There's No Place like Home: Information Asymmetries, Local Asset Concentration, and Portfolio Returns

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Abstract

We provide robust evidence showing local information plays a significant role in local asset concentrations and return outperformance. Using a unique setting with significant cross-market information asymmetries and large sample of individual commercial property holdings, we find property portfolio managers concentrate an economically significant portion of their portfolios in their headquarter location. We further document a significant positive relation between local concentration and portfolio returns in markets where information asymmetry is most severe. Through numerous robustness and loan-level identification tests, we further confirm an information-based channel of asset concentration and return effects that is distinct from risk-based or behavioral explanations.

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1. Introduction

A long-standing puzzle in financial economics is the empirical observation that investors often choose to overweight local firms and investments in their portfolios.[1] In so doing, investors fail to take sufficient advantage of diversification opportunities, which stands in contrast to the predictions of standard portfolio theory (e.g., Sharpe, 1964). Although local bias among investors has been documented extensively across market participants, firms, and geographic markets, important questions still remain: to what extent is the subsequent return performance of a portfolio of assets tied to these geographic allocation/selection decisions and through which primary channel does this differential performance arise?

This paper explores the information-based channel of local asset concentration and its performance effects in a unique investment setting with significant cross-market information asymmetries. We find that greater local asset concentration in a portfolio is associated with higher realized returns. This local concentration effect is not explained by ex-ante, risk-based pricing effects and is concentrated in geographic markets in which information asymmetry between local and non-local market participants is most severe. We further identify the information-based channel by aligning the relative outperformance of locally concentrated portfolios with reduced financing costs at the local investment level.

The existing theoretical literature provides two main explanations for the high level of local investment observed among market participants, both of which are linked to the causal role of geographic proximity. In the first explanation, proximity provides an information advantage to investors due to costly information acquisition. Investors with an information advantage in their home market choose to hold a greater proportion of local assets than the marginal investor in that market due to more informed cash flow forecasts and reduced uncertainty surrounding those forecasts. Although investors can attempt to undo their information disadvantage in distant markets by choosing to learn about non-

[1] For example, evidence of local bias in investment decisions has been documented among individual equity investors (e.g., Ivkovic and Weisbenner, 2005), institutional investors (e.g., Baik, Kang, and Kim, 2010; Choi et al. 2017), bond underwriters (Butler, 2008), managers of mutual funds (e.g., Coval and Moskowitz, 1999, 2001; Hau, 2001; Pool, Stoffman, and Yonker, 2012) hedge fund managers (Teo, 2009), investors in private commercial real estate (CRE) markets (Garmaise and Moskowitz, 2004), and in the origination decisions of lenders (Giannetti and Laeven, 2012). Local bias is also prominently featured in the long-standing international home-bias puzzle in which investors in different countries tilt holdings towards their domestic market (e.g., French and Poterba, 1991).

local markets, investors sacrifice excess returns.[2] As a result, investors with a local information advantage choose not to learn what others already know about more distant markets, but rather specialize in what they already know (Van Niewerburgh and Veldkamp, 2009). This reinforcing effect can create an even larger information wedge between local and non-local investors that leads to sustained information asymmetry and increasing returns to information in local asset markets.

An alternate explanation for why investors choose to invest locally is that geographic proximity creates a familiarity bias. This cognitive bias may also lead to local investment concentrations and under-diversification. However, under this premise, local investment does not necessarily lead to higher expected returns because investors make allocation and selection decisions based on biased, rather than informed, choices (Huberman, 2001; Seasholes and Zhu, 2010; Pool, Stoffman and Yonker, 2012). In equilibrium, portfolio allocation decisions based on familiarity biases or similar cognitive biases should not enhance the portfolio's return performance.[3]

Despite theoretical explanations and empirical evidence of investor and portfolio manager preferences for local investments across asset classes, less is known about the return implications associated with local asset concentrations or the drivers of that performance. The information advantages associated with locally concentrated portfolios can help local portfolio managers earn excess returns through a variety of mechanisms, including lower search costs, greater valuation accuracy (skill)[4], and reduced

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[2] If both local and non-local investors know, for example, that a demand or supply shock has increased the expected cash flows on a non-local asset, both the local and non-local investor will bid up the price of the non-local asset, thereby eliminating any ex-ante excess (risk-adjusted) return.

[3] It is important to note that familiarity bias is distinct from information driven familiarity choices whereby familiarity can result in enhanced information-based choices and outcomes. For instance, Ben-David, Birru, and Rossi (2017) show that insiders with industry familiarity trade firms in their own industry more frequently in their own stock portfolio and earn abnormal returns from doing so. This is consistent with the interpretation that industry familiarity is an advantage in stock picking.

[4] If a local investor has information about the direction of future cash flows—that is not yet fully reflected in market prices—she can buy at market prices before positive news is fully capitalized and/or sell at market prices before negative news is fully reflected. Because the local investor is more certain about payoffs on local assets (e.g., Van Nieuwerburgh and Veldkamp, 2009), she can earn excess (risk-adjusted) returns even when purchasing at market prices. However, as Garcia and Norli (2012) note, information-based models that generate excess information acquisition by market participants may in fact generate more informed prices, which would lower the equilibrium ex-ante equity premium. This alternative implication of information-based models (e.g., Van Nieuwerburgh and Veldkamp, 2009) would actually make information-based outperformance less likely to be observed in realized returns.

financing/transaction costs.[5] However, the existence of a positive relation between local portfolio concentrations and ex-post returns in the cross section is also consistent with the ex-ante pricing of this concentrated risk by stock investors. For example, under Merton's (1987) limited attention hypothesis, stocks with lower investor recognition are expected to offer higher returns to compensate investors for insufficient diversification. To the extent firms with high local asset concentration are also those with lower investor recognition, a positive relation between local asset concentrations and firm returns could be driven, at least in part, by concentrated portfolio risk that is priced ex-ante (Garcia and Norli, 2012).[6] In short, our incomplete understanding of the relation between local asset concentrations and return performance is due, in part, to the challenge of isolating the effects of the investor's information advantage from the impact of systematic risk factors on relative performance.

The typical focus on assets traded in relatively liquid public markets has increased the difficulty of differentiating information-based effects found in the cross-section from alternative risk-based explanations of home bias due to the rapid incorporation of information into transaction prices in these markets. However, in illiquid, highly segmented markets composed of heterogeneous assets, relative information advantages have important implications for equilibrium portfolio allocation decisions and performance outcomes.

These information asymmetries and the value of local information are especially significant in commercial real estate (CRE) markets (e.g., Garmaise and Moskowitz, 2004). Consider, for example, the choice of asset location in CRE investments. The investment decision requires significant due diligence rooted in a deep understanding of a city's

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[5] Reduced financing and transaction costs can occur through both information and reputation-based channels. For example, lenders with a local presence have the ability to discern a local manager's information advantage and incorporate this information into the loan spread, thereby reducing the cost of financing a particular transaction. At the same time, personal relationships and repeat business with local owners, brokers, appraisers, and other service providers can result in an increased deal flow and lower financing/transaction costs. Through a series of local lender identification tests and associated robustness checks, we provide evidence consistent with an information-based channel.

[6] Easley and O'Hara (2004) provide an alternative information-based, ex-ante explanation where investors demand a higher return to hold stocks with greater private information to compensate uninformed investors for their perceived inability to react to new information as quickly as informed local investors. To the extent firms with high local asset concentrations are also those with high levels of private information, a positive ex-post relation between local asset concentration and firm returns could be driven by information asymmetry that is priced ex-ante, not insufficient diversification.

economic base, the linkages and infrastructure available within the urban matrix, the competitiveness of local capital markets, and other sources of competitive advantage embedded within the geographic landscape. Furthermore, market segmentation and frictions in private CRE markets can impede the timely capitalization of demand and supply shocks into asset values, thereby allowing more informed local investors to trade on private information regarding these shocks before they are fully capitalized. Using granular asset level data and observed cross-sectional heterogeneity in local asset market information environments in the CRE market, we provide robust evidence showing local asset concentrations and return outperformance are driven by an information-based channel that is distinct from ex-ante, risk-based or behavioral explanations.

We focus our information-based tests on the performance of commercial property portfolios owned by equity real estate investment trusts (REITs). The property portfolios of equity REITs provide an ideal experimental setting to test the effects of home market concentrations on returns. In particular, the parallel market setting of equity REITs allows us to define two distinct layers of investment: the REIT manager's investment in a portfolio of real assets and the marginal equity investor's investment in the listed REIT's stock. Along the first dimension, we identify whether REIT managers exhibit local bias by allocating a greater proportion of their property portfolio to local assets. Using property level data from SNL's Real Estate Database, we directly observe and measure a firm's home bias by computing the proportion of the property portfolio held in the metropolitan statistical area (MSA) in which the REIT is headquartered. Because the majority of an equity REIT's asset base must be invested in income-generating CRE, this property-level data also enables us to more accurately measure portfolio concentrations than other commonly used approaches in the literature that indirectly infer a firm's geographic exposure.[7] Such indirect proxies can introduce considerable noise into the measurement of local asset concentration, which our direct measure of concentration overcomes.

We find that equity REITs hold, on average, approximately 20 percent of their portfolios in their home market, which constitutes an economically significant portion of their property portfolio. In comparison, the average portfolio concentration for firms not headquartered in that MSA is approximately 1.4 percent. However, home market concentrations range from 0-100% across REITs and are time-varying.

[7] For example, Garcia and Norli (2012) and Bernile et al. (2015) infer a firm's geographic footprint by counting the number of times a U.S. state's name appears in the firm's 10-K.

We next examine the performance effects of the REIT manager's allocation decisions at the property portfolio level using the realized returns of the equity REIT. We begin by characterizing the portfolio's degree of "localness" using our local asset concentration measures. In so doing, we make use of cross-sectional variation in the level of local asset concentration to identify asset pricing and return performance implications of local bias.[8] In particular, we first sort REITs into high, medium, and low home market concentration buckets, and perform calendar-time portfolio regressions to test for performance effects (alpha), controlling for standard asset pricing factors. We also estimate cross-sectional (Fama-MacBeth, 1973) regressions of REIT returns on time-varying local asset concentrations to test for performance effects, controlling for firm level characteristics.[9]

Importantly, we find the average monthly return on an equally-weighted portfolio of high home concentration firms exceeds the return of the low home concentration portfolio by 40 basis points. In our cross-sectional regression analysis, we further document a positive relation between home market concentrations and subsequent firm returns that is both statistically and economically significant. In fact, the predicted annual returns on high home concentration firms are 3.4% higher than those of low home concentration firms, holding fixed other firm characteristics.

Since performance outcomes are observed at the REIT (property portfolio) level, the relative outperformance of local asset concentration strategies can result from either the realized return effects of the manager's local information advantage in the REIT's underlying property investments (i.e., the first layer of investment) or as compensation for concentrated portfolio risk that is priced ex-ante by the marginal investor in the REIT stock (i.e., the second layer of investment).[10] However, due to this distinct separation of

[8] Garcia and Norli (2012) also make use of cross-sectional variation in the degree of firm "localness" to shed light on risk-based asset pricing implications of local bias.

[9] Most prior studies in CRE markets have used price premiums or discounts from observed transaction prices, relative to an estimated market value, to determine the wealth effects of geography (e.g., Agarwal et al., 2017; Kurlat and Strobel, 2015; Chinco and Mayer, 2016). Because true market value is not observable, inferences about the wealth effects of geography are potentially subject to significant measurement error. Our focus on the total returns earned by the marginal investor in the REIT's stock helps reduce this potential measurement error issue in our analysis.

[10] While prior mutual fund research (e.g., Coval and Moskowitz, 2001) has also made use of a portfolio setting to examine the implications of home bias in asset allocation decisions, additional complexities arise when examining the source of locally concentrated fund outperformance. For example, investors in the mutual fund are not pricing the fund and therefore cannot theoretically demand a risk premium for investing in the fund even if the fund holds local assets. In contrast, the REIT portfolio's performance is determined by both the manager's property portfolio decisions and

ownership inherent in the REIT structure, we are able to exploit cross-sectional heterogeneity in information asymmetry across geographic markets at the property investment level to identify the information-based channel of relative outperformance. This unique feature of equity REITs allows us to better isolate performance effects that result from the portfolio manager's local information advantage from the ex-ante pricing of systematic risk by the investor in the REIT stock. [11]

We utilize three distinct classification systems to identify differences in information environments across MSA locations: the percentage of total property value in the MSA that represent land (e.g., Kurlat, 2016, Kurlat and Stroebel, 2014), the percentage of foreign and other non-local buyers (e.g., Bae, Stulz and Tan, 2008), and the extent to which buyers or sellers employ brokers in transactions (e.g, Levitt and Syverson, 2008).[12] We expect geographic markets with high average land shares, low foreign investment, and low broker usage to have greater information asymmetry. We then re-estimate our portfolio and cross-sectional regressions conditioning on the degree of asymmetric information in the REIT's home market to identify whether the positive association between local asset concentration and returns is most prominent in markets where information asymmetries are more severe.

Conditioning on the degree of asymmetric information in the REIT's home market, we document significant outperformance among high home concentration firms in markets characterized by high information asymmetry. In contrast, high home concentrations in low information asymmetry markets are not associated with superior returns relative to low home concentrations. These results are consistent with increasing returns to information generated by the local investor's relative information advantage in markets where the information wedge between local and non-local participants is most pronounced.

However, if these high information asymmetry markets are perceived to be riskier ex-ante, their greater realized returns may represent compensation to investors for a

the expectations of the marginal investor in the REIT stock. Furthermore, the underlying assets of the mutual fund portfolio have disperse ownership, which can also independently influence the price at which the mutual fund manager purchases and sells the underlying asset. In contrast, each underlying asset in a REIT portfolio is a unique property, often with a single owner.

[11] Several institutional characteristics of equity REITs, such as the 90 percent dividend distribution requirement, high levels of institutional ownership, and the ongoing certification and monitoring that accompanies their frequent capital market access, also serve to reduce the relative influence of agency costs on performance, thereby providing a cleaner link between the information-based channel of investment selection and return performance.

[12] In a recent study focused on home bias in international stock portfolios, Choi et al. (2017) utilize a similar conditional framework based on the degree of home market information uncertainty to identify information-based performance effects associated with portfolio concentration.

manager's willingness to bear additional risk (e.g., Garcia and Norli, 2012; Easley and O'Hara, 2002). To address this potential alternative explanation, we construct further tests that examine the relation between a REIT's portfolio concentrations in markets with greater information asymmetries and returns, independent of the REIT's home market asset concentration. We find no support for this alternative risk-based explanation.

Concentrated portfolio exposure to other geographic risk factors may also produce results consistent with our findings. For example, our information-based return effects may also be correlated with land supply constraints (e.g., Saiz, 2010) and local government regulations associated with certain geographic locations. Furthermore, the variation in state laws that govern the foreclosure process can differentially impact property values due to increased costs and greater uncertainty.[13] However, our measure of home concentration remains positive and highly significant, even when controlling for local supply elasticity and legal risk effects.

Finally, to further sharpen and confirm our identification of the information-based return channel, we perform two additional tests incorporating loan-level data from Thomson-Reuters LPC Dealscan. First, we conduct a difference-in-difference analysis of loan spreads quoted by local and non-local lenders on firms with high versus low home concentrations. With a risk-based explanation that ignores the information advantage of the local borrower, high asset concentrations should lead to higher average loan spreads due to the greater perceived risk to the lender associated with a concentrated portfolio. However, if local lenders can discern whether high local asset concentrations are the result of the manager's superior local information, incorporating this information into their assessment should put downward pressure on quoted loan spreads. In other words, there is an information asymmetry component that may be priced by the local lender, but not by the non-local bank. This test further identifies the mechanism through which the information advantage of local portfolio concentrations impacts performance. Our difference-in-difference analysis provides evidence that local lenders price the information advantage by offering lower spreads to local firms with high home concentrations. We extend this framework by implementing a two staged least squares (2SLS) instrumental variable (IV) approach, in which the use of a local lender instruments for a firm's level of home market

[13] For example, judicial foreclosure states impose significant time and financial constraints on lenders seeking to foreclose on a delinquent borrower.

concentration, and continue to find a positive relation between local asset concentration and firm returns.

Our paper makes several key contributions to the literature. First, we contribute to the literature on home bias explanations and their performance consequences. We document that in markets with high information asymmetry, geographic proximity influences local investment concentrations and return performance. Our findings provide empirical support for Van Niewerburgh and Velldkamp's (2009) theoretical framework hypothesizing endogenous information acquisition and local bias. Consistent with their theoretical notions of information-based asset concentration and return effects, we provide novel and robust evidence showing local information asymmetries play a significant role in asset concentration and corresponding return outperformance. Our results extend the prior literature on the relevance of geographic proximity to the cost of acquiring information, which in turn influences the behavior of investors and the pricing of assets.[14] Our results also provide a unique contrast and extension to Garcia and Norli's (2012) findings by examining the performance effects of local asset concentrations in markets characterized with greater information asymmetry. We also provide additional evidence that aligns the relative outperformance of locally concentrated portfolios with reduced financing costs at the local investment level. This result further extends recent work on information advantages associated with portfolio concentration (e.g., Choi et al., 2017) by showing an important mechanism through which information advantages impact returns.

Second, we contribute to the literature on measures of asset concentration. We employ a more accurate measure of local asset concentration using time-varying property-level asset holdings and compare the characteristics and performance of this measure to the state count measure used in the literature (Garcia and Norli, 2012). We show that a state count measure of asset concentration tends to roughly capture the true concentration of a REIT's property portfolio only at the extremes–both highly concentrated and highly dispersed asset holdings. This measurement error can mask important cross-sectional variation in the degree of concentration of a firm's asset portfolio and its return effects.

[14] For example, studies show the effects of distance manifest themselves through higher search costs related to information acquisition problems in home bias and investment performance (Coval and Moskowitz, 1999, 2001; Ivkovic and Weisbenner, 2005; Kedia, Panchapagesan and Uysal, 2008; Teo, 2009), equity analysis (Malloy, 2005; Bae, Stulz, and Tan, 2008), bond underwriting (Butler, 2008), institutional ownership and equity performance (Baik, Kang, and Kim, 2010), regulatory enforcement (Kedia and Rajgopal 2011), dividend payments (John, Knyazeva, and Knyazeva, 2011), and board of director decisions (Alam, Chen, Ciccotello, and Ryan, 2013), among others.

Third, we contribute to the literature on information in bank loan decisions, emphasizing the effects of local information asymmetry and borrower proximity.[15] Physical proximity lowers the cost of acquiring information because lenders can more easily collect private (soft) information about local borrowers and are better informed about local markets and economic conditions (Petersen and Rajan, 1994, 2002; Presbitero, Udell, and Zazzaro, 2014).[16] Consistent with this strategic information acquisition view, we provide evidence that local banks offer better loan pricing terms to local investors in markets characterized by heightened information asymmetry.

Finally, we contribute to the financial integration literature by showing that local asset linkages can help firms overcome endogenous boundaries to obtain better loan access and terms. We find that banks with a local presence are able to pierce informational asymmetries concerning local real estate assets and better screen borrowers based on their relative informational advantage, thereby distinguishing between information-based and transactional lending. Taken together, our results provide novel empirical evidence supporting information-based explanations of asset concentration and their return effects that are distinct from risk-based or behavioral explanations of local bias.

The remainder of the paper proceeds as follows. Section 2 describes our data and discusses our construction of firm-level, time-varying geographic concentration measures. Section 3 presents results from our portfolio sort approach and Fama-MacBeth cross-sectional regressions of the effects of home market concentrations on returns, as well as our series of robustness checks. We provide concluding remarks in the final section.

2. Data and Variable Construction

We focus our analysis on the local asset concentrations of equity REITs. With the availability of granular property holding data, we are able to measure a firm's local asset

[15] The special role of financial intermediaries in the production of information has long been recognized. Prior research highlights how bank loans often have a large private information component, where lenders use a combination of "soft" and "hard" information when granting and pricing credit (Berger and Udell, 1995; Houston and James, 1996; Dennis and Mullineaux, 2000; Berger, Dai, Ongena and Smith, 2003; Mian, 2006; and Carey and Nini, 2007).

[16] Recent theoretical work highlights the role of distance in bank lending. Almazan's (2002) model shows a bank's monitoring expertise is a decreasing function of the distance between borrower and bank, whereas Hauswald and Marquez (2006) examine strategic information acquisition in credit markets when a bank's ability to gather information varies with its distance to the borrower -- showing the existence of location-based cost advantages in bank lending. Agarwal and Hauswald (2010) also show that distance erodes a lender's ability to collect proprietary (soft) intelligence.

exposure by computing the proportion of the property portfolio held within a particular MSA. We collect the following data from SNL's Real Estate Database on an annual basis for each property held by a listed equity REIT during the period 1996 to 2013: property owner (institution name), property type, geographic location, acquisition date, sold date, book value, initial cost, and historic cost. Our analysis begins in 1996 (end of 1995) because this is the first period for which SNL provides historic cost and book value information at the property level. We focus our analysis on properties held by core REITs; that is, REITs classified by CRSP-Ziman as focusing on apartment, office, industrial, or retail properties.[17] We define a firm's home market as the MSA in which the firm is headquartered. Our property dataset includes 291,849 property-year observations over our 1996-2013 sample. As of the beginning of 2013, core REITs owned 15,510 properties with a reported book value of $242 billion, of which 1,109 properties ($39.4 billion book value) were owned in their home market. This represents approximately 16 percent of the book value of core properties in the SNL property dataset.

Our sample consists of 104 equity REITs headquartered in 34 unique MSAs with representation across all regions of the U.S.[18] Panel A of Figure 1 displays the distribution of firms by headquarter location. Although we observe greater concentrations of firms headquartered in large metropolitan markets such as Boston, Chicago, Los Angeles, New York, San Francisco and Washington, D.C., there are a number of firms headquartered in smaller markets such as Baltimore, Denver, Houston, and Orlando. The geographic dispersion of headquarter locations across regions also allows us to isolate the home market effect from a purely regional or individual market effect.

[17] Our focus on core property types is predicated on the availability of cross-sectional variation in the level of home concentration amongst equity REITs within a particular property type. In our Section 3 analysis of the relation between home market concentrations and returns, we sort our equity REIT sample, by property type, into firms with high, medium, and low home concentrations. Small sample sizes amongst non-core REITs (e.g., Self-Storage, Timber, Infrastructure, Data Center, and Specialty) preclude the effective sorting of REITs into three home concentration terciles. For example, as of October 31, 2017, FTSE NAREIT identified only six self-storage REITs, four timber REITs, four infrastructure REITs, five data center REITs, and eleven "specialty" REITs.

[18] Specific headquarter locations include Atlanta (GA), Baltimore (MD), Bethesda (MD), Boston (MA), Bridgeport (CT), Chicago (IL), Cleveland (OH), Charlotte (NC), Dallas (TX), Denver (CO), Detroit (MI), Edison (NJ), Fort Worth (TX), Greensboro (NC), Houston (TX), Indianapolis (IN), Jackson (MS), Jacksonville (FL), Kansas City (MO), Los Angeles (CA), Lake County (IL), Memphis (TN), Miami (FL), Minneapolis (MN), New York (NY), Omaha (NE), Orlando (FL), Philadelphia (PA), Raleigh (NC), Rochester (NY), San Diego (CA), San Francisco (CA), Saint Louis (MO), and Washington, D.C.

2.1. Local Asset Concentrations

We construct yearly time-varying measures of geographic concentrations in a firm's headquarter location to measure local asset concentrations. We first sort each core REIT's properties by MSA and identify those properties owned in the firm's headquarter location. We then compute the percentage of firm *f*'s portfolio held in its home MSA *m* at the beginning of year *T* as follows:

$$HOME\_CONC_{f,m,T} = \frac{\sum_{i=1}^{N_{m,T}}(ADJCOST_{i,m,T})}{\sum_{m=1}^{N_T}\left(\sum_{i=1}^{N_{m,T}}(ADJCOST_{i,m,T})\right)} \quad , \qquad (1)$$

where $ADJCOST_{i,m,T}$ is the "adjusted cost" of property *i* in Metropolitan Statistical Area *m* at the beginning of year *T*. *ADJCOST* is defined by SNL as the maximum of (1) the reported book value, (2) the initial cost of the property, and (3) the historic cost of the property including capital expenditures and tax depreciation.[19] The total number of properties held by firm *f* in a particular MSA at the beginning of year *T* is denoted as $N_{m,T}$. The total number of MSAs in which the firm invested in year *T* is denoted as N_T.

2.2. Other Geographic Asset Concentration Measures

We utilize a similar methodology to construct two additional single market concentration measures for comparison to our local asset concentration variable. *SINGLE_CONC* is defined as the largest percentage of a firm's total property portfolio located in a specific MSA, which may include its home market, within a particular year. *SINGLE_CONC_NON_HOME*, is defined as the largest percentage of a firm's property portfolio located in a market outside of the firm's headquarter location within a particular year. These two concentration measures capture the effect of single market asset concentration on asset returns, without isolating home market exposure, and are designed to help disentangle information asymmetry explanations of return differences from risk-based explanations.

We also construct two broader geographic portfolio concentration measures for comparison to our local asset concentration variable. In particular, we construct Herfindahl indices as follows:

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[19] SNL's initial cost variable (SNL Key Field: 221778) is defined as the historic cost currently reported on the financial statements, which may be different than the cost reported at time of purchase. SNL's historic cost variable (SNL Key Field: 221782) is defined as the book value of the property before depreciation.

$$Herfindahl\ Index\ (HI_t) = \sum_{m=1}^{M} P_{m,t}^2 , \quad (2)$$

where $P_{m,t}$ is the proportion of a firm's assets located in MSA *m* as of the beginning of year *t*. *PORTFOLIO_HERF*, is the Herfindahl Index of a firm's geographic portfolio concentration, including investments in their headquarter market, within a particular year. *NON_HOME_HERF, is* the Herfindahl Index of a firm's geographic portfolio concentration, excluding investments in its headquarter market. These broader portfolio measures are also designed to help distinguish the risk-based return effects of overall portfolio concentration from the effects associated with the information advantages of home market concentrations.

2.3. Summary Statistics of Geographic Asset Concentrations

Panel A of Table 1 presents descriptive statistics for our firm-level concentration measures. On average, firms hold 20.3% of their property portfolio in their home market, with a range of 0.0 percent to 100.0 percent. We also observe significant cross-sectional and time series variation in firm-level exposures to their home market. To demonstrate cross-sectional differences across headquarter locations, we plot average home market concentrations by MSA in Panel B of Figure 1. For comparison, we also plot the average portfolio concentration in each MSA for firms not headquartered in that MSA (i.e., outsiders). Firms hold significantly greater portions of their portfolios in their local market than outsiders. Los Angeles is the extreme case. Seven firms are headquartered in Los Angeles. These firms hold, on average, 68.5 percent of their portfolio in L.A. In contrast, firms headquartered outside of L.A. hold just 3.4 percent of their portfolios in L.A.

Figure 2 displays the time series distribution of average local asset concentrations from 1996 to 2013. Average home market concentrations vary over time, ranging from 18.1 percent in 2002 to 24.0 percent in 1997. Inspection of Table 1 reveals that, on average, REITs hold 32.7 percent of their portfolios in a single MSA, which could include their home market. The largest concentration in non-home markets averages 21.1 percent.

2.4. Comparison of Geographic Concentration and State Count Measures

In prior work focusing on local asset concentration, Garcia and Norli (2012) and Bernile et al. (2015) utilize a text-based approach to infer a firm's geographic footprint by counting the number of times a U.S. state's name appears in the firm's 10-K. While state count measures are simple to construct, states could be mentioned in a 10-K for many reasons unrelated to the geography of a firm's assets and business interests. In our context, such measures may be inadequate proxies for cross-sectional variation in the degree of asset concentration. Furthermore, firms that do own and operate assets in a number of states may still hold a significant portion of their portfolio in their local market. In this case, firms with large home market concentrations may be misclassified as non-local if they also hold relatively small concentrations in a number of locations outside of their headquarter market. Thus, state count measures have the potential to introduce considerable noise into the measurement of local asset concentration, which can lead to biased inferences.

To better understand how our local asset concentration measure compares to those used in the prior literature, we construct a state count variable in the spirit of Garcia and Norli (2012). In particular, we count the number of individual states in which an equity REIT owns property within a particular year.[20] The correlation between our home market concentration and state count measure is -0.41 over our sample period. This negative correlation is consistent with the generalization that portfolios with high local asset concentrations are less likely to hold additional assets across a wide variety of states.

Figure 3 plots the distribution of average home market concentrations by state count category. It is best to interpret this comparison in the context of Garcia and Norli's (2012) classification of local firms. The authors identify firms that do business in 3 or less states (20^{th} percentile) as "local" and those that do business in greater than 11 states (80^{th} percentile) as "geographically dispersed."[21] REITs that own and operate properties within 3 states or less (20^{th} percentile) have average home market concentrations that range from 30 to nearly 60 percent of their total asset value. In contrast, REITs with a state count in the 80^{th} percentile (those with state counts greater than or equal to 19 in our sample), hold approximately 4 percent of their assets in their home market. Thus, on average, the state

[20] Note that this state count measure refines the text-based approach by reducing noise associated with states mentioned in the 10K that are unrelated to a firm's asset holdings. Given that an equity REIT often reports property holdings in their annual financial statements, this measure should be positively correlated with a pure text-based state count measure.

[21] As an additional robustness check, we replace home market concentration in our cross-sectional tests with a state count dummy variable equal to one if state count is less than or equal to three and zero otherwise, and still obtain a positive and statistically significant, albeit weaker, relation between local asset concentration and return performance. The complete set of results are reported in the Internet Appendix (Table IA.1)

count measure tends to roughly capture the true concentration of a REIT's property portfolio at the two extremes. However, the correlations between our two measures within these tails of the distribution are only moderate. For example, the correlation between home market concentration and state count is only -0.16, for firms with state count classifications in the 20th percentile. This implies that low state counts can very well be associated with high asset concentrations in non-local markets.

What we observe between these extremes also highlights the inherent limitation of inferring true geographic asset concentration from a state count measure. For example, REITs with property exposure in 15 states have on average an economically significant 20 percent of their portfolio concentrated in their home market. Furthermore, at least one firm in this state count group has as much as 66 percent of its property portfolio concentrated in its headquarter market. Thus, the use of a state count classification strategy would appear to mask important cross-sectional and within state count variation in the degree of local concentration of a firm's asset portfolio and its return effects. In contrast, our measure captures the true proportion of asset holdings in the firm's headquarter market, thereby providing a more accurate depiction of the portfolio's local asset concentration.

3. Geographic Concentration and Returns

To investigate how stock returns are related to the degree of geographic concentration, we construct three equal-weighted portfolios based on the degree of asset concentration for each of our geographic concentration measures. We first obtain monthly firm-level return data from the CRSP-ZIMAN database for our full sample period. Next we sort firms by property type specialization into home market concentration terciles (low, medium and high) as of the beginning of each year. We then calculate monthly equal-weighted returns for each concentration portfolio, rebalancing portfolio constituents at the beginning of each year. Panel B of Table 1 displays average returns for each portfolio.

If local asset concentrations reflect the information advantage managers enjoy in their home market, we would expect higher returns on portfolios with high concentrations relative to those with low concentrations. In other words, portfolio managers with an information advantage are able to profit by trading on "partially unpriced neighborhood characteristics" (Kurlat and Stroebel, 2015). Firms with low home market concentrations experience an average monthly return of 0.92%. Firms with high home market concentrations experience an average monthly return of 1.35%. The 43 basis point monthly (5.2 percent annually) return difference is economically large and highly significant.

An alternate explanation for this positive return spread is that portfolios with greater home market concentrations are riskier and therefore must provide investors higher expected returns. Thus, a risk-based explanation for the return differential would require a positive spread between high and low home market concentrations regardless of whether the concentration is in the portfolio manager's local market. However, examination of our other asset concentration measures does not reveal a significant return difference across high and low concentration portfolios. Thus, geographic concentration, per se, is not associated with higher returns.

3.1. Calendar Time Portfolio Regression Results

Although our univariate return comparisons are consistent with our information-based hypothesis, it is possible that the documented relation between home market concentration and firm returns is compensation for exposure to other common risk factors. We therefore estimate the following calendar-time portfolio regression model to take this concern into account:

$$r_{p,t} - r_{f,t} = \alpha_P + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 PS\_LIQ_t + \beta_6 RE_t + \varepsilon_t . \quad (3)$$

$r_{p,t}$ is the equal-weighted monthly return on a given concentration portfolio and $r_{f,t}$ is the corresponding risk-free rate as measured by the yield on the 1-month Treasury bill. The explanatory variables include the following standard asset pricing controls: the market portfolio proxy, *MKT*; the size factor, *SMB*; the book-to-market factor, *HML*; momentum, *MOM*; (e.g., Fama and French 1996; Liew and Vassalou, 2000; Lettau and Ludvigson, 2001; Jegadeesh and Titman, 1993; Carhart, 1997) and the traded liquidity factor of Pastor and Stambaugh (2003), *PS_LIQ*.[22] To control for broader real estate market exposure, we also

[22] See Ken French's website: (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html). *MKT* is the value-weighted return in excess of the US Treasury. *SMB* ("small minus big") is designed to measure the additional return investors earned in a particular month by investing in companies with relatively small market capitalizations. This "size premium" is computed as the average return for the smallest 30 percent of stocks minus the average return of the largest 30 percent of stocks in that month. *HML* (high minus low) is designed to measure the "value premium" obtained by investing in companies with high book-to-market values. *HML* is computed as the average return for the 50 percent of stocks with the highest B/M ratio minus the average return of the 50 percent of

include a real estate risk factor (*RE*), defined as the return on the FTSE NAREIT equity REIT index orthogonalized with respect to the stock market portfolio.[23]

Table 2 reports factor loadings and Jensen's alphas for equally-weighted portfolios formed using our previously defined terciles of home market concentration. Focusing on the first row of the table, the portfolio of firms with high local asset concentration produce an economically large and statistically significant Jensen's alpha of 0.40 percent monthly (p-value=0.007). Thus, even when controlling for other common risk factors, firms with high home concentrations earn positive abnormal returns. For the low home concentration portfolio, we estimate an alpha that is statistically indistinguishable from zero. Both high and low home concentration portfolios exhibit strong sensitivities to *MKT*, *SMB*, *HML*, *MOM*, and *RE* factors, while their liquidity factor exposure is insignificant.

We also calculate the difference in monthly returns between our high and low local asset concentration portfolios. We then regress this series of monthly return differences on the six risk factors as follows:

$$\begin{aligned} R_{HIGH,t} - R_{LOW,t} = {} & (\alpha_{HIGH} - \alpha_{LOW}) + (\beta_{1HIGH} - \beta_{1LOW})MKT_t + (\beta_{2HIGH} - \beta_{2LOW})SMB_t \\ & + (\beta_{3HIGH} - \beta_{3LOW})HML_t + (\beta_{4HIGH} - \beta_{4LOW})MOM_t \\ & + (\beta_{5HIGH} - \beta_{5LOW})PSLIQ_t + (\beta_{6HIGH} - \beta_{6LOW})RE_t + \varepsilon_{p,t}\ . \end{aligned} \tag{4}$$

The results in Table 2 confirm an economically and statistically significant (p-value=0.009) difference in alphas between the high and low local asset concentration portfolios. The positive difference in alphas is consistent with managers generating long-run value for shareholders by taking advantage of local information advantages in their asset allocation decisions.

3.2. Cross-Sectional Regression Results

As an alternative to our univariate and portfolio-based analyses, we utilize cross-sectional regressions similar to Fama MacBeth (1973) to examine the extent to which local asset concentrations explain the cross-sectional variation in returns. In particular, for each year of our sample period we estimate the following cross-sectional regression:

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stocks with the lowest B/M ratio each month. *MOM* is the average return on high prior return portfolios minus the average return on low prior return portfolios.

[23] The FTSE NAREIT Equity Index is a market capitalization weighted index measuring returns on equity REITs that meet minimum size and liquidity criteria and are listed on the NYSE/Amex or Nasdaq.

$$RET_{i,t} = c_0 + \sum_{m=1}^{M} c_{i,m} Z_{m,i,t} + \varepsilon_{i,t} \quad , \tag{5}$$

where $RET_{i,t}$ is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. $Z_{m,i,t}$ is a vector of M firm characteristics that includes: the natural log of *SIZE,* defined as the firm's aggregate market capitalization; *M/B*, defined as the market value of assets divided by the book value of assets; *MOMENTUM*, defined as the firm's cumulative return over the prior calendar year; *VOLATILITY*, defined as the standard deviation of the firm's daily returns over the prior calendar year; *ILLIQ* , defined as the natural logarithm of the stock's Amihud (2002) illiquidity measure; and *LEV*, defined as total debt divided by the book value of total assets. These firm characteristics are measured at the end of the year prior to which returns are measured. We also include property-type fixed effects in our regression estimation. Annual excess returns averaged 12.9 percent with a standard deviation of 26.5 percent.[24]

Table 3 presents the time series averages and associated p-values of the 18 annual cross sectional regression coefficients obtained from estimating equation (5).[25] Focusing first on the results presented in column (1), we document a strong positive relation between the level of a firm's local asset concentration and subsequent annual returns. The average coefficient estimate on *HOME_CONC* is 0.067 and is highly significant at the 1 percent level (p-value=0.001).[26] To compare the economic magnitude of this estimate with the findings from our portfolio sort approach, we multiply the coefficient estimate of 0.067 by

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[24] Summary statistics for our set of firm characteristics are provided in Table A1 in the appendix.

[25] For presentation brevity, we only report coefficients on our asset concentration measures. Please see the Internet Appendix (Table IA.2) for additional details.

[26] It is important to note that our estimated outperformance result is attenuated in cases where non-local properties are obtained through firm merger and acquisition activity. For example, consider a firm that is currently headquartered in New York, NY and acquires a firm headquartered in Chicago, IL that has a high level of geographic exposure to its home market. This acquisition has the potential to create an information advantage in Chicago for the New York based acquirer through the associated acquisition of managerial expertise in the non-local market. However, our home market concentration measure only captures the firm's exposure to New York. Thus, the return effect of the firm's local information advantage is identified with noise for the acquiring firm. Using the CRSP database, we identify 54 acquisitions of publicly listed real estate companies by 33 unique REITs in our dataset. As an additional robustness check, we eliminate all firm-year observations pertaining to firms involved in M&A activity and then re-estimate our Fama-MacBeth regressions on the remaining subset of firms. We observe a larger positive effect of home market concentration on returns (the average coefficient estimate on *HOME_CONC* is 0.083) that remains significant at the 1 percent level. It is also important to note that we identified only 6 acquisitions of listed REITs that were headquartered in a different MSA location than the acquiring REIT and only 3 cases in which firms established a new headquarter location post-acquisition. Overall, we find that our results are robust to the impact of M&A or headquarter change activity.

the average home concentration of the high home concentration portfolio (0.515) and the low home concentration portfolio (0.004), respectively, and compute the difference. The predicted returns on high home concentration firms are 3.4% higher than those of low home concentration firms, holding fixed other firm characteristics. This is similar in magnitude to the univariate comparisons of Table 1, even after controlling for the influence of firm characteristics on the cross-section of returns. These results are consistent with managers utilizing their local information advantage to generate positive returns by concentrating their asset portfolios in their home market.[27]

The next 4 columns of Table 3 repeat the above analysis, but replace our local asset concentration measure with alternate geographic concentration measures. If asset concentration by MSA is associated with higher returns because of portfolio concentration risk exposure, we would expect these alternate concentration measures to also be positive and significantly related to returns. However, their collective insignificance further supports the hypothesis that it is the information advantage associated with local concentrations that leads to higher returns, not compensation for concentrated portfolio risk. Interestingly, the average coefficient on *SINGLE_CONC_NON_HOME* is negative and significant at the 1 percent level. This indicates that an increase in asset concentration in the firm's largest market outside of the REIT's local MSA is associated with significantly lower returns in the cross-section.

As an additional test, we augment each of the previous specifications reported in columns (2)-(5) by including the *HOME_CONC* variable. As reported in columns (6)-(9) of Table 3, we consistently observe a significant positive relation between local MSA concentrations and subsequent returns, even after controlling for other firm characteristics and asset concentrations in other geographic markets.

3.3. Further Tests of Home Concentration, Returns, and Information Asymmetries

If the information advantage enjoyed by local investors influences asset allocation decisions and enables portfolio managers to earn greater returns as a result, we would expect this effect to be most prevalent in geographic markets in which information asymmetries are more pronounced (e.g., Garmaise and Moskowitz, 2004). Thus, we design

[27] To mitigate concerns related to sample selection bias amongst firms who hold high local market concentrations, we estimate a Heckman (1979)-two stage estimation that includes the inverse mills lambda in the second stage regression and find similar results.

three empirical tests in which we condition our analysis on the information environment of the headquarter MSA.

Our first measure of information asymmetries draws upon the theoretical model of Kurlat (2016). In this framework, the informed agent (local investor) has better information regarding difficult to value asset characteristics such as the value of neighborhood or location attributes. Furthermore, the effect of this information advantage will be stronger for assets whose values are more dependent on neighborhood, versus structure, characteristics. Using data on residential real estate markets, Kurlat and Stroebel (2014) find that this information advantage is most prominent in markets in which the value of a property is more dependent on the value of land relative to the structure.[28]

Using SNL data, we decompose the initial cost of each commercial property in our database into a land (location) and structural component. We then calculate the percentage of total property value attributable to the land for each property in each year. Next, for each property type focus and MSA, we calculate a value-weighted average across all properties in each year. More formally we define *Land Share* as follows:

$$Land\ Share_{m,T} = \frac{\sum_{i=1}^{N_{m,T}}(LAND\_COST_{i,m,T})}{\sum_{i=1}^{N_{m,T}}(ADJCOST_{i,m,T})} \quad , \tag{6}$$

where $LAND\_COST_{i,m,T}$ is the "initial cost" of land for property i in Metropolitan Statistical Area m at the beginning of year T. *ADJCOST*, as previously defined, is the adjusted total cost of property i in MSA m at the beginning of year T. The total number of properties in a particular MSA at the beginning of year T is denoted as $N_{m,T}$. We expect information asymmetries relating to total property values to be more severe in MSAs with greater *Land Share* values.

We next obtain data from Real Capital Analytics (RCA), a national real estate data vendor specializing in tracking CRE transaction activity. The RCA data includes quarterly sales volumes (both dollar amount and number of properties), investor type, and broker usage (number and dollar volume of deals) for property transactions with a sale price in

[28] In related work, Davis and Heathcote (2007), Bostic et al. (2007) and Bourassa et al. (2011) point to the role of land share (that is, the ratio of land value to total property value) in capturing a property's relative exposure to the local fundamentals that influence property prices.

excess of $2.5 million.[29] The RCA data begin in 2001 and track approximately 45 major MSAs by property type.[30]

Our second method of classification uses RCA data to identify the degree of non-local investment within a particular MSA. There is an extensive literature on the information advantage of local investors and analysts. For example, Bae, Stulz,and Tan, (2008) provide evidence that local analysts exhibit more precision in their ability to analyze a firm due to better access to information and that this local information advantage is strongest in investment environments that draw the least attention from foreign analysts and investors.[31] We follow this logic by constructing a measure of the proportion of non-local buyers within a particular property type, MSA, and year. In particular, we define *Foreign Investment* as follows:

$$Foreign\ Investment_{m,T} = \frac{NON\_LOCAL\ MV_{m,T}}{TOTAL\ MV_{m,T}} \quad , \tag{7}$$

where $NON\_LOCAL\ MV_{m,T}$ is the sum of the sale prices of properties purchased by non-local investors (defined as the sum of foreign investors and non-local private investors) in MSA *m* at time *T*. $TOTAL\ MV_{m,T}$ is the sum of all sale prices of properties sold in MSA *m* at time *T*. We expect less transparency and greater local information advantages to exist in MSAs with lower *Foreign Investment*.

Our third approach to categorizing the information environment of a MSA draws upon the use of a broker to mitigate information asymmetries that may exist between buyers and sellers in CRE transactions. There is an extensive literature examining the use of intermediaries to help relatively uninformed market participants overcome information asymmetries associated with a particular transaction (e.g., Levitt and Syverson, 2008). In real estate markets, brokers possess specialized market knowledge that can offset information advantages that may otherwise have existed between buyer and seller. We utilize the proportion of completed transactions in which a broker was involved to identify

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[29] Investor types include Cross-Border, Equity Fund, Institutional, Non-Listed REIT, Private (Non-Local), Private (Local), Public, and Other.

[30] We thank Steve Williams and Willem Vlaming for graciously providing the RCA data.

[31] Baik, Kang, and Kim (2010) also provide a link between information asymmetry and the presence of local institutional investors.

cross-sectional differences in information environments. More formally, we define *Broker Usage* as follows:

$$Broker\ Usage_{m,T} = \frac{\sum_{i=1}^{N_{m,T}}(BROKERED\ DEAL_{i,m,T})}{\sum_{i=1}^{N_{m,T}}(DEAL_{i,m,T})}\ , \tag{8}$$

where $BROKERED\ DEAL_{i,m,T}$ is an indicator variable set equal to one if the transaction involved the use of a broker, and zero otherwise, for property i in MSA m in year T. $DEAL_{i,m,T}$ is an indicator variable set equal to one for each property i in MSA m that sold in year T. The total number of properties in a particular MSA at the beginning of year T is denoted as $N_{m,T}$. We expect greater information asymmetries to exist in MSAs with lower *Broker Usage*.

Panel A of Table 4 displays summary statistics for our three measures of information asymmetry. On average, 25.5% of a CRE transaction value is attributable to land, although we observe significant variation over time and across MSAs. Foreign investors constitute approximately a quarter of buyers (25.7%), on average, within a MSA and year. There is also significant variation in their participation across markets and time as the standard deviation is 16.8%. On average, over half (55.1%) of the transactions in the RCA data involve the use of a broker, although we again observe substantial cross-sectional and time series variation.

To exploit the significant cross-sectional variation in our information asymmetry proxies, we begin by sorting MSAs into high- and low- information asymmetry environments. High information asymmetry MSAs are those with *Land Share* values greater than the median (*High Land Share*), *Foreign Investment* percentages less than the median (*Low Foreign*), or *Broker Usage* percentages less than the median (*Low Broker*) for a particular property type and within a given year. Panel B of Table 4 provides summary statistics of home market concentrations for each category. Consistent with our information-based hypothesis, we observe greater average and median home market concentrations in high information asymmetry environments (e.g., *High Land Share*, *Low Foreign*, and *Low Broker* MSAs), although differences in broker usage are minor.

3.3.1. Returns Sorted by Geographic Concentration and Information Environment

To investigate how stock returns are related to the degree of geographic concentration within a particular information environment, we sort firms by property type specialization into geographic concentration terciles (low, medium and high) as of the beginning of each year within each information environment. We then calculate monthly equally-weighted returns for each portfolio, rebalancing portfolio constituents at the beginning of each year. Panel C of Table 4 displays average returns for each portfolio.

We observe economically large and statistically significant differences in returns across high and low home market concentration portfolios in our *High Land Share*, *Low Foreign*, and *Low Broker* MSA classifications. Specifically, the return spreads are 73, 51, and 66 basis points on a monthly basis (8.7%, 6.1%, and 8.0% annually), respectively. Consistent with our information-based hypothesis, high home concentrations are associated with greater returns, unconditionally, in markets where information asymmetries are more severe.

To further investigate whether our unconditional results reflect compensation for exposure to other common risk factors, we again calculate the difference in excess monthly returns between our high and low home concentration portfolios for each information environment. We then regress these conditional return differences on *MKT*, *SMB*, *HML*, *MOM*, *PS_LIQ*, augmented by *RE* to capture market-based risk factors. Table 5 reports results from these high-minus-low calendar time portfolio regressions.[32] In the first two rows of Panels A, B, and C, we document economically large and statistically significant differences in Jensen's alphas for high-minus-low home market concentrations (p-values equal to 0.005, 0.068, and 0.024, respectively). The positive and significant differences in alphas are consistent with managers exhibiting greater information advantages in markets with greater information asymmetries. In contrast, we do not find the significant alphas for the high-minus-low portfolios in low information asymmetry environments (bottom two rows of Panels A, B, and C).

3.3.2. Cross-Sectional Regressions by Information Environment

We next augment our Fama MacBeth (1973) specifications with variables that condition on the information environment of the headquarter MSA. Our classification variables are defined as follows: *HILAND* is a dummy variable equal to one if a firm is headquartered in a high *Land Share* MSA within a property type and year, and zero

[32] For presentation brevity, we only report differences in alpha and beta estimates for each specification. Please see the Internet Appendix (Table IA.3) for additional details on the individual high and low home concentration portfolio regressions within each information asymmetry group.

otherwise; *LOFOREIGN* is a dummy variable equal to one if a firm is headquartered in a low *Foreign Investment* MSA within a particular property type and year, and zero otherwise; and *LOBROKER* is a dummy variable equal to one if a firm is headquartered in a low *Broker Usage* MSA within a particular property type and year. Our variables of interest are the interaction between each of these classification variables and our primary measure of local asset concentration, *HOME_CONC*. Similar to our univariate and portfolio comparisons, we expect the local asset concentration effect to be stronger in markets where local information advantages are the most pronounced.

Table 6 presents the time series averages and associated p-values of the cross sectional regression coefficients.[33] Focusing first on the results presented in columns (1), (3), and (5), we continue to document a strong positive relation between the level of a firm's local asset concentration and subsequent annual returns, controlling for the influence of the MSA's information environment. The average coefficient estimates on *HOME_CONC* are 0.065, 0.073, and 0.080, respectively and significant at the 1 percent level (p-value=0.000) in each regression. These values are similar in magnitude to those originally reported in Table 3. In columns (2), (4), and (6), we observe positive and significant values on the following interaction terms: *HOME_CONC*HILAND, HOME_CONC*LOFOREIGN,* and *HOME_CONC*LOBROKER*. The magnitudes of the estimated interaction coefficients are economically and statistically significant. Upon inclusion of the interaction term, the estimated coefficient on *HOME_CONC* is not statistically different from zero. Thus, it appears that the relation between local asset concentrations and returns is concentrated in MSAs with high information asymmetry.

3.4. Robustness Check: Home Concentration and MSA Risk

Our previous results suggest that firms with greater local asset concentrations earn higher returns when information asymmetries are most severe. However, if MSA's with significant information asymmetries are also perceived to be riskier ex-ante, then greater required returns may represent ex ante compensation to investors for the additional risk (e.g., Garcia and Norli, 2012). We construct further robustness checks to address this concern by examining the relation between returns and asset concentrations in markets

[33] For presentation brevity, we only report coefficients on our home concentration measures and interaction terms. Please see the Internet Appendix (Table IA.4) for additional details.

with greater information asymmetries, independent of their local asset concentration. In particular, we construct three additional asset concentration variables: *HILAND_CONC* is the percentage of a firm's total property portfolio located in high *Land Share* markets, excluding their home market concentration; *LOFOREIGN_CONC* is the percentage of a firm's total property portfolio located in low *Foreign Investment* markets, excluding their home market concentration; and *LOBROKER_CONC* is the percentage of a firm's total property portfolio located in low *Broker Usage* markets, excluding their home market concentration. If managers earn greater returns due to the increased compensation required for bearing additional portfolio risk, then we would expect firms with greater concentration in these "riskier" MSAs to earn higher returns, regardless of whether these MSAs were local markets.

We repeat our main cross-sectional regressions replacing our local asset concentration measure with each of the variables described above. Panel A of Table 7 presents the time series averages and associated p-values of the cross sectional regression coefficients.[34] In column 1, we observe an insignificant relation between *HILAND_CONC* and subsequent returns. Thus, it does not appear that firms earn higher returns for bearing additional portfolio risk in high *Land Share* MSAs. When adding *HOME_CONC* to this specification (column 2), we continue to document a significant relation between home market concentrations and excess returns, while *HILAND_CONC* remains insignificant. We obtain similar results (columns 3 and 5) when using *LOFOREIGN_CONC* and *LOBROKER_CONC* in place of *HILAND_CONC,* respectively. In addition, *HOME_CONC* continues to be economically large and statistically significant (p-value=0.000) in columns 4 and 6, while neither *LOFOREIGN_CONC* nor *LOBROKER_CONC* is statistically different from zero. These results also suggest that local asset concentrations are associated with greater returns due to the information advantage of local managers, rather than the perceived risk associated with increased portfolio concentration.

3.5. Further Robustness: Alternate Risk-Based Explanations

We continue to investigate alternate explanations of our main result by examining the relation between other geographic risk factors and firm returns. For example, our

[34] For presentation brevity, we only report coefficients on our home concentration measure and measures capturing the asset concentration in high information asymmetry markets. Please see the Internet Appendix (Table IA.5) for additional details.

information-based return effects may also be correlated with land constraints and local government regulations associated with certain geographic locations. Saiz (2010) identifies a significant relation between land supply elasticity and property values. Relatively inelastic MSAs, (e.g., New York, Los Angeles, and Miami) tend to have higher land values and increased regulations on development. Thus, increased asset concentration in these MSAs may in itself have a direct impact on firm returns, outside of the information-based effect experienced by local investors.

We utilize the findings of Saiz's (2010) to classify REIT headquarter locations by their relative supply elasticity. In particular, we construct a dummy variable, *INELAST*, that is equal to one if a firm is headquartered in a MSA below the median supply elasticity of all headquarter MSAs as of the beginning of a particular year, and zero otherwise. We begin by including *INELAST* as an additional control variable in our primary regression specification. In panel B of Table 7, we observe a positive and marginally significant relation between *INELAST* and firm returns (column 1); that is, firms located in relatively supply constrained MSAs appear to earn greater returns than their peers.[35] However, the estimated coefficient on *HOME_CONC* remains positive and highly significant (p-value=0.000) even when controlling for the impact of MSA supply elasticities. In column 2, we interact *HOME_CONC* with *INELAST* and find no evidence that our local asset concentration result is most prominent in low elasticity MSAs.

Firms who concentrate their asset portfolios in a specific geographic region may also be subject to legal risks that vary across regions. For example, the variation in state laws that govern the foreclosure process can impact the degree to which regional shocks impact property values in a particular MSA. In 21 states, lenders must follow a judicial foreclosure process that can impose significant time and financial constraints on a lender. For example, as of 2015 the judicial foreclosure process in New York took 900 days, on average, from initiation to completion.[36] Not only are borrowers in these states afforded additional time and reduced living expenses, but there are also incentives for lenders to negotiate settlements that are favorable to the borrowers due to the costs lenders face when pursuing the judicial foreclosure process. Thus, investors purchasing property in these states may face an additional legal risk that others who invest in non-judicial foreclosure states do not.

[35] For presentation brevity, we only report coefficients on our home concentration measure and our alternate MSA risk measures. Please see the Internet Appendix (Table IA.6) for additional details.
[36] "New York Regulator Seeks Faster Foreclosures." By Joe Light. Wall Street Journal. May 19, 2015.

If local asset concentrations are primarily in MSAs that impose additional legal risks, then the relation between home market concentration and firm returns may reflect cross-sectional variation in legal risk rather than the information advantage of a local manager.

We construct a dummy variable, *JUDICIAL*, that is equal to one if a firm is headquartered in a state that adheres to a judicial foreclosure process, and zero otherwise. In panel B of Table 7, we observe an insignificant relation between *JUDICIAL* and firm returns (column 3). Moreover, the estimated coefficient on *HOME_CONC* remains economically large and statistically significant. Furthermore, the inclusion of the interaction term *HOME_CONC*JUDICIAL* does not significantly alter the effect of home market asset concentrations on firm returns in judicial versus non-judicial foreclosure states. Taken together with our previous empirical results, our additional robustness checks continue to point to the information advantage of local managers, not the increased risk associated with portfolio concentration in these locations, as the underlying determinant of greater returns in the cross-section of firms.

3.6. Identification Tests Using Loan Spreads

We strengthen the identification of an information-based channel through two additional empirical tests. Our identification approach seeks to isolate the information advantage of local market portfolio concentrations from other explanations of the positive relation between local asset concentration and returns. We draw upon an extensive literature that aligns the geographic proximity of lenders with information asymmetry as motivation for our primary identification tests.[37]

Our basic premise is that, all else equal, high geographic concentrations of assets should lead to higher loan spreads due to the greater perceived risk associated with concentrated portfolios. However, lenders with a local presence have the ability to discern whether a borrower's high local asset concentration is directly related to the portfolio manager's information advantage and incorporate this information into the loan spread, thereby piercing the information veil. In other words, there is an information asymmetry component that may be priced by the local lender, but not by the non-local bank. This

[37] Prior literature has utilized geographic proximity as a proxy for information asymmetry (e.g., Sufi, 2007; Costello, 2013), precision of information signals (Ayers, Ramalingegowda, and Yeung, 2011; Chhaochharia, Kumar, andNiessen-Ruenzi,2012), quality of information (Hollander and Verriest, 2016; Hauswald and Marquez, 2006; Almazan, 2002), cost of information acquisition (Lerner,1995; Coval and Moskowitz,2001; Butler,2008; Tian, 2011), and access to local information (e.g., Coval and and Moskowitz,1999; Agarwal and Hauswald,2010).

ability of the local lender is of particular importance in relatively illiquid and heterogeneous asset markets, such as the private CRE market, due to the relative opacity of local market information.

We construct our identification tests using loan level data obtained from Thomson-Reuters LPC Dealscan database.[38] In particular, we collect the following information for all REIT loans in our sample: (1) loan spread, defined as the reported coupon spread above LIBOR on the drawn amount plus any recurring annual fee (i.e., "All-in-Spread Drawn"); (2) maturity, defined as the loan term expressed in months; (3) lender name; and (4) lender headquarter location. We supplement our lender location data by collecting branch location data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits database.[39] Loan and lender data are available for approximately 70 percent of the firms in our dataset. Our final sample consists of 620 loan-year observations from 1996-2013. We classify loans as involving a local lender if the bank has a branch location in to the REIT's headquarter MSA.[40] We also sort firms into high and low home market concentrations based on whether their local asset concentration is above or below the sample median as of the beginning of each year. We then conduct a difference-in-difference analysis of average loan spreads to identify the information advantage of local market portfolio concentrations.

Panel A of Table 8 displays the results of our difference-in-difference analysis. Conditioning on the use of a local lender, we document lower spreads for firms with high local asset concentrations relative to those with low home market portfolio concentrations. The difference in loan spread is both statistically (p-value=0.013) and economically significant (19 basis points). Furthermore, in comparing loan spreads among high home market concentration firms across lender classifications, we identify significantly lower spreads for firms utilizing a local lender (58 basis points). These results are consistent with local lenders incorporating information advantages associated with local asset concentration into the cost of financing. In sharp contrast, non-local lenders charge significantly greater loan spreads (47 basis points) to firms with high home market

[38] Over 80 percent of loans in our dataset are Term Loans and Revolvers/Lines of Credit with a term greater than 1 year.
[39] See https://www5.fdic.gov/idasp/advSearch_warp_download_all.asp?intTab=1 for further details.
[40] In a subsequent robustness check, we utilize a more restrictive definition of a local lender similar to Hollander and Verriest (2016) and others (e.g., Ross, 2010; Bushman and Wittenberg-Moerman, 2012) in which we match based on lender headquarter location, rather than branch location, and obtain similar results.

concentrations relative to those with low local asset concentrations. This result is consistent with the perception of increased portfolio concentration risk in the absence of a perceived information advantage. Finally, the difference-in-difference across these two dimensions is statistically (p-value=0.000) and economically significant (66 basis points).[41]

Panel B of Table 8 extends our conditional loan spread analysis by examining differences in firm returns across the dimensions described previously. We present results from a difference-in-difference analysis similar to that of Panel A. Consistent with our loan spread results, we document greater returns for firms with high local asset concentrations *and* a local lender. The difference-in-difference estimate is both statistically (p-value=0.024) and economically significant (9.2 percent annually).

Finally, we use the local lender classification in an instrumental variable (IV) approach to better isolate the information-based impact of home market concentration on returns. In particular, we utilize a two-staged least squares (2SLS) estimation in which the use of a local lender serves as an instrument for a firm's level of home market concentration. We define *LOCAL LENDER* as a dummy variable set equal to one if a firm utilized a lender with a branch location in its home (headquarter) market, and zero otherwise.[42] In column 1 of Panel C, we report results from our first stage regression.[43] *LOCAL LENDER* is positively related to *HOME_CONC* at the 1 percent level. That is, firms utilizing a local lender have higher home concentrations. Additionally, the F-statistic from the first stage estimation is 14.28, thus mitigating concerns of a weak instrument. In column 2 of Panel C, we document a positive and significant relation between *HOME_CONC_IV* and *RET* at the 5 percent level. This further supports our primary finding that high home concentration is associated with greater returns and is consistent with the effect being transmitted through the information-based channel. Taken together with our loan spread analysis, these results provide additional evidence that firm returns are impacted by the geographic information related to a firm's assets, not by the asset concentration itself.

[41] To ensure that our results are not driven by the effect of repeat lending (e.g., Petersen and Rajan, 1994; Berger and Udell, 1995; Ivashina, 2009), we conduct an additional difference-in-difference analysis excluding follow-on loans with a local lender and continue to find statistically and economically significant results.

[42] A firm is classified as doing business with a local lender beginning in the year it initializes the loan with the lender and remains this way for the duration of the loan's maturity.

[43] For presentation brevity, we only report coefficient estimates on *LOCAL LENDER* and *HOME_CONC_IV*. Please see the Internet Appendix (Table IA.7) for additional details.

4. Conclusion

Standard portfolio theory points to a risk-based explanation for the link between geographically concentrated portfolios and expected returns. In particular, investors expect higher returns as compensation for bearing risk associated with insufficient portfolio diversification. However, to the extent local asset concentrations are driven by the inherent information advantages of local investors, relative performance should reflect the local investor's lower cost of information acquisition, reduced financing costs, and the more precise signal of the local asset's payoff. Although there is clear tension between risk and information-based channels of outperformance, little is known about the performance implications of local bias as it relates to the apparent information advantage of local investors.

This study presents both direct and indirect evidence of the information-based impact of local asset concentration on returns through the use of granular asset level data and observed differences in the information environments of local asset markets. Our robust and novel evidence reconciles some puzzling findings in the prior home bias literature. Although home bias is often viewed as an irrational response in the face of positive diversification benefits, we show that local asset concentration can be a rational response with beneficial return outperformance when significant information asymmetries exist. Our results, therefore, identify critical conditions under which home bias is rational and beneficial, which is consistent with Van Niewerburgh and Velldkamp's (2009) theoretical model of information acquisition and local bias. Our findings also extend a recent stream of research focused on the importance of local information to individual and institutional investors (e.g., Baik, Kang, and Kim, 2010; Garcia and Norli, 2012; Choi et al., 2017), local analysts (e.g., Bae and Stulz, 2008), industry insiders (e.g., Ben-David, Birru, and Rossi, 2017), and lenders (e.g., Gianetti and Laeven, 2012; Hollander and Verriest, 2016), by considering the significant role local information plays in the portfolio decisions of commercial real estate investors.

Given that information asymmetries are important in real estate transactions due to market frictions that exist in relatively illiquid and highly segmented private markets, we focus our analysis of the relation between local market concentration and return performance on the property portfolio decisions of equity REIT managers, who buy and sell properties in the private commercial real estate (CRE) market. The separation of ownership inherent in the REIT structure also provides an ideal experimental framework to directly measure a firm's local market exposure, as well as distinguish between information- and risk-based effects of home market concentrations on investor returns. Using property level data from SNL's Real Estate Database, we find that Equity REITs hold, on average, approximately 20 percent of their portfolios in their home market, which constitutes an economically significant portion of their property portfolio. In comparison, the average portfolio concentration in a particular MSA for firms not headquartered in that market is approximately 1.4 percent. This is consistent with REIT managers overweighting asset allocations to their local market to take advantage of their information advantage.

Using both a portfolio sort approach and Fama-MacBeth (1973) cross-sectional regressions to examine performance effects of local asset concentration, we document a positive relation between home market concentrations and firm returns that is both statistically and economically significant. Furthermore, these effects are magnified when local asset concentration is achieved in markets characterized by high information asymmetry and are robust to additional empirical tests examining potential alternate risk-based hypotheses and sample selection issues.

We further strengthen our identification of the information-based channel of outperformance through a series of difference-in-difference tests and an instrumental variable estimation that focus on a local lender's ability to pierce the information veil of the local borrower. In particular, we provide additional evidence that aligns the relative outperformance of locally concentrated portfolios with reduced financing costs at the local investment level, showing an important mechanism through which information advantages impact returns. Overall, this study contributes to our understanding of the return implications of local bias and shows the importance of the information advantage of local investors and its performance effects in highly segmented markets with significant information asymmetries.

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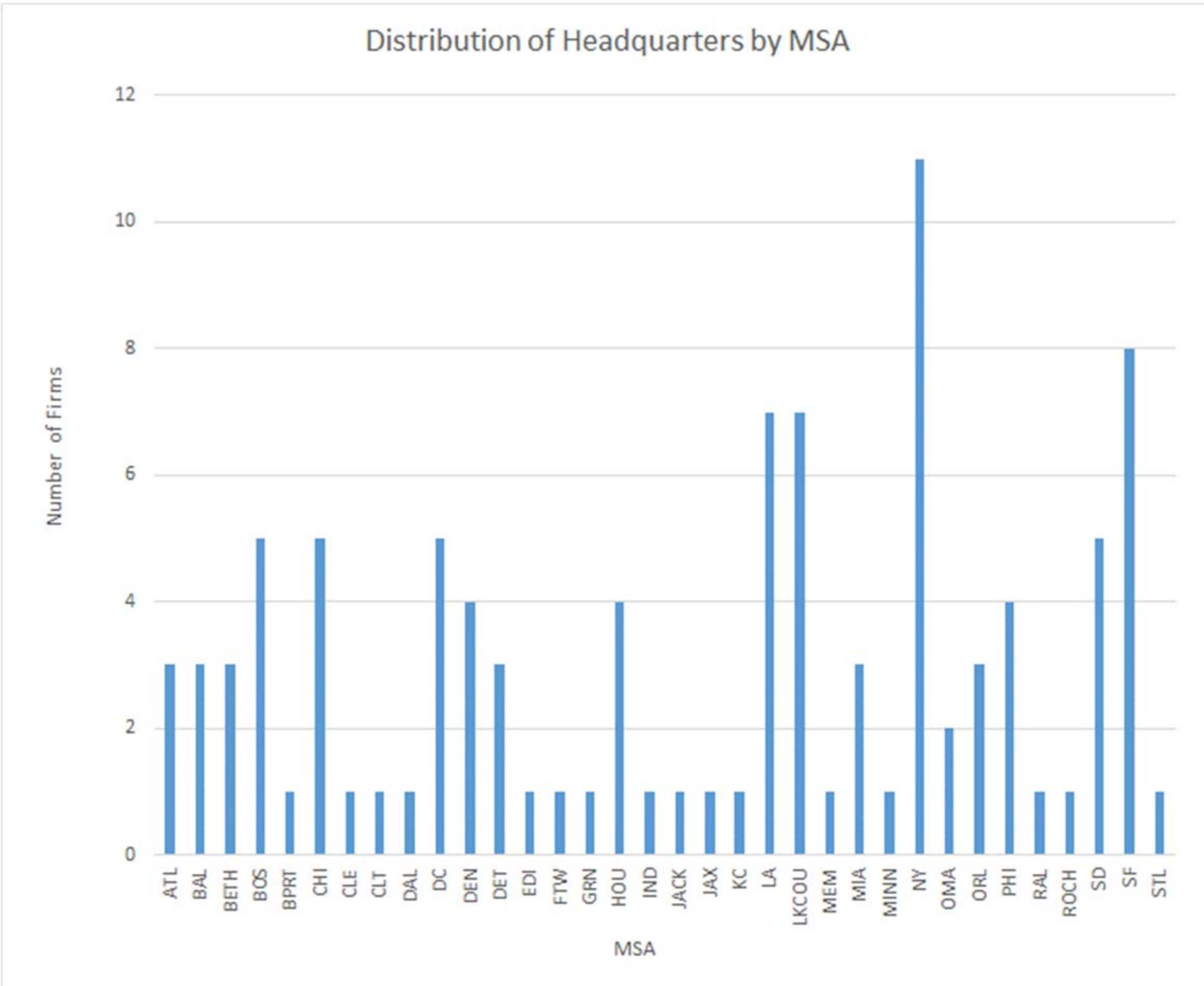
Figure 1: Sample Distribution and Local Asset Concentration by Headquarter Location

This figure plots the sample distribution of firms (Panel A) and average local asset concentrations (Panel B) by headquarter location. Headquarter location is defined at the metropolitan statistical area (MSA) level. Home Concentration is defined as the percentage of a firm's total property portfolio located in the headquarter market. Outsider Concentration is defined as the percentage of a firm's total property portfolio located in the MSA for firms not headquartered in that location. All portfolio concentrations are calculated using adjusted cost measures obtained from SNL. The sample period is 1996-2013.

Panel A – Distribution of Firms by Headquarter MSA



Panel B: Average Local Asset Concentrations by Headquarter MSA

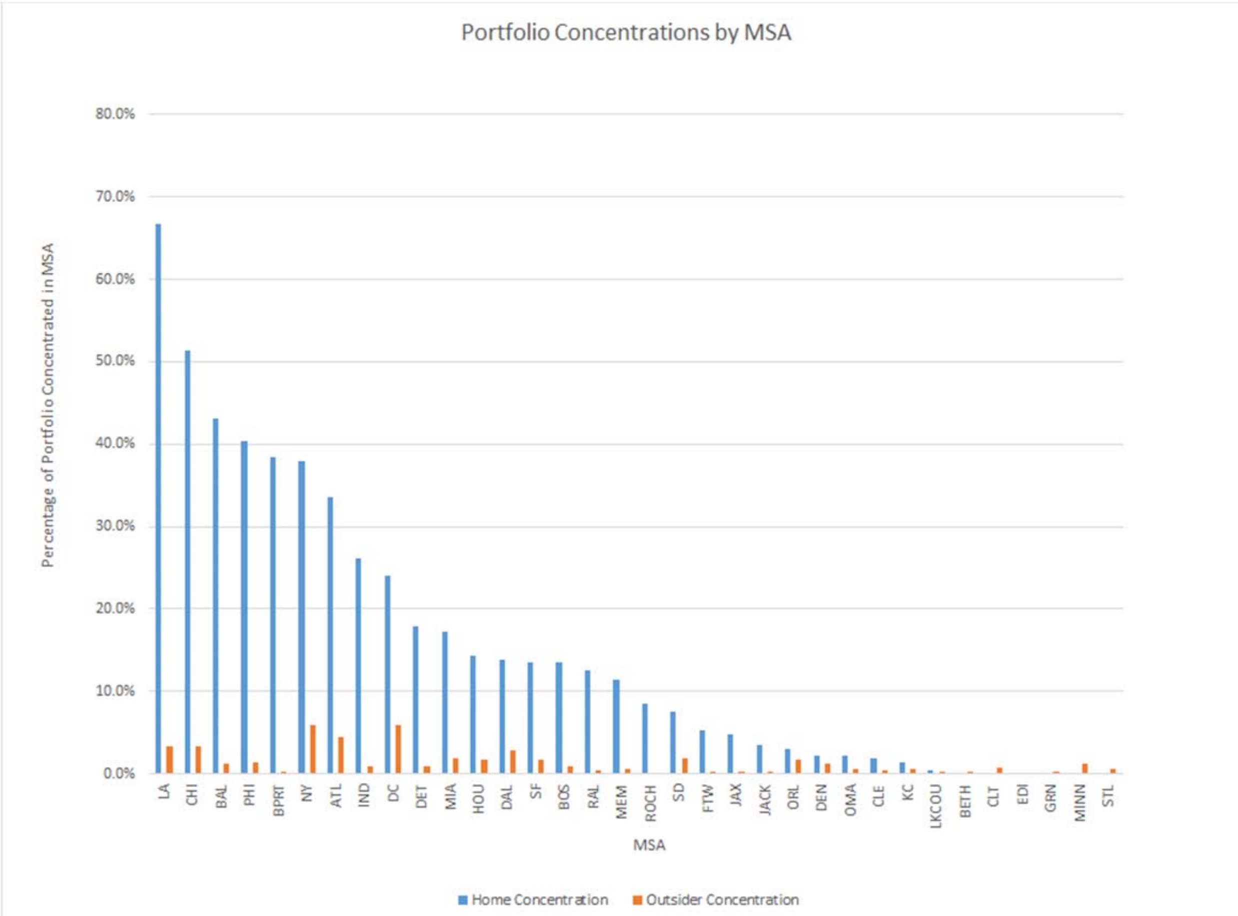


Figure 2: Average Local Asset Concentrations by Year

This figure plots the time series variation in the mean portfolio concentrations held in the firm's home market by year. Home Concentration is defined as the percentage of a firm's total property portfolio located in the headquarter market. All portfolio concentrations are calculated using adjusted cost measures obtained from SNL. The sample period is 1996-2013.

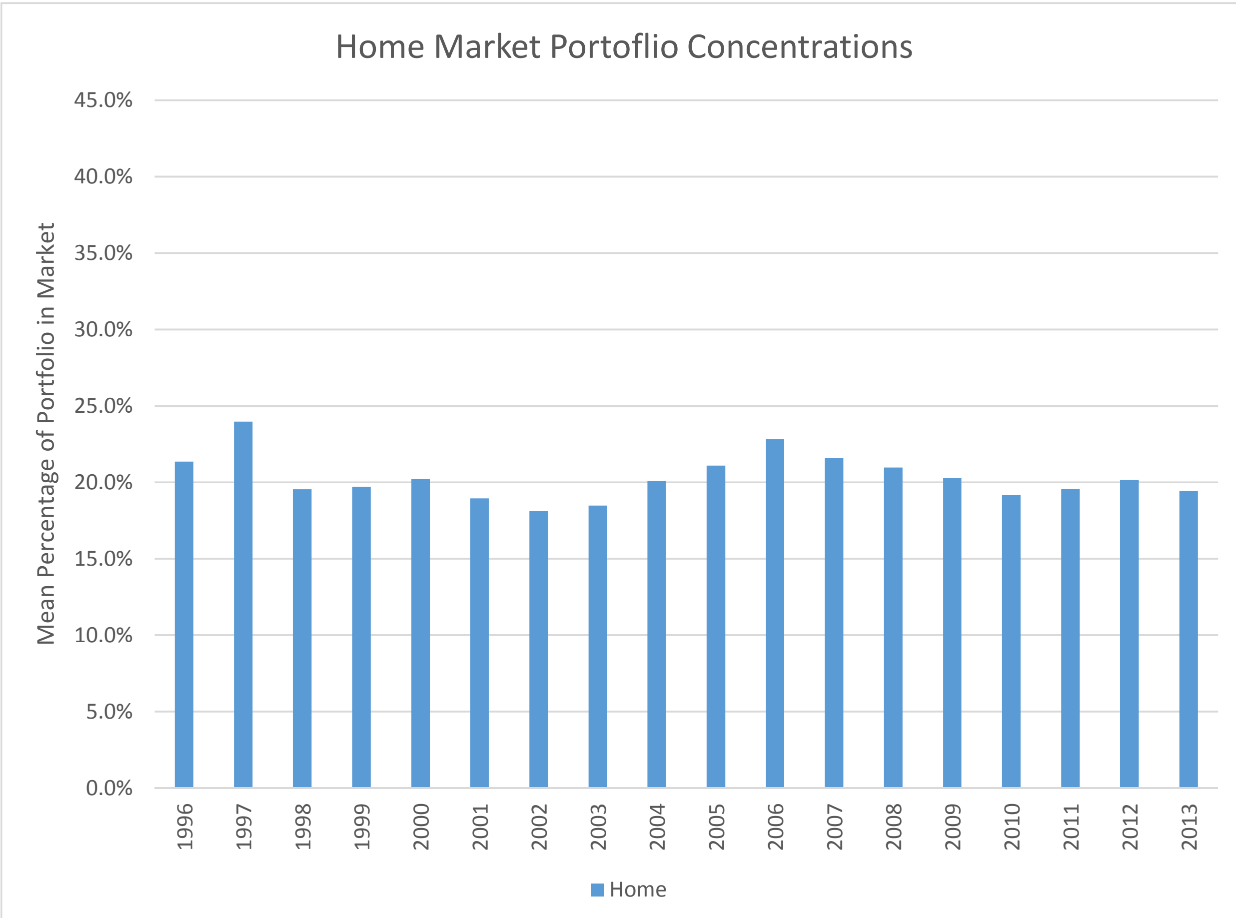


Figure 3: Comparison of Home Concentration and State Count Measures

This figure plots the distribution of average home market concentrations by state count (Panel A) and correlations between home market concentration and state count measure (Panel B). Home Concentration is defined as the percentage of the total property portfolio located in the firm's headquarter market using adjusted cost obtained from SNL. State count is constructed in the spirit of Garcia and Norli (2012) as the number of states in which properties are owned within a particular year. The sample period is 1996-2013.

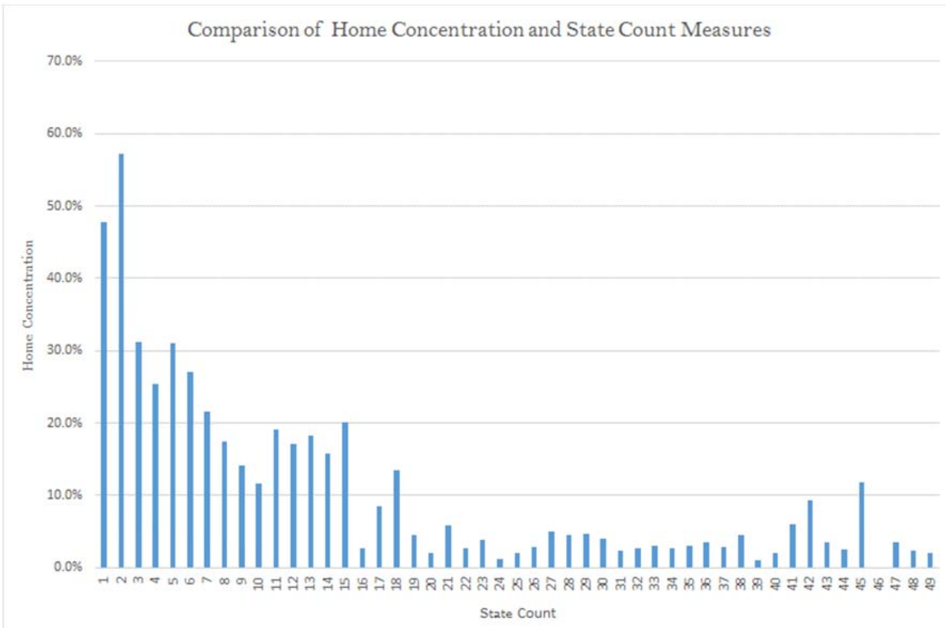


Table 1: Geographic Concentration Measures and Portfolio Returns – Summary Statistics

This table reports summary statistics of our geographic concentration measures (Panel A) and univariate comparisons of equal-weighted portfolio returns sorted by geographic concentration (Panel B). Home Concentration is defined as the percentage of a firm's total property portfolio located in the headquarter market. Single Market Concentration (With-Home) is defined as the largest percentage of a firm's total property portfolio located in any market, which may include the firm's headquarter location. Single Market Concentration (Non-Home) is defined as the largest percentage of a firm's total property portfolio located in a market outside of the firm's headquarter location. Portfolio concentration (With Home) is the Herfindahl Index of a firm's geographic property portfolio concentration, including investments in their headquarter market. Portfolio concentration (Non-Home) is the Herfindahl Index of a firm's geographic property portfolio concentration, excluding investments in their headquarter market. All portfolio concentrations are calculated using adjusted cost measures obtained from SNL. Portfolio returns are constructed using monthly returns. Firms are sorted into High, Mid, and Low tercile portfolios at the beginning of each year. Differences in average portfolio returns are calculated using two sample T-tests. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013. The number of firm-year observations is 1,044.

Panel A: Summary Statistics for Geographic Concentration Measures

	Mean	Median	SD	Min	Max
Home Market Concentration	0.203	0.091	0.267	0.000	1.000
Single Market Concentration (With Home)	0.327	0.241	0.267	0.000	1.000
Single Market Concentration (Non-Home)	0.211	0.142	0.208	0.000	1.000
Portfolio Concentration (With Home)	0.403	0.355	0.234	0.090	1.000
Portfolio Concentration (Non-Home)	0.321	0.254	0.241	0.000	1.000

Panel B: Average Returns on Portfolios Sorted by Geographic Concentration

	Low	Mid	High	High-Low
Home Market Concentration	0.919	1.091	1.353	0.434***
Single Market Concentration (With Home)	1.084	1.111	1.134	0.050
Single Market Concentration (Non-Home)	1.143	1.238	0.941	-0.202
Portfolio Concentration (With Home)	1.169	1.126	1.039	-0.130
Portfolio Concentration (Non-Home)	1.171	1.185	0.972	-0.199

Table 2: Calendar Time Portfolio Regressions by Home Market Concentrations

This table reports results from calendar time portfolio regressions. *HIGH* is the equal-weighted return on the portfolio of firms in the upper tercile of home market concentration. *LOW* is the equal-weighted return on the portfolio of firms in the lower tercile of home market concentration. Portfolio returns are constructed using monthly returns. Firms are sorted into High, Mid, and Low tercile portfolios at the beginning of each year. The calendar time regression model is as follows:

$$r_{p,t} - r_{f,t} = \alpha_P + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 PS\_LIQ_t + \beta_6 RE_t + \varepsilon_t$$

where $r_{p,t}$ is the equal-weighted portfolio return and $r_{f,t}$ is the risk-free rate (yield on the 1-month Treasury Bill). The set of control variables in our calendar time portfolio regressions are the three Fama-French risk factors (*MKT*, *SMB*, and *HML*) augmented by momentum (*MOM*), Pastor and Stambaugh's market liquidity measure (*PS_LIQ*) and an orthogonalized real estate factor (*RE*). P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013.

	α	*MKT*	*SMB*	*HML*	*MOM*	*PS_LIQ*	*RE*
HIGH	0.004***	0.762***	0.565***	0.908***	-0.134***	-0.019	0.849***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.414)	(0.000)
LOW	0.000	0.714***	0.490***	0.866***	-0.156***	-0.063	0.881***
	(0.996)	(0.000)	(0.000)	(0.000)	(0.000)	(0.414)	(0.000)
HIGH-LOW	0.004***	0.048	0.075**	0.042	0.022	0.044*	-0.032
	(0.009)	(0.296)	(0.029)	(0.395)	(0.402)	(0.089)	(0.546)

Table 3: Fama MacBeth Regressions – Time Series Averages of Cross-Sectional Regression Coefficients

This table reports time series averages of annual cross-sectional regression coefficients from the following Fama MacBeth regression model:

$$RET_{i,t} = c_0 + \sum_{m=1}^{M} c_{i,m} Z_{m,i,t} + \varepsilon_{i,t}$$

where *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. $Z_{m,i,t}$ is one of M firm characteristics: *SIZE is* the natural log of the firm's aggregate market capitalization; *M/B* is the market value of assets divided by the book value of assets; *MOMENTUM* is the firm's cumulative return over the prior year; *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure; *VOLATILITY* is the standard deviation of the firm's daily returns over the prior calendar year; *LEV* is total debt divided by the book value of total assets; *HOME_CONC* is the percentage of a firm's total property portfolio located in the headquarter market; *SINGLE_CONC* is defined as the largest percentage of a firm's total property portfolio located in any market, which may include the firm's headquarter location. *SINGLE_CONC_NON_HOME* is defined as the largest percentage of a firm's total property portfolio located in a market outside of the firm's headquarter location. *PORTFOLIO_HERF* is the Herfindahl Index of a firm's geographic property portfolio concentration, including investments in their headquarter market. *NON_HOME_HERF* is the Herfindahl Index of a firm's geographic property portfolio concentration, excluding investments in their headquarter market. All portfolio concentrations are calculated using adjusted cost measures obtained from SNL. All regressions include property type fixed effects. *N* is the number of firm-year observations. The sample period is 1996-2013.

	RET	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*
HOME_CONC	0.067***	-	-	-	-	0.082***	0.048**	0.077***	0.064***
	(0.001)	-	-	-	-	(0.001)	(0.044)	(0.000)	(0.010)
SINGLE_CONC	-	0.014	-	-	-	-0.033	-	-	-
	-	(0.599)	-	-	-	(0.341)	-	-	-
SINGLE_CONC_NON_HOME	-	-	-0.081***	-	-	-	-0.059*	-	-
	-	-	(0.003)	-	-	-	(0.086)	-	-
NON_HOME_HERF	-	-	-	0.021	-	-	-	0.041	-
	-	-	-	(0.642)	-	-	-	(0.398)	-
PORTFOLIO_HERF	-	-	-	-	0.053	-	-	-	0.020
	-	-	-	-	(0.311)	-	-	-	(0.744)
Property Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1044	1044	1044	1044	1044	1044	1044	1044	1044
R^2	0.43	0.42	0.43	0.43	0.43	0.44	0.44	0.45	0.45

Control Variables: *SIZE, M/B, MOMENTUM, VOLATILITY, ILLIQ, LEV*

Table 4: Further Tests of Information Asymmetry Using HQ Location Classifications

This table reports summary statistics of headquarter location classifications pertaining to the information asymmetry associated with the metropolitan statistical area (MSA), home concentrations within these location groups, and average returns on equal-weighted portfolios associated with each subgroup. *Land Share* is defined as the average percentage of a property's value attributed to land, (cost of land divided by the total cost of the property) within an MSA for a particular year and property type. *Foreign Investment* is the percentage of non-local property buyers relative to total investors in a particular MSA for a particular year and property type using dollar volume of investment. *Broker Usage* is the percentage of total sale transactions that utilize either a sell-side or buy-side broker in a particular MSA for a particular year and property type. Cost data is obtained from SNL for the full sample period of 1996-2013. Foreign investment and brokerage data is provided by Real Capital Analytics (RCA) for the 2001-2013 sub-period. Location classification sorts are defined to be above and below the median value of the distribution for each sample year and property type. Firms are sorted into High, Mid, and Low tercile portfolios of home concentration at the beginning of each year. Portfolio returns are constructed using monthly returns and on an equal-weighted basis. Differences in average portfolio returns are calculated using two sample T-tests. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. *N* is the number of firm-year observations. Percentages are expressed in decimal form.

Panel A: Summary Statistics – Information Asymmetry (Valuation Uncertainty) Measures

	Mean	Median	SD	Min	Max	N
Land Share	0.255	0.257	0.045	0.097	0.477	1044
Foreign Investment	0.257	0.232	0.168	0.000	1.000	733
Broker Usage	0.551	0.569	0.179	0.000	1.000	733

Panel B: Summary Statistics – Home Market Concentrations by Location Classifications

	Mean	Median	SD	Min	Max	N
Low Land Share	0.149	0.066	0.195	0.000	1.000	533
High Land Share	0.259	0.116	0.316	0.000	1.000	511
Low Foreign	0.239	0.126	0.285	0.000	1.000	398
High Foreign	0.155	0.045	0.229	0.000	1.000	335
Low Broker	0.202	0.095	0.276	0.000	1.000	399
High Broker	0.199	0.084	0.245	0.000	1.000	334

Panel C: Average Returns on Portfolios Sorted by Home Market Concentration and Location Classification

	Low	Mid	High	High-Low
Low Land Share	0.953	1.162	1.248	0.295
High Land Share	0.739	1.096	1.464	0.725***
Low Foreign	0.821	1.222	1.326	0.505**
High Foreign	1.156	1.039	1.441	0.285
Low Broker	0.912	1.098	1.576	0.664***
High Broker	1.035	1.113	0.956	-0.079

Table 5: Portfolio Regressions by Home Market Concentrations and Location Classifications

This table reports results from calendar time portfolio regressions. *HIGH* is the equal-weighted return on the portfolio of firms in the upper tercile of home market concentration. *LOW* is the equal-weighted return on the portfolio of firms in the lower tercile of home market concentration. *Land Share* is defined as the average percentage of a property's value attributed to land, (cost of land divided by the total cost of the property) within an MSA for a particular year and property type. *Foreign Investment* is the percentage of non-local property buyers relative to total investors in a particular MSA for a particular year and property type using dollar volume of investment. *Broker Usage* is the percentage of total sale transactions that utilize either a sell-side or buy-side broker in a particular MSA for a particular year and property type. Location classification sorts are defined to be above or below the median value of the distribution for each sample year and property type. Portfolio returns are constructed using monthly returns. Firms are sorted into High, Mid, and Low tercile portfolios at the beginning of each year within each location classification group. The calendar time regression model is as follows:

$$r_{p,t} - r_{f,t} = \alpha_P + \beta_1\, MKT_t + \beta_2\, SMB_t + \beta_3\, HML_t + \beta_4\, MOM_t + \beta_5\, PS\_LIQ_t + \beta_6\, RE_t + \varepsilon_t$$

where $r_{p,t}$ is the equal-weighted portfolio return and $r_{f,t}$ is the risk-free rate (yield on the 1-month Treasury Bill). The set of control variables in our calendar time portfolio regressions are the three Fama-French risk factors (MKT, SMB, and HML) augmented by momentum (*MOM*), Pastor and Stambaugh's market liquidity measure (PS_LIQ) and an orthogonalized real estate factor (*RE*). P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013 for Land Share sorts and 2001-2013 for Foreign Investment and Broker Usage sorts.

Panel A: High Home vs. Low Home Portfolio Performance by Land Share

	α	*MKT*	*SMB*	*HML*	*MOM*	*PS_LIQ*	*RE*
HIGH-LOW	0.006***	0.101*	0.067	0.128*	0.053	0.053	-0.021
(High Land Share)	(0.005)	(0.080)	(0.264)	(0.072)	(0.214)	(0.140)	(0.760)
HIGH-LOW	0.002	0.101*	0.067	0.128*	0.053	0.053	-0.021
(Low Land Share)	(0.381)	(0.080)	(0.264)	(0.072)	(0.214)	(0.140)	(0.760)

Panel B: High Home vs. Low Home Portfolio Performance by Foreign Investment

	α	*MKT*	*SMB*	*HML*	*MOM*	*PS_LIQ*	*RE*
HIGH-LOW	0.005*	0.041	-0.079	0.069	-0.012	0.131***	-0.016
(Low Foreign)	(0.068)	(0.700)	(0.406)	(0.472)	(0.861)	(0.008)	(0.887)
HIGH-LOW	0.001	0.187**	0.180	-0.081	0.150*	0.039	-0.182**
(High Foreign)	(0.646)	(0.027)	(0.167)	(0.544)	(0.056)	(0.614)	(0.030)

Panel C: High Home vs. Low Home Portfolio Performance by Broker Usage

	α	*MKT*	*SMB*	*HML*	*MOM*	*PS_LIQ*	*RE*
HIGH-LOW	0.005**	0.112	0.088	0.271**	-0.081	0.010	0.100
(Low Broker)	(0.024)	(0.160)	(0.266)	(0.013)	(0.279)	(0.800)	(0.219)
HIGH-LOW	-0.001	0.069	-0.049	-0.197	0.144**	0.203*	-0.260**
(High Broker)	(0.881)	(0.530)	(0.756)	(0.214)	(0.049)	(0.052)	(0.030)

Table 6: Fama MacBeth Regressions with Location Classifications

This table reports time series averages of annual cross-sectional regression coefficients from the following Fama MacBeth regression model:

$$RET_{i,t} = c_0 + \sum_{m=1}^{M} c_{i,m} Z_{m,i,t} + \varepsilon_{i,t}$$

where *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. $Z_{m,i,t}$ is one of M firm characteristics: *SIZE is* the natural log of the firm's aggregate market capitalization; *M/B* is the market value of assets divided by the book value of assets; *MOMENTUM* is the firm's cumulative return over the prior year; *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure; *VOLATILITY* is the standard deviation of the firm's daily returns over the prior calendar year; *LEV* is total debt divided by the book value of total assets; *HOME_CONC* is the percentage of a firm's total property portfolio located in the headquarter market; *HILAND* is a dummy variable equal to one if a firm is headquartered in a high *Land Share* MSA and zero otherwise; *LOFOREIGN* is a dummy variable equal to one if a firm is headquartered in a low *Foreign Investment* MSA and zero otherwise; *LOBROKER* is a dummy variable equal to one if a firm is headquartered in a low *Broker Usage* MSA and zero otherwise. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013 for the *Land Share* sorts and 2001-2013 for the *Foreign Investment* and *Broker Usage* sorts. All regressions include property type fixed effects. *N* is the number of firm-year observations.

	Land Share		*Foreign Investment*		*Broker Usage*	
	RET	*RET*	*RET*	*RET*	*RET*	*RET*
HOME_CONC	0.065***	-0.032	0.073***	-0.004	0.080***	0.003
	(0.000)	(0.403)	(0.000)	(0.934)	(0.000)	(0.932)
HILAND	0.010	-0.014	-	-	-	-
	(0.318)	(0.288)	-	-	-	-
*HOME_CONC*HILAND*	-	0.138***	-	-	-	-
	-	(0.008)	-	-	-	-
LOFOREIGN	-	-	0.011	-0.005	-	-
	-	-	(0.486)	(0.771)	-	-
*HOME_CONC*LOFOREIGN*	-	-	-	0.101**	-	-
	-	-	-	(0.047)	-	-
LOBROKER	-	-	-	-	0.015	-0.007
	-	-	-	-	(0.315)	(0.638)
*HOME_CONC*LOBROKER*	-	-	-	-	-	0.118**
	-	-	-	-	-	(0.031)
Property Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1044	1044	733	733	733	733
R^2	0.43	0.45	0.45	0.47	0.45	0.47
Control Variables: *SIZE, M/B, MOMENTUM, VOLATILITY, ILLIQ, LEV*						

Table 7: Further Robustness Check – Alternate Explanations

This table reports time series averages of annual cross-sectional regression coefficients from the following Fama MacBeth regression model:

$$RET_{i,t} = c_0 + \sum_{m=1}^{M} c_{i,m} Z_{m,i,t} + \varepsilon_{i,t}$$

where *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. $Z_{m,i,t}$ is one of M firm characteristics: *SIZE is* the natural log of the firm's aggregate market capitalization; *M/B* is the market value of assets divided by the book value of assets; *MOMENTUM* is the firm's cumulative return over the prior year; *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure; *VOLATILITY* is the standard deviation of the firm's daily returns over the prior calendar year; *LEV* is total debt divided by the book value of total assets; *HOME_CONC* is the percentage of a firm's total property portfolio located in the headquarter market; *HILAND_CONC* is the percentage of a firm's total property portfolio located in high Land Share MSA's, excluding their home market concentration; *LOFOREIGN_CONC* is the percentage of a firm's total property portfolio located in low Foreign Investment MSA's, excluding their home market concentration; *LOBROKER_CONC* is the percentage of a firm's total property portfolio located in low Broker Usage MSA's, excluding their home market concentration; *INELAST* is a dummy variable equal to one if a firm is headquartered in a location below the median supply elasticity and zero otherwise. We utilize Saiz (2010) supply elasticity measures as our elasticity proxy; *JUDICIAL* is a dummy variable equal to one if a firm is headquartered in a state that follows a judicial foreclosure process in the case of default. P-values are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample period is 1996-2013 for the *Land Share* sorts and 2001-2013 for the *Foreign Investment* and *Broker Usage* sorts. All regressions include property type fixed effects. *N* is the number of firm-year observations.

Panel A: Home Concentration and MSA Risk

	Land Share		*Foreign Investment*		*Broker Usage*	
	RET	*RET*	*RET*	*RET*	*RET*	*RET*
HOME_CONC	-	0.076***	-	0.078***	-	0.072***
	-	(0.000)	-	(0.000)	-	(0.000)
HILAND_CONC	0.015	0.046	-	-	-	-
	(0.617)	(0.111)	-	-	-	-
LOFOREIGN_CONC	-	-	-0.022	-0.008	-	-
	-	-	(0.334)	(0.754)	-	-
LOBROKER_CONC	-	-	-	-	-0.038	-0.018
	-	-	-	-	(0.198)	(0.557)
Property Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1044	1044	733	733	733	733
R^2	0.42	0.43	0.43	0.44	0.43	0.45
Control Variables: *SIZE, M/B, MOMENTUM, VOLATILITY, ILLIQ, LEV*						

Panel B: Home Concentration, Supply Elasticity, and Legal Risk

	Supply Elasticity		*Legal Risk*	
	RET	*RET*	*RET*	*RET*
HOME_CONC	0.054***	0.031	0.066***	0.026
	(0.000)	(0.248)	(0.000)	(0.504)
INELAST	0.025*	0.019	-	-
	(0.069)	(0.212)	-	-
*HOME_CONC*INELAST*	-	0.030	-	-
	-	(0.315)	-	-
JUDICIAL	-	-	0.007	-0.005
	-	-	(0.356)	(0.709)
*HOME_CONC*JUDICIAL*	-	-	-	0.058
	-	-	-	(0.226)
Property Type Fixed Effects	Yes	Yes	Yes	Yes
N	1044	1044	1044	1044
R^2	0.44	0.45	0.43	0.44
Control Variables: *SIZE, M/B, MOMENTUM, VOLATILITY, ILLIQ, LEV*				

Table 8: Further Identification Tests of Information Asymmetry Using Loan Spreads

This table reports summary statistics of loan spreads (Panel A), returns (Panel B), and a 2SLS instrumental variable estimation examining the relation between local asset concentration and firm returns (Panel C). *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. $Z_{m,i,t}$ is one of M firm characteristics: *SIZE is* the natural log of the firm's aggregate market capitalization; *M/B* is the market value of assets divided by the book value of assets; *MOMENTUM* is the firm's cumulative return over the prior year; *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure; *VOLATILITY* is the standard deviation of the firm's daily returns over the prior calendar year; *LEV* is total debt divided by the book value of total assets; *HOME_CONC* is the percentage of a firm's total property portfolio located in the headquarter market; *LOCAL LENDER* is a dummy variable equal to one if a firm utilized a lender with a branch located in its home (headquarter) market and zero otherwise. A firm is classified as doing business with a local lender beginning in the year it initializes the loan with the lender and remains this way for the duration of the loan's maturity. Non-Local Lenders are those banks that are headquartered outside of the firm's headquarter MSA. Loan spreads are obtained from the Loan Pricing Corporation (LPC)/ Dealscan database and are defined as the reported coupon spread above LIBOR on the drawn amount plus any recurring annual fee (i.e., "All-in-Spread Drawn"). Loan spreads are expressed in basis points. Differences in mean loan spreads are calculated using two sample T-tests. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. *N* is the number of firm-year observations. All regressions include property type fixed effects. The sample period is 1996-2013.

Panel A: Univariate Loan Spread Comparisons by Home Concentration and Local Lender

	Low Home Concentration	High Home Concentration	Difference (High – Low)
	Mean	Mean	Mean
Local Lender	153.219	133.791	-19.428**
Non-Local Lender	145.317	191.951	46.634***
Difference (L-NL)	7.902	-58.160***	-66.062***

Panel B: Univariate Return Comparisons by Home Concentration and Local Lender

	Low Home Concentration	High Home Concentration	Difference (High – Low)
	Mean	Mean	Mean
Local Lender	0.097	0.167	0.070***
Non-Local Lender	0.088	0.066	-0.022
Difference (L-NL)	0.009	0.101***	0.092**

Panel C: Instrumental Variable Analysis Using Local Lender

	(1) *HOME_CONC*	*(2)* *RET*
Stage 1:		
LOCAL LENDER	0.675***	-
	(0.000)	-
F-Statistic	14.28	-
Stage 2:		
HOME_CONC_IV	-	0.118**
	-	(0.028)
Property Type Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
N	1044	1044
Adjusted R^2	0.26	0.50
Control Variables: *SIZE, M/B, MOMENTUM, VOLATILITY, ILLIQ, LEV*		

Appendix A1: Firm Characteristics – Summary Statistics

This table reports summary statistics of annual firm characteristics and returns. *RET* is the firm's annual excess return ($R_{i,t} - R_{f,t}$) with respect to the yield on the 1-month Treasury bill. *SIZE* is the natural log of the firm's aggregate market capitalization. *M/B* is the market value of assets divided by the book value of assets. *MOMENTUM* is the firm's cumulative return over the prior year. *VOLATILITY* is the standard deviation of the firm's daily returns over the prior calendar year. *ILLIQ* is the natural logarithm of the stock's Amihud (2002) illiquidity measure. *LEV* is total debt divided by the book value of total assets. *HOME_CONC* is the percentage of a firm's total property portfolio located in the headquarter market. Percentages are expressed in decimal form. The number of firm-year observations is 1,044. The sample period is 1996-2013.

Panel A: Firm Characteristics and Returns – Descriptive Statistics

	Mean	Median	SD	Min	Max
RET	0.129	0.134	0.265	-0.951	1.170
SIZE	13.421	13.607	1.527	8.608	16.804
M/B	1.841	1.840	0.466	0.670	3.771
MOMENTUM	0.068	0.069	0.256	-0.950	0.939
VOLATILITY	0.019	0.014	0.013	0.001	0.117
ILLIQ	-5.159	-5.480	2.440	-11.377	4.058
LEV	0.421	0.416	0.156	0.000	0.937

Panel B: Correlations amongst Firm Characteristic and Home Concentration

	SIZE	*M/B*	*MOMENTUM*	*VOLATILITY*	*ILLIQ*	*LEV*
HOME_CONC	-0.056	0.092	0.070	0.005	0.059	0.031