine the relation between shareholder wealth and events that significantly alter expectations regarding the firm's level of diversification or focus. Such studies are required to address the possible problem of self-selection and endogeneity in the data similar to those that have been noted in the finance literature. Therefore, using well-specified self-selection models to capture ex-ante expectations on firms' self-selection process and to mitigate endogeneity issue is important.

3. Sample Construction and Variable Measurement

3.1. Sample Construction

3.1.1. Sell-off Events

We search in Factiva to collect news announcements on property sales by REITs. Factiva applies Intelligent Indexing® in order to assign unique company codes to Dow Jones News Search (DJNS) articles that represent the companies that are the subject of the articles. Because of the Intelligent Indexing, Factiva is considered effective in identifying articles relevant to specific companies. By conducting rigours search in (1) Wall Street Journal, (2) Dow Jones Newswire and (3) Business Wires, we gather 1,271 articles on property sell-offs from January 1, 2003 to December 31, 2013 by all the US Equity REITs included in the FTSE National Association of Real Estate Investment Trusts (NAREIT) US equity REIT Index.

We follow Campbell, Petrova and Sirmans (2006) and focus on property sell-offs with total value greater than $20 million. For each property sale, we define an event date as the first trading day that the sell-off announcement appears in any of the three forth-mentioned publications if the announcement is made prior to 3:59 pm. If the announcement is made after 3:59 pm, we use the next trading day as the event date. Events are deleted if there are any other major corporate announcements during the event window. The sample selection process gives us 161 property sell-offs. We delete 8 observations without property-level information. 154 sell-offs are used in our baseline regressions.

3.1.2. REIT Underlying Properties

We construct a comprehensive panel data of historical property holdings at REIT-property-year level based on the SNL Financial database, Factiva news search on property acquisitions and

dispositions and on REITs mergers and acquisitions. Specifically, we start with the most current property holdings by all the REITs and track backward with historical property acquisitions and dispositions. To account for delisted and newly listed REITs, we follow Feng, Price and Sirmans (2011) and manually construct a comprehensive list of US public equity REITs identified by NAREIT from 1993-2015. Our sample is comprised of all equity REITs that are constituents of the FTSE NAREIT US equity REIT Index.[13]

Our final sample includes 3,797 firm-year observations and 344,010 firm-property-year observations from 2003 to 2013. We further divide our sample into two groups, sell-off firms and non-sell-off firms. Our non-sell-off sample for testing the propensity of firm-level asset sell-offs includes all REIT-years except REITs that are in the sell-off sample. There are 100 firm-year and 1,157 property-firm-year observations (3,697 firm-year and 332,853 property-firm-year observations) in the sell-off sample (non-sell-off sample).[14]

3.1.3. Cumulative Abnormal Returns (CARs) and Control Variables

We compute CARs using CRSP value weighted market index, excess returns of small caps over big caps (SMB), excess returns of value over growth (HML), and momentum factor as systemic risk factor loadings. We follow Wiley (2013) and use an estimation period that includes one year of stock returns and ends 50 trading days before the event window. Event windows include (1) a trading day before the asset sale until the trading day (-1, 0), (2) the trading day when the asset sale occurs (0, 0), (3) the trading day when the asset sale occurs until the trading day after (0, +1), (4) the trading days before the asset sale until the trading day after (-1, +1), (5) five trading

[13] The FTSE NAREIT US Real Estate index contains all Equity REITs not designated as Timber REITs or Infrastructure REITs.

[14] 206 property-firm-year observations without information regarding remaining properties held by the sellers available are dropped from the full sample of 1,363 property-firm-year observations.

days before the asset sale until the trading day before (-5, -1), and (6) five trading days before the asset sale until five trading days after the asset sale (-5, +5).

Data on deal sizes are verified manually by matching Factiva search results with EDGAR SEC filings. We obtain stock price data from CRSP and financial data from COMPUSTAT-CRSP Merged database, respectively.

3.2. Distance Proxies

We calculate a firm-property-year distance, d_{ijt}, for each underlying property j sold or held by firm i in year t. Firm-property distances need to be aggregated for each transaction as there are more than one underlying property for each REIT-year and multiple properties sold in a sell-off transaction. Firm-year distance is calculated by taking the arithmetic mean and median of all firm-property distances for each firm-year or sell-off using the following expressions

$$AggregateDistance_{i,t} = \frac{1}{n}\sum_{j=1}^{n} d_{ijt}$$

$$MedianDistance_{i,t} = median_i(d_{ijt}), \tag{1}$$

where d_{ijt} represents the firm-property distance in year t, n equals to the number of properties sold or held by firm i.

4. Results

4.1. Asset Sell-offs and Market Reactions

Table 1 summarizes the annual frequency of property sell-offs, total value and average deal size from 2003 to 2013. There are 161 transactions with a total value of approximately $33 billion. The average deal size is $204 million. The number of sell-offs and the average deal size plummeted

around the Global Financial Crisis (GFC) in 2008 and 2009. In unreported results, there are 68 unique sellers (defined by their CRSP PERMNO), of which 32 appear only once and 17 appear more than three times.

In Table 2, we divide our sample by property type and by their stated use of proceeds announced in the publications. The largest group by property type is office and industrial properties (41%). Most of the sell-off firms (45%) do not announce the use of sale proceeds. Among sell-offs with stated purposes, the largest group is to reduce debt (18.6%). Only 2.5% (1.9%) of sell-offs are to distribute dividends (to repurchase shares). In our sample, the breakdown by property type is qualitatively similar to Campbell et al. (2006), which examine equity REIT property sell-offs between 1992 and 2002. However, the breakdown by the use of sale proceeds is different from Campbell et al. (2006) as the largest group in our more recent sample is fund acquisition.

Panel A of Table 3 shows summary statistics CARs based on six different event windows, (-1,0), (0,0), (0,1), (-1,1), (-5,5) and (-5,0), which represent the one-day before, one-day, one-day ahead, three-day, eleven-day, and six-day windows, respectively. All CARs are positive and significant at 1% level except for the six-day window. Compared the CAR magnitude with prior studies, the mean in three-day window (-1, 1) is 1.18%, which is very close to the finding in Glascock, Davison and Sirmans (1991) and is greater than 0.8% reported in Campbell et al. (2006.).[15]

In Panel B, we separate our asset sales into two groups based on the distribution of distances from disposed properties to their headquarters. If the distance of a disposed property is

[15] In unreported results, we find that, consistent with Campbell et al (2006), the average CAR in three-day window is significantly positive for sales that are not structured as Section 1031 transactions while there is no evidence of CAR for Section 1031 transactions.

greater than the sample median, it is assigned to the below-median group. Otherwise, it is assigned to the above-median group. If the deal consists of multiple properties, we use the average distance.

By comparing CARs of sell-offs with relatively short distance (in the below-median group) and that with relatively large distance (in the above-median group), we find that CARs of nearby sell-offs are positively significant while that of distant sell-offs are statistically insignificant. The *t*-statistics (=2.00) of mean difference and *z*-statistics (=1.69) of rank-sum tests (for median difference) between these two groups are significant. Unreported results suggest a similar pattern in all windows.[16] It reveals that the abnormal returns of sell-offs are higher if disposed properties are located in a relatively short distance from the headquarter location of its holding company, in favor of the managerial alignment explanation. By further separating our asset sales into four distance quartiles, Panel C confirms the negative relation between distance and CAR as we observe a monotonically decreasing pattern across distance quartiles.

The finding of a negative relation between market reaction to property sales and the distance of sell-off properties to their HQs is new and complements previous studies such as Hartzell, Sun, and Titman (2014), who find evidence of regional diversification discount of REITs utilizing a sample of equity REITs over the 1995-2003 period.

Hartzell, Sun, and Titman (2014) also suggest that the regional diversification discount is mitigated when institutions have a greater equity stake as institutions monitor the REITs more effectively than retail investors. We predict that firms located in areas with larger population has stronger monitoring effect as population can be used as an approximation of the size of potential

[16] In unreported results, for each property-year, we define Distant as an indicator variable that takes value of one if it is located above median distance of the other underlying properties. For multiple property sales, we calculate aggregate this variable at deal level by taking the average. We investigate the sub-sample of CARs with Distant above median and that below median and find similar results.

director pool (Knyazeva, Knyazeva, and Masulis, 2013); therefore, benefits to the shareholders associated with local selloffs is smaller. To test this prediction, we sort CARs over three-day window into different subgroups based upon four distance quartiles and median local population, which is measured by the population of the county where a REIT is headquartered.[17]

In Panel D, our results suggest that the positive relation between selloff CARs and geographic proximity only exists among REITs headquartered in counties with population below sample median (*Small Population*). There is no such relation for REITs headquartered in counties with population above sample median (*Large Population*). Moreover, CARs are larger for *Small Population* group than for *Large Population* group in the first three distance quartiles.

In an alternative measure of monitoring based on population, we follow Loughran and Schultz (2005) and define a REIT as in a "top-ten" MSA if its headquarter is in one of the ten largest metropolitan areas of the U.S. according to the 2010 Census.[18] We define the rest of the REITs in our sample as in "non-top-ten" MSAs. Information asymmetry concern is likely to be more severe among firms in smaller MSAs than those in larger ones due to the lack of monitoring effect. Consistent with Panel D, results in Panel E suggest that the negative relation between CARs and distance only exists among property selloffs by non-top-ten-MSA REITs.

As business cycle might exert different effects on small and on big MSAs and potentially drive the previously documented results, in Panel F, we use the fall of Lehman Brothers (May 28, 2009) as the cutting point. Selloffs occur prior to May 28, 2009 are defined as Pre-Recession

[17] We also divide the selloff CARs into different subgroups four distance quartiles and small-, medium-, and large-population groups. We find that the monotonic declining relation between CARs and distance only exists among the small-population group. The results are reported in Panel E.
[18] Loughran and Schultz (2005) define firms as urban, small-city or rural based on their location relative to the largest MSAs in terms of population.

selloffs; the rest of the selloffs are defined as Post-Recession selloffs. We did not find too much evidence that our previous findings are affected by business cycle: Small (non-top-ten) MSA selloffs experienced a decline in CARs during the post-recession period but such effect does not exist in large (top-ten) MSA selloffs.

4.2. The Impact of Distance on Market Reactions – OLS Regressions of CARs on the Determinants of Abnormal returns

To further investigate the heterogeneity among sell-off firms, our next step is to conduct multivariate analysis controlling for firm-level and deal-level characteristics. We follow Wiley (2013) and perform three sets of tests based on firm-level determinants of CARs: (1) fundamentals, (2) source of fund and (3) use of fund. In addition, we add tests based on deal-level characteristics as documented in the literature (Lang, Poulsen, and Stulz, 1995; Campbell et al., 2006; Wiley et al., 2010; Wiley, 2013). We report summary statistics of these determinants in Table 4 Panel A and regression results in Panel B, C, D and E.

4.2.1 Fundamentals

The difference in market reactions are driven by differences in firm fundamentals. The model of the impact of distance on market reactions with firm fundamentals is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Cash + \beta_3 Firm\ Size + \beta_4 ROA + \beta_5 Debt + \beta_6 Coverage + \beta_7 Tobin's\ Q + \beta_8 DC + \varepsilon, \quad (2)$$

where *Distance Proxies* include average and median firm-property distance described in Equation (1). *Cash* is cash and short-term investments (CHE) divided by total assets (AT). *Firm Size* is the quarterly reported book value of total assets (AT) in millions of USD. Return on assets (*ROA*) is expressed as the quarterly net income (NI) over total assets (AT). *Debt* equals to the sum

of total long-term debt (DLTT) and debt in current liabilities (DLC) divided by total assets (AT). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IB) divided by the sum of preferred dividends (DVP) and interest and related expenses (XINT). *Tobin's Q* equals total book assets (AT) plus the market cap (PRCC_C*CSHO) minus common equity (CEQ), all divided by total book assets (AT). *DC* is an indicator variable which equals one if a firm's coverage ratio is below the sample median in the last fiscal quarter prior to the announcement, and zero otherwise. All the fundamental variables are lagged.

Table 4 Panel A presents summary statistics and Panel B includes regression results of the relation between investor reactions and underlying property distance to the selling REIT's headquarter. In both Model (1) and (2), the coefficient estimates of distance proxies are negative and statistically significant, controlling for firm fundamentals. The effect is also economically significant: one standard deviation increase in average (median) distance decreases CARs by 117 (114) basis points from the mean (median).[19]

Coefficient estimates of control variables have expected signs and are consistent across model specifications. Since we restrict our analysis to the short event window (3 days) and avoid property selloffs coincide with other events, i.e., mergers and acquisitions, coefficient estimates on most *ex ante* fundamental return predictors are insignificant. There is a positive and statistically significant relation between CAR and pre-announcement debt ratio. Lang, Poulsen and Stulz (1995) suggest that asset sale may help avoid recapitalization costs that would have to be paid to raise funds on capital markets when the firm's debt overhang is large. Therefore, lower cost of

[19] From Table 4, Panel A, the standard deviation of average (median) distance is 0.961 (1.001); from Table 4, Panel B, the coefficient estimate on average (median) distance is -1.216 (-1.142). Therefore, one standard deviation change in average (median) distance leads to -1.216 * 0.961= 1.17 (-1.142 * 1.001= 1.14) percent, or 117 (114) basis points from the mean (median), decrease in CAR.

refinancing might explain the positive relation between CAR and pre-announcement debt ratio. On the other hand, the positive relation between CAR and pre-announcement debt ratio could also be explained by lower agency cost if debt plays a useful role in disciplining management.

The results based on continuous distance measures might be driven by outliners. As a result, we use an alternative binary measure of distance, *Nearby*, which equals to 1 if *median distance* in Equation (1) is less than the sample median of the 154 selloff observations and 0 otherwise. In Model (3), we find that *Nearby* dummy is positively associated with the abnormal returns. This finding indicates that our previous results based on the other distance measures are robust and supports the managerial alignment hypothesis.

4.2.2 Sources of Fund and Use of Fund

In addition to ex ante firm's fundamentals, sources of funds and use of funds are also likely to affect ex post sell-off stock performance. For instance, Lang, Poulsen, and Stulz (1995) find that firms paying out the proceeds are typically poor performers and highly levered firms. Lang, Poulsen, and Stulz (1995) address the importance of both sets of variables. They suggest that managers are self-interest individuals who pursue their own objectives and are likely to be empire builders. Empirically testing managerial alignment involves both sources of funds and use of funds. Therefore, including these two sets of variables as control variables help disentangle the effects of our distance measures, firm's fundamentals, and firm's financing and investment activities.

Consistent with the literature (e.g. Wiley, 2013), we conduct analysis with sources of funds and use of funds as control variables separately. We control for funding generated from the proceeds of an asset sale and/or from the capital markets. The model of the impact of distance on market reactions with sources of funds is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Selloff + \beta_3 Gain + \beta_4 DebtIssues + \beta_5 EquityIssues + \varepsilon, \quad (3)$$

where *Distance Proxies* and *Selloff* are defined the same as Section 4.2.1. *Gain* is the reported gain or loss generated from the sale of property (SRET). *Debt Issues* is the total new long-term debt issued (DLTISY). *Equity Issues* is the total proceeds from the sale of common and preferred stock (SSTKY). All the sources of fund variables are lagged.

Next, we address the question how funding raised in the previous step is spent. Funding can be used to retire debt, to distribute as preferred and/or common dividends, and/or to invest in new projects. Therefore, we follow Wiley (2013) and include potential usage of funds as control variables in our analysis. The model of the impact of distance on market reactions with use of funds is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Selloff + \beta_3 DeltaDebt + \beta_4 DeltaPreferredEquity + \beta_5 DeltaCommonEquity + \beta_6 DeltaInvestment + \varepsilon, \quad (4)$$

where *Distance Proxies* and *Selloff* are defined the same as Section 4.2.1. *Delta Debt* is the difference in debt reduction (DLTRY) from the previous fiscal year (t-2) divided by total long-term debt (DLTTY), in the last fiscal year prior to the sell-off announcement (t-1). *Delta preferred* equals the difference in preferred dividends paid (DVPY) from the previous fiscal year (t-2) divided by total liabilities (LT). *Delta common equity* equals the difference in cash dividends paid (DVY) from previous fiscal year (t-2), divided by the market cap (PRCC_C*CSHO). *Delta investment* equals the difference in increased investments (IVLTY).

Results in Panel C and D of Table 4 conform the negative relation between property-HQ distance and market reaction to property sell-offs: the coefficient estimates of different distance measures are negative in all the model specification. The coefficients of continuous distance measures are smaller compared with those in Panel B. The coefficient estimates of control variables associated with the sources of funds and use of funds have consistent signs as in Wiley (2013) but are statistically insignificant.[20]

4.2.3 Deal-level Characteristics

For each transaction, we hand collected detailed information on the purpose of the sale and the usage of sale proceeds which is unarguably important as it affects investors' prospect on the asset sell-off and thus can affect post sell-off stock performance. The model of the impact of distance on market reactions with deal-level dummies and firm's fundamentals is

$$\begin{aligned} CAR = {} & \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Deal\ Size + \beta_3 Geographic\ Focus + \\ & \beta_4 URSTD + \beta_5 URLTD + \beta_6 EXCH + \beta_7 Recession + \beta_8 Pay\ Dividend + \\ & \beta_9 Cash + \beta_{10} lnrsize + \beta_{11} ROA + \beta_{12} dassets + \beta_{13} Coverage + \\ & \beta_{14} Tobin's\ Q + \beta_{15} DC, \end{aligned} \tag{5}$$

where *Distance Proxies*, *Selloff*, and fundamental variables (*Cash*, *lnrsize*, *ROA*, *dassets*, *Coverage*, *Tobin's Q*, and *DC)* are defined the same as Section 4.2.1. *Deal Size* equals to the transaction price divided by total book assets (AT). *Geographic Focus* is an indicator variable equals to 1 if the stated goal of a particular asset sale is geographic focus and 0 otherwise. *URSTD (URLTD)* is an indicator variable equals to 1 if proceeds from sale are announced to be used to

[20] There are two potential explanations for this. First, Wiley (2013) use abnormal returns over intermediate window (5 weeks) as dependent variable but we follow Campbell et al. (2006) and use abnormal returns over the short horizon (3 days) as dependent variable. Second, Wiley (2013) focus on apartment and office properties through 2010, but our sample covers all major types of properties through 2013.

reduce short-term (long-term) debt. *Pay Dividend* is an indicator variable equals to 1 if proceeds from sale are announced to be distributed as dividends. Prior studies suggest that distributing dividends to shareholders may signal either the seller's financial solvency, or a less-entrenched management team, or both. *EXCH* is an indicator variable equals to 1 if 1031 tax-free exchange is used. *Recession* is an indicator variable equals to 1 if announcement date is in the recession period defined by NBER US Business Cycle Expansions and Contractions.[21]

In Panel E with more controls of deal level characteristics, we find that the negative relation between CAR and the proximity of sell-off properties to their HQs is still robust. The magnitude of the coefficients are very similar to those in Panel C and D, even controlling for *Geographic Focus*, whether the purpose of a particular sale is to increase the geographic focus of the selling REIT. Regarding deal-level indicators, we find that market reactions are positively associated with the application of sale proceeds to the retirement of short-term debt (*URSTD*), deal size (*Deal Size*) and *Pay Dividend* dummy.

4.3. Matched Sample based on Two-stage Sequential Model of Asset Sell-off Decisions

Although our cross-sectional regression results in Section 4.2 suggest that investors react more positively to sell-offs of nearby assets, controlling a large set of aspects that might affect the abnormal returns of asset sell-offs, selection bias may occur at firm-level because we only observe the market reaction-distance relation among firms that self-select to be sellers. For example, firms that are more financially constraint, holding more geographically dispersed properties are more likely to become sellers. A possible solution is to construct a matched sample of firms with similar characteristics of sell-off firms.

[21] http://www.nber.org/cycles.html

However, one complication arises because, given that a sell-off is likely at *firm-level*, selection bias may occur at *property-level* because assets being sold maybe fundamentally different than those being hold. For example, it is well-documented in literature that REITs tend to specialize in operating a single type of property or in a more focused geographic area (Capozza and Seguin (1999), Campbell, Petrova, and Sirmans (2003), Hartzell, Sun, and Titman (2014), Ro and Ziobrowski (2012)). If an underlying property is of a different type from the majority of the other holding properties or is located in a distant area compared with the majority, it is more likely to be sold. As a result, the typical firm-level matching is not sufficient to mitigate this endogeneity problem.

Our matching sample is constructed based on a two-stage *sequential* decision making process, in which the first stage is to estimate the likelihood of asset sell-off occurs at firm-level and the second stage is to estimate, conditional on the firm-level sell-off, the likelihood of a property being sold within the firm. Next, the joint probability is the product of firm-level sell-off probability and the property-level conditional probability as follows

$$P(seller = 1)_{i,t} = \beta_0 + \beta_1 Size_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 \frac{FFO_{i,t-1}}{Total\ Assets_{i,t-1}} + \beta_4 Debt\ Ratio_{i,t-1} + \beta_5 Tobin's\ Q_{i,t-1} + \beta_6 Cash_{i,t-1} + \beta_7 Sales\ Growth_{i,t-1} + \beta_8 Coverage_{i,t-1} + \beta_9 Momentum_{i,t-1} + \beta_{10} DC_{i,t-1} + Firm\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon, \tag{6}$$

$$P(ppty\ sold = 1 | seller = 1)_{i,j,t} = \gamma_0 + \gamma_1 Nearby_{i,j,t-1} + \gamma_2 Diverse_{i,j,t-1} + \gamma_3 Office_j + \gamma_4 Retail_j + \gamma_5 Multifamily_j + \gamma_5 Industrial_j +$$

$$\gamma_6 Leisure_j + \gamma_7 HealthCare_j + \gamma_8 OtherType_j +$$

$$Property\ Fixed\ Effects\ +\ Year\ Fixed\ Effects\ +\ \varepsilon, \qquad (7)$$

where $P(ppt\ sold = 1, seller = 1)_{i,j,t}$ is the joint probability that property *j* is disposed by firm i in year t, $P(seller = 1)_{i,t}$ is the probability of sell-off by firm i in year t, $P(ppty\ sold = 1|seller = 1)_{i,j,t}$ is the conditional probability that property *j* hold by firm *i* is disposed, given that $P(seller = 1)_{i,t} = 1$.

Firm-level determinants of asset sale are selected based on prior studies and include *Size*, *ROA*, *FFO/TA*, *Debt Ratio*, *Tobin's Q*, *Cash*, *Sales Growth*, *Coverage*, *Momentum* and *DC*. *FFO/TA* is the ratio of funds from operations (FFO) to total assets (AT). *Sales Growth* is the annual percentage change in total revenue (REVT). The remaining variables are the same as in Equation (2). For property-level characteristics, *Nearby* is a dummy variable that takes one if the distance of a property been sold (held) to seller's headquarter is less than the sample median and zero otherwise. *Diverse* is a dummy variable that equals one if the property type of the property been sold (held) is different from seller's property type and zero otherwise. *Hold Time* describes how many years has a property been held by a particular seller. *Office*, *Retail*, *Multifamily*, *Industrial*, *Health Care*, *Hotel* and *Others* are indicator variables of property types. CRSP permanent security identification numbers (PERMNOs) are used to identify property sellers.

Table 5 presents the comparison between firm-level and property-level characteristics of sell-off firms with that of non-sell-off firms. The last two columns report *t*-test statistics of the mean differences between sell-off firms and non-sell-off firms and their significance. The "*Firm-level*" comparison suggests a stark difference between these two groups: sell-off firms are larger, have better operating performance prior to the sell-off, hold more debt and less cash, consistent

with Campbell et al. (2006) and Warusawitharana (2008). These comparisons are statistically significant. The "*Property-level*" comparison suggests that the sell-off firms adopt a "pecking order" and tend to dispose distant properties (Landier, Nair and Wulf, 2009; Peterson and Rajan, 2002; and Peterson, 2004). If the underlying property is different from the majority, it is more likely to be disposed. In addition, sell-off firms tend to hold properties for a shorter period of time. Breaking down the underlying properties by type, there is a large discrepancy in property compositions between sell-off firms and control firms. REITs are more likely to dispose of office and industrial properties. Together, both firm-level and property-level comparisons between sell-off REITs and control REITs suggest that it is important to control for heterogeneities at firm level and property level.

Table 6 presents our results of two-stage sequential analysis with binary outcome variables. Results of the first stage of firm-level sell-off decision in Equation (6) and that of the second stage of property-level sell-off decision in Equation (7) are included in Panel A and Panel B, respectively. In Column (1), a selloff firm is firstly matched to a non-selloff firm with the closest holding distance. Holding distance is defined as the average geographic distance between firm headquarters and properties been held. Then we estimate Probit model with the selloff sample and distance-matched non-selloff sample (hereby distance-matched model). Therefore, there is no property matching corresponding to Column (1). Results based on logit model and Probit model are shown in Column (2) and (3), respectively. To accommodate repeated sales, we repeat our analysis with the number of properties sold as weights, shown in Column (4) and (5), respectively.

Results in Panel A suggest that REITs are more likely to become sellers if they are larger, have higher ROA, have high debt ratio and less cash. These results are largely consistent with Warusawitharana (2008). Based upon his theoretical framework, firms that are exposed to a

negative profitability shock find themselves with more assets to reach optimal size.[22] In Panel B, consistent with REITs pursuing a focusing strategy, properties located near its headquarters and of a different type from the majority of the underlying properties are more likely to be sold. In addition, industrial properties are more likely to be disposed relative to the other types.

The results of the two-stage sequential model in Table 6 suggest that there are selection problems at both firm level and property level. Our next step is to construct a matched sample of properties based on the *predicted* joint probability that a property *j* is disposed by firm *i* in year *t*, which is the product of the *predicted* probability calculated based on the first-stage estimates in Equation (7) (shown in Panel A) and the *predicted* conditional probability based on the second-stage estimates in Equation (8) (shown in Panel B) as follows

$$P(ppt\ sold \widehat{= 1, s}eller = 1)_{\iota,J,t} = P(sel\widehat{ler =} 1)_{\iota,t} \times P(ppty\ sold \widehat{= 1|}seller = 1)_{\iota,J,t} \quad (9)$$

For a given firm-year, we calculate our propensity score for a given firm-year by aggregating the predicted joint probabilities at property-level as an average predicted probability as shown below.

$$Propensity\ Score_{i,t} = \frac{\sum_{j=1}^{J} P(ppt\ sold=1, seller=1)_{i,j,t}}{J}, \quad (10)$$

Next, we calculate absolute differences between the average predicted probabilities (propensity scores) of firms in our sell-off sample (treatment group) and that in the non-sell-off

[22] However, one of our findings contradicts his prediction. We find ex ante profitability positively predicts the probability of a property being disposed. One explanation for this is that our sample period coincides with the capital recycling phase of REITs (2003-2007), through which REITs became net sellers. Although REITs enjoyed high growth and profitability due to property appreciation during this period, the majority of the managers of REITs realized the upcoming threat brought by overvalued properties and actively disposed those particular properties.

firms. We then rank the absolute differences and keep firms in the non-sell-off sample using the nearest neighborhood 1:1 with replacement (Rosenbaum and Rubin, 1983).[23] The match is performed in year *t*-1, prior to the sell-off.

Results based on propensity score matched sample are presented in Table 7. Tests based on firm fundamentals, source of fund and use of fund are presented in Panel A, B and C, respectively. In Panel A, we include the sell-off sample (treatment group, as in Panel B of Table 4) and the control groups constructed using five different propensity score matching methods. We use lagged fundamental variables and sell-off dummy as control variables. We regress three-day cumulative abnormal returns on *Average Distance*, *Sell-off dummy*, and firm's fundamentals.

The coefficient estimates of return predictors (fundamentals, sources of funds, and use of funds) are largely consistent with results reported in Table 4. It is worthwhile noting that the distance measure, *Average Distance*, is the average of all the firm-property distances prior to the asset sell-off. The coefficient estimates for *Average Distance* are negative and statistically significant. *ROA*, which is defined the same as previously, has negative and significant coefficient only when distance-matched model is applied to construct our control sample. This is potentially due to the bad match by simply distance-matched model, which ignores property-level information. *Dassets* has positive and significant coefficient estimates under distance-matched and Probit Model weighted by the number of underlying properties. This is consistent with the financing hypothesis of asset sales to some extent. We use sources and use of funds variables as control

[23] We repeat our tests using (1) nearest neighbor 1:1 with replacement, (2) nearest neighbor 1:1 without replacement, (3) nearest neighbor 1:3 without replacement and (4) a sample including all firms within the region of common support of their propensity scores. Results are qualitatively similar.

variables in Panel B and C, respectively, and find that our results on distance are robust to the inclusion of different control variables.

4.4. What Explains the Negative Relation between Distance and CARs

In the previous sections, we conclude a negative relation between post sell-off stock return and distance measures, suggesting a dominant role of managerial alignment. In this section, we investigate the role of social factors (local union power, population, etc.) and managerial concern for employees as documented in Landier, Nair and Wulf (2009). High local union power (employee friendliness) might lead to distortions in management's incentive to maximize shareholder wealth, due to the managerial concern for nearby employees. Therefore, REITs located in ex ante high union power area are likely to hold properties within local or proximate areas ex post. Population size is important for at least two reasons. First, Landier, Nair and Wulf (2009) find that the managerial alignment effect only exists in small towns, where managers are likely to be more visible. Moreover, larger population size indicates larger pools of local director talent, therefore better monitoring effect (Knyazeva, Knyazeva and Masulis, 2013). Therefore, we evaluate if the effect of proximity on post sell-off stock performance varies by size of community. In other words, we explore if the proximity-firm value linkage is stronger when the manager is more visible in the community.[24]

4.4.1. Labor Union Power and Geographic Concentration

As stated in Landier, Nair, and Wulf (2009), geographic dispersion of firms is related to corporate actions such as employee friendliness and divestitures. Proximity between a firm's headquarters location and its division locations can cause misalignment of interest between

[24] Landier, Nair and Wulf (2009) use the population of the county in which the headquarters is located as a measure of size of community. We use the same definition in our study.

managers and shareholders because of more frequent interactions between managers and nearby employees. This proximity can cause detrimental effect on shareholder wealth. In this section, we tests whether geographical concentration and employee friendliness are related. Similar to Landier et al (2009), we regress *Geographic HHI*, a geographic concentration measure, on *Union Power*, a measure of employee friendliness. *Union Power* is the state-level union coverage (membership) density adopted from Hirsch and Macpherson (2003). *Geographic HHI* is a Herfindahl-Hirschman index that measures the geographic concentration of a firm's property holdings. We calculate this measure based on Hartzell, Sun and Titman (2014) as,

$$\text{Herfindahl Index (HHI)} = \sum_{i=1}^{I} P_I^2, \tag{11}$$

where P_i is the proportion of a REIT's properties located in geographic location (city) *i*. In other words, we examine how property management teams can exert influence on managers ex post via its proximity to the firm's headquarter location. The regression coefficient estimates are reported in Table 8.

We find a positive and significant relation between *Geographic HHI* and *Union Power*, which confirms our prediction that high *Union Power* ex ante lead to misalignment of interest between managers and shareholders, whereby managers are more likely to dispose distant assets relative to nearby ones. The outcome of this misalignment of interest is captured by the higher geographic proximity between a particular firm headquarters location and properties held ex post.

4.4.2. Population and Effect of Distance on CAR

To explore the driving force behind the negative relation between CAR and distance measures, we focus on population around a particular firm's headquarter location. There are at least two reasons for us to examine population. First, as mentioned in Landier, Nair, and Wulf

(2009), managers are more visible in small population communities where social factors are likely to play an important role. If the effect of distance on CAR is purely information driven, one should not expect to find different results. Second, monitoring effect on managers is stronger in large population communities relative to small ones because population are positively correlated with director pool. The monitoring effect from directors strengthens corporate governance and mitigates misalignment of interest between managers and shareholders (Knyazeva, Knyazeva, and Masulis (2013)). Both reasons indicate that the effect of distance on CAR should be more prominent in small population communities relative to large ones.

To empirically test these implications, in Table 9 we divide our matched sample into high and low population sample (Less population=0 and 1, respectively) by comparing the population around a particular firm's headquarter to the sample median population. Population data is obtained from the U.S. Census Bureau in the year 2010 at county level. Consistent with our predictions, the effect of distance on CAR becomes more negative and significant for low population sample. However, we didn't find any evidence for high population sample. This finding further supports our previous results that both informational and social factors are important in affecting post sell-off stock returns via proximity and this effect is more robust among low population firms relative to high population ones.

4.4.3. Market Depth as an Alternative Explanation that Supports Information Asymmetry

Our results are supportive of managerial alignment effect in the literature, especially for firms that are located in less-populated MSAs. However, one could argue that the negative relation between market reaction to asset sales and property-HQ distance might be affected by market depth, which is essentially driven by information asymmetry. For example, even when the sell-off properties are far from the HQ, the information asymmetry could be low in an active market if

there are abundant sales transactions and comparables. If it is the case, finding a negative relation between CAR and distance of disposed properties to their HQs becomes a story about information dissemination and is irrelevant to managerial alignment.

To investigate this issue, we take advantage of our property-level dataset and conduct analysis to see whether the selloff distance is determined by market depth. In Appendix 1, Panel A and B, we use two proxies for market depth (total appraisal value and total number of properties sold). We would expect a positive relation between market depth and average selloff distance within a certain MSA if more observable settled deals available to the market participants mitigate information concern, and market participants are confident with negotiating deals from further distance.

Based upon Appendix 1, Panel A and B, we do not observe a clear pattern that average selloff distance increases with more properties sold, either in terms of total appraisal value or total number of properties. For instance, New York-Newark-Jersey City, NY-NJ-PA MSA ranked highest in terms of total appraisal value ($2,538 million). However, the average selloff distance is only around 848 kilometers (or 527 miles), which is much less than the sample mean of 1,322 kilometers (or 821 miles). Washington-Arlington-Alexandria, DC-VA-MD-WV MSA ranked second (third) in terms of total appraisal value (total number of properties sold), and the average distance for Washington-Arlington-Alexandria, DC-VA-MD-WV MSA is about 557 kilometers (or 346 miles). In Panel C and D, we didn't observe a clear relation between distance and market depth at least for top MSA of properties selloffs in each year.

Together, results in Appendix 1 suggest that there is virtually no relation between selloff distance and market depth. Moreover, most MSAs listed among the top MSAs for property selloffs are among the top 10 MSAs ranked by population. It is likely that REITs headquartered in non-

top 10 MSAs (which are considered as distant investors to the top 10 MSAs) are not able to invest in top 10 MSAs due to market frictions, such as higher cost of obtaining capital, etc. In Appendix 2, we listed all selloffs that are conducted by REITs headquartered in non-top 10 MSAs.

5. Discussions and Conclusion

In this research, we investigate how geographic dispersion of asset dispositions and of REIT Headquarters affects shareholder wealth through the vendor of property sell-offs by the U.S. equity REITs. We find evidence that the geographic distance between a firm's headquarter location and property (properties) been disposed negatively affects sell-off stock performance of the firm's shareholders. Our major findings are threefold.

First, using different distance measures and different sets of sell-off controls, we find distance measures have negative and significant effect on post sell-off stock performance.

Second, we conduct propensity score matching based on a sequential choice process to mitigate potential self-selection and endogeneity concerns. Specifically, we estimate the firm-level sell-off likelihood in the first stage and the property-level likelihood of being sold, given a sell-off decision is made, in the second stage. The matched sample is constructed based on propensity scores by multiplying the predicted probability in the first stage and the conditional probability in the second stage. Results based on the two-step sequential choice matched sample using different model specifications and models suggest that that the effect of distance on CAR is still negative and significant and managerial alignment effect plays a dominant effect.

Finally, we analyze the potential driving force(s) behind the managerial alignment effect by examining the role of distance on CAR using size of local community. When we divide firms into large and small population subsamples, we find that the effect of distance on CAR only exists

among firms headquartered in less populated areas. Therefore, we identify that informational and social factors together determine post sell-off shareholder wealth through geographic proximity only in less populated areas. Moreover, we find that high local union power ex ante leads to geographic concentration of property holdings by REITs ex post. Overall, our findings are in favor of the managerial alignment explanation.

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Table 1: Property Sell-offs by Equity REITs, 2003-2013

This table describes a sample of property sell-offs by U.S. equity REITs from 2003 to 2013 with sale price exceeding USD 20 million.

Year	Total Number of Transactions	Total Value (Million USD)	Average Deal Size (Million USD)
2003	16	1676	105
2004	18	1839	102
2005	17	2608	163
2006	24	7556	315
2007	19	4391	231
2008	3	293	98
2009	8	514	64
2010	4	2578	645
2011	15	2892	193
2012	17	3582	211
2013	20	4914	246
Total	161	32843	204

Table 2: Property Sell-offs by REIT Type and Stated Use of Proceeds, 2003-2013

This table presents property sell-offs by REIT property type and by stated use of proceeds based on a sample of property sell-offs by U.S. equity REITs from 2003 to 2013 with sale price exceeding USD 20 million. Sell-offs are divided into different groups based on property type, including multi-family, office and/or industrial, diversified, and shopping center or regional mall. Sell-offs are divided into different groups based on stated use of proceeds from property sales. Information on selling REITs' property type is from SNL Financial and information on the stated use of proceeds is obtained from press releases.

Category	N	%
Sell-offs by REIT Property Type		
Multi-Family	20	12.4
Office and/or Industrial	66	41
Diversified	16	9.9
Shopping Center or Regional Mall	24	14.9
Other	35	21.7
Total	161	100
Sell-offs by Stated Use of Proceeds		
Fund acquisitions	11	6.8
Mixed use	15	9.3
Reduce debt (General)	30	18.6
Reduce long-term debt	2	1.2
Reduce short-term debt	8	5.0
Repurchase shares	3	1.9
Distribute dividends	4	2.5
Other	15	9.3
Not stated	73	45.3
Total	161	100

Table 3: Market Reactions to Equity REIT Property Sell-offs

This table presents summary statistics of cumulative abnormal returns (CARs). Panel A presents CARs based on six event windows, (-1,0), (0,0), (0,1), (-1,1), (-5,5), (-5,-1), which represent respectively the one-day before, one-day, one-day ahead, three-day, eleven-day, and six-day windows. In Panel B, we divide 3-day CARs, our main variable of interest, into (1) distance below median and (2) distance above median subsamples based on the comparison between average firm-property distance of a particular firm and the sample median of firm-property distances. In Panel C, we divide 3-day CARs, number of properties sold (held), deal size, and property appraisal value into 4 quartiles based on firm-property distances. In Panel D, we sort 3-day CARs into different subgroups based upon firm-property distance and population. In Panel E, we sort 3-day CARs into different subgroups based upon firm-property distance and REIT headquarter locations. We follow Loughran and Schultz (2005) and define an REIT as in "top-ten MSA" if its headquarters is in one of the ten largest metropolitan areas of the U.S. according to the 2010 Census. We define the rest of the REITs in our sample as in "non-top-ten MSAs". In Panel F, we sort 3-day CARs into different subgroups based upon REIT headquarter locations and pre- & post-recession periods (the fall of Lehman Brothers on May 28, 2009 is used as the cutting point). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% level of Portfolio Time-Series (CDA) *t* statistics, respectively.

Panel A: Cumulative Abnormal Returns (CARs)

	N	CAR	% Negative	*t*-stat	*z*-stat
CAR (-1, 0)	161	0.74***	40.99	4.06	1.99
CAR (0)	161	0.71***	41.61	5.52	2.21
CAR (0,1)	161	1.15***	40.99	6.29	2.20
CAR (-1, +1)	161	1.18***	43.48	5.26	2.14
CAR (-5, +5)	161	1.49***	42.86	3.49	1.08
CAR (-5, -1)	161	0.44	44.10	1.52	-0.48

Panel B: CAR (-1, 1) by Nearby Sell-offs versus Distant Sell-offs

Distance to HQs	Mean	Std Dev	Q1	Median	Q3
Below Median	2.047	5.926	-0.72	1.45	3.51
Above Median	0.465	3.447	-1.29	-0.04	2.36

Panel C: CAR (-1,1) by Distance Quartile

Distance to HQs	# sell-offs	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat	# Ppties Sold	Deal Size (USD mil)	# Ppties Held	Appraisal Value (USD mil)
Q1 (0-25 percentile)	39	132.15	2.19*	1.804	139	6058	8871	393039.8
Q2 (25-50 percentile)	38	917.24	1.93**	2.673	210	5318	12396	234084.6
Q3 (50-75 percentile)	39	1631.90	0.93	0.616	880	10690	17822	335486.1
Q4 (75-100 percentile)	38	2629.15	0.12	1.076	147	6485	13617	316032.4

Panel D: CAR (-1,1), sort by Distance and HQ County Population (Small and Large)

	Small Population			Large Population		
Distance Quartile	Avg. distance(in km)	CAR (-1,1)	CDA *t*-stat	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat
Q1 (0-25 percentile)	183.69	2.73***	5.424	83.18	1.42	0.489
Q2 (25-50 percentile)	890.10	2.10**	2.378	944.37	1.43	1.324
Q3 (50-75 percentile)	1599.21	1.59	0.413	1662.95	1.00	0.414
Q4 (75-100 percentile)	2682.59	-0.50	-0.129	2575.71	0.61	1.434

Panel E: CAR (-1,1), sort by Distance and HQ MSA Population (Non-top-ten MSAs and Top-ten MSAs)

	Non-top-ten MSAs			Top-ten MSAs		
Distance Quartile	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat
Q1 (0-25 percentile)	348.47	4.35**	2.60	88.44	2.04***	3.381
Q2 (25-50 percentile)	1197.10	3.26***	3.24	767.37	0.21	0.819
Q3 (50-75 percentile)	1642.48	2.10***	10.12	1656.21	0.93	1.091
Q4 (75-100 percentile)	2368.71	0.00	-1.56	2747.05	-0.11*	-2.109

Panel F: CAR (-1,1), sort by sub-periods and HQ MSA Population (Non-top-ten MSAs and Top-ten MSAs)

	Non-top-ten MSAs		Top-ten MSAs	
Sub-period	Avg. distance (in km)	CAR (-1,1)	Average distance (in km)	CAR (-1,1)
Pre-Recession	1522.47	2.04	1472.86	-0.17
Post-Recession	1132.57	1.17	1077.26	0.66

Table 4: Determinants of CARs

This table includes summary statistics and regression results of determinants of CARs. Panel A presents summary statistics on distance proxies, firm-level characteristic and deal-level characteristics. Panel B presents regression results based on firm fundamentals. Panel C (D) presents regression results based on source of fund (use of fund). Panel E presents regression results based on deal-level determinants. The dependent variable is three-day window cumulative abnormal returns, CAR (-1,+1). *Average distance* (*Median distance*) is the average (median) distances of all the properties disposed by a particular firm (in 1,000 kilometers). We scaled the distance measures in order to better interpreting its economic meaning. Since our historical property portfolios are constructed such that they were rebalanced annually, we compute the *Average (Median) Holding distances* at firm-year level instead of deal level for each seller (in 1,000 kilometers). *Number of Properties Sold (Held)* is defined as the total number of properties sold (held) in an average firm-year. *Firm Size* (*lnrsize*) is the natural logarithm of the quarterly total assets of the firm in millions of dollars (ATQ). *ROA* (Return on assets) is expressed as the quarterly net income (NIQ) over total assets (ATQ). *Debt Ratio* (dassets) equals to the sum of total long-term debt (DLTTQ) and debt in current liabilities (DLCQ) divided by total assets (ATQ). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IBQ) divided by the sum of preferred dividends (DVPQ) and interest and related expenses (XINTQ). *Tobin's Q* equals total book assets (ATQ) plus the market cap (PRCCQ*CSHOQ) minus common equity (CEQQ), all divided by total book assets (ATQ). *Gain* is the reported quarterly gain or loss generated from the sale of property (SRETQ). *Debt Issues* is the total new long-term debt issued (DLTISY). *Equity Issues* is the total proceeds from the sale of common and preferred stock (SSTKY). *Delta Debt* is the difference in debt reduction (DLTRY) from the previous fiscal quarter (t-2) divided by total long-term debt (DLTTQ), in the last fiscal quarter prior to the sell-off announcement (t-1). *Delta preferred* equals the difference in preferred dividends paid (DVPQ) from the previous fiscal quarter (t-2) divided by total liabilities (LTQ). *Delta common equity* equals the difference in cash dividends paid (DVY) from previous fiscal quarter (t-2), divided by the market cap (PRCCQ*CSHOQ). *Delta investment* equals the difference in increased investments (IVLTQ). *Deal Size* is the transaction price of the selloff divided by the total book assets (ATQ). *Geographic Focus* is an indicator variable equals to 1 if the stated goal of a particular asset sale is geographic focus and 0 otherwise. *URSTD* is an indicator variable equals to 1 if proceeds from sale are announced to be used to reduce short-term debt. *URLTD* is an indicator variable equals to 1 if proceeds from sale are announced to be used to reduce long-term debt. *Pay Dividend* is an indicator variable equals to 1 if proceeds from sale are announced to be distributed as dividends. *EXCH* is an indicator variable equals to 1 if 1031 tax-free exchange is used. *DC* is an indicator variable equals to 1 if a particular firm's interest coverage ratio is below the sample median at the end of the last fiscal quarter prior to the announcement. *Recession* is an indicator variable equals to 1 if announcement date is in the recession period defined by NBER US Business Cycle Expansions and Contractions (http://www.nber.org/cycles.html). All quarterly variables are lagged. Robust standard errors are used and *t*-statistics are shown in parentheses. *, ** and *** stand for 10%, 5% and 1% significance level, respectively.

Panel A: Summary Statistics

	N	Mean	Median	Std. Dev.
Distance Proxies				
Average Distance (dmean, in 1,000 km)	154	1.322	1.296	0.961
Median Distance (dmedian, in 1,000 km)	154	1.293	1.199	1.001
Nearby	154	0.025	0.500	0.160
Distance Proxies and Number of Properties (Firm-Year)				
Average Holding Distance (in 1,000 km)	100	0.945	0.684	0.835
Median Holding Distance (in 1,000 km)	100	0.772	0.497	0.845
Number of Properties Sold	100	156	94	159
Number of Properties Held	100	12	3	34
Firm-level Characteristics				
Fundamentals				
Cash	154	0.032	0.016	0.047
Firm Size (lnrsize)	154	7.850	8.105	1.713
ROA	154	0.007	0.004	0.021
Debt Ratio (dassets)	154	0.472	0.542	0.215
Coverage	154	0.671	0.284	2.336
Tobin's Q	154	1.234	1.236	0.338
DC	154	0.610	1	0.489
Source of Fund				
Gain	154	5.145	0	26.18
Debt Issues	154	700.2	303.2	1598.3
Equity Issues	154	133.5	12.28	292.3
Use of Fund				
Delta Debt	154	0.0362	0.0331	0.2245
Delta Preferred	154	0.0002	0	0.0016
Delta Common Equity	154	0.0031	0.0107	0.0328
Delta Investment	154	0.0047	0.0121	0.0948
Deal-level Characteristics				
Geographic Focus	154	0.214	0	0.412
URSTD	154	0.013	0	0.114
URLTD	154	0.045	0	0.209
EXCH	154	0.065	0	0.247
Pay Dividend	154	0.026	0	0.160
Recession	154	0.110	0	0.314

Panel B: Firm Fundamentals

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-1.216**		
	(-2.54)		
Median distance		-1.142***	
		(-2.62)	
Nearby			1.944**
			(2.09)
Cash	-10.855	-10.816	-10.074
	(-1.41)	(-1.40)	(-1.25)
Firm Size (lnrsize)	-0.462	-0.458	-0.444
	(-1.31)	(-1.29)	(-1.23)
ROA	14.436	15.960	21.082
	(0.70)	(0.78)	(0.96)
Debt Ratio (dassets)	5.708*	5.673*	5.193*
	(1.89)	(1.90)	(1.75)
Coverage	-0.078	-0.086	-0.138
	(-0.47)	(-0.52)	(-0.81)
Tobin's Q	0.155	0.156	0.155
	(0.13)	(0.13)	(0.12)
DC	0.075	0.052	-0.025
	(0.07)	(0.05)	(-0.02)
Intercept	3.907**	3.771**	1.464
	(2.14)	(2.11)	(0.90)
R Squared	10%	10%	9%
Number of Obs	154	154	154

Panel C: Source of Fund

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.941**		
	(-2.18)		
Median distance		-0.893**	
		(-2.24)	
Nearby			1.644**
			(1.98)
Gain	0.002	0.002	0.002
	(0.38)	(0.35)	(0.30)
Debt Issues	-0.00007	-0.00007	-0.00011
	(-0.73)	(-0.72)	(-1.27)
Equity Issues	-0.001	-0.001	-0.001
	(-1.35)	(-1.40)	(-1.36)
Intercept	2.731***	2.649***	0.699
	(3.08)	(3.17)	(1.49)
R Squared	4%	3%	3%
Number of Obs	154	154	154

Panel D: Use of Fund

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.984**		
	(-2.48)		
Median distance		-0.919**	
		(-2.53)	
Nearby			1.629**
			(2.01)
Delta Debt	0.412	0.442	0.530
	(0.25)	(0.27)	(0.32)
Delta Preferred	-242.7	-238.9	-236.5*
	(-1.49)	(-1.47)	(1.74)
Delta Common	17.074	16.555	14.578
	(0.52)	(0.50)	(0.45)
Delta Investment	-3.393	-3.451	-3.255
	(-0.93)	(-0.95)	(-0.92)
Intercept	2.588***	2.476***	0.475
	(3.15)	(3.21)	(1.10)
R Squared	5%	4%	4%
Number of Obs	154	154	154

Panel E: Deal-level Determinants

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.985**		
	(-2.44)		
Median distance		-0.924**	
		(-2.46)	
Nearby			1.819**
			(2.06)
Deal Size	0.000	0.000	0.000*
	(1.53)	(1.52)	(1.71)
Geographic Focus	-0.883	-0.900	-1.104
	(-1.13)	(-1.15)	(-1.32)
URSTD	2.366*	2.488*	2.973**
	(1.97)	(1.96)	(2.35)
URLTD	0.147	0.194	-0.132
	(0.05)	(0.07)	(-0.05)
EXCH	0.466	0.526	0.549
	(0.40)	(0.45)	(0.49)
Recession	4.154**	4.077**	4.134**
	(2.13)	(2.09)	(2.11)
Pay Dividend	8.554*	8.758*	8.546*
	(1.76)	(1.80)	(1.73)
Cash	-17.104**	-17.248**	-17.492**
	(-2.42)	(-2.47)	(-2.42)
Firm Size (lnrsize)	-0.615	-0.596	-0.500
	(-1.53)	(-1.48)	(-1.25)
ROA	36.590	37.800	40.502
	(1.44)	(1.50)	(1.52)
Debt Ratio (dassets)	3.134	3.131	3.045
	(1.53)	(1.54)	(1.44)
Coverage	-0.140	-0.144	-0.159
	(-0.68)	(-0.70)	(-0.74)
Tobin's Q	-0.835	-0.833	-0.897
	(-0.55)	(-0.55)	(-0.60)
DC	1.272*	1.251*	1.109
	(1.71)	(1.69)	(1.49)
Intercept	5.989	5.740	3.032
	(1.40)	(1.34)	(0.67)
R Squared	30%	29%	29%
Number of Obs	154	154	154

Table 5: Firm-level and Property-level Comparisons between Sell-off Firms and Non-sell-off Firms

This table compares firm-level and property-level descriptive statistics of a sample of REITs with asset sales from 2003 to 2013 and a sample of REITs without asset sale (control sample) during the same period. *Firm Size* is the annual reported book value of total assets (AT) in millions of USD. *ROA* (Return on assets) is expressed as the annual net income (NI) over total assets (AT). *FFO/Total Assets* equals to funds from operations (FFO) divided by total assets (AT). *Debt Ratio* (*dassets*) equals to the sum of total long-term debt (DLTT) and debt in current liabilities (DLC) divided by total assets (AT). *Cash* is expressed as cash and short-term investments (CHE) divided by total assets (AT). *Sales Growth* is the most recent annual percentage change in total revenue (REVT). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IB) divided by the sum of preferred dividends (DVP) and interest and related expenses (XINT). *Momentum* is the aggregated stock return from month t-12 to t-2. *DC* is an indicator variable which equals 1 when a firm's coverage ratio is below the sample median in the last fiscal year prior to the announcement, 0 otherwise. *Nearby* is a dummy variable that takes one if the distance of a deal is less than the sample median and 0 otherwise. *Diverse* is a dummy variable that equals 1 if the property type of the property been disposed is different from the property type of a particular firm identified by CRSP permanent security identification number (PERMNO) and 0 otherwise. *Hold Time* describes how long has (had) a property been held by a particular company. Health care, hotel, industrial, office, retail, multifamily, and other are indicator variables of major property types. "N.A." means that the median of a variable is not shown if it's a dummy. The last column reports t-test statistics and significance. *, ** and *** stand for 10%, 5% and 1% significance level, respectively.

	(1) Non-sell-off				(2) Sell-offs				(1)-(2)	
	N	Mean	Median	Std Dev	N	Mean	Median	Std Dev	*t*-stat	
Firm-level	(firm-year)				(firm-year)					
Firm Size	3,697	1803.358	666.803	3274.583	100	4919.646	2803.544	5862.672	-9.13	***
ROA	3,697	0.026	0.027	0.128	100	0.028	0.023	0.051	-0.14	
FFO/Total assets	3,697	0.025	0	0.090	100	0.039	0.044	0.031	-1.52	*
Debt Ratio	3,697	0.455	0.478	0.223	100	0.522	0.542	0.142	-3.04	***
Tobin's Q	3,697	1.252	1.184	0.475	100	1.272	1.227	0.281	-0.42	
Cash	3,697	0.045	0.017	0.092	100	0.028	0.017	0.039	1.80	**
Sales Growth	3,697	46.615	7.676	1057.434	100	6.025	2.735	24.893	0.38	
Coverage	3,697	6.614	0.606	93.387	100	0.580	0.429	1.112	0.65	
Momentum	3,697	0.14	0.136	0.880	100	0.124	0.157	0.309	0.19	
DC	3,697	0.492	0	0.500	100	0.5	1	0.503	-0.16	
Property-level	(property-year)				(property-year)					
Hold Time	332,853	11.880	10	7.298	1,157	6.790	6	4.572	23.71	***
Nearby	332,853	0.556	1	0.497	1,157	0.476	0	0.499	5.44	***
Diverse	332,853	0.285	0	0.451	1,157	0.656	1	0.475	-27.93	***
Health Care	332,853	0.085	0	0.279	1,157	0.008	0	0.088	9.42	***
Hotel	332,853	0.037	0	0.189	1,157	0.041	0	0.199	-0.75	
Industrial	332,853	0.107	0	0.309	1,157	0.273	0	0.446	-18.18	***
Office	332,853	0.130	0	0.336	1,157	0.186	0	0.389	-5.63	***
Retail	332,853	0.281	0	0.449	1,157	0.123	0	0.328	11.95	***
Multifamily	332,853	0.137	0	0.343	1,157	0.091	0	0.287	4.54	***
Other	332,853	0.156	0	0.363	1,157	0.249	0	0.433	-8.67	***

Table 6: Two-stage sequential model of property sell-offs

This table reports results of coefficient estimates used to calculate predicted probabilities of asset sell-offs at firm-level in Panel A and (conditional) predicted probabilities of asset sell-offs at property-level in Panel B. In Panel A of firm-level, the dependent variable is an indicator variable equals to one if a firm sells any properties in a specific year, and zero otherwise. Model (1) reports probit results based on a sample of firm-year with sell-offs and a sample of firm-year without sell-off matched with average firm-holding property distance. Model (2) ((3)) report coefficient estimates based on logit (probit) model without weights. Model (4) ((5)) report coefficient estimates based on logit (probit) model with weights of the inverse of the number of properties held by firm *i* in year *t*. In Panel B of property-level, the dependent variable is an indicator variable equals to 1 if a property is disposed in a specific year, given the holding company is a seller in that year; and zero otherwise. The estimation of firm-level propensity is indicated by P(seller = 1), and the estimation of property-level propensity is indicated by P(property sold = 1 | seller = 1). Model (1) ((2)) report results based on logit (probit) model. Coefficient estimates and *t* statistics (in parentheses) are reported. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A: The probability of property sell-offs at firm-level

Dependent variable:	(1) Probit, distance	(2) Logit	(3) Logit, weighted	(4) Probit	(5) Probit, weighted
Firm Size	0.00006***	0.0001***	0.0001***	0.00006***	0.00006***
	(7.58)	(6.17)	(8.07)	(6.00)	(9.13)
ROA	0.343	5.436*	8.766***	2.550*	4.689***
	(1.57)	(1.76)	(3.91)	(1.68)	(4.39)
FFO/Total Assets	0.757***	2.076	5.251***	1.048	3.071***
	(2.61)	(0.59)	(3.33)	(0.64)	(3.31)
Debt Ratio	0.545**	0.706	0.777***	0.329	0.644***
	(2.38)	(1.00)	(2.64)	(1.02)	(3.81)
Tobin's Q	0.023	-0.190	0.197	-0.071	0.075
	(0.26)	(-0.51)	(1.17)	(-0.40)	(0.74)
Cash	-1.756	-0.467	-10.659***	-0.161	-5.525***
	(-1.48)	(-0.21)	(-6.55)	(-0.16)	(-6.31)
Sales Growth	-0.00007	-0.00008	-0.00017	-0.00004	-0.0001
	(-1.63)	(-0.48)	(-1.35)	(-0.43)	(1.49)
Coverage	-0.00027	-0.097*	-0.207***	-0.051*	-0.054***
	(-0.93)	(-1.75)	(-3.21)	(-1.67)	(-2.66)
Momentum	-0.003	-0.239	0.030	-0.100	0.016
	(-0.11)	(-0.67)	(0.75)	(-0.60)	(0.66)
DC	-0.015	0.106	0.096	0.064	0.124**
	(-0.15)	(0.42)	(0.89)	(0.54)	(1.98)
Intercept	-2.357***	-3.596***	-1.174***	-1.999***	-0.853***
	(-16.13)	(-6.97)	(-4.79)	(-8.16)	(6.02)
Log likelihood	-432.61	-376.05	-1883.93	-374.44	-1892.25
Pseudo R-squared	6.43%	5.24%	8.59%	5.64%	8.19%
Number of Obs	3,797	2,055	3,120	2,055	3,120

Panel B: The conditional probability of property sell-offs at property-level

Dependent variable: P(property sold = 1 | seller =1)	(1) Logit	(2) Probit
Nearby	-0.408***	-0.212***
	(-6.26)	(-6.55)
Diverse	1.010***	0.422***
	(13.47)	(11.38)
Health Care	-1.027***	-0.443***
	(-2.67)	(-2.84)
Leisure	0.653***	0.302***
	(2.77)	(2.63)
Industrial	1.062***	0.524***
	(5.64)	(5.69)
Office	0.139	0.054
	(0.70)	(0.57)
Retail	0.068	0.045
	(0.34)	(0.47)
Multifamilty	0.356*	0.166*
	(1.72)	(1.66)
Other	2.621***	1.378***
	(13.32)	(13.85)
Intercept	-3.453***	-1.820***
	(-17.68)	(-19.24)
Log likelihood	-3555.84	-3584.75
Pseudo R-squared	14.54%	13.85%
Number of Obs	16,102	16,102

Table 7: OLS Regression of CAR on distance and fundamentals using matched samples

This table presents the regression results of determinants of CARs, using sell-off and matched samples from Model (1) – (5) in Table 6. Panel A presents regression results based on firm fundamentals. Panel B (C) presents regression results based on source of fund (use of fund). In Model (1) and Model (2) of Panel A, a sell-off firm is first matched with 10 non-sell-off firms using the nearest propensity scores, which are calculated as the predicted probabilities at firm-level based on Model (1) Panel A in Table 6. Next, the percentile of the (average) distance between the disposed property (properties) and headquarter of the sell-off firm is matched with the percentiles of the average distance between the holding properties and headquarter of the non-sell-off firms. The non-sell-off firm with the smallest absolute difference of percentile is selected. In Model (3) and Model (4) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (2) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (1) Panel B in Table 6. In Model (5) and (6) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (4) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (2) Panel B in Table 6. In Model (7) and (8) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (3) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (1) Panel B in Table 6. In Model (9) and (10) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (5) Panel A in Table 7 and the conditional predicted probability at property-level based on Model (2) Panel B in Table 6. In Model (1) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (1) and (2) Panel A. In Model (2) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (3) and (4) Panel A. In Model (3) of Panel B and Panel C, a sample of sell-off firms is matched with is matched with the same control sample in Model (5) and (6) Panel A. In Model (4) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (7) and (8) Panel A. In Model (5) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (9) and (10) Panel A. The matching is conducted by using the nearest neighborhood 1:1 except for Model (1) and (2) of Panel A and Model (1) of Panel B and C. The dependent variable is cumulative abnormal return (CAR) over three days around sell-off announcements, CAR (-1,1). *Sell-off* is a dummy equals to 1 if a particular firm disposes properties on an even date, zero otherwise. *Average distance* is the test variable, which is defined as the arithmetic average firm-property distances of all the properties disposed by a selling firm. Other variables are defined in Table 4. Robust standard errors are used and *t*-statistics are shown in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels, respectively.

Panel A: Matched Sample – Fundamentals

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Matched with	Probit, distance	Probit, distance	predicted prob. based on logit	predicted prob. based on logit	predicted prob. based on probit	predicted prob. based on probit	predicted prob. based on logit, weighted	predicted prob. based on logit, weighted	predicted prob. based on probit, weighted	predicted prob. based on logit, weighted
Sell-off	1.201**	1.452**	1.044*	1.046	1.059*	1.118	0.974*	1.260*	1.002*	0.869
	(2.28)	(2.25)	(1.89)	(1.51)	(1.93)	(1.65)	(1.77)	(1.89)	(1.88)	(1.38)
Average distance	-0.493*	-0.627**	-0.448*	-0.423*	-0.400*	-0.416*	-0.486**	-0.457**	-0.551**	-0.473**
	(-1.87)	(-2.45)	(-1.88)	(-1.87)	(-1.70)	(-1.76)	(-2.06)	(-2.05)	(-2.35)	(-2.17)
Cash		-9.304		5.840		-1.526		1.664		-2.373
		(-1.18)		(0.94)		(-0.70)		-0.31		(-0.43)
Firm Size		-0.276		-0.129		-0.392		-0.398		-0.380
		(-0.98)		(-0.44)		(-1.20)		(-1.40)		(-1.37)
ROA		-59.40*		-18.22		-0.479		-20.22		2.768
		(-1.71)		(-0.78)		(-0.02)		(-1.15)		(0.19)
Debt Ratio		4.951*		2.914		2.560		3.272		4.367**
		-1.93		(1.42)		(1.09)		(1.44)		(2.14)
Coverage		0.583		0.091		-0.131		-0.021		-0.102
		(1.45)		(0.36)		(-0.42)		(-0.25)		(-1.39)
Tobin's Q		0.042		-0.819		-1.008		-0.831		-0.532
		(0.05)		(-0.95)		(-0.89)		(-0.71)		(-0.57)
DC		-0.031		-0.192		-0.259		-0.953		-0.009
		(-0.03)		(-0.22)		(-0.25)		(-1.05)		(-0.01)
Intercept	0.568	0.576	0.678	1.343	0.615	4.077	0.787*	3.845	0.825*	2.588
	(1.53)	(0.28)	(1.58)	(0.54)	(1.37)	(1.38)	(1.74)	(1.60)	(1.89)	(1.15)
R squared	4%	12%	3%	6%	2%	6%	3%	7%	3%	10%
Number of Obs	247	247	252	252	252	252	252	252	252	252

Panel B: Matched Sample – Source of Fund

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)
	Probit, distance	Logit	Probit	Logit weighted	Probit weighted
Sell-off	1.393**	1.153*	0.707	1.148*	1.050*
	(2.50)	(1.93)	(1.19)	(1.92)	(1.85)
Average distance	-0.495*	-0.425*	-0.407*	-0.446*	-0.532**
	(-1.86)	(-1.78)	(-1.73)	(-1.89)	(-2.28)
Gain	-0.015	-0.012	-0.014	-0.014	-0.006
	(-1.50)	(-1.43)	(-1.49)	(-1.48)	(-0.79)
Debt Issues	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.57)	(-0.22)	(-0.09)	(-0.73)	(0.09)
Equity Issues	-0.002**	-0.001	-0.002	-0.002**	-0.002
	(-2.16)	(-0.82)	(-1.54)	(-2.29)	(-1.51)
Intercept	0.742*	0.728*	1.231***	0.952**	0.956**
	(1.86)	(1.65)	(2.90)	(2.02)	(2.09)
R squared	5%	3%	2%	4%	4%
Number of Obs	247	252	252	252	252

Panel C: Matched Sample – Use of Fund

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)
	Probit, distance	Logit	Probit	Logit weighted	Probit weighted
Sell-off	1.221**	1.118*	0.936*	0.969*	0.962*
	(2.28)	(1.96)	(1.81)	(1.74)	(1.80)
Average distance	-0.538**	-0.492**	-0.533**	-0.473*	-0.582**
	(-1.97)	(-2.02)	(-2.32)	(-1.93)	(-2.44)
Delta Debt	-0.693	-0.438	-2.015*	-1.571	-0.578
	(-0.65)	(-0.28)	(1.93)	(-1.40)	(-0.66)
Delta Preferred	-102.86*	-128.3	-95.63	-87.45	19.95
	(-1.92)	(-1.39)	(-1.05)	(-0.92)	(0.23)
Delta Common Equity	23.853	27.948	32.81***	20.02	5.521
	(0.77)	(0.92)	(2.70)	(1.29)	(0.75)
delta investment	-3.558	-3.345	-0.462*	-0.823	-3.252**
	(-0.93)	(-1.21)	(-1.90)	(-0.73)	(-2.40)
Intercept	0.566	0.602	0.839**	0.785*	0.921**
	(1.41)	(1.36)	(2.15)	(1.68)	(2.10)
R squared	6%	6%	13%	6%	5%
Number of Obs	247	252	252	252	252

Table 8: Regression of local (state) union power on property holding's geographic concentration index

This table presents the regressions for the local (state) union power factors, using sell-off and matched samples from Model (2) – (5) in Table 7. The dependent variable is *Geographic HHI*, which is the Herfindahl-Hirschman Index that measures the geographic concentration of a particular firm at city level (Hartzell, Sun, and Titman 2014). Local union power is measured by state union coverage density or union membership density. Data on union power measures are obtained from Hirsch and Macpherson (2003). *Sell-off* is defined in Table 8. Column 1 to 4 report OLS regression results based on matched samples from different PSM analysis. Robust standard errors are used and *t*-statistics are shown in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A

Geographic HHI (City)	(1)		(2)		(3)		(4)	
Union Coverage Density	0.007	***	0.006	***	0.008	***	0.008	***
	(3.32)		(2.63)		(3.29)		(3.40)	
sell-off	0.025		0.025		0.053	***	0.069	***
	(1.19)		(1.08)		(2.60)		(3.04)	
Intercept	-0.023		-0.003		-0.050		-0.073	*
	(-0.71)		(-0.09)		(-1.47)		(-1.96)	
Model	Logit		Probit		Logit - Weighted		Probit - Weighted	
R squared	8%		5%		13%		14%	
Number of obs	281		264		226		231	

Panel B

Geographic HHI (City)	(1)		(2)		(3)		(4)	
Union Membership Density	0.007	***	0.006	***	0.008	***	0.009	***
	(3.31)		(2.62)		(3.26)		(3.40)	
sell-off	0.024		0.025		0.053	***	0.069	***
	(1.17)		(1.08)		(2.60)		(3.04)	
Intercept	-0.014		0.004		-0.041		-0.063	*
	(-0.46)		(0.10)		(-1.28)		(-1.83)	
Model	Logit		Probit		Logit - Weighted		Probit - Weighted	
R squared	8%		5%		13%		14%	
Number of obs	281		264		226		231	

Table 9: OLS Regression of low and high populated counties

This table presents the OLS regressions for CAR in different subsamples. Firms are separated into different subsamples based upon the population around their headquarters. The dependent variable is cumulative abnormal return (CAR) over three days around sell-off announcements, CAR (-1,1). Sell-off and Average distance are defined as Table 7. Panel A to D presents results with respect to average distance, our main test variable, using sell-off and matched samples from sequential logit, sequential Probit, sequential logit with weights, and sequential Probit with weights, respectively. In each panel, we report regression results for the full sample, for firms headquartered in less-populated counties, and for firms headquartered in highly-populated counties separately in Column 1 to 3. Less-populated counties are defined as counties with population below the sample median. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A: matched sample from logit

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.044*	0.637	1.494*
	(1.89)	(0.76)	(1.85)
Average distance	-0.448*	-0.296	-0.847**
	(-1.88)	(-0.91)	(-2.19)
Intercept	0.678	0.324	1.394**
	(1.58)	(0.60)	(2.06)
R squared	3%	1%	7%
Number of Obs	252	111	123

Panel C: matched sample from logit with weights

Variables	All	Less Populated=0	Less Populated=1
Sell off	0.974*	1.361	0.995*
	(1.77)	(1.50)	(1.25)
Average distance	-0.486**	-0.034	-0.951**
	(-2.06)	(-0.09)	(-2.53)
Intercept	0.787*	-0.633	2.008***
	(1.74)	(-0.85)	(3.07)
R squared	3%	2%	6%
Number of Obs	252	113	125

Panel B: matched sample from Probit

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.059*	0.386	1.737**
	(1.93)	(0.41)	(2.25)
Average distance	-0.400*	-0.148	-0.798**
	(-1.70)	(-0.37)	(-2.30)
Intercept	0.615	-0.443	1.096*
	(1.37)	(-0.53)	(1.84)
R squared	2%	1%	8%
Number of Obs	252	114	121

Panel D: matched sample from Probit with weights

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.002*	0.183	1.906**
	(1.88)	(0.20)	(2.54)
Average distance	-0.551**	-0.251	-0.942***
	(-2.35)	(-0.68)	(-2.65)
Intercept	0.825*	0.738	1.087*
	(1.89)	(0.92)	(1.95)
R squared	3%	1%	11%
Number of Obs	252	116	124

Appendix 1: Top MSA of Property Dispositions

This table presents top MSAs of property holdings and dispositions ranked by total appraisal value (of all properties disposed within a particular MSA) and total number of properties sold within a particular MSA from 2003 to 2013. Average REIT-properties sold distances (in kilometers) are included for top MSAs. In Panel A and B, top 10 MSAs with the highest number of total appraisal value or highest total number of properties sold are listed, respectively. In Panel C and D, for each year during 2003 – 2013, top 1 MSA with the highest number of total appraisal value or highest total number of properties sold are listed, respectively. Panel E includes all selloffs that occurred in small towns (non-top 10 MSAs). MSAs are ranked by population according to 2010 Census.

Panel A: Top 10 MSAs by Total Appraisal Value of Property Dispositions

MSA Name	Avg. Distance (in kilometers)	Property Value (millions of USD)	# Properties Sold
New York-Newark-Jersey City, NY-NJ-PA	847.70	2538.20	37
Washington-Arlington-Alexandria, DC-VA-MD-WV	557.59	1631.85	66
Atlanta-Sandy Springs-Roswell, GA	1296.57	1437.78	134
Dallas-Fort Worth-Arlington, TX	1157.62	729.77	94
San Francisco-Oakland-Hayward, CA	1259.65	626.69	8
Houston-The Woodlands-Sugar Land, TX	1345.41	521.09	46
Baltimore-Columbia-Towson, MD	555.48	508.95	55
Jacksonville, FL	2968.49	403.54	46
Los Angeles-Long Beach-Anaheim, CA	1317.92	390.55	13
Nashville-Davidson-Murfreesboro-Franklin, TN	2581.17	388.48	41

Panel B: Top 10 MSAs by Total Number of Properties Disposed

MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (millions of USD)
Atlanta-Sandy Springs-Roswell, GA	1296.57	132	1437.78
Dallas-Fort Worth-Arlington, TX	1157.62	91	729.77
Washington-Arlington-Alexandria, DC-VA-MD-WV	557.59	66	1631.85
Baltimore-Columbia-Towson, MD	555.48	55	508.95
Houston-The Woodlands-Sugar Land, TX	2968.49	46	403.54
Jacksonville, FL	1345.41	46	521.09
Minneapolis-St. Paul-Bloomington, MN-WI	1370.99	45	252.23
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	491.41	44	360.82
Nashville-Davidson-Murfreesboro-Franklin, TN	2581.17	41	388.48

Chicago-Naperville-Elgin, IL-IN-WI	471.58	38	278.10

Panel C: Top MSA by Total Appraisal Value of Property Dispositions

Year	CBSA Code	MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (USD million)
2003	31080	Los Angeles-Long Beach-Anaheim, CA	1386.26	4	303.02
2004	41860	San Francisco-Oakland-Hayward, CA	2460.92	2	202.86
2005	12060	Atlanta-Sandy Springs-Roswell, GA	1411.55	81	292.46
2006	35620	New York-Newark-Jersey City, NY-NJ-PA	1084.99	7	850.09
2007	35620	New York-Newark-Jersey City, NY-NJ-PA	1078.84	10	292.59
2008	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	1269.15	1	104.96
2009	28140	Kansas City, MO-KS	2574.83	6	168.97
2010	41940	San Jose-Sunnyvale-Santa Clara, CA	2980.54	1	84.77
2011	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	272.20	20	365.09
2012	35620	New York-Newark-Jersey City, NY-NJ-PA	238.08	3	970.95
2013	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	433.64	31	610.36

Panel D: Top MSA by Total Number of Properties Disposed

Year	CBSA Code	MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (USD million)
2003	33100	Miami-Fort Lauderdale-West Palm Beach, FL	1321.60	6	67.57
2004	16980	Chicago-Naperville-Elgin, IL-IN-WI	278.58	29	108.78
2005	12060	Atlanta-Sandy Springs-Roswell, GA	1411.55	81	292.46
2006	19820	Detroit-Warren-Dearborn, MI	855.89	19	256.55
2007	19100	Dallas-Fort Worth-Arlington, TX	199.31	38	208.64
2008	19100	Dallas-Fort Worth-Arlington, TX	514.64	4	40.03
2009	28140	Kansas City, MO-KS	2574.83	6	168.97
2010	35380	New Orleans-Metairie, LA	1789.26	1	84.77
2011	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	272.20	20	365.09
2012	26420	Houston-The Woodlands-Sugar Land, TX	227.19	25	123.25
2013	27260	Jacksonville, FL	3050.26	32	183.43

Appendix 2: Selloffs in the non-Top 10 HQ MSAs

Event date	Company name	CAR(-1,1)	Avg. disntance	Headquarter MSA	Rank (by population)
10/18/2010	ProLogis	3.87	1789.25	San Francisco–Oakland–Hayward, CA	11
12/18/2013	Terreno Realty Corporation	2.16	1160.25	San Francisco–Oakland–Hayward, CA	11
7/10/2006	Glenborough Realty Trust	-1.06	1725.31	San Francisco–Oakland–Hayward, CA	11
4/7/2005	Glenborough Realty Trust Inc.	2.7	1462.52	San Francisco–Oakland–Hayward, CA	11
9/3/2009	Ramco-Gershenson Properties Trust	1.71	663.38	Detroit-Warren-Dearborn, MI	12
9/19/2005	Ramco-Gershenson Properties Trust	2.67	1296.50	Detroit-Warren-Dearborn, MI	12
3/31/2003	Pan Pacific Retail Properties	1.82	634.63	San Diego-Carlsbad, CA	17
1/27/2003	Pan Pacific Retail Properties Inc.	-0.44	1242.18	San Diego-Carlsbad, CA	17
4/4/2012	Corporate Office Properties Trust	-2.26	236.52	Baltimore-Columbia-Towson, MD	20
2/2/2012	Corporate Office Properties Trust	-0.85	989.56	Baltimore-Columbia-Towson, MD	20
12/19/2011	Corporate Office Properties Trust	3.66	163.69	Baltimore-Columbia-Towson, MD	20
7/2/2012	Corporate Office Properties Trust	5.45	150.76	Baltimore-Columbia-Towson, MD	20
9/29/2006	Corporate Office Properties Trust	-1.69	108.58	Baltimore-Columbia-Towson, MD	20
7/28/2006	Corporate Office Properties Trust	2.36	1726.56	Baltimore-Columbia-Towson, MD	20
5/7/2012	Corporate Office Properties Trust	1.76	96.76	Baltimore-Columbia-Towson, MD	20
7/17/2012	UDR Inc.	1.41	1399.49	Denver-Aurora-Lakewood, CO	21
3/7/2003	Parkway Properties Inc.	2.35	1630.09	Orlando-Kissimmee-Sanford, FL	27
6/9/2006	Developers Diversified Realty Corp.	-1.57	2678.91	Cleveland-Elyria, OH	29
8/6/2004	Glimcher Realty Trust	-0.17	1837.45	Columbus, OH	32
1/6/2009	Glimcher Realty Trust	21.3	1149.32	Columbus, OH	32
7/25/2006	Duke Realty Corporation	2.99	2278.02	Indianapolis-Carmel-Anderson, IN	33
1/6/2009	Kite Realty Group Trust	7.26	1134.97	Indianapolis-Carmel-Anderson, IN	33
2/21/2012	Kite Realty Group Trust	-3.17	2704.51	Indianapolis-Carmel-Anderson, IN	33
9/30/2005	Duke Realty Corporation	1.33	1713.38	Indianapolis-Carmel-Anderson, IN	33
12/6/2007	Essex Property Trust Inc.	-0.83	2074.83	San Jose-Sunnyvale-Santa Clara, CA	34
9/11/2013	American Campus Communities, Inc.	1.09	1142.86	Austin-Round Rock, TX	35
8/14/2013	Regency Centers Corporation	1.03	2641.27	Jacksonville, FL	40
8/23/2012	Sovran Self Storage, Inc.	1.24	1090.67	Buffalo-Cheektowaga-Niagara Falls, NY	47
5/29/2009	Highwoods Properties, Inc.	-2.02	2859.93	Raleigh, NC	48
1/15/2009	Highwoods Properties, Inc.	28.42	389.97	Raleigh, NC	48
1/21/2003	Highwoods Properties, Inc.	5.14	1679.91	Raleigh, NC	48
6/7/2005	Highwoods Properties Inc.	0.45	1608.97	Raleigh, NC	48
12/17/2007	Highwoods Properties, Inc.	-2.45	2536.39	Raleigh, NC	48

4/10/2006	Colonial Properties Trust	-0.04	1722.31	Birmingham-Hoover, AL	49
10/25/2005	BNP Residential Properties, Inc.	2.67	2604.77	Birmingham-Hoover, AL	49
4/27/2006	CBL & Associates Properties Inc.	2.32	1437.70	Birmingham-Hoover, AL	49
7/8/2005	Colonial Properties Trust	4.64	1638.84	Birmingham-Hoover, AL	49
12/26/2007	Colonial Properties Trust	6.1	238.03	Birmingham-Hoover, AL	49
10/11/2005	Colonial Properties Trust	0.65	988.40	Birmingham-Hoover, AL	49
9/3/2013	CBL & Associates Properties, Inc.	-1.53	1646.31	Birmingham-Hoover, AL	49
7/3/2008	Colonial Properties Trust	0.33	1333.22	Birmingham-Hoover, AL	49
10/2/2006	Colonial Properties Trust	1.11	144.98	Birmingham-Hoover, AL	49
2/1/2006	Home Properties, Inc.	2.61	855.89	Rochester, NY	51
10/2/2006	Home Properties, Inc.	3.51	498.44	Rochester, NY	51
4/9/2013	Home Properties	-0.39	2050.46	Rochester, NY	51
4/1/2013	Starwood Hotels & Resorts Worldwide, Inc.	5.37	1442.77	Bridgeport-Stamford-Norwalk, CT	58
7/29/2003	Starwood Hotels & Resorts Worldwide,Inc.	3.43	1712.82	Bridgeport-Stamford-Norwalk, CT	58

Essay 2

Geographic Proximity and Competition for Scarce Capital:

Evidence from U.S. Stocks and REITs

1. Introduction and Literature Review

An in-depth understanding of the disaggregated, micro aspects of financial capital determinants is crucial 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 opposed to the local level, without simultaneously considering a comprehensive set of asset classes (that is, having considered only REITs or common stocks, but not both in the same analysis).

In particular, a small strand of 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. Their research indicates that investors' local preference in equity markets generates strong investor clienteles and thus state-level segmentation.

Another important reason for studying financial capital is that it has important implications for market liquidity due to liquidity spirals (Brunnermeier and Pedersen, 2009) and segmentation by its nature (Agarwal and Hauswald, 2010). Glascock and Lu-Andrews (2014) are among the first to empirically test the relation between aggregated market and funding liquidity. They find a reinforcing relationship between the two liquidity measures at the national level. Other recent studies show that, at the state level, market liquidity is also positively affected by funding liquidity and local macroeconomic conditions due to market segmentation (Bernile, Korniotis, Kumar, and

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

Wang, 2015). An enhanced understanding of financial capital conditions at the local level is clearly important for a more complete comprehension of market liquidity.

Perhaps the most important determinant of corporate capital structure is financial flexibility (Graham and Harvey, 2001). 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 (Demos and McKeon, 2011), and through equity repurchases and payouts (Brav et al., 2005; Bonaime et al., 2013).[2]

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. Such spillovers might lead to inaccurate estimates of financial capital determinants (because of ignoring the indirect effects) due to violation of the Stable Unit Treatment Value Assumption (SUTVA), which assumes that spillovers do not exist. Nordlund (2016) is the first to address this issue among studies of financial flexibility. He develops a profit maximization model to explain why indirect effects might occur among firms with different costs of capital. He assumes that firms may enter into covenants with one another to coordinate their actions. Using covenant violations, he finds that non-violating firms benefit from the violating ones by preying

2 For a good review on financial flexibility, one can refer to Denis (2011).

strategically upon them. That is, non-violating firms are “treated” indirectly, which thus violates SUTVA. Due to competition between violating and non-violating firms, the indirect treatment effect, or the spillover effect, is negative.

However, based upon Garmaise and Batividad (2016)’s argument, the firm-level analysis of Nordlund (2016) is subject to an important endogeneity issue. Specifically, Nordlund (2016)’s thesis does not fully explain where the indirect effect comes from. The indirect effect can either be an outcome of competition between geographic neighbors, or across firms within a particular industry. Implications on the former scenario are not addressed in Nordlund (2016). However, these implications can be important when financial capital conditions are affected by local economic conditions. In our theoretical 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. In other words, we uncover evidence in support for the hypothesis that there is competition for scarce capital.

More generally, spatial spillover effects are widely studied in the economics literature, as an important source of pure externalities, in which some entities generate non-compensated benefits (or costs) upon others. Moreover, they highlight the role played by geographic proximity in the complex processes of local endogenous interactions. Different types of spatial spillovers have

been pinpointed in the literature, including, but not limited to, Knowledge Spillovers,[3] Industry Spillovers,[4] and Growth Spillovers[5] (Capello, 2009).

The theoretical model in our paper is most closely related to the Growth Spillovers concept. We consider a situation where capital utilized by stocks and/or REITs in some locations may crowd-out the ability of firms in another region to obtain and/or use capital. We accomplish this by considering the effects of state (MSA)-level macroeconomic conditions on US stocks' and equity REITs' financial capital conditions and its spillovers across state borders. This is a more specific model than the financial flexibility spillovers considered by Nordlund (2016), and the state-level analysis of Bernile et al. (2015). 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 theory implies that either positive or negative spillovers are possibilities, however the actual sign of the spillovers is a question that we test for empirically. We then

[3] *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).

[4] *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 entrée and higher costs of local inputs, market competitiveness would 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.

[5] *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.

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.[6] We also examine whether or not REITs exhibit different spillover patterns than stocks in the context of financial capital. Our key findings are that there is competition for scarce capital among stocks (and REITs) in different U.S. states (MSAs); several macroeconomic variables are significant predictors of state-level financial capital conditions; and generally speaking, stocks and REITs behave similar to each other.

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 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:

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

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

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:

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

First order conditions include:

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

and in words, this says 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 $r_1 = \gamma\varphi_1$.[7]

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:

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

[7] We assume that the nominal price of capital, γ, is equal across the U.S. and allow variation in the "real" price of capital, *r*.

where $\lambda_1(\lambda_2)$ is the shadow price of output for firm 1(firm 2).

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

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

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:

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

and for firm 2:

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

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:

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

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

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

Equation (ix) 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:

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

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

Also,

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

therefore, the reaction function for firm 1 is downward sloping 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:

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

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 $\frac{\partial\log(K_1)}{\partial\log(K_{AVG})}$.

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 (xi). 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, and the sign and significance on this term will enable us to test equation (xi). Initially, we build up our empirical model by following Glascock and Lu-Andrews (2014) and Bernile et al. (2015), so we start by using the following panel regression models. We extend the national-level analysis of Glascock and Lu-Andrews (2014), by using the *State/MSA Coverage Ratio* as our measure of the representative firm's level of capital.[8] First, we regress *State Coverage Ratio* on the lagged change in state and national coincident indexes (*Change in SCI* and *Change in NCI*),

[8] We didn't include control variable for risk since *State Coverage Ratio* has been risk-adjusted. Here we take state-level analysis as an example because most macroeconomic variables are available at state level.

$$State\ Coverage\ Ratio_{s,t+1} = \alpha_0 + \beta_{SCI} \cdot Change\ in\ SCI_{s,t} + \beta_{NCI} \cdot Change\ in\ NCI_t$$

$$+\delta_t + \varepsilon_{s,t}, \tag{1}$$

where 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* for predictive regressions.[9] It is calculated as the natural logarithm of the mean of the interest coverage ratios of all the firms (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.[10]

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

$$State\ Coverage\ Ratio_{s,t+1} = \alpha_0 + \beta_{SCI} \cdot Change\ in\ SCI_{s,t} + \mu_s + \delta_t + \varepsilon_{s,t}, \tag{2}$$

State fixed effects, μ_s, effectively control for unobservable heterogeneity across U.S. states. *Change in NCI* is excluded because it does not vary cross-sectionally.

Lastly, since the interpretation of composite indexes are limited, we adopt individual state (regional) macroeconomic factors instead of changes in composite indexes to unveil the full picture. Specifically, we regress *State Coverage Ratio* on state (regional) macroeconomic variables with fixed effects in equation (3) and (4),

$$State\ Coverage\ Ratio_{s,t+1} = \alpha_0 + \beta_{unemp} \cdot Ln(unemployment\ rate)_{s,t}$$

[9] 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.
[10] We also adopt leading variables such as *PSEA* and *PNEA* instead of coincident indexes.

$$+\beta_{GSP} \cdot Gross\ State\ Product\ Growth_{s,t} +$$

$$\beta_{stmort} \cdot Ln(State\ Mortgage\ Deduction)_{s,t}$$

$$+\beta_{HPI} \cdot State\ House\ Price\ Growth_{s,t} + \mu_s$$

$$+\delta_t + \varepsilon_{s,t}, \tag{3}$$

$$State\ Coverage\ Ratio_{s,t+1} = \alpha_0 + \beta_{unemp} \cdot Ln(unemployment\ rate)_{s,t}$$

$$+\beta_{GSP} \cdot Gross\ State\ Product\ Growth_{s,t} +$$

$$\beta_{stmort} \cdot Ln(State\ Mortgage\ Deduction)_{s,t}$$

$$+\beta_{HPI} \cdot State\ House\ Price\ Growth_{s,t} +$$

$$+Ln(Regional\ CPI)_{R,t} + \mu_s + \delta_t + \varepsilon_{s,t} \tag{4}$$

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.[11]

3.2. Spatial Lag and Spatial Multiplier

In order to examine the issue of cross-state/cross-MSA spillovers and test for the sign and significance of equation (xi), we need to adapt our state (MSA)-level models described above. A useful tool for this analysis is spatial econometrics, which typically includes a spatial autoregressive model (hereby SAR model) and sometimes a spatial Durbin model (hereby SDM model). The SAR model is a formulation of the idea of spatial spillovers – levels of the outcome variable *y* (i.e.,

[11] We also estimate equation (3) using MSA-level data.

State/MSA Coverage Ratio) depend on the levels of y in neighboring geographic units. 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 (5a) and spatial Durbin's model combined with a spatial autoregressive model (5b) can be expressed as follows, respectively.[12]

$$Y = \rho WY + X\beta + u \tag{5a}$$

$$Y = \rho WY + X\beta + WX\theta + u \tag{5b}$$

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.[13] There are 20 (21) states and the time periods range from the first quarter of 1985 (1994) to the fourth (third) quarter of 2014 for stocks (REITs).[14] ρ, θ, and β are parameters to be estimated. W is the spatial weighting matrix, with individual elements consisting of the inverse-distances (where the weight state/MSA j has on state/MSA i equals the inverse of the distance between states/MSAs i and j, normalized by the sum of the weights between state/MSA i and all other states/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'

[12] (Cohen, 2010)

[13] 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.

[14] 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).

endogenous variable, which is the financial capital measure, *State/MSA Coverage Ratio*. It has been shown (e.g., Kelejian and Prucha, 1998) that Equations (5a) and (5b) can be estimated by instrumental variables techniques. For Equation (5a), X is the appropriate instrument for itself, and WX is the instrument for WY. Similarly, for Equation (5b), X is the appropriate instrument for itself, WX is the instrument for itself, and W^2X is the instrument for WY.[15] 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*).

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 (5a) would be written as:

$$Y_{CT} = \rho Y_{NY} + X_{CT}\beta + u_{CT} \tag{6a}$$

$$Y_{NY} = \rho Y_{CT} + X_{NY}\beta + u_{NY} \tag{6b}$$

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

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

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%.[16] 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.

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). A detailed explanation on variables can be found in the Appendix.

Due to the application of spatial models, we only include states that have more than 15 headquartered stocks over the entire sample period.[17] 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)

[16] The overestimation of the effect of *Ln*(*Unemployment Rate*) on *State Coverage Ratio* is approximately 60.8% for REITs.
[17] We only include MSAs that have more than 5 headquartered stocks (Pirinsky and Wang, 2006) or at least one REIT in each quarter.

stocks (REITs) from 1985-2014 (1994-2014).[18] Over the entire sample period, California (California) and Texas (New York) are the states with the most and second most stock (REIT) headquarters. With 1932 (81) and 1168 (43) stocks (REITs) currently or used to locate in California (California) and Texas (New York), respectively. Missouri has the only 164 (4) stock (REIT) headquarters. An average state in our sample has approximately 103 (17) stock (REIT) headquarters for each quarter.

We use the state (MSA) centroid as the location of a state (MSA)'s representative stock (REIT) in order to mitigate the concern that headquarter location choice is endogenous to the stock (REITs). Since state borders were settled far back to the 19th century (prior to when most listed securities were issued), it is less of a concern that our spatial weighting matrix might be endogenous by itself. The latitude and longitude coordinates of each state centroid in our sample are reported in Table 1.[19]

Summary statistics of the variables used in our analysis are reported in Table 2 for stocks and REITs, respectively. We use *State/MSA Coverage Ratio* to proxy for state (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).

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

[18] 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.
[19] 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).

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

where $IBQ_{i,s,q}$ is the income before extraordinary items of stock (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 stock (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,

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

Quarterly financial statement data, most currently obtained from the Compustat quarterly database, is used to compute *State Coverage Ratio*.[20] We manually adjust for headquarter relocations using a combined dataset of headquarter relocation announcements.[21] We use *State/MSA Coverage Ratio* as the proxy for state/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 HPI growth is obtained from Federal Housing Finance Agency (FHFA) website. National macroeconomic data are acquired from the Federal Reserve Bank of St. Louis Database (FRED). We also download State and National Coincident (Leading) Indexes from the

[20] We calculate *MSA Coverage Ratio* in a similar manner.

[21] 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.

Federal Reserve Bank of Philadelphia (FRED). Quarterly change in the coincident indexes are calculated as the mean of monthly changes within a specific quarter. Quarterly predicted economic activities 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.[22]

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*/*MSA coverage ratio* for stocks and REITs. Section 5.2 explains the interpretation of 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 Appendix. We follow Bernile, Korniotis, Kumar, and Wang (2015) and include information of 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

[22] Data on the MSA unemployment rate, gross MSA product, MSA income growth, and MSA HPI growth is obtained from the same data sources.

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 household's 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 higher level of return to human capital (*State income growth* or *MSA income growth*) leads to higher financial capital in the next quarter.

As in Bernile, Korniotis, Kumar, and Wang (2015), 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. These forward-looking measures predict the 6-month growth of the corresponding coincident indexes with variables that lead the economy.[23] 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 (higher) price levels (*Regional CPI*) should lead to higher level of financial capital (*State coverage ratio*) for

[23] 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.

stocks (REITs) in the next quarter. REITs hold real estate and are resistant to inflation. 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*).

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 4a) assumes only the dependent variable has spatial dependence while SDM (equation 4b) assumes both the dependent variable and certain independent variables (i.e., in our example, state or MSA macroeconomic variables) have spatial dependence.[24]

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. 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:

[24] 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.

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

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 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*, which are similar to the panel regression results, and *total effects*, which 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 (1) by regressing the measure of state financial capital – aggregated measure of *State coverage ratio* – on the change in state and national coincident indexes

(*Change in SCI, Change in NCI*), with quarterly fixed effects.[25] 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 *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.

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.[26]

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-

[25] 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.
[26] 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 more fierce 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 are 3.477 and 0.545 for stocks and REITs, respectively.

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 is 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).

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.

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 fiercer 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 (3) by substituting the *Change in SCI* with the state-level macroeconomic variables in Table 6.

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. 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 inflation (*Ln*(*Regional CPI*)) and test equation (4). All state macroeconomic variables (as well as state and quarter fixed effects) remain in our sample. The results are reported in Table 7.

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.

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 resistant to inflation (Glascock, Lu and So, 2002). Their inflation-hedging characteristic is especially attractive to investors when local inflation is high. Therefore, REITs distinguish themselves from stocks in that their financial capital conditions is positively, not negatively, correlated with local inflation.

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 ($W \times$ *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.

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 applies to state-level data. 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 MSA-level than 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 Table 6 with MSA-level data. The results are reported in Table 8.

The results in Table 8 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 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 paper we have developed a theoretical model to describe the capital usage behavior of REITs and stocks. We empirically test the comparative statics implications of this model, in order to answer the question: is there competition for scarce capital among firms in different states/MSAs?

Overall, our findings are threefold. First, we find evidence of competition for scarce capital across state (MSA) borders. This evidence is further pronounced by the spatial multiplier effects (which in this case, these are actually spatial "diminisher" effects because they are smaller than 1). Second, state/MSA macroeconomic variables, especially local labor market conditions, economic development, and inflation, significantly predict capital usage in the next quarter. Finally, although both REITs and stocks are similar in that they demonstrate competition for scarce capital, REITs nevertheless maintain some characteristics that resemble their underlying real estate.

There are several potential extensions and areas for future work that we 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 are shown to exhibit co-movement. Investor proximity effects, or local bias, might be explained by knowledge spillovers between investors, or common shock 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 firm's assets instead of firm headquarters. We use firm headquarters to define firm location because most information transmission and decision-making occur at firm headquarters. However, for some companies such as REITs, this may not hold true universally. 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.
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
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
State coverage ratio	1										
Change in SCI	0.10*	1									
Change in NCI	0.12*	0.84*	1								
PSEA	0.10*	0.91*	0.72*	1							
PNEA	0.13*	0.77*	0.89*	0.81*	1						
Ln(unemp)	0.08*	-0.19*	-0.18*	-0.05	-0.05	1					
FHFA HPI growth	-0.00	0.35*	0.28*	0.32*	0.28*	-0.36*	1				
GSP growth	-0.05	0.45*	0.40*	0.54*	0.54*	-0.37*	0.41*	1			
Ln(stmort)	0.01	0.05*	0.00	0.05	-0.00	-0.14*	0.01	0.05	1		
Ln(regional CPI)	0.00	-0.26*	-0.29*	-0.43*	-0.54*	0.22*	-0.24*	-0.72*	-0.02	1	
State income growth	0.10*	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 natural logarithm of *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 natural logarithm of *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 × *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 natural logarithm of *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 ≈ 0.65
(t statistics)	– –		**(-8.34)**	
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 natural logarithm of *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 – 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 natural logarithm of *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 - State 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 - State 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 - State 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 - State 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 natural logarithm of *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 ($W \times$ *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. 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 natural logarithm of *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 ($W \times$ *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)	–	–	–		**-0.504**	***	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			

Essay 3

REIT Liquidity Spillover Effects and Competition for Scarce Capital

1. Introduction

It is widely believed that REIT liquidity can be impacted by macroeconomic factors. However, the detailed mechanisms and processes of this relationship have not been extensively studied. States that share a common border, or that are otherwise reasonably close geographically, can exhibit various patterns of interaction with each other relative to information that can affect REIT pricing. For instance, REITs with headquarters in Connecticut can be affected by state-level macroeconomic news in nearby New York or Massachusetts. This can affect the liquidity of Connecticut REITs and cause either more or less demand for these REITs. Coval and Moskowitz (2001) demonstrate this effect relative to mutual fund investing. They find that having locally specialized knowledge allows local investors to earn superior investment return. On the other hand, competition for scarce financial capital (Nordlund, 2016; Wang, Cohen, and Glascock, 2017) indicates that improvement in a particular state's market liquidity condition might have detrimental effect on its geographic neighbors, especially when the aggregate level of liquidity is low. We combine these ideas of geographic effects via macroeconomic variables and local knowledge/competition in this research. We look specifically at how state-level macroeconomic factors affect market liquidity for REITs.

Several recent studies have devoted attention to national and state-level macroeconomic variables' effects on REITs' liquidity, both funding liquidity and market liquidity. The reinforcing relationship between funding liquidity and market liquidity of firms has been intensively studied at national level for U.S. equities and national macroeconomic factors seem to affect firms' market liquidity only through funding liquidity (see the work of Brunnermeier and Peterson, 2009; and Glascock and Lu-Andrews, 2014). This effect, which became known as the channel effect between market liquidity and funding liquidity, is not well established at the state level. In this research, we

address this issue by asking whether or not the channel effect exists at state level and, if so, how can we assess and interpret its spillover benefits or costs across geographic boundaries. Our empirical results confirm, consistent with evidence at the national level, that state macro-economic factors affect state market liquidity through state funding liquidity.

A key part of our effort is to examine the feedback effects, or "endogenous" local effects, between neighboring geographic units. These feedback effects are of vital importance because they capture an alternative causation channel which did not receive enough attention in the existing literature. As suggested by Marshall (1890) and Manski (1993), there are at least two causation channels. One is common exposure to some unobserved factor X, where X affects A and B independently ($X \rightarrow A, X \rightarrow B$). The other is dependent on the interactions between A and B, where X either indirectly affects A through B, or affects B through A ($X \rightarrow B \rightarrow A \; or \; X \rightarrow A \rightarrow B$).[1] The former channel (direct effects) has been studied extensively in the existing literature while the latter (indirect effects) has been largely neglected.[2] One exception, however, is the recent work by Dougal, Parsons, and Titman (2015), whereby the authors find that, at least for investment opportunities, these interactions are important. Firm A's investment opportunities are improved given that another local Firm B within/across industries has a banner year. Therefore, local firms behave similarly not because of a systematic exogenous factor, but rather because the endogenous choices of local companies influence each other, or the "endogenous" local effects. Since the local information environment and competition for scarce capital largely influence and shape local

[1] One example regarding these interactions would be the knowledge spillovers across employees and firms. For instance, an employee at firm A learns or develops new skills, and, through social interactions, these skills diffuse to employees of firm B. That is, employees of firm B are treated indirectly through "endogenous" interactions.
[2] Feedback effects and indirect effects are used interchangeably in this study.

liquidity, we believe these feedback effects, or "endogenous" local effects, are especially important in our research.

In order to empirically estimate the feedback effects, we enhance our work and extend previous work by using spatial econometric methods to mitigate biases that may be present due to cross-sectional heterogeneity. Spatial econometric methods, including the Spatial Autoregressive Model and Spatial Durbin's Model, have a wide range of applications in finance and economics studies. For instance, Cohen (2010) examines the importance of "broader" economic effects of transportation infrastructure on productivity by applying the spatial multiplier effect, which is later further explored and clarified in Small and Steimetz (2012). However, in our analysis of cross-state REIT liquidity, we find a negative and statistically significant spatial spillover effect for market liquidity. Our results are likely to be explained by market competitiveness (Industry Spillovers with respect to the competition for scarce capital) rather than the traditional knowledge spillover-based explanation.[3] We find that funding liquidity (*State coverage ratio*), economic development (*Gross State Product*), and state housing collateral (*State House Price Index Growth*) are the most important state-level determinants of REITs' liquidity.

We have three key findings in this paper. First, state macroeconomic factors provide explanatory power for market liquidity. Second, there is a reinforcing relation between funding and market liquidity at state-level. Third, we observe negative spatial spillover effects for market liquidity.

The remainder of the paper is organized as follows: section 2 summarizes existing literature; section 3 develops empirical models; section 4 provides a discussion of the data and the

[3] One can refer to Capello (2009) to see how to classify different spillover effects.

construction of the variables; section 5 gives the empirical results and a discussion of those implications; and, section 6 the conclusions.

2. Literature Review

Recent findings suggest that assets' liquidity varies with economic conditions and across geographic locations. Brunnermeier and Pederson (2009, hereafter BP) propose a theoretical framework which suggests a mutually reinforcing relation between funding liquidity and market liquidity of publicly listed U.S. stocks. They define the market liquidity of an asset as the difference between the transaction price and the fundamental value while funding liquidity refers to speculators' scarcity (or shadow cost) of capital.

The solution of their model leads to two types of equilibriums, one is a liquid equilibrium and the other is a low-liquidity/high margin equilibrium. In the latter case, margin increases with volatility and speculators reduce positions due to funding problems, causing market illiquidity (destabilizing). On the other hand, losses on existing positions held by speculators would amplify the funding problems and speculators will again reduce shares and thus prices further move away from fundamentals. The former scenario is referred to as margin spiral and the latter is named the loss spiral in BP. Both scenarios constitute the broader picture of liquidity spirals in Figure 1.

Empirically, BP find that during recession periods, when margin requirements may be high, investors trading on margin undergo a funding liquidity shock and this then affects market liquidity. More generally, BP's model applies to all asset classes, or the commonality of liquidity across assets. Speculators optimally invest in securities that provide them with the greatest expected profit (i.e., illiquidity) per capital use and thus shocks to speculators' funding liquidity affect all securities. Therefore, market liquidity is correlated across stocks, and stocks and bonds and this commonality is driven at least in part by BP's funding-liquidity mechanism (Chordia, Roll

and Subrahmanyam, 2005; BP, 2009). Moreover, funding constraints are more likely to be hit during market downturns and thus business cycles are likely to affect market liquidity by influencing fundamental volatility. Later research provides support for BP's thesis (see for example, Jensen and Moorman, 2010; Naes et al., 2011). Loughran and Schultz (2005) find that after adjusting for size and other factors, the shares of rural firms trade much less often than urban firms. Their finding suggests that access to local information and social factors can also affect liquidity cross-sectionally.

REITs are known for their unique corporate structure and regulatory driven payout policy. Given their high payout policy, REITs have to access capital markets frequently and thus they may be more sensitive to the changes in capital markets, which vary with macroeconomic conditions. Glascock and Lu-Andrews (2014) confirm BP's thesis using U. S. equity REITs. In their work, they specifically test the channel effect exhibited in Figure 2.

In order to empirically test the channel effects, they use aggregated Amihud's (2002) Illiquidity (ILLIQ) and aggregated Turnover ratio as measures of market liquidity and debt service coverage ratio, loan-to-value ratio, number of loans, and TIGHTEN to proxy for funding liquidity. The national macroeconomic variables used in their study are the rate of growth in Industrial production (IPG), the change in realized inflation rate (CPI), the change in unemployment rate (UNEMP), the change in GDP (GDP_CHANGE) and several variables that capture the condition of the credit market. These variables are adopted from Chen et al. (1986), Ferson and Harvey (1999), and Watanabe (2004). Interestingly, although IPG, CPI and credit market variables seem to have strong predictability on nationwide funding liquidity measures, GDP_CHANGE and UNEMP are silent. This result necessitates our study at state level because macroeconomic variables such as GDP_CHANGE and UNEMP are likely to affect funding liquidity locally, not

nationwide. Moreover, by examining the macroeconomic effects on funding liquidity across different business phases, Glascock and Lu-Andrews (2014) find that the effects tend to be time-varying and behave differently between expansions and recessions. They also confirm that the market liquidity risk is associated with funding liquidity as well. Overall, their work suggests a channel through which macroeconomic factors affect REITs' funding liquidity and thus indirectly affect REIT market liquidity. The key outcome of their research is that increases in debt to equity reduce market liquidity for REIT stocks, which motivates our designation of the aggregated coverage ratio. We are specifically investigating how the financial leverage of real estate REIT firms and market trading liquidity at state level, as have been suggested by Glascock and Lu-Andrews (2014).

Finally, while evidence has accumulated for the influence of national macroeconomic effects, the effects, if any, of state-level variables on market and funding liquidity is not well established. Recent work shows that where a firm is headquartered, and the distance from shareholders, lenders, stakeholders, and other firms, matters. Bernile et al. (2015) are among the first to examine whether state-level economic conditions affect the liquidity of stocks issued by local firms. They study stocks' liquidity at local level for several reasons. First, while national monetary policy variables have been shown to be significant predictors of capital market liquidity, the other real national economic factors do not seem to have strong effects on securities' liquidity. Secondly, studies on the "Local bias" have shown that a significant portion of the ownership and trading of stocks are local. The extent of the "Local bias" and localized trading behavior make investors' portfolio risk, return and trading liquidity subject to local business cycle, either due to investors' local informational advantage or due to some behavioral bias (i.e., "Familiarity bias").

Moreover, local economic conditions are likely to affect the risk aversion of local investors and thus they should affect investors' willingness to trade.

In order to study the local macroeconomic effect on stocks' trading liquidity, Bernile et al. (2015) adopt the theoretical framework of Vayanos and Wang (2012a, hereby VW), which can be expressed as,

$$\lambda = \frac{\alpha\sigma^2}{1-\pi},$$

where λ represents illiquidity, α is the investor risk aversion, σ^2 is the volatility of risky assets, and π is the fraction of liquidity suppliers. Based on this model, VW indicate that asset liquidity levels decrease when investors' level of risk aversion and asset return volatility are higher, and when there are fewer liquidity suppliers. Motivated by VW, Bernile et al. (2015) propose and empirically test the two following hypotheses. First, they test if there is a positive relation between local economic conditions and the subsequent liquidity of local stocks; Second, whether the relation between local economic conditions and local liquidity is amplified when 1) the shareholder base is more local, 2) there are larger differences in trading of local stocks by local and nonlocal investors, 3) local funding constraints are more binding, and 4) the local information environment is more opaque. Their results support the point of view that local labor market situation, local labor income growth and local housing collateral ratio significantly predict local security liquidity. And this local macroeconomic effect is particularly strong for firms whose shares are mostly owned and traded by local investors, such as small firms (non-S&P 500 firms) and rural firms (Loughran and Schultz, 2005). Interestingly, funding constraint are shown to not only amplify macroeconomic effects on securities' market liquidity, but explains most of it. Potential a simultaneity issue might bias the authors' results here since it can either be the case that state

funding constraint amplifies macroeconomic effects on stocks' liquidity (direct local macroeconomic effect), or that macroeconomic variables only affect stocks' liquidity through funding liquidity (indirect local macroeconomic effect, the channel effect).

However, Bernile et al. (2015) do not establish a clear channel effect between funding liquidity and market liquidity, nor do they address the interaction causation channel (Manski, 1993; Dougal, Parsons, and Titman, 2015). Many reasons could explain the importance of introducing spatial analysis tools into the study of liquidity. For instance, as mentioned in the first paragraph, Loughran and Schultz (2005) notice the significant difference between the liquidity condition of U.S. rural and urban-based companies. Dougal, Parsons, and Titman (2015) find significant "endogenous" local effects on firms' investment opportunities. Moreover, Cooper and Ovtchinnikov (2015) propose and use a geographical-based vibrancy index and find that firm location characteristics along with geographic distance drive firm policies and profitability. They also find the local effects are strong and add additional and higher explanatory power than do industry effects. Last but not least, when the market liquidity condition of neighboring states are indirectly affected by the liquidity/economic condition of a particular state, coefficient estimates of panel regression estimates will be biased due to the violation of Stable Unit Treatment Value Assumption (SUTVA), which assumes that spillovers do not exist (Nordlund, 2016).

Spatial Spillover effects are widely studied in the Economics literature, as an important source of pure externalities, producing non-compensated benefits (or costs) for receivers. Moreover, they highlight the role played by geographic proximity in the complex processes of local endogenous interactions. Different types of spatial spillovers have been pinpointed in the literature, including, but not limited to, *Knowledge Spillovers, Industry Spillovers,* and *Growth Spillovers* (Capello, 2009).

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).

The second type of spillovers that are extensively examined by researchers are the *Industry Spillovers*. They are defined as the situation in which firms located in the same geographic area 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 entrée and higher costs of local inputs, market competitiveness would 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.

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 labor force to the other regions may offset unemployment in one region.

Our paper is closely related to the national-level analysis of Glascock and Lu-Andrews (2014), and the state-level analysis of Bernile et al. (2015) in that we examine the channel through which state-level macroeconomic dynamics affect US equity REITs' funding liquidity and thus affect their market liquidity. Considering the existence of potential spatial heterogeneity across state borders, we apply both panel regression methods, with state and quarter fixed effects, and spatial econometrics tools to capture the spillover effect of funding liquidity and market liquidity. 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).

3. Empirical Model

3.1. Panel Predictive Regression on Liquidity Variables

Initially, we follow Glascock and Lu-Andrews (2014) and Bernile et al. (2015) by using the following panel regression models. First, we regress natural logarithm of state market liquidity measures on the lagged changes in state and national coincident indexes (*Change in SCI* and *Change in NCI*),

$$Liquidity_{s,t+1} = \beta_0 + \beta_1 Change\ in\ SCI_{s,t} + Change\ in\ NCI_t + \delta_t + \epsilon_{s,t}, \quad (1)$$

where t = 1994Q1, 1994Q2, …, 2014Q4, and s = 1, 2, …, N (N is the total number of states with REIT headquarters; r is the number of geographic regions for which CPI data are available; there are 4 such regions in the U.S). In the first predictive regression, two market illiquidity measures are adopted in this study. One is the negative natural logarithm of State Amihud Illiquidity, -*Log*(*State Amihud Illiquidity*), and the other is the negative logarithm of State Relative Spread, -*Log*(*State Relative Spread*). Both variables are constructed as the value-weighted mean

of all REITs located within a specific state, where the weight assigned to each REIT is the inverse of the REIT's market capitalization from last month (Bernile et al., 2015). The other variables are as defined in the Appendix. We include quarter fixed effects, δ_t, to control for unobservable heterogeneity across states and general price changes over time.

In our next set of regressions, we regress state market liquidity measures on the lagged state-level macroeconomic factors with state and quarter fixed effects,

$$Liquidity_{s,t+1} = \beta_0 + \beta_1 Change\ in\ SCI_{s,t} + \mu_s + \delta_t + \epsilon_{s,t}, \tag{2}$$

since *Change in NCI* is excluded, we include both state fixed effects, μ_s, and quarter fixed effects, δ_t.

In order to examine the state-level channel effect between market liquidity and funding liquidity, which was explored in a national-level analysis of Glascock and Lu-Andrews (2014), we regress state market liquidity measures (*-Log*(*State Amihud Illiquidity*) or *-Log*(*State Relative Spread*)) on changes in state (and national) coincident index(es) with state and quarter fixed effects.[4] It is calculated as the natural logarithm of the mean of the interest coverage ratios of all the firms headquartered within a particular state.

$$Liquidity_{s,t+1} = \beta_0 + \beta_1 State\ Coverage\ Ratio_{s,t} + \beta_1 Change\ in\ SCI_{s,t} +$$

$$\beta_2 Change\ in\ NCI_t(+\mu_s) + \delta_t + \epsilon_{s,t}, \tag{3}$$

where *State Coverage Ratio* is our proxy of state-level funding liquidity. It is calculated as the natural logarithm of the mean of the interest coverage ratios of all the firms headquartered within a particular state.

[4] State fixed effects are excluded when *Change in NCI* is included.

Last, in order to disentangle the effects of individual state macroeconomic variables, we re-estimate Equation (1), (2), and (3) by regressing state market liquidity measures (-*Log*(*State Amihud Illiquidity*) or -*Log*(*State Relative Spread*)) on state funding liquidity and state and regional macroeconomic variables ($X_{s,t}$) with state and quarter fixed effects,

$$Liquidity_{s,t+1} = \theta_0 + \theta_1 State\ Coverage\ Ratio_{s,t} + \theta_2 X_{s,t} + Log(Regional\ CPI)_{R,t} + \\ + \mu_s + \delta_t + \tau_{s,t}, \quad (4)$$

where $X_{s,t}$ include the natural logarithm of quarterly state unemployment rate, *Log*(*Unemployment rate*), quarterly change in gross state product, *Gross State Product Growth*, quarterly change in state personal income, *State Personal Income Growth*, the natural logarithm of quarterly state mortgage deduction, *Log*(*State Mortgage Deduction*), and quarterly change in FHFA state house price index, *State House Price Index Growth*. *Log*(*Regional CPI*) is included to test the effect of local inflation on the market liquidity proxies. All variables are defined in the Appendix.

3.2. Spatial Lag and Spatial Multiplier

In order to examine the issue of cross-state spillovers, we need to adapt our state-level models described above. A useful tool for this analysis is spatial econometrics, which typically includes a spatial autoregressive model (hereby SAR model) and a spatial Durbin model (hereby SDM model). SAR model is a formulation of the idea of spatial spillovers – levels of the outcome variable *y* (i.e., local liquidity) depend on the levels of *y* in neighboring geographic units. On the flip side, 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 and spatial Durbin's model can be expressed as follows, respectively.[5]

$$Y = \rho WY + X\beta + u \tag{5a}$$

$$Y = \rho WY + X\beta + WX\theta + u \tag{5b}$$

Here *Y* represents a vector of state-level market liquidity measures and *X* represents a matrix of *State Coverage Ratio* and lagged state macroeconomic variables, and *N* is the number of states and *T* the number of time periods covered by the data.[6] There are 21 states and the time periods range from the first quarter of 1994 to the fourth quarter of 2014. ρ, θ, and β are parameters to be estimated. *W* is the spatial weighting matrix, which typically includes contiguity matrix (where all contiguous neighbors receive equal weight) or the inverse-distance matrix (where the weight equals the inverse of the distance between geographic unit *i* and *j* normalized by the row sum). 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 market liquidity measures, *-Log*(*State Amihud Illiquidity*) or *-Log*(*State Relative Spread*). It has been shown (e.g., Kelejian and Prucha, 1998) that Equation (5a) and (5b) can be estimated by instrumental variables techniques.[7] For Equation (5a), X is the appropriate instrument for itself, WX is the instrument for WY. Similarly, for Equation (5b), X is the appropriate

[5] (Cohen, 2010).
[6] We create a balanced panel of state-level liquidity measures and state-level macroeconomic factors by keeping states 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-level centroid. The reasons are twofolds. First, all the measures are aggregated at the state-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.
[7] Also refer to as the Gershgorin's Theorem (Cohen, 2002).

instrument for itself, WX is the instrument for itself, and W^2X is the instrument for WY. The coefficient estimate, ρ, represents the effect on a state's market liquidity as a result of a change in the weighted average of all other states' market liquidity. Also, each element of the vector of coefficient estimates, θ, represents the effect on a state's market liquidity of a change in the weighted average of one of the macroeconomic variables in *X*.

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 gross state product (*Gross State Product Growth*) and Y is the market liquidity (-*Log*(*State Amihud Illiquidity*)). Then the two rows of observations in Equation (5a) would be written as:

$$Y_{CT} = \rho Y_{NY} + X_{CT}\beta + u_{CT} \tag{6a}$$

$$Y_{NY} = \rho Y_{CT} + X_{NY}\beta + u_{NY} \tag{6b}$$

If X_{CT} increases by 1%, this leads to a $\beta\%$ 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 Table 7, Panel A if the direct effect on *Gross State Product Growth*, $\beta_{gsp\ growth} = 0.099, \rho = -0.372$, then the total effect (including the spatial multiplier effect) is $0.099 \times \frac{1}{1-(-0.372)} \approx -0.073$. Had we ignored the indirect (spatial) effects, this would have led to an overestimation of the impact by approximately 37% and a clear violation of Stable Unit Treatment

Value Assumption (SUTVA).[8] 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 funding liquidity on a particular state's funding liquidity.

4. Data

In this paper, we use both national and state-level data to examine how macroeconomic conditions can affect equity REITs' market and funding liquidity. A detailed explanation on variables can be found in the Appendix.

We use the negative natural logarithm of State Amihud Illiquidity, -*Ln*(*state Amihud Illiquidity*), or the negative natural logarithm of State Relative Spread, -*Ln*(*state relative spread*) to proxy for state market liquidity conditions.[9] -*Ln*(*state Amihud Illiquidity*) is our main market liquidity variable, it can be computed as the logarithm of the average of quarterly average of absolute daily return to the product of absolute daily price and daily volume for all REITs in a particular state, weighted by the shares of market capitalization.

Specifically, for individual REIT *i* headquartered in state *s* in quarter *q*,

$$ILLIQ_{i,s,q} = \frac{1}{D_{i,s,q}} \sum_{q=1}^{D_{i,s,q}} \frac{|R_{i,s,q,d}|}{Vol_{i,s,q,d}}, \tag{7}$$

where $D_{i,s,q}$ represents the trading days available for firm *i* headquartered in state *s* within a quarter q, $R_{i,s,q,d}$ is the daily stock return, $Vol_{i,s,q,d}$ is the daily trading volume. The relative spread measure is the ratio of the daily closing bid-ask spread divided by the midpoint of the daily

8 The overestimation would be 59% relative to panel regression estimate ($\frac{-0.035-(-0.022)}{-0.022} = 59\%$).

9 We also consider alternative market liquidity measures such as turnover and trading volume for our analysis. We found similar results and will provide them upon request.

closing bid-ask spread. Suppose there are a total of N REITs headquartered in state s. Then for state s in quarter q, we compute the -*Ln*(*state Amihud Illiquidity*) and -*Ln*(*state relative spread*) as,

$$-Ln(State\ Market\ Liquidity)_{s,q} = -Ln(\sum_{i=1}^{N} \frac{Mkt\ Cap_{i,s,q-1}}{State\ Mkt\ Cap_{s,q-1}} LIQ_{i,s,q}), \quad (8)$$

where $Mkt\ Cap_{i,s,q-1}$ represents the market capitalization of REIT *i* headquartered in state *s* within a quarter q-*1*. $State\ Mkt\ Cap_{s,q-1}$ represents the market capitalization of all REITs headquartered in state *s* within a quarter q. $LIQ_{i,s,q}$ is either *Amihud Illiquidity* or *relative spread* of REIT *i* headquartered in state *s* within a quarter *q*. Daily and monthly stock price data obtained from CRSP are used to compute -*Ln*(*state Amihud Illiquidity*) and -*Ln*(*state relative spread*). -*Ln*(*state Amihud Illiquidity*) and -*Ln*(*state relative spread*) and state market liquidity condition are positively correlated. To be specific, higher value of *Log*(*State Amihud Illiquidity*) or *Log*(*State Relative Spread*) indicates higher state market liquidity.

We aggregate the firm-level interest coverage ratio at state level to obtain our funding liquidity measure, *State Coverage Ratio*. Details regarding the computation of *State Coverage Ratio* can be found in Appendix. COMPUSTAT quarterly items are used to calculate firm-level interest coverage ratio. We follow Wang, Cohen, and Glascock (2017) and use *State Coverage Ratio* as the main variable of state funding liquidity because it captures the easiness of an equity REIT investor getting access to capital to some extent.

Specifically, for an individual REIT *i* headquartered in state *s* in quarter *q*,

$$Interest\ Coverage\ Ratio_{i,s,q} = \frac{IBQ_{i,s,q}}{DVPQ_{i,s,q} + XINTQ_{i,s,q}}, \quad (9)$$

where $IBQ_{i,s,q}$ is the income before extraordinary items of 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 REIT level interest coverage ratio at state level to obtain *State Coverage Ratio*. *Suppose* that there are a total of *N* REITs headquartered in state *s*, then for state *s* in quarter *q*, we compute *State Coverage Ratio* as,

$$State\ Coverage\ Ratio_{s,q} = \frac{1}{N}\sum_{i=1}^{N} Interest\ Coverage\ Ratio_{i,s,q}, \tag{10}$$

Quarterly financial statement data and most current obtained from Compustat quarterly database is used to compute *State Coverage Ratio*. We use *State Coverage Ratio* as the proxy for state funding liquidity because it captures the easiness of a REIT getting access to capital to some extent.

We use state centroid as the location of a state representative REIT in order to mitigate the concern that headquarter location choice is endogenous to the REITs. Since state borders were settled far back to the 19 century (prior to most listed securities were issued), it is less of a concern that our spatial weighting matrix might be endogenous by itself. The latitude and longitude coordinates of each state centroid in our sample are reported in Table 1.

Data on the state unemployment rate and regional consumer price index 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).[10] Marginal tax rates and state mortgage deduction are acquired from the Feenberg Taxism database on NBER's website.[11] National macroeconomic data are acquired from Federal Reserve Bank of St. Louis Database (FRED). We also download State and National Coincident Indexes from Federal Reserve Bank of

10 Based on our communications with individuals at the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis, this regional data is the closest available measure of state-level inflation. Quarterly *GSP Rate* is available from 2005Q2, before 2005Q2, we use annual *GSP Rate*. We also download national macroeconomic data from Federal Reserve Bank of St. Louis Database (FRED).

11 http://users.nber.org/~taxsim/

Philadelphia (FRED).[12] Quarterly change in the coincident indexes are calculated as the mean of monthly changes within a specific quarter. Summary statistics of the variables used in our analysis are reported in Table 2. We also report pairwise correlation tables of all variables used in our analysis in Table 3.

Since REITs represent a relatively homogeneous asset class with real estate as their underlying assets, we only 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) in order to maintain a balanced panel for spatial analysis. We ended up with 21 states with 367 unique REITs defined by permanent security identification number (PERMNO) from 1994-2014. Over the entire sample period, California and New York are the states with the most and second most REIT headquarters. With 81 and 43 REITs currently or used to locate in California and New York, respectively. Missouri has the only 4 REIT headquarters. An average state in our sample has approximately 17 REIT headquarters per quarter.

5. Empirical Results

Our findings naturally fall into three categories. Part 1 briefly discusses the predicted effects of macroeconomic variables and funding liquidity measure, *State Coverage Ratio*, on the market liquidity measures, -*Ln*(*state Amihud Illiquidity*) and -*Ln*(*state relative spread*). Part 2 shows the interpretation of spatial lag and spatial multiplier, and the distinction between the Spatial Autoregressive (SAR) Model and Spatial Durbin's (SDM) Model. Part 3 estimates the predictive panel regressions, SAR and SDM Models and report regression results.

5.1. Macroeconomic effects on local funding liquidity

12 See Crone (2002) for details on the construction of the state economic indices.

The predicted effects of state macroeconomic variables and *State Coverage Ratio* on the market liquidity measures are reported in the Appendix. We follow Bernile, Korniotis, Kumar, and Wang (2015) and include information of local business cycle, i.e., income growth (*PI growth*), unemployment rate (*Ln*(*state unemployment rate*)), and housing price index growth (*FHFA HPI growth*), into our analysis of local macroeconomic effects on the market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) of local REITs. Unemployment rate (*Ln*(*state unemployment rate*)) and income growth (*PI growth*) capture local (state-level) labor market conditions and return to human capital, respectively. Ceteris paribus, lower unemployment rate (*Ln*(*state unemployment rate*)) and higher income growth (*PI growth*) lead to higher market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) in the next quarter. Housing price index growth (*FHFA HPI growth*) reflects funding liquidity to some extent because it measures local household's borrowing capacity conditional on their housing equity. Therefore, higher housing price index growth (*FHFA HPI growth*) positively predicts future market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)).

In addition to Bernile, Korniotis, Kumar, and Wang (2015), we include variables that capture local economic development (*GSP 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 local market liquidity, we obtain state and national coincident indexes (*Change in SCI*, *Change in NCI*) from Federal Reserve Bank of Philadelphia (FRED).[13] Based on the theoretical model developed in Section 3, we predict that larger increase in economic development (*GSP growth*) and economic activities (*Change in SCI*, *Change in NCI*), higher level

[13] Since market liquidity proxies are forward-looking, we also adopt predicted economic activities proxies into our analysis. We found similar results and will provide them upon request.

of borrowing flexibilities (*Ln*(*state mortgage deduction*)), and lower price level (*Regional CPI*) indicate higher market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) in the next quarter.

To empirically test the reinforcing relation between market and funding liquidity, or the *Channel Effect* (Brunnermeier and Pedersen, 2009; Glascock and Lu-Andrews, 2014), we employ *State Coverage Ratio* as a measure of funding liquidity. Since market liquidity tends to comove with funding liquidity, we predict that *State Coverage Ratio* at quarter *t* positively predicts market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) in the next quarter.

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 model) and the spatial Durbin's model (Hereafter SDM model). SAR and SDM models are two of the most commonly used models in studies applying Spatial Econometrics. The main difference between SAR and SDM is that SAR (equation 5a) assumes only the dependent variable has spatial dependence while SDM (equation 5b) assumes both the dependent variable and certain independent variables (i.e., in our example, state macroeconomic variables) have spatial dependence. In our study, SDM is potentially more robust to cross-sectional heterogeneity than SAR but is subject to multicollinearity issue. We present both SAR and SDM results in the next subsection.

We use a row-normalized inverse distance matrix. First, data on the centroid location is obtained for each state (shown in Table 1). Then we calculate the average distance between centroids in states *i* and *j* as haversine distance (earth surface is approximately spherical). The haversine formula is expressed as:

$$d_{ij} = 2r \cdot \arcsin\left(\sqrt{sin^2\left(\frac{lat_j - lat_i}{2}\right) + \cos(lat_i)\cos(lat_j)sin^2(\frac{lon_j - lon_i}{2})}\right), \tag{11}$$

where d_{ij} is the geographic distance between state i's centroid (state i's latitude and longitude coordinates are lat_i and lon_i, respectively) and state j's centroid (state j's latitude and longitude coordinates are lat_j and lon_j, respectively). r is the earth radius (r = 6,378 kilometers, or 3,959 miles). It is worthwhile noticing that the centroid of each state were exogenously determined and are not subject to selection biases. Each weight in the inverse distance matrix can be expressed as $w_{i,j} = \frac{d_{i,j}}{\sum_{m=1}^{N-1} d_{i,m}}$, where $d_{i,j}$ is the distance between the centroids of states *i* and *j*, $d_{i,m}$ is the distance between the centroids of state *i* and any state *m* (excluding state *i*), and *N* is the total number of states.

In order to show how the coefficient estimates can vary across panel regressions and spatial autoregressive (SAR) model, we report panel regression results, *direct effects*, which are similar to the panel regression results, and *total effects*, which 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. We also report the spatial multiplier next to the spatial rho. According to our discussion in the model section, the spatial multiplier is $\frac{1}{1-\rho}$. We estimate the spatial multiplier utilizing this equation.

5.3. Regression results and interpretation

We test the sign and significance of equation (1) using panel regressions and spatial autoregressive models (equation 5a) in Table 4. By regressing the measure of state market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) on the change in state and national coincident indexes (*Change in SCI, Change in NCI*), with quarterly fixed effects. We find that -

Ln(*state Amihud Illiquidity*) is more influenced by state-level economic activities (*Change in SCI*) than national ones (*Change in NCI*). The coefficient estimates on the *Change in SCI* is statistically significant and economically meaningful, while the coefficient estimates on the *Change in NCI* is significant in the panel regression analysis but insignificant in the spatial analysis. However, -*Ln*(*state relative spread*) seems to be affected by both state-level economic activities (*Change in SCI*) and national ones (*Change in NCI*).

We predict that there is cross-sectional heterogeneity in market liquidity of state representative REITs. Some states might compete with their neighbors by drawing funding liquidity away from their neighbors, and competition for funding liquidity is likely to cause negative spillovers (externalities) on the market liquidity of their neighbors, through the impact of channel effect.

Empirically, we apply SAR and SDM model to test this conjecture. We find that the impact of market liquidity across state borders is asymmetric, with some states more influential in the equity markets than their geographic neighbors. We find a negative and statistically significant coefficient on the spatial lagged market liquidity measure, $W \times [-Ln(Amihud)]\ or\ W \times [-Ln(spread)]$ (ρ).[14]

A negative spillover effect also indicates overestimation of the effect of local economic activities on the market liquidity for REITs. In the SAR model, coefficient estimates of the direct effect largely resemble those of the panel regressions. For instance, the direct effect of *Change in*

[14] Notice that the market liquidity measure of state *i* itself always receives a spatial weight of 0; therefore, ρ only captures the effect of neighboring states' market liquidity on state *i*'s market liquidity. And neighboring states receive larger weights because of the segmentation of capital markets.

SCI is 1.588 (0.606) when -*Ln*(*state Amihud Illiquidity*) (-*Ln*(*state relative spread*)) is used as dependent variable. The corresponding panel regression coefficient estimate is 1.619 (0.629).

Spatial spillover effects unveil the real impact of *Change in SCI* on the market liquidity measures, through the spatial multiplier. Spatial multiplier equals to the inverse of one minus the coefficient estimate on the spatial lagged market liquidity measure, or $1/1-\rho$, since ρ is negative, spatial multiplier is less than 1. And the total effect, or the sum of the direct effect and indirect (spillover) effect, is the product of direct effect and spatial multiplier.[15] Total effect is the true impact of local economic activities on the market liquidity. In our study, the direct effect (and the panel regression estimates) is biased upward relative to the total effect and thus is inaccurate. The total effect of *Change in SCI* is 1.280 (0.456) when -*Ln*(*state Amihud Illiquidity*) (-*Ln*(*state relative spread*)) is used as dependent variable, which is considerably smaller than the corresponding direct effect of 1.588 (0.606), and the panel regression coefficient estimate of 1.619 (0.629).

In order to further examine the relation between state economic activities and state market liquidity, we exclude *Change in NCI* and use state and quarter fixed effects instead. By including state fixed effects, we could examine whether the spatial spillovers are driven by unknown state-level characteristics. However, since regional and national macroeconomic variables do not vary across states, they are excluded after state fixed effects are adopted. Results with state fixed effects for equation (2) are reported in Table 5.

Results in Table 5 largely resemble those reported in Table 4. The coefficient estimates of the spatial lagged market liquidity measure ($W \times [-Ln(Amihud)]$ or $W \times [-Ln(spread)]$) and

[15] Same rationale applies to the other macroeconomic variables.

the *Change in SCI* are statistically significant and economically meaningful. Therefore, our results are not likely to be driven by state-level omitted variables.

In Table 6, we examine the reinforcing relation between market and funding liquidity, or the *Channel Effect*. That is, capital accessibility of local REITs would positively predicts local market liquidity. The empirical framework is expressed as equation (3). We re-estimate Table 4 and 5, but with inclusion of *State Coverage Ratio* as a measure of funding liquidity. Consistent with the *Channel Effect* documented at the national level, we find a positive relation between state-level market and funding liquidity. The coefficient estimates on *State Coverage Ratio* are positive and statistically significant.

However, the usage of changes in state (national) coincident indexes (*Change in SCI*, *Change in NCI*) ignores the specifics of how state-level macroeconomic variables affect state funding liquidity. For instance, whether *Change in SCI* takes effect on future *State coverage ratio* through local labor market conditions, local economic development, or collateral channel is not well understood. Relatedly, one may argue that interpretation of the composite indexes is not as intuitive as individual macroeconomic variables. Admittedly, with limitations imposed on a single index of local economic activities, we couldn't restrict our analysis to the state and national composite indexes. Moreover, since the usage of state fixed effects might conceal valuable information of regional or national economic activities. Therefore, we substitute *Change in SCI* in Table 4 – 6 with state-level macroeconomic variables and regional inflation (*Ln*(*Regional CPI*)). Equation (4) is estimated in Table 7. State and quarter fixed effects are included. The results are reported in Table 7.

According to our theoretical framework, we adopt state macroeconomic variables that are likely to capture different aspects of state-level business cycle, including income growth (*PI growth*), 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*)). We find that local economic development (*GSP growth*), local housing price index growth (*FHFA HPI growth*), and local inflation (*Regional CPI*) significantly predict REITs' market liquidity. Specifically, higher local economic development (*GSP growth*), higher local housing price index growth (*FHFA HPI growth*), and lower local inflation (*Regional CPI*) are associated with higher market liquidity (-*Ln*(*state Amihud Illiquidity*) or -*Ln*(*state relative spread*)) in the next quarter. The effects of local labor market conditions (*Ln*(*state unemployment rate*)) and return to local human capital (*Income growth*) on local market liquidity are statistically insignificant.

Negative spatial spillovers do not seem to be affected by the inclusion of state macroeconomic variables rather than local economic activity index. Coefficient estimate on the spatial lagged market liquidity, or ρ, is -0.366 (-0.462) when -*Ln*(*state Amihud Illiquidity*) (or -*Ln*(*state relative spread*)) is used as the dependent variable. The corresponding spatial multiplier is 0.73 (0.68), which are comparable to those reported in Table 4 – 6 (0.75 to 0.81). 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 returns the similar degree of spatial spillovers as using index measures. However, using individual macroeconomic variables facilitates us to better interpreting the mechanism of how local economic activities affect local funding liquidity. The *Channel Effect* is also robust to the inclusion of individual local

macroeconomic variables (Panel C and D), as we observe a positive and significant relation between *State Coverage Ratio* and market liquidity proxies.

It is likely that our previous results are driven by the spatial dependence of independent variable(s), or the state macroeconomic variables. In order to mitigate this concern, we repeat our analysis in Table 4 – 6 with Spatial Durbin's (SDM) model. We do not include individual macroeconomic variables due to rising concern of multicollinearity bias. Only the coefficient estimate on the spatial lagged market liquidity, or ρ, and the direct effect are reported in this Table 8. State-level macroeconomic variables, such as *State Coverage Ratio* and *Δ SCI* are assumed to have spatial dependence. Quarter fixed effects are included. Overall, our results do not seem to be affected by the spatial dependence of independent variable(s).

Thus far, we find that there is spatial dependence of state market liquidity by using different model specifications, and it is not affected by the spatial dependence of local macroeconomic variables. We interpret this negative spatial spillover effects by examining different subperiods (5-year, 10-year) and the Great Recession. We assume that there is, in general, a declining trend in the absolute value of market liquidity spillover effects across state borders. However, its absolute value is likely to increase when the market experiences a negative liquidity shock, such as the Great Recession during 2008 – 2009.

First, we examine subperiods of different length (5-year, 10-year) over a 20-year period (1994Q1 – 2013Q4). The dependent variable is -*Ln*(*state Amihud Illiquidity*). We didn't observe a declining trend in the coefficient estimate on the spatial lagged market liquidity, or ρ, with 5-year subperiods. When using the 10-year subperiods, we find that the liquidity spillover effect, which is measured by ρ, is smaller in the second subperiod than the first, but is still comparable.

Next, we specifically look at the 6-quarter period that is within the Great Recession defined by NBER website.[16] The dependent variable is -*Ln*(*state Amihud Illiquidity*). Interestingly, the magnitude of the liquidity spillover effect across state borders more than tripled in absolute value during the Great Recession (from -0.246 in Table 6 to -0.838 in Table 10). Based on Wang, Cohen, and Glascock (2017), when market is illiquid, REITs from different states compete more fiercely for scarce capital. And liquidity suppliers might favor REITs with better access to the capital markets than their geographic neighbors, resulting in a competition effect on market liquidity across state borders. Therefore, the negative liquidity spillover effect is likely to be explained by the competition for scarce capital between REITs from different states. The results are reported in Table 10.

Finally, in order to explicitly establish the relation between local economic activities, funding and market liquidity, we conduct a two-stage least squares analysis. Instrumental variables are the change in state coincident index (*Change in SCI*) and *Governor*, a dummy variable that equals to 1 when the state governor is republican, and 0 otherwise. Republican governors are more likely to adopt a tight local fiscal policy, and negatively affect the amount of capital that is available to the local markets.

In the first stage, we regress *State Coverage Ratio* on *Change in SCI* and *Governor*, with inclusion of state and quarter fixed effects. Both panel regression and spatial autoregressive models are estimated, and *Change in SCI* appears to have a significant impact on *State Coverage Ratio*, while *Governor* has no statistically meaningful effect. There is negative and significant spillovers

[16] From Dec, 2007 – Jun, 2009, our period starts from 2008Q1 – 2009Q2.

on *State Coverage Ratio* across neighboring states, indicating overestimation of coefficients when applying panel regression model.

In the second stage, we regress the negative natural logarithm of *State Amihud Illiquidity* on the predicted value of *State Coverage Ratio* from the first stage using SAR model and *Change in SCI*. State and quarter fixed effects are included. We find that, while the coefficient on *Change in SCI* is not significant, the predicted value of *State Coverage Ratio* has a positive and significant impact on the local market liquidity condition. Therefore, local macroeconomic variables affect market liquidity only through funding liquidity.

Overall, our findings are threefold. First, there are negative market liquidity spillovers for REITs across state borders. Second, state macroeconomic variables, especially local economic development (*GSP growth*), local housing price index growth (*FHFA HPI growth*), and local inflation (*Regional CPI*), significantly predict state market liquidity of REITs in the next quarter. Third, the negative market liquidity spillover across state borders is explained by the competition for scarce capital, and is much greater during the Great Recession.

6. Conclusions

We examine the funding liquidity and market liquidity of U.S. equity REITs at the state level. We confirm that a reinforcing relation between both types of liquidity measures exists at the state level (that is, a channel effect), and that they are both affected state macroeconomic factors. We employ a spatial econometric analysis and find robust and significantly negative spillover effects of market liquidity, i.e., market liquidity of neighboring state(s) can affect market liquidity of a specific state. We find similar evidence when we include the funding liquidity measure as an independent variable. We also find that adjusting the parameter estimates on state macroeconomic

factors for the spatial multiplier can dramatically change their estimates of economic magnitude. This underscores the importance of using spatial modeling to avoid potential biased estimates of state macroeconomic effects on liquidity of REITs. Our results indicate that the competition for scarce capital across state borders shapes market liquidity at state level.

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Appendix: Variable Definitions

State-level	
-Ln(State Amihud Illiquidity)	Negative natural logarithm of the value-weighted state portfolio Amihud Illiquidity measure of REITs headquartered in the state, positively associated with the state's market liquidity condition. We compute the average of Amihud Illiquidity measures of all REITs headquartered in one state weighted by their market capitalization of the last quarter to get Amihud Illiquidity for that particular state. The data is obtained from CRSP daily database.
-Ln(State Relative Spread)	Negative natural logarithm of the value-weighted state portfolio relative spread of REITs headquartered in the state, positively associated with the state's market liquidity condition. We compute the average of Relative Spread of all REITs headquartered in one state weighted by their market capitalization of the last quarter to get relative spread of that particular state. The data is obtained from CRSP daily database.
State coverage ratio Expected sign: (+)	Quarterly state interest coverage ratio, which equals to the mean (median) of interest coverage ratios of all REITs 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.
Change in SCI (in percentage) Expected sign: (+)	Quarterly 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 downloaded from Federal Reserve Bank of Philadelphia (FRED).
Ln(state unemployment rate) Expected sign: (–)	Natural logarithm of quarterly state-level unemployment rate (in percentage), which equals to the mean (median) 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).
PI growth (in percentage) Expected sign: (+)	Quarterly state-level personal income growth rate. 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.

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 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 downloaded from Federal Reserve Bank of Philadelphia (FRED).
Other	
State Republican Governor Expected sign: (–)	An indicator variable that equals 1 when the state governor is republican (more likely to have a constrained state fiscal policy) and 0 otherwise.

Figure 1: Liquidity Spirals

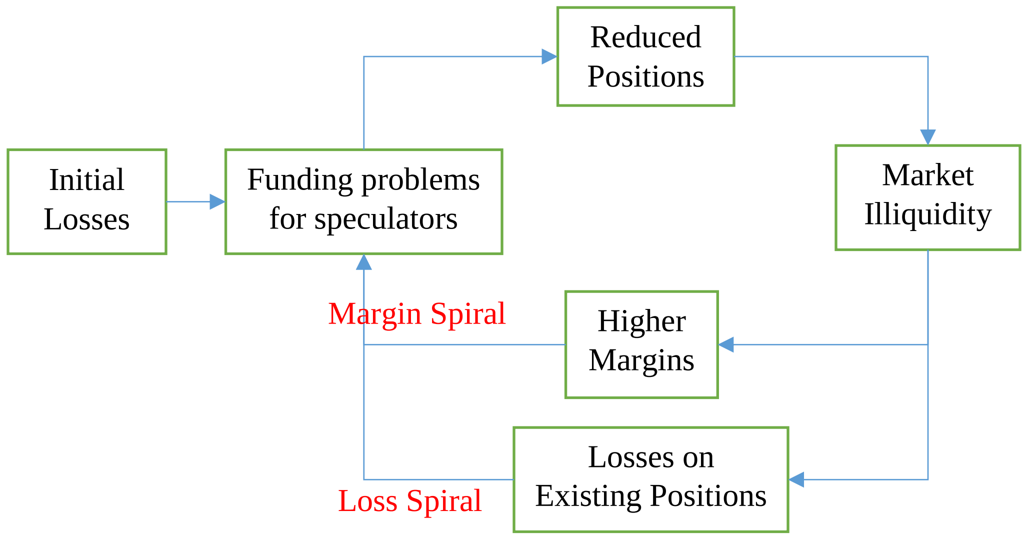

Figure 2: Liquidity Channel Effect

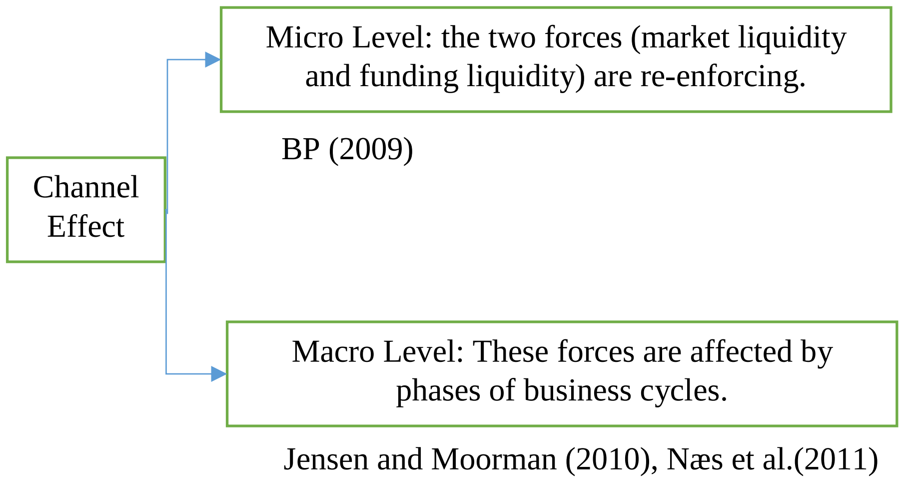

Table 1: States and Centroid coordinates

This table reports the 21 states that host 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. A comprehensive list of U.S. equity REITs defined by NAREIT can be downloaded from S. McKay Price's website. Sample period is from 1994Q1 to 2014Q3. The sample starts from 1994Q1 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 1 REIT in each quarter in order to maintain a balanced panel for spatial analysis. We only require a state to have 1 REIT each quarter 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. We report state name, state abbreviation, latitude, longitude. Latitude and longitude are the geographic coordinates of a state's centroid.

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

Table 2: Summary Statistics

All variables are defined in Appendix. Summary statistics of the variables are reported for equity real estate investment trusts (REITs). A comprehensive list of U.S. equity REITs defined by NAREIT can be downloaded from S. McKay Price's website. Sample period is from 1994Q1 to 2014Q3. We require a particular state to have at least one REIT in each quarter in order to maintain a balanced panel. We report number of observations, mean, median, standard deviation, 25 percentile and 75 percentile in Column 1 to 6, respectively.

Variable	# Obs	Mean	Median	Std. Dev.	25 Pct.	75 Pct.
REITs, 1994Q1 – 2014Q3						
-Ln(state Amihud Illiquidity)	1,764	4.53	4.62	2.38	3.20	6.19
-Ln(state relative spread)	1,764	6.26	6.35	1.55	4.77	7.61
State coverage ratio	1,764	0.70	0.65	0.96	0.30	1.04
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
Ln(state unemployment rate)	1,764	1.73	1.69	0.32	1.50	1.93
FHFA HPI growth (in pct.)	1,764	0.82	0.95	1.78	0.13	1.70
GSP growth (in pct.)	1,764	4.45	4.58	2.65	3.10	6.00
PI growth (in pct.)	1,764	1.13	1.16	1.12	0.65	1.68
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 equity real estate investment trusts (REITs). In the first row, number 1 – 11 represents -Ln(Amihud), -Ln(spread), …, Ln(regional CPI), respectively. * indicates the statistical significance at 1% level.

	1	2	3	4	5	6	7	8	9	10	11
-Ln(Amihud)	1										
-Ln(spread)	0.75*	1									
State coverage ratio	-0.07*	-0.19*	1								
Change in SCI	-0.01	-0.07*	0.17*	1							
Change in NCI	-0.02	-0.06*	0.16*	0.87*	1						
Ln(unemp)	0.21*	0.51*	-0.21*	-0.26*	-0.25*	1					
FHFA HPI growth	-0.02	-0.10*	0.10*	0.38*	0.30*	-0.34*	1				
GSP growth	-0.17*	-0.30*	0.19*	0.71*	0.61*	-0.51*	0.44*	1			
PI growth	-0.07*	-0.13*	0.12*	0.54*	0.49*	-0.29*	0.20*	0.49*	1		
Ln(stmort)	-0.21*	-0.15*	-0.08*	0.02	-0.05	-0.09*	-0.01	0.13*	0.10*	1	
Ln(regional CPI)	0.51*	0.80*	0.25*	-0.26*	-0.28*	0.52*	-0.22*	-0.48*	-0.24*	-0.14*	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 negative natural logarithm of *State Amihud Illiquidity* (Panel A) or *State Relative Spread* (Panel B) at quarter t+1. Independent variables are the Change in State and National Coincident Indexes (*Change in SCI*, *Change in NCI*, both are included in all Panels) at quarter t. All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × [-*Ln*(*Amihud*)] or *W* × [-*Ln*(*spread*)]). *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 – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]		SAR – [-Ln(Amihud)]	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × [-Ln(Amihud)]	– –	–	**-0.251** ***	Multiplier ≈
(t statistics)	– –		**(-3.23)**	0.80
Change in SCI	1.619 ***	– –	1.588 ***	1.280 ***
(t statistics)	(6.75)	– –	(6.65)	(6.02)
Change in NCI	-68.478 ***	– –	-16.177	-12.986
(t statistics)	(-13.8)	– –	(-0.46)	(-0.46)
Number of Obs	1743		1743	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	54%		55%	
State Fixed Effects	No		No	
Quarter Fixed Effects	Yes		Yes	

Panel B – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]		SAR – [-Ln(spread)]	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × [-Ln(spread)]	– –	–	**-0.332** ***	Multiplier ≈
(t statistics)	– –		**(-4.22)**	0.75
Change in SCI	0.629 ***	– –	0.606 ***	0.456 ***
(t statistics)	(6.74)	– –	(6.50)	(6.01)
Change in NCI	-45.850 ***	– –	-181.18 ***	-135.70 ***
(t statistics)	(-23.7)	– –	(-10.4)	(-12.9)
Number of Obs	1743		1743	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	90%		90%	
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 negative natural logarithm of *State Amihud Illiquidity* (Panel A) or *State Relative Spread* (Panel B) at quarter t+1. Independent variables are the Change in State Coincident Indexes (*Change in SCI* is included in all Panels) at quarter t. All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × [-*Ln*(*Amihud*)] or *W* × [-*Ln*(*spread*)]). *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 – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]				SAR – [-Ln(Amihud)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	–		**-0.244**	***	Multiplier ≈	
(t statistics)	–	–			**(-3.14)**		0.80	
Change in SCI	1.631	***	–	–	1.601	***	1.289	***
(t statistics)	(6.80)		–	–	(6.73)		(6.14)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	54%				55%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]				SAR – [-Ln(spread)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(spread)]	–	–	–		**-0.328**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.18)**		0.75	
Change in SCI	0.637	***	–	–	0.613	***	0.461	***
(t statistics)	(6.82)		–	–	(6.61)		(6.10)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	90%				90%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table 6: Channel Effect – 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 negative natural logarithm of *State Amihud Illiquidity* (Panel A, C) or *State Relative Spread* (Panel B, D) at quarter t+1. Independent variables are the Change in State Coincident Indexes (*Change in SCI* is included in all Panels) and *State Coverage Ratio* at quarter t; we include *State Coverage Ratio* to examine the liquidity channel effect documented by Brunnermeier and Pedersen, 2009, and Glascock and Lu-Andrews, 2014). Change in National Coincident Index (*Change in NCI*) is excluded in Panel C and D because of the inclusion of state fixed effects. All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (W × [-*Ln*(*Amihud*)] or W × [-*Ln*(*spread*)]). 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 – Channel Effect – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]				SAR – [-Ln(Amihud)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	_		**-0.246**	***	Multiplier ≈	
(t statistics)	–	–			**(-3.17)**		0.80	
State coverage ratio	0.102	***	–	–	0.096	**	0.077	**
(t statistics)	(2.71)		–	–	(2.56)		(2.52)	
Change in SCI	1.567	***	–	–	1.521	***	1.225	***
(t statistics)	(6.52)		–	–	(6.75)		(6.10)	
Change in NCI	-68.325	***	–	–	-12.522		-9.841	
(t statistics)	(-13.8)		–	–	(-0.36)		(-0.35)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	55%				55%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Panel B – Channel Effect – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]				SAR – [-Ln(spread)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(spread)]	–	–	–		**-0.324**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.13)**		0.76	
State coverage ratio	0.062	***	–	–	0.060	***	0.045	***
(t statistics)	(4.25)		–	–	(4.11)		(3.98)	
Change in SCI	0.597	***	–	–	0.568	***	0.430	***
(t statistics)	(6.42)		–	–	(6.48)		(5.93)	
Change in NCI	-45.758	***	–	–	-178.49	***	-134.60	***
(t statistics)	(-23.8)		–	–	(-10.3)		(-18.8)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	90%				90%			
State Fixed Effects	No				No			
Quarter Fixed Effects	Yes				Yes			

Panel C – Channel Effect – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]				SAR – [-Ln(Amihud)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	–		**-0.239**	***	Multiplier ≈	
(t statistics)	–	–			**(-3.08)**		0.81	
State coverage ratio	0.102	***	–	–	0.095	**	0.078	**
(t statistics)	(2.69)		–	–	(2.55)		(2.52)	
Change in SCI	1.578	***	–	–	1.533	***	1.248	***
(t statistics)	(6.57)		–	–	(6.84)		(6.11)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	55%				55%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel D – Channel Effect – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]				SAR – [-Ln(spread)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(spread)]	–	–	–		**-0.320**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.09)**		0.76	
State coverage ratio	0.062	***	–	–	0.059	***	0.045	***
(t statistics)	(4.20)		–	–	(4.08)		(3.94)	
Change in SCI	0.605	***	–	–	0.575	***	0.438	***
(t statistics)	(6.49)		–	–	(6.60)		(6.04)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	90%				90%			
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 negative natural logarithm of *State Amihud Illiquidity* (Panel A, C) or *State Relative Spread* (Panel B, D) at quarter t+1. Independent variables are the state, regional, and national macroeconomic variables (state, regional, and national macroeconomic variables are included in all Panels) and *State Coverage Ratio* (Panel C, D); we include *State Coverage Ratio* to examine the liquidity channel effect documented by Brunnermeier and Pedersen, 2009, and Glascock and Lu-Andrews, 2014) at quarter t. State macroeconomic variables include *Log(Unemployment rate)*, *Gross State Product Growth*, *State Personal Income Growth*, *Log(State Mortgage Deduction)*, and *State House Price Index Growth*. Regional macroeconomic variable is *Log(Regional CPI)*, which is a proxy for local inflation. All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × [-*Ln*(*Amihud*)] or *W* × [-*Ln*(*spread*)]). *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 – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]				SAR – [-Ln(Amihud)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	–		**-0.372**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.58)**		0.73	
Log(Unemployment rate)	-0.035		–	–	0.030		0.022	
(t statistics)	(-0.12)		–	–	(0.10)		(0.10)	
Gross State Product Growth	0.104	***	–	–	0.099	***	0.073	***
(t statistics)	(4.66)		–	–	(4.78)		(4.39)	
State Personal Income Growth	-0.001		–	–	0.007		0.005	
(t statistics)	(-0.01)		–	–	(0.16)		(0.16)	
Log(State Mortgage Deduction)	0.088		–	–	0.101		0.073	
(t statistics)	(0.71)		–	–	(0.87)		(0.87)	
State House Price Index Growth	0.083	***	–	–	0.083	***	0.060	***
(t statistics)	(2.94)		–	–	(3.16)		(3.08)	
Log(Regional CPI)	-27.347	***	–	–	-30.135	***	-21.936	***
(t statistics)	(-7.52)		–	–	(-8.39)		(-7.68)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	57%				57%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel B – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]				SAR – [-Ln(spread)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	–		**-0.479**	***	Multiplier ≈	
(t statistics)	–	–			**(-5.93)**		0.68	
Log(Unemployment rate)	0.065		–	–	0.038		0.026	
(t statistics)	(0.57)		–	–	(0.34)		(0.34)	
Gross State Product Growth	0.039	***	–	–	0.035	***	0.024	***
(t statistics)	(4.49)		–	–	(4.42)		(4.14)	
State Personal Income Growth	0.009		–	–	0.012		0.008	
(t statistics)	(0.48)		–	–	(0.68)		(0.68)	
Log(State Mortgage Deduction)	-0.012		–	–	-0.009		-0.006	
(t statistics)	(-0.26)		–	–	(-0.20)		(-0.21)	
State House Price Index Growth	0.038	***	–	–	0.038	***	0.025	***
(t statistics)	(3.50)		–	–	(3.76)		(3.63)	
Log(Regional CPI)	-13.752	***	–	–	-15.130	***	-10.146	***
(t statistics)	(-9.82)		–	–	(-10.9)		(-9.80)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	90%				90%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel C – Channel Effect – Negative Ln(state Amihud illiquidity)

Model	GLS – [-Ln(Amihud)]				SAR – [-Ln(Amihud)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(Amihud)]	–	–	_		**-0.369**	***	Multiplier ≈	
(t statistics)	–	–			**(-4.55)**		0.73	
State coverage ratio	0.102	***	–	–	0.102	***	0.074	***
(t statistics)	(2.77)		–	–	(2.77)		(2.73)	
Log(Unemployment rate)	0.031		–	–	0.073		0.053	
(t statistics)	(0.10)		–	–	(0.27)		(0.26)	
Gross State Product Growth	0.101	***	–	–	0.098	***	0.072	***
(t statistics)	(4.50)		–	–	(4.76)		(4.52)	
State Personal Income Growth	-0.001		–	–	-0.002		-0.001	
(t statistics)	(-0.03)		–	–	(-0.03)		(-0.04)	
Log(State Mortgage Deduction)	0.093		–	–	0.107		0.077	
(t statistics)	(0.75)		–	–	(0.92)		(0.92)	
State House Price Index Growth	0.083	***	–	–	0.083	***	0.060	***
(t statistics)	(2.94)		–	–	(3.13)		(3.04)	
Log(Regional CPI)	-27.530	***	–	–	-30.516	***	-22.205	***
(t statistics)	(-7.58)		–	–	(-8.11)		(-8.36)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	57%				57%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Panel D – Channel Effect – Negative Ln(state relative spread)

Model	GLS – [-Ln(spread)]				SAR – [-Ln(spread)]			
Variable	Direct Effect		Total Effect		Direct Effect		Total Effect	
W × [-Ln(spread)]	–	–	–		**-0.472**	***	Multiplier ≈	
(t statistics)	–	–			**(-5.86)**		0.68	
State coverage ratio	0.064	***	–	–	0.063	***	0.043	***
(t statistics)	(4.53)		–	–	(4.50)		(4.35)	
Log(Unemployment rate)	0.106		–	–	0.071		0.048	
(t statistics)	(0.94)		–	–	(0.67)		(0.67)	
Gross State Product Growth	0.036	***	–	–	0.034	***	0.023	***
(t statistics)	(4.23)		–	–	(4.31)		(4.13)	
State Personal Income Growth	0.008		–	–	0.008		0.005	
(t statistics)	(0.41)		–	–	(0.46)		(0.46)	
Log(State Mortgage Deduction)	-0.009		–	–	-0.006		-0.004	
(t statistics)	(-0.20)		–	–	(-0.13)		(-0.13)	
State House Price Index Growth	0.038	***	–	–	0.038	***	0.025	***
(t statistics)	(3.51)		–	–	(3.72)		(3.61)	
Log(Regional CPI)	-13.867	***	–	–	-15.306	***	-10.300	***
(t statistics)	(-9.96)		–	–	(-10.6)		(-10.7)	
Number of Obs	1743				1743			
Spatial Weighting Matrix	No				Inverse-distance matrix			
R Squared	90%				90%			
State Fixed Effects	Yes				Yes			
Quarter Fixed Effects	Yes				Yes			

Table 8 – Spatial Durbin's Model (SDM) – Only Direct Effects Are Reported.

In this table, we report regression results of Spatial Durbin's (SDM) model. The dependent variable is the negative natural logarithm of *State Amihud Illiquidity* or *State Relative Spread* at quarter t+1. Independent variables are the Change in State Coincident Index (*Change in SCI*), Change in National Coincident Index (*Change in NCI*), and *State Coverage Ratio* at quarter t; we include *State Coverage Ratio* to examine the liquidity channel effect documented by Brunnermeier and Pedersen, 2009, and Glascock and Lu-Andrews, 2014). We re-estimate Table 4 – 6, but assuming spatial dependence of state-level variables, i.e., *State Coverage Ratio* (*W × Coverage*), *Δ SCI* (same as *Change in SCI*, *W × Δ SCI*). All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W × Dep. Var.*). *W* is the row-normalized inverse-distance matrix. Only direct effect is reported in this table. Quarter fixed effect is always included. t-statistics are reported beneath the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Dep. Var.	W × Dep. Var.	Coverage	W × Coverage	Δ SCI	W × Δ SCI	Δ NCI	State FE.	R^2
-Ln(Amihud)	-0.247***	–	–	1.460***	-2.450*	-16.691	No	55%
(t-statistics)	(-3.17)	–	–	(6.09)	(-1.83)	(-0.46)	–	–
-Ln(Amihud)	-0.242***	0.083**	-0.139	1.417***	-2.270*	-15.321	No	56%
(t-statistics)	(-3.12)	(2.18)	(-0.83)	(5.91)	(-1.69)	(-0.42)	–	–
-Ln(Amihud)	-0.240***	–	–	1.472***	-2.449*	–	Yes	55%
(t-statistics)	(-3.09)	–	–	(6.18)	(-1.83)	–	–	–
-Ln(Amihud)	-0.235***	0.082**	-0.138	1.430***	-2.269*	–	Yes	56%
(t-statistics)	(-3.03)	(2.18)	(-0.83)	(5.99)	(-1.70)	–	–	–
-Ln(Spread)	-0.325***	–	–	0.563***	-0.774	-178.8***	No	90%
(t-statistics)	(-4.14)	–	–	(6.04)	(-1.48)	(-10.2)	–	–
-Ln(Spread)	-0.318***	0.057***	-0.023	0.536***	-0.696	-178.2***	No	90%
(t-statistics)	(-4.05)	(3.85)	(-0.36)	(5.76)	(-1.33)	(-10.1)	–	–
-Ln(Spread)	-0.322***	–	–	0.570***	-0.763	–	Yes	90%
(t-statistics)	(-4.09)	–	–	(6.15)	(-1.46)	–	–	–
-Ln(Spread)	-0.314***	0.056***	-0.022	0.543***	-0.685	–	Yes	90%
(t-statistics)	(-4.01)	(3.83)	(-0.34)	(5.87)	(-1.32)	–	–	–

Table 9 – Subperiod Analysis

In this table, we report regression results of Spatial Autoregressive (SAR) model for different subperiods. The dependent variable is the negative natural logarithm of *State Amihud Illiquidity* at quarter t+1. Independent variables are the Change in State Coincident Index (*Change in SCI*), Change in National Coincident Index (*Change in NCI*), and *State Coverage Ratio* at quarter t; we include *State Coverage Ratio* to examine the liquidity channel effect documented by Brunnermeier and Pedersen, 2009, and Glascock and Lu-Andrews, 2014). We re-estimate Table 4 for each five or ten-year subperiods over a 20-year period (1994Q1–2013Q4). All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W × Dep. Var.*). *W* is the row-normalized inverse-distance matrix. Direct and total effects are reported in this table. Quarter fixed effect is always included. t-statistics are reported beneath/parallel to the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Dependent Variable: Negative Ln(state Amihud illiquidity)										
Subperiod	W × Dep. Var.	Effect	Coverage	t-statistics	Δ SCI	t-statistics	Δ NCI	t-statistics	State FE.	R^2
5-year subperiods										
1994Q1 –	-0.520***	Direct	–	–	0.736**	1.96	10.962	0.46	No	56%
1998Q4	(-3.33)	Total	–	–	0.487*	1.90	7.116	0.45	–	–
1999Q1 –	-0.333**	Direct	–	–	-0.237	-0.50	5.051	1.58	No	11%
2003Q4	(-1.97)	Total	–	–	-0.180	-0.49	3.811	1.55	–	–
2004Q1 –	-0.496***	Direct	–	–	1.423***	3.62	-2.365*	-1.70	No	24%
2008Q4	(-3.07)	Total	–	–	0.942***	3.29	-1.567	-1.63	–	–
2009Q1 –	-0.386**	Direct	–	–	0.535	1.63	-284.7*	-1.81	No	40%
2013Q4	(-2.29)	Total	–	–	0.393	1.58	-205.0*	-1.81	–	–
1994Q1 –	-0.510***	Direct	0.051**	2.12	0.676*	1.93	15.615	0.66	No	56%
1998Q4	(-3.28)	Total	0.034**	2.07	0.445*	1.85	10.337	0.65	–	–
1999Q1 –	-0.386**	Direct	0.508***	5.02	-0.329	-0.76	5.611*	1.82	No	16%
2003Q4	(-2.26)	Total	0.365***	4.59	-0.237	-0.75	4.004*	1.80	–	–
2004Q1 –	-0.502***	Direct	0.112	1.32	1.354***	3.65	-2.194	-1.61	No	24%
2008Q4	(-3.10)	Total	0.073	1.30	0.894***	3.30	-1.456	-1.55	–	–
2009Q1 –	-0.387**	Direct	-0.090	-1.02	0.531*	1.71	-265.4*	-1.70	No	40%
2013Q4	(-2.29)	Total	-0.066	-1.01	0.387	1.64	-187.8*	-1.72	–	–

10-year subperiods											
1994Q1 –	-0.541***	Direct	–	–	0.936**	2.50	4.966	1.39	No	27%
2003Q4	(-4.25)	Total	–	–	0.606**	2.43	3.188	1.39	–	–
2004Q1 –	-0.486***	Direct	–	–	0.871***	3.37	-299.6*	-1.74	No	35%
2013Q4	(-4.16)	Total	–	–	0.584***	3.25	-199.8*	-1.73	–	–
1994Q1 –	-0.535***	Direct	0.131***	3.35	0.814**	2.32	5.518	1.57	No	28%
2003Q4	(-4.22)	Total	0.084***	3.20	0.526**	2.23	3.549	1.56	–	–
2004Q1 –	-0.487***	Direct	0.179***	2.67	0.807***	3.33	-269.1	1.58	No	36%
2013Q4	(-4.17)	Total	0.119***	2.60	0.539***	3.20	-177.6	1.59	–	–

Table 10 – Financial Crisis – NBER Definition

In this table, we report regression results of Spatial Autoregressive (SAR) model for the most recent recession period (Dec, 2007–Jun, 2009) defined by NBER website. The dependent variable is the negative natural logarithm of *State Amihud Illiquidity* at quarter t+1. Independent variables are the Change in State Coincident Index (*Change in SCI*), Change in National Coincident Index (*Change in NCI*), and *State Coverage Ratio* at quarter t; we include *State Coverage Ratio* to examine the liquidity channel effect documented by Brunnermeier and Pedersen, 2009, and Glascock and Lu-Andrews, 2014). We re-estimate Table 4 for the most recent recession period which lasts for 6 quarters (2008Q1–2009Q2). All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *Dep. Var.*). *W* is the row-normalized inverse-distance matrix. Direct and total effects are reported in this table. Quarter fixed effect is always included. t-statistics are reported beneath/parallel to the coefficient estimates in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Dependent Variable: Negative Ln(state Amihud illiquidity)										
Subperiod	W × Dep. Var.	Effect	Coverage	t-statistics	Δ SCI	t-statistics	Δ NCI	t-statistics	State FE.	R^2
2008Q1 –	-0.838***	Direct	–	–	-0.114	-0.22	4.770*	1.77	No	17%
2009Q2	(-2.89)	Total	–	–	-0.052	-0.18	2.436*	1.84	–	–
2008Q1 –	-0.838***	Direct	-0.011	-0.12	-0.153	-0.31	5.256**	1.98	No	17%
2009Q2	(-2.88)	Total	-0.005	-0.10	-0.076	-0.28	2.729**	2.04	–	–

Table 11: Channel Effect –Two-Stage Least Squares (2SLS) Analysis

In this table, we present the two-stage least squares estimation based on panel regressions and Spatial Autoregressive (SAR) model. The dependent variable is the *Stage Coverage Ratio* in stage 1, and negative natural logarithm of *State Amihud Illiquidity* in stage 2. Independent variables are the Change in State Coincident Indexes (*Change in SCI* is included in all Panels) and *Governor*, a dummy variable that equals to 1 if the state governor is republican, and 0 otherwise. All variables are defined in Appendix. The magnitude of spatial spillover effect (feedback effect) is measured by the coefficient estimates, ρ, of the spatial lagged outcome variable (*W* × *Stage Coverage Ratio* or *W* × [-*Ln*(*spread*)]). *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 – Stage 1

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	0.521 ***	– –	0.572 ***	0.349 **
(t statistics)	(3.32)	– –	(3.74)	(3.63)
Governor	-0.043	– –	-0.031	-0.019
(t statistics)	(-0.92)	– –	(-0.73)	(-0.73)
Number of Obs	1743		1743	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	18%		19%	
State Fixed Effects	Yes		Yes	
Quarter Fixed Effects	Yes		Yes	

Panel B – Stage 2

Model	GLS – [-Ln(Amihud)]		SAR – [-Ln(Amihud)]	
Variable	Direct Effect	Total Effect	Direct Effect	Total Effect
W × [-Ln(Amihud)]	– –	–	**-0.241** ***	Multiplier ≈
(t statistics)	– –		**(-3.11)**	0.81
$\widehat{State\ coverage\ ratio}$	5.029 **	– –	5.016 **	4.076 **
(t statistics)	(2.47)	– –	(2.47)	(2.45)
Change in SCI	-1.297	– –	-1.327	-1.078
(t statistics)	(-1.08)	– –	(-1.10)	(-1.11)
Number of Obs	1743		1743	
Spatial Weighting Matrix	No		Inverse-distance matrix	
R Squared	55%		55%	
State Fixed Effects	Yes		Yes	
Quarter Fixed Effects	Yes		Yes	