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

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Abstract

Using a large, granular sample of individual commercial property holdings and a unique setting with significant cross-market information asymmetries, we provide robust evidence that local information plays a significant role in asset concentration and return performance. Consistent with the information advantages associated with geographic proximity, we find that property portfolio managers concentrate an economically significant portion of their portfolios in their headquarter location. In particular, managers hold, on average, approximately 20 percent of their portfolios in their home market, while the average portfolio concentration for those not headquartered in that location is approximately 1.4 percent. We also document a significant positive relation between home market concentration and portfolio returns using portfolio sort approaches and cross-sectional regressions. The average monthly return on the high home concentration portfolio exceeds the return of the low home concentration portfolio by 40 basis points. We further exploit cross-sectional heterogeneity in information asymmetry across markets for local and non-local investors to demonstrate that this home market effect is concentrated in geographic markets in which information asymmetry between buyers and sellers is most severe. Finally, using bank loan-level data, we further confirm the identification of the information-based return channel. Overall, our results provide novel evidence on information-based channels of asset concentration and their return effects that are distinct from risk-based explanations.

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1. Introduction

A long-standing puzzle in financial economics is the empirical observation that many investors actively choose to heavily overweight local investments in their portfolios. 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). [1] Although local bias among investors has been documented extensively across market participants, firms, and geographic markets, important questions still remain: for example, what drives investors to choose local assets and to what extent is subsequent return performance tied to these geographic allocation and selection decisions?

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 a perceived information advantage in their home market will 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-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 also leads to local investment

[1] For example, evidence of local bias in investment decisions has been documented among individual equity investors (e.g., Ivkovic and Weisbenner, 2005), 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).

[2] If both local and non-local investors know that, for example, 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 excess (risk-adjusted) return.

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 Yonkers, 2012). In equilibrium, concentrated risk arising from familiarity biases or similar cognitive biases should result in lower relative return performance. By focusing our analysis on the performance effects of local bias in investment environments characterized by significant information asymmetries, we provide new support for information-induced concentration effects that are distinct from other behavioral explanations of home bias.

Despite evidence of investor preferences for local investments across asset classes, less is known about the underlying drivers of positive return performance associated with local asset concentration. This gap in the literature is due, in part, to the challenge of isolating information-based effects (e.g., Van Niewerburgh and Veldkamp, 2009) from the impact of concentrated portfolio risk (e.g., Garcia and Norli, 2012) on relative performance. That is, while potential information advantages associated with local asset concentrations may provide portfolio managers with an opportunity to outperform their peers, insufficient portfolio diversification may also require greater compensation to investors for bearing additional risk.

Focusing on assets traded in relatively liquid public markets has made it difficult for prior empirical research to differentiate information-based effects from competing risk-based explanations of home bias as information is rapidly incorporated into transaction prices. However, in illiquid, highly segmented markets composed of heterogeneous assets, relative information advantages have especially important implications for equilibrium portfolio allocation decisions and performance outcomes. These information asymmetries and the value of local information are especially significant in private 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 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 likely impede the timely capitalization of demand and supply shocks into asset values, thereby allowing more informed local investors to trade on these shocks before they are fully capitalized.

Using granular asset level data and observed differences in local asset market information environments in the CRE market, we provide robust evidence showing local asset concentrations and outperformance consistent with the information-based channel and distinct from competing risk-based explanations. In particular, we focus our information-based tests on the performance of commercial property portfolios owned by equity real estate investment trusts (REIT), thereby providing a market setting in which managers buy, operate, and sell properties in the relatively illiquid private CRE market. With an equity market capitalization of approximately $1 trillion in late 2016 and increased attention on public real estate investments given the recent establishment of its own Global Industry Classification Standard (GICS) sector, understanding the return effects of local bias on this asset class is of particular importance to participants in both CRE and broader public equity markets.

The property portfolios of equity REITs also provide an interesting setting to test home market concentration effects in returns for several reasons. First, by defining local asset concentration at the property portfolio level, we are able to characterize portfolios, rather than investors, as local. By distinguishing between locally concentrated and geographically diverse portfolios, our empirical tests are able to shed light on the performance implications of home bias, as well as allow for cross-sectional variation in the degree of local asset concentration in a manner similar to that of Garcia and Norli (2012).

Second, we can 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 commonly used approaches in the literature. 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. Such proxies can introduce considerable noise into the measurement of local asset concentration, which is an issue our direct measure of concentration circumvents.

Third, the geographic segmentation of CRE markets provides significant cross-sectional heterogeneity in the opacity of local information environments across geographic locations. This asset class feature allows us to better isolate the effects of home market concentrations on performance in investment environments characterized by varying degrees of information asymmetry.

Finally, several institutional characteristics of REITs suggest these firms face lower agency costs than their peers in other sectors. For example, the 90 percent dividend distribution requirement and high levels of institutional ownership require REITs to face ongoing certification and monitoring from capital market participants that better aligns REIT investment decisions with the interests of shareholders.[3] In the presence of increased monitoring, a manager's decision to concentrate investment in the local market is more likely to reflect her perceived information advantage than any personal benefit associated with investing locally. Focusing our analysis on this sector results in a cleaner link between the information-based channel of investment selection and return performance.

We begin by gathering property-level holdings data from SNL's Real Estate Database for equity REITs trading on U.S. equity exchanges. For each equity REIT, we first measure the extent to which the manager concentrates her property portfolio holdings in her local market (i.e., the headquarter/home market measured at the MSA level) at the beginning of each year from 1996-2013. Our final sample consists of 291,849 property-year observations of REIT holdings for 104 equity REITs headquartered in 34 unique MSAs with representation across all U.S. regions.

We then use a portfolio sort approach to examine the relation between equity REIT home market concentrations and REIT return performance. Using our property-level data, we sort REITs into high, medium, and low home market concentration buckets, with annual rebalancing, and compare the unconditional return performance of the portfolios. We then run calendar-time portfolio regressions to test for performance effects (alpha), controlling for standard asset pricing factors. As an additional test, we also run cross-sectional (Fama-MacBeth) regressions of annual REIT returns on firm-level home market allocations and standard firm-level control variables.

Consistent with theoretical notions of information-based asset concentration and return effects, we provide robust evidence that local information plays a significant role in asset concentration and return performance. 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.

[3] REITs are required to pay out 90 percent of annual taxable income on an ongoing basis to maintain their REIT status. In practice most REITs pay out at least 100 percent of taxable income in order to completely avoid taxation at the entity level.

However, home market concentrations range from 0-100% across REITs and over time. Importantly, we also find that 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 firm returns that is both statistically and economically significant. We also perform additional robustness tests, including analyses of alternative risk-based explanations of the positive risk-adjusted returns we observe for REITs with high home market concentrations, and continue to find results that are consistent with information-based channels of asset concentration.

We next design a series of empirical tests that exploit cross-sectional heterogeneity in information asymmetry across geographic markets to further identify the channel through which high home concentrations impact returns. In particular, we utilize three distinct classification systems to identify differences in information environments across MSA locations: the percentage of total property value 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). We expect geographic markets with high average land shares, low foreign investment, and low broker usage to have greater information asymmetry.

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 buyers and sellers is most pronounced.

However, if these high information asymmetry markets are perceived to be riskier ex-ante, their greater realized returns may also represent compensation to investors for a manager's willingness to bear additional risk (e.g., Garcia and Norli, 2012). We therefore 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, to address this potential alternative explanation. We find no support for this alternative risk-based explanation.

Concentrated portfolio exposure to other geographic risk factors may also produce results that are consistent with our information-based 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, firms who concentrate their asset portfolios in a specific geographic area may also be subject to mortgage-related legal risks that vary across regions. In particular, the variation in state laws that govern the foreclosure process can differentially impact property values due to increased costs and greater uncertainty.[4] If increased asset concentration occurs in supply constrained markets or in locations that impose additional legal risks, then the relation between home market concentration and firm returns may also reflect cross-sectional variation along these two dimensions. Following Saiz (2010), we classify headquarter locations by their relative supply elasticity and include this variable in additional tests to mitigate concern that our results are driven by cross-sectional variation in local supply constraints. To address the alternative legal risk explanation, we create an indicator variable that is set equal to one if a firm is headquartered in a judicial foreclosure state, and zero otherwise, and include this variable in additional specifications. The estimated coefficient on our home concentration variable remains positive and highly significant even when controlling for local supply elasticity and legal risk effects. Moreover, in additional interaction tests, we do not find evidence that our documented local asset concentration result is significant in low elasticity markets or judicial foreclosure states.

Finally, to further sharpen and confirm our identification of the information-based return channel, we perform two additional tests. First, we conduct a difference-in-difference analysis of loan spreads quoted by local and non-local lenders on firms with high and low home concentrations using loan-level data from Thomson-Reuters LPC Dealscan database. 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. Our difference-in-difference analysis provides evidence that

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

local lenders price the information advantage by offering lower spreads to local firms with high home concentrations. We extend this framework by implementing an instrumental variable (IV) approach in which the use of a local lender instruments for a firm's level of home market concentration. Using a two-staged least squares (2SLS) estimation, we continue to find a positive relation between local asset concentration and firm returns.

Overall, our paper makes several important contributions to the local-bias and financial intermediary literatures. First, 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.

Second, we contribute to the literature on local bias explanations. Our results support prior literature that provides evidence 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.[5] In particular, we document that geographic proximity influences local investment concentrations and performance in markets with high information asymmetry. Our findings provide support for information-based explanations of local bias arising from sustained information asymmetries.

Third, we contribute to the literature on information in bank loan decisions, emphasizing the effects of local information asymmetry and borrower proximity.[6] Physical proximity lowers the cost of acquiring information because lenders can more easily collect

[5] 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), 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.

[6] 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).

better 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).[7] 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 also 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. In particular, 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 theoretical notions 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 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

[7] Recent theoretical work also highlights the role of distance in bank lending. Almazan (2002) provides a model showing 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.

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. 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.[8] 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.

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

[8] 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.

book value, (2) the initial cost of the property, and (3) the historic cost of the property including capital expenditures and tax depreciation.[9] 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:

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

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.

[9] 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.

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.[10] 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 (20th percentile) as "local" and those that do business in greater than 11 states (80th percentile) as "geographically dispersed."[11] REITs that own and operate properties within 3 states or less (20th 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 80th 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 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

[10] 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.

[11] 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.

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*.[12] To control for broader real estate market exposure, we also 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.[13]

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.

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[12] 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 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.

[13] 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.

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:

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

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:

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

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.[14]

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

Table 3 presents the time series averages and associated p-values of the 18 annual cross sectional regression coefficients obtained from estimating equation (5). 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). A standard deviation increase in home market concentration generates an increase in subsequent annualized returns of 6.7 percent. 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.[15]

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.

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

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 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.[16]

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:

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

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

[16] 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.

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 excess of $2.5 million.[17] The RCA data begin in 2001 and track approximately 45 major MSAs by property type.[18]

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. 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:

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

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

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

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

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 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. 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 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. 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 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. 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 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. 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.[19] 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. 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

[19] "New York Regulator Seeks Faster Foreclosures." By Joe Light. Wall Street Journal. May 19, 2015.

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.[20]

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 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.[21] In particular, we collect the following information for all

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[20] 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).

[21] Over 80 percent of loans in our dataset are Term Loans and Revolvers/Lines of Credit with a term greater than 1 year.

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.[22] 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.[23] 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 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).[24]

[22] See https://www5.fdic.gov/idasp/advSearch_warp_download_all.asp?intTab=1 for further details.
[23] 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.

[24] 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

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.[25] In column 1 of Panel C, we report results from our first stage regression. *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.

4. Conclusion

Standard portfolio theory points to a risk-based explanation for the link between asset concentration 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

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analysis excluding follow-on loans with a local lender and continue to find statistically and economically significant results.

[25] 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.

local investors, relative performance should reflect the local investor's reduced cost of information acquisition and more precise signal of the local asset's payoff. Although there is clear tension between the 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.

Given that information asymmetries are likely to be 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 the return performance of equity REIT managers, who buy and sell properties in the private commercial real estate (CRE) market. Using property level data from SNL's Real Estate Database, we are able to directly observe and measure a firm's local market exposure by computing the proportion of the property portfolio held within a particular geographic region. This refines the measurement approach of prior work by Garcia and Norli (2012), who are only able 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. This refinement, however, relies on the parallel investment environment that characterizes the commercial real estate sector. 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.

We use both a portfolio sort approach and Fama-MacBeth (1973) cross-sectional regressions to examine whether the return performance of equity REITs is related to the home market concentrations of commercial property portfolios. We find that the 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 after controlling for potential differences in macroeconomic risk exposures. Using cross-sectional (Fama-MacBeth, 1973) regressions of annual REIT returns on standard firm-level control variables augmented by firm-level home market allocations, we also document a positive relation between home market concentrations and firm returns that is both statistically and economically significant. These results are robust to additional empirical tests examining potential alternate risk-based hypotheses and sample selection issues.

If significant information advantages of local investors influence their asset allocation decisions and enable property portfolio managers to earn greater returns as a result, we 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 further condition our analysis on the information environment of the headquarter MSA. In particular, we utilize three distinct classification systems to identify differences in information environments across geographic locations: the percentage of total property value that represent land (e.g., Kurlat, 2016, Kurlat and Stroebel, 2014), the percentage of foreign (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). Using both a portfolio sorting approach and Fama-MacBeth (1973) cross-sectional regressions, we document significant outperformance associated with high home concentration firms in markets characterized by high information asymmetry.

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 and quote loan spreads that reflect the information advantage associated with local asset concentration. The results of our difference-in-difference and instrumental variable analysis support our conclusion that the relative outperformance of firms with high local market concentrations is driven by information advantages, not risk. Overall, this study contributes to our understanding of the pricing implications of local bias and points to the importance of the information advantage of local investors in driving relative outperformance in highly segmented markets with significant information asymmetries.

References

Agarwal, Sumit, and Robert Hauswald. 2010. Distance and private information in lending. *Review of Financial Studies* 23, 2757–2788.

Alam, Zinat, Mark Chen, Conrad Ciccotello, and Harley Ryan. 2014. Does the Location of Directors Matter? Information Acquisition and Board Decisions. *Journal of Financial and Quantitative Analysis* 49(1): 131-164.

Almazan, Andres. 2002. A model of competition in banking: bank capital versus expertise. *Journal of Financial Intermediation* 11, 87–121.

Amihud, Yakov. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5, 31-56.

Ayers, Benjamin, Santhosh Ramalingegowda, and P. Eric Yeung. 2011. Hometown advantage: The effects of monitoring institution location on financial reporting discretion. *Journal of Accounting and Economics* 52: 41-61.

Bae, Kee-Hong, Rene Stulz, and Hongping Tan. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics* 88: 581-606.

Berger, Allen, Qinglei Dai, Steven Ongena and David Smith. 2003. To what extent will the banking industry be globalized? A study of bank nationality and reach in 20 European nations. *Journal of Banking and Finance* 27: 383-415.

Bernile, Gennaro, Alok Kumar, and Johan Sulaeman. 2015. Home away from Home: Geography of Information and Local Investors. *The Review of Financial Studies* 28(7): 2009-2049.

Berger, Allen, and Gregory Udell. 1995. Relationship lending and lines of credit in small firm finance. *Journal of Business* 68, 351–381.

Bostic, Raphael W., Stanley D. Longhofer, and Christian L. Redfearn, 2007. Land Leverage: Decomposing Home Price Dynamics. *Real Estate Economics* 36(2), 183-208.

Bourassa, Steven C., Martin Hoesli, Donato Scognamiglio, and Sumei Zhang, 2011, Land Leverage and House Prices. *Regional Science and Urban Economics* 41, 134-144.

Bushman, Robert, and Regina Wittenberg-Moerman. 2012. The role of bank reputation in 'certifying' future performance implications of borrowers' accounting numbers. *Journal of Accounting Research* 50, 883–930.

Butler, Alexander. 2008. Distance Still Matters: Evidence from Municipal Bond Underwriting, *Review of Financial Studies 21(2): 763-784.*

Carey, Mark and Greg Nini. 2007. Is the Corporate Loan Market Globally Integrated: A Pricing Puzzle. *The Journal of Finance* 62(6): 2969-3007.

Carhart, Mark, 1997, On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1), 57-82.

Chhaochharia, Vidhi, Alok Kumar, and Alexandra Niessen-Ruenzi, 2012. Local investors and corporate governance. *Journal of Accounting and Economics* 54, 42–67.

Costello, Anna. 2013. Mitigating incentive conflicts in inter-firm relationships: evidence from long-term supply contracts. *Journal of Accounting and Economics* 56, 19–39.

Coval, Joshua, and Tobias Moskowitz, 1999, Home Bias at Home: Local Equity Preference in Domestic Portfolios, *Journal of Finance 54(6): 2045-2073.*

Coval, Joshua, and Tobias Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

Davis, Morris and Jonathan Heathcote, 2007. The Price and Quantity of Residential Land in the United States, *Journal of Monetary Economics* 54, 2595-2620.

Dennis, Steven and Donald Mullineaux. 2000. Syndicated Loans. *Journal of Financial Intermediation* 9: 404-426.

Fama, Eugene and James MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81(3): 607-636.

Fama, Eugene F. and Kenneth French. 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51(1): 55-83.

French, Kenneth and James Poterba. 1991. Investor Diversification and International Equity Markets. *The American Economic Review* 81(2): 222-226.

Garcia, Diego and Oyvind Norli. 2012. Geographic Dispersion and Stock Returns. *Journal of Financial Economics* 106: 547-565.

Garmaise, Mark and Tobias Moskowitz. 2004. Confronting Information Asymmetries: Evidence from Real Estate Markets. *Review of Financial Studies* 17(2): 405-437.

Gianetti, Mariassunta and Luc Laeven. 2012. The flight home effect: Evidence from the syndicated loan market during financial crises. *Journal of Financial Economics* 104: 23-43.

Hau, Harald., 2001. Location matters: an examination of trading profits. *Journal of Finance* 56(5): 1959–1983.

Hauswald, Robert, and Robert Marquez. 2006. Competition and strategic information acquisition in credit markets. *Review of Financial Studies* 19: 967–1000.

Hollander, Stephan, and Arnt Verriest. 2016. Bridging the gap: the design of bank loan contracts and distance. *Journal of Financial Economics* 119: 399-419.

Houston, Joel and Christopher James. 1996. Bank Information Monopolies and the Mix of Private and Public Debt Claims. *The Journal of Finance* 51(5): 1863-1889.

Huberman, Gur. 2001. Familiarity Breeds Investment. The Review of Financial Studies 14(3): 659-680.

Ivashina, Victoria. 2009. Asymmetric information effects on loan spreads, *Journal of Financial Economics* 92: 300-319.

Ivkovic, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content and the geography of individual investors' common stock investments, *Journal of Finance* 60, 267–306.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48(1): 65–91.

John, Kose, Anzhela Knyazeva and Diana Knyazeva. 2011. Does geography matter? Firm location and corporate payout policy. *Journal of Financial Economics* 101(3): 533-551.

Kedia, Simi, Venkatesh Panchapagesan, and Vahap Uysal. 2008. Geography and acquirer returns. *Journal of Financial Intermediation* 17(2): 256-275.

Kedia, Simi and Shivaram Rajgopal. 2011. Do the SEC's enforcement preferences affect corporate misconduct? *Journal of Accounting and Economics* 51(3): 259-278.

Kurlat, Pablo. 2016. Asset Markets with Heterogeneous Information. *Econometrica* 84(1): 33-85.

Kurlat, Pablo and Johannes Stroebel. 2015. Testing for Information Asymmetries in Real Estate Markets. *Review of Financial Studies* 28(8): 2429-2461.

Lerner, Josh. 1995. Venture Capitalists and the Oversight of Private Firms. *The Journal of Finance* 50(1): 301-318.

Lettau, Martin and Sydney Ludvigson. 2001. Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia are Time-Varying. *Journal of Political Economy* 109(6): 1238-1287.

Levitt, Steven and Chad Syverson. 2008. Market distortions when agents are better informed: the value of information in real estate transactions. *The Review of Economics and Statistics* 90(4): 599-611.

Liew, Jimmy and Maria Vassalou. 2000. Can Book-to-Market, Size and Momentum be Risk Factors that Predict Economic Growth? *Journal of Financial Economics* 57: 221-245.

Malloy, Christopher. 2005. The Geography of Equity Analysis. *The Journal of Finance* 60(2): 719-755.

Mian, Atif. 2006. Distance Constraints: The Limits of Foreign Lending in Poor Economies. *The Journal of Finance* 61(3): 1465-1505.

Pastor, Lubos and Robert F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111: 642-685.

Petersen, Mitchell, and Raghuram Rajan. 1994. The benefits of lending relationships: evidence from small business data. *Journal of Finance* 49, 3–37.

Petersen, Mitchell, and Raghuram Rajan. 1994. Does Distance Still Matter? The Information Revolution in Small Business Lending. *The Journal of Finance* 57(6), 2533-2570.

Pool, Veronika, Noah Stoffman, and Scott Yonker 2012. No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice. *Review of Financial Studies* 25(8): 2563-2599.

Presbitero, Andrea, Gregory Udell, and Alberto Zazzaro. 2014. The Home Bias and the Credit Crunch: A Regional Perspective. *Journal of Money, Credit and Banking* 46(1): 53-85.

Ross, David. 2010. The "dominant bank effect:" how high lender reputation affects the information content and terms of bank loans. *Review of Financial Studies* 23, 2730–2756

Saiz. Albert. 2010. The Geographic Determinants of Housing Supply. *The Quarterly Journal of Economics* 125(3): 1253-1296.

Seasholes, Mark and Ning Zhu. 2010. Individual Investors and Local Bias. *The Journal of Finance* 65(5): 1987-2010.

Sharpe, William. 1964. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance* 19(3): 425-442.

Sufi, Amir. 2007. Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. *Journal of Finance* 62:629-668.

Teo, Melvyn, 2009. The geography of hedge funds. *Review of Financial Studies* 22, 3531–3561.

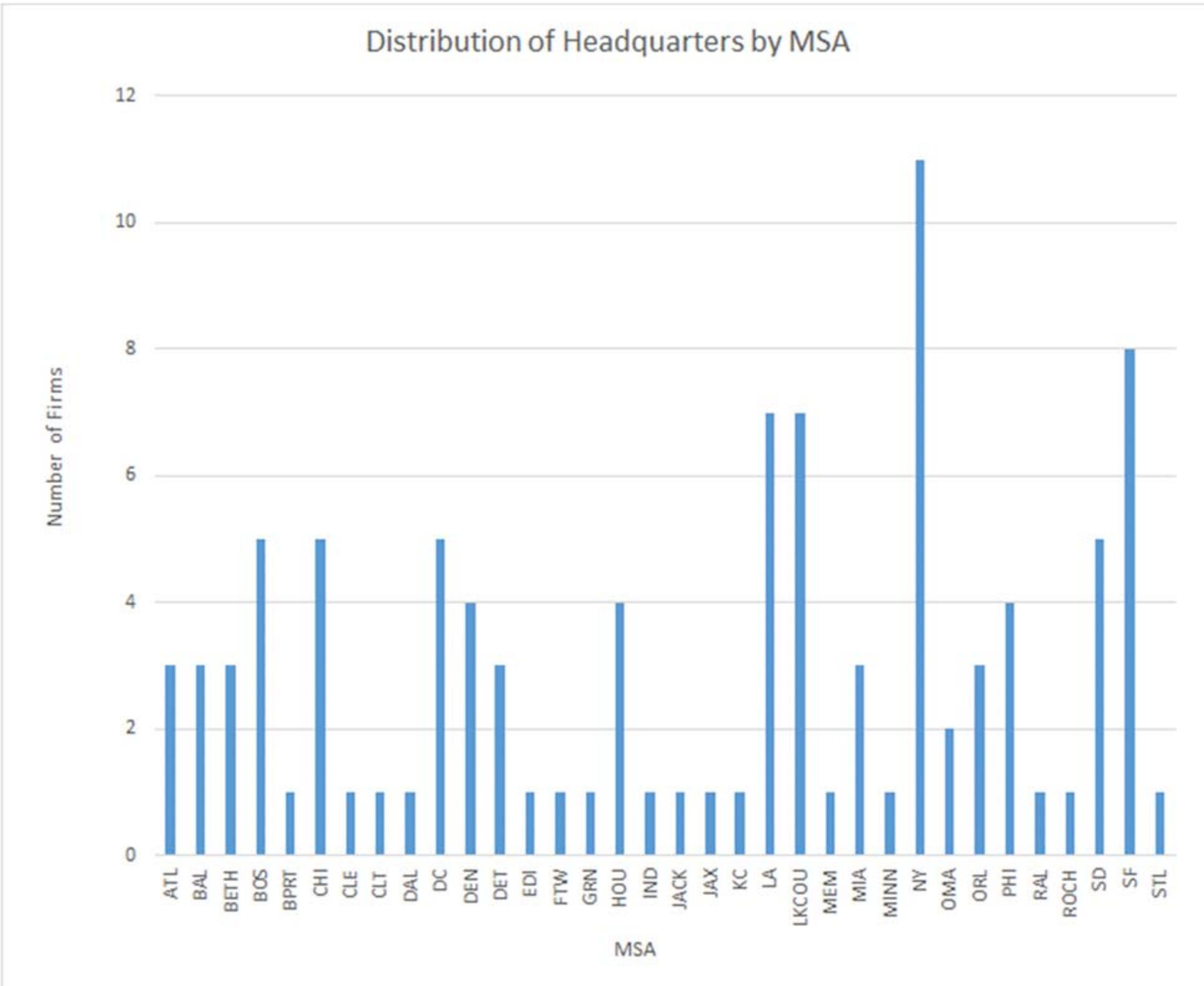
Tian, Xuan. 2011. The causes and consequences of venture capital stage financing. *Journal of Financial Economics* 101, 132–159.

Van Nieuwerburgh, Stijn and Laura Veldkamp. 2009. Information Immobility and the Home Bias Puzzle. *Journal of Finance* 64(3): 1187-1215.

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

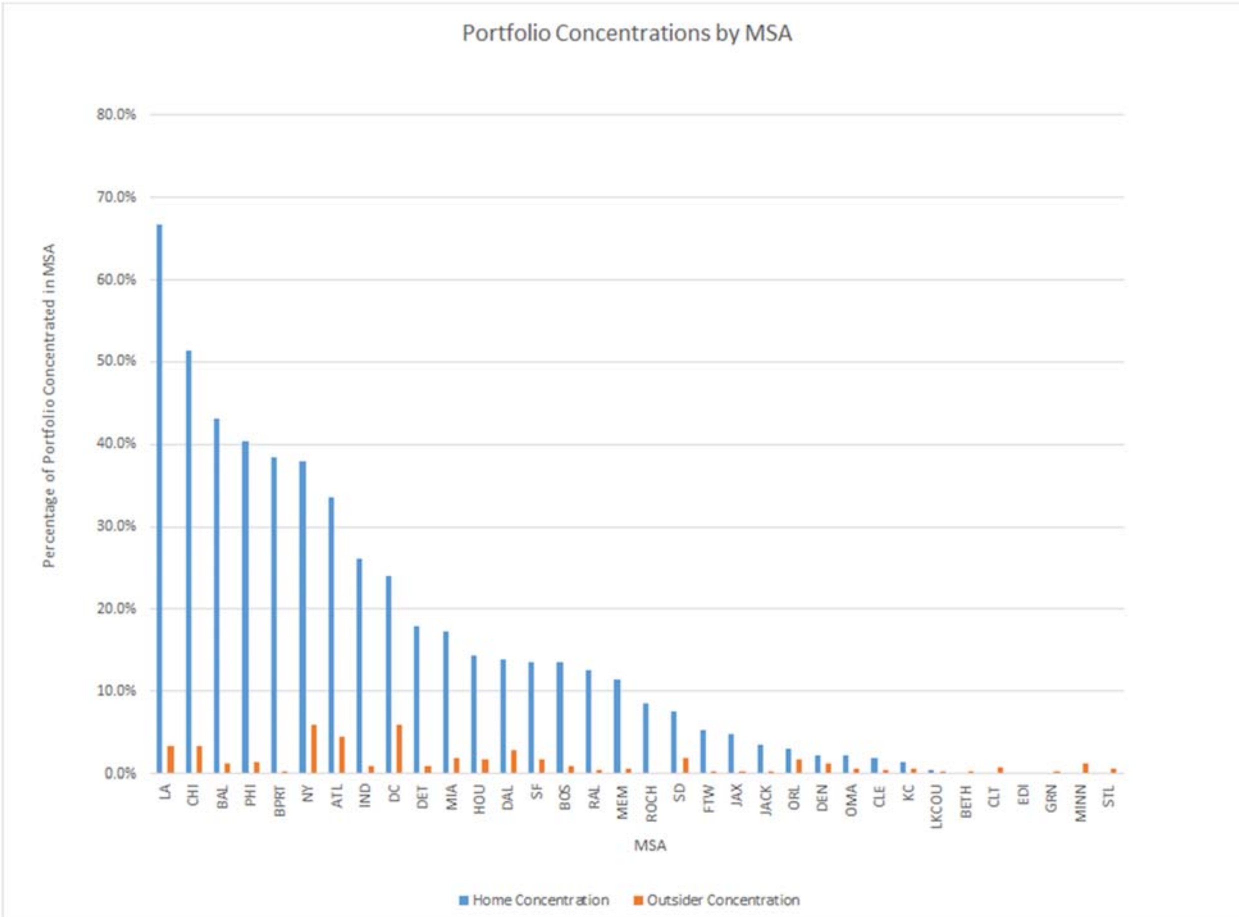


Figure 2: Average Local Asset Concentrations by Year

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.

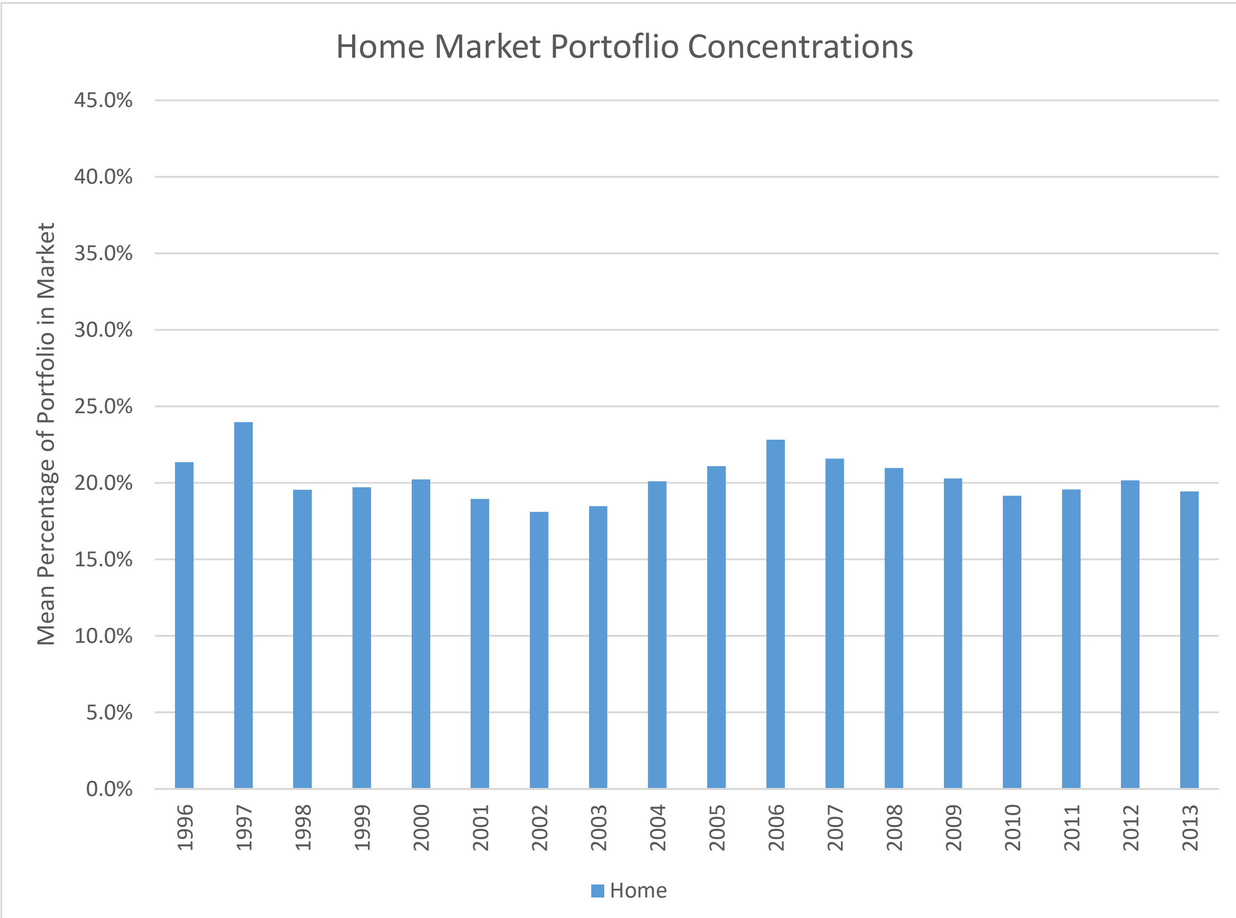


Figure 3: Comparison of Home Concentration and State Count Measures

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.

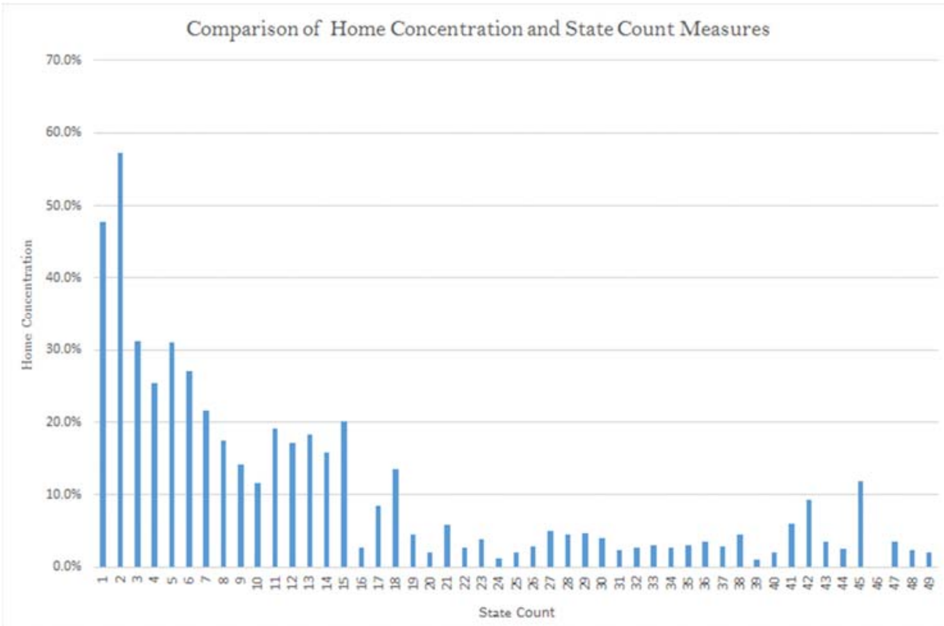


Table 1: Geographic Concentration Measures and Portfolio Returns – Summary Statistics

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)	*(2)*
	HOME_CONC	*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 R2	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. Percentages are expressed in decimal form. The number of firm-year observations is 1,044. The sample period is 1996-2013.

	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