Local Economic Conditions and Local Equity Preferences:

Evidence from Mutual Funds during the U.S. Housing Boom and Bust*

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December 2016

Abstract

This paper examines the impact of local economic conditions on mutual fund preferences for geographically proximate stocks and consequently fund performance. Specifically, we demonstrate that mutual funds favouritism towards firms located within close geographic proximity varies with local housing price shocks. A decrease in local house prices is strongly associated with an increase in mutual fund home bias and results in a portfolio adjustment towards safer and higher quality holdings. This previously undocumented behavioral bias is of first order importance, as the shift in mutual fund preferences towards local stocks induced by deterioration in local economic conditions is associated with mutual fund underperformance: a one percentage point increase in home bias causes a decrease in a fund's characteristic-adjusted 3-month future return by 35.3 bps.

Keywords: Home bias, Investor behaviour, local information advantage, non-fundamental information, house prices

JEL classification: F30, G15, G23

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*We thank Susan Christoffersen and Christian Laux and seminar participants at the Copenhagen Business School and Wirtschaftsuniversitaet Wien.

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Mutual funds operate in and react to changing economic conditions. Recent empirical and theoretical studies have shown that external conditions affect mutual fund performance and asset allocation decisions.[1] While previous research documents a strong relationship between market-wide conditions (e.g. business cycle) and fund returns, there is relatively little known about how local economic conditions affect a fund's asset management and, consequently, performance. In particular, time-varying local conditions may fuel fund manager's intrinsic biases and consequently affect a fund outcomes.

We examine how variation in local house prices affects mutual fund preferences towards geographically proximate stocks. To our knowledge, this is the first study directly relating local economic conditions (proxied by local house price growth) to mutual fund portfolio choices and performance.[2] Recent studies document that mutual funds prefer firms with nearby headquarters. However, the mechanism driving local equity preference is subject to ongoing debate. The finance literature offers two main hypothesis explaining investors' home bias: informational advantage and familiarity bias. For example, Coval and Moskowitz (2001) and Ivković and Weisbenner (2005) argue that fund managers have superior information concerning local stocks. On the other hand, Grinblatt and Keloharju (2001), Seasholes and Zhu (2010), and Pool, Stoffman, and Yonker (2012) argue that investors' preferences towards local stocks are driven by familiarity bias.

By examining the relationship between local house price growth and mutual fund portfolio choices, we contribute to the discussion on the mechanisms driving local equity preferences. Previous literature examines the level or degree of mutual fund home bias and explanations based on information advantage or familiarity are related to fund or asset characteristics. In contrast, we examine how the degree of home bias *changes* in response to *changes* in the fund's external environment. Our study thus exploits the changing local dynamics of a fundâĂŹs environment, whereas earlier work relied largely on static proxies. This allows us to use exogenous variation in local economic shocks for causal inference regarding fund behavior. We find that mutual funds respond to changes in local housing prices by shifting the degree of home bias in their equity portfolios: Negative house price shocks cause funds to tilt their portfolio in favor of nearby equity holdings. However, we do not find that housing price shocks are related to what we call 'fund tangibles' (net flows, liquidity position, etc.). Thus, the relationship between the home bias and house price shocks that we document is not driven by fund investors' reaction to a change in local economic

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[1] e.g. Ferson and Schadt (1996), Elton, Gruber, and Blake (1995), Vayanos (2004), and Korniotis and Kumar (2013).

[2] House price growth is a good indicator of local economic conditions. For example, Leamer (2007) argues that housing is the most important sector in economic recessions. In a series of papers, Mian and Sufi (2011); Mian, Rao, and Sufi (2013), and Mian and Sufi (2014) document that exogenous local house price shocks have strong effects on local demand. Charles, Hurst, and Notowidigdo (2016) show that the housing demand was a strong predictor of the employment-to-population ratio of US metropolitan areas in the 2000s. Stroebel and Vavra (2014) show that local house price growth is associated with local retail prices, and that the link is driven by demand or local consumer behavior.

conditions. Asset information advantages or familiarity are likely unrelated to local housing price shocks. For example, we do not expect local information availability to be systematically related to the magnitude of house price growth during the housing boom. Thus, our findings suggest a bias in fund manager behavior that is unrelated to information or familiarity. This previously undocumented behavioral bias is of first order importance, as the shift in mutual fund preferences towards local stocks induced by deterioration in local economic conditions is associated with mutual fund underperformance.

Our paper uses data on US open-ended mutual funds from Morningstar. Our sample includes mutual funds that actively invest in US equity between January 2002 and December 2009. We split our sample into two time periods to exploit the dramatic changes in housing prices across the US during the housing boom (2002-2005) and bust (2006-2009). Our data on housing prices are extracted from Zillow and aggregated to the Core Based Statistical Area (CBSA) level, which we refer to as cities. We then match mutual funds to cities using the location of the mutual fund's head office to create a panel of data covering our two time periods. The key relationship we investigate is how local housing price shocks affect mutual fund portfolio choices. To motivate this relationship, consider Figure 1, which plots the annual fraction of a fund's portfolio held in local stocks (within 100 km) and mean housing prices across the US. The aggregate data suggests that the degree of mutual fund home bias is inversely related to US housing prices. While this time-series relationship is suggestive, we aim to isolate a causal relationship by exploiting the cross-section dimension of our panel and asking whether portfolio shifts in the fraction of local equity holdings are stronger in cities with larger house price shocks. Our empirical strategy is similar to Mian and Sufi (2011); Mian et al. (2013); Mian and Sufi (2014) who exploit the large variation of house price appreciation and depreciation across cities during the housing boom and bust. We relate house price growth to mutual fund portfolio adjustments at the city-level using a first-differenced regression framework. While this approach controls for time-invariant factors related to city-level house prices and manager behavior, there is the potential for time-varying omitted factors to confound our estimates. Thus, we use the Saiz (2010) measure of topographical land constraint as an instrument to isolate exogenous variation in house price growth as in Mian and Sufi (2011).

Our investigation begins by analyzing whether local economic conditions affect mutual fund net-flows or liquidity decisions. Investor withdrawals in response to local economic downturns, for example, may cause fund managers to rationally alter their portfolio composition. Both OLS and IV results indicate that investors' demand and supply of cash is unresponsive to the variation in local economic conditions. We also find that fund cash, US equity holdings, and active liquidity management do not co-vary with housing price shocks. Taken together, these results suggest that housing price shocks do not significantly affect investors liquidity demand and, thus, do not create a fundamental need for funds to alter their asset allocation strategies.

We then examine our main relationship of interest by creating several measures of home bias and relating these measures to local housing price growth. Our main measure of home bias is a weighted average of the distance between fund headquarters and the firm headquarters of each asset in their portfolio, where the weights are the share of the asset within the portfolio. We calculate this measure at the beginning and the end of our two sub-periods for each fund, and we document that the average city-level change in home bias is strongly related to house price growth. We show that this relationship is not being driven by any particular city and is robust to alternative measures of home bias. Moreover, this relationship is present in each sub-period: During the boom, cities that experienced larger positive house price growth reduced their home bias the most, while during the bust, cities that experienced larger negative house price growth increased their home bias the most. We find that a one percentage point reduction in house prices is associated with a decrease in mean distance between a mutual fund and its holdings by 36 km and increases the fraction of local assets in a fund's portfolio by 0.73 percentage points. Figure 2 depicts our basic reduced form results. The figure contains four panels, where the panels on the left show two key relationships during the housing boom. In particular, the top left panel shows that housing prices grew more in cities that were more land topographically constrained. In the bottom left panel, we show that home bias *decreases* more in land constrained cities. The panels on the right document the symmetry of our results: more constrained cities had larger declines in house prices and *increases* in home bias.

In order to better understand these results, we investigate whether local economic conditions are related to other types of shifts in portfolio composition. To do this, we use stock quality and safety measures constructed by Asness, Frazzini, and Pedersen (2013). We create an index of portfolio quality for each fund by computing a share weighted average of asset quality. We construct an index of portfolio safety in the same way. We show that shifts in portfolio quality and safety are strongly related to house price growth. In particular, when house prices fall, funds increase both the safety and quality of their portfolios. This is suggestive evidence that mutual fund managers may be responding to perceived risk or uncertainty when local economic conditions shift. We further investigate this by splitting the holdings of each fund into local and distant stocks, and examine quality and safety shifts within each of these sub-portfolios. We find that mutual funds adjust the quality of both the local and distant components of their portfolios in response to house price shocks, but only adjust the safety of the distant portfolio. This may suggest that fund managers perceive local holdings to be safer.

Finally, we investigate the consequences of house price driven portfolio shifts in terms of fund performance. To begin, we relate future fund performance directly with local house price shocks. We find that a one percentage point reduction in local house prices is associated with a 25 bsp and 51 bsp decrease in future 3- and 6-month characteristic-adjusted returns, respectively. We then split fund portfolios into local and distant stocks, and calculate the future performance of each sub-portfolio. We find that underperformance is concentrated in the portfolio of local stocks. We view these relationships as reduce-form, but we are more interested in the relationship between future performance and changes in funds' home bias. To overcome endogeneity issues, we instrument our measures of home bias with the Saiz (2010) measure of local land constraints. Not surprisingly given our results above, local land constraints are strongly related to measures of home bias. In particular, during the housing bust, mutual funds in more constrained cities became more home biased, and vice versa in the boom period. Our two-stage least squares estimates suggest that home bias causes underperformance. A one percent increase in the fraction of local stocks in a portfolio decreases 6-month characteristic-adjusted returns by 69.9 basis points. The negative relationship between future performance and shifts in favoritism toward local stocks are robust across different measures of home bias and stronger after 5 months. Thus, our results suggest that shifts in portfolio composition that are driven by housing price shocks are not informed adjustments.

Our paper contributes to the active and growing literature that investigates the relationship between portfolio decisions and the experiences of managers. This literature documents that portfolio decisions are impacted by manager age, gender, experience, political views, manager-director college networks, or even local religious beliefs.[3] Additionally, prior research has shown that mutual funds have home bias in their preference for domestic assets over foreign ones, and also within the US for geographical proximate firms. Our paper investigates how the *strength* of these local preferences shift with local external conditions. We show that city-level housing price shocks (1) do not impact fund tangibles, such as net-flows, and thus create no fundamental need to alter funds' portfolios, (2) symmetrically impact measures of funds' home bias, and portfolio quality and safety, and (3) drive shifts in fund home bias that are significantly related to fund performance. While the finance literature largely focuses on the information advantages and familiarity hypotheses to explain home bias, our results suggest that other biases are at play. In particular, the symmetry of the impact of positive and negative house price shocks suggests that fund managers are responding to perceived risk and view local assets as relatively safe. The behavior we document cannot be explained by information advantage, since negative shocks lead to fund underperformance. Nor can they be explained by familiarity since positive shocks reduce local favoritism and, thus, funds do not simply "invest in what they know" (Pool et al. 2012). Rather, our findings suggest that fund reaction to house price shocks reflects a response to perceived risk and fund managers view local assets as being safer, and this behavioral bias leads to poorer fund performance.

The paper is organized as follows. In the next section, we relate our analysis to the existing literature. In section 2, we describe the data and the variable construction in detail. In Section 3, we explain our approach to estimation. Section 4 reports the empirical results. Section 5 concludes.

[3] Barber and Odean (2001) find that male investors are more overconfident and are characterized by excessive trading. Cohen, Frazzini, and Malloy (2008) document that a fund manager asset allocation decision is strongly influenced by connections with firm board members, that used to go to the same collage as the fund manager. Hong and Kostovetsky (2012) find evidence that fund managers who donate money to political campaigns are less likely to invest in socially irresponsible companies. Shu, Sulaeman, and Yeung (2012) document that mutual fund located in areas with high fraction of Catholics have stronger preferences for high volatility assets than funds domiciled in Protestant-dominated areas.

1. Related Literature

This paper is related to, and combines, three lines of literature. First, we contribute to the discussion on the origin of home bias. Second, the paper adds to a relatively new and growing strand of literature discussing the impact of personal traits and biases on investors' decisions. The third contribution of our analysis lies in an examining how mutual fund manager's decisions are affected by changing local (economic) conditions.

1.1. Importance of mutual fund location

This paper contributes to the literature on the importance of mutual fund location. Previous studies mainly focus on informational advantages versus behavioral biases stemming from fund location relative to the stocks in his portfolio. Yet there is little consensus regarding the importance of a manager's familiarity with a stock in portfolio selection decision. Coval and Moskowitz (2001) argue that fund managers have superior information about local stocks, which is reflected in high abnormal returns generated by those holdings. Ivković and Weisbenner (2005) come to similar conclusion by looking at individual investors' portfolios. However, Grinblatt and Keloharju (2001), Huberman (2001), and Seasholes and Zhu (2010) find opposite evidence. They argue that fund managers familiarity bias results in overweighting local stocks in a fund's portfolio and consequently in a lower fund's performance. Fund manager's behavior can also be affected by local culture. According to Shu et al. (2012), local religious beliefs affect mutual fund managers' risk taking behavior (return volatility, portfolio concentration, turnover, absolute return gap, and tournament-related competition), though highly competitive environment. Previous studies provide evidence of information spill-over effects within a city. Hong, Kubik, and Stein (2005) document that fund's manager trading decisions are more susceptible to the trades of other managers in the same city than to the trades of managers from a different city, suggesting an information transmission across mutual funds located in the same city. A city's demographics also seem to notably affect fund manager behavior.[4] Christoffersen and Sarkissian (2009) document a positive correlation between mutual fund performance and the city size. They argue that this relationship is mainly due to managers with greater experience. This indicates that large cities produce learning externalities that fund manager take advantage of.

1.2. Personal traits and biases

Our paper also contributes to the existing literature on investorsâĂŹ personal biases and traits. The effect of overconfidence on managers' decision making has been studied by both empiricists and theorists. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) and Odean (1998) argue

[4]See Christoffersen and Sarkissian (2011).

in their theoretical frameworks that overconfident investors trade more frequently, which may not counterbalance average trading costs. According to Odean (1999) and Barber and Odean (2001), overconfidence induced excessive trading is associated with underperformance among individual investors. Christoffersen and Sarkissian (2011) relate a mutual fund turnover to manager's biases and characteristics. They find that inexperienced, more educated male managers located in financial centers increase their trading after recent good performance. But gradually, they recognize their true abilities and decrease their trading frequency over time. Bodnaruk and Simonov (2016) investigate how institutional investors aversion to losses (disposition effect) affects a portfolio's composition and performance. They argue that institutional investors with loss-aversion manage portfolios with lower downside risk, perform more poorly, and have shorter careers in asset management. Managers' personal traits and biases do not only affect asset allocation decision of institutional investors, they are also reflected in corporate finance decision making.[5]

1.3. Time-varying economic conditions

Finally, this paper is related to studies that link both mutual fund performance and manager's behavior to the variation in economic conditions over time. Previous research provides an evidence of time-varying mutual fund alphas and betas.[6] Glode (2011) claims that while mutual funds underperform in expansion periods, they outperform in recessions. Kacperczyk, van Nieuwerburgh, and Veldkamp (2014) argue that mutual fund manager's skills varies overtime. Their results suggest that successful managers adroitly pick stocks in booms and time the market well in recessions.[7] Further, mutual fund managers actively manage portfolio's liquidity in response to time-varying market volatility. Rzeźnik (2016) shows that fund managers actively tilt their portfolio towards more liquid assets in face of market volatility induced outflows.[8] Last, our study is closely related to Pool, Stoffman, Yonker, and Zhang (2014). They focus on the impact of shocks to manager's wealth (due to real estate bubble burst) on his risk-taking behavior. They argue that a manager experiencing shocks to his wealth decreases the riskiness of his portfolio relative to a manager who does not experience any wealth shock. Our analysis, however, uses the variation in house price changes to provide a potential explanation for fund manager's preferences toward geographically proximate securities. We show that a mutual fund adjusts its degree of home bias in response to

[5] See e.g. Malmendier and Tate (2005), Cronqvist, Makhija, and Yonker (2012), or Malmendier, Tate, and Yan (2011).

[6] E.g. Ferson and Schadt (1996), Christopherson, Ferson, and Glassman (1998), and Moskowitz (2000) relate fund performance to business-cycle variation.

[7] See also Kacperczyk, van Nieuwerburgh, and Veldkamp (2016) for a theoretical model of time-varying managerial skills.

[8] Vayanos (2004) provides a theoretical model, where fund managers actively adjust the liquidity of their portfolios in response to the changes in market volatility.

changes in local economic conditions. This suggest that mutual fund's preferences for local stocks are unrelated to informational advantages or manager's familiarity.

2. Data and methodology

We use data from three main sources: CRSP, Morningstar and Zillow. This section provides a brief summary of those datasets. We also define and describe the construction of our main variables.

2.1. Data and sample

Stock returns, headquarter addresses, and other relevant market and accounting data come from the intersection of the CRSP daily and monthly files as well as COMPUSTAT. We restrict our analysis to common stocks (share codes 10 and 11) with a valid postal address. We include penny stocks into our analysis, though eliminating stock with share price lower than 5 dollars does not quantitatively affect our results.

Data on mutual fund holdings comes from Morningstar. Our focus is on US active mutual funds investing in US equity. We include funds with at least 1 million dollars of total net assets (TNA) in order to reduce the incubation bias.[9] We require funds to have available information about the value of their holdings at the end of 2001 for mutual funds in the boom period and at the end of 2005 for the bust period. We discard mutual funds with missing postal addresses.

2.2. Measuring investors' biases

To estimate our main relationship of interest, we need to construct variables that capture mutual fund manager's preferences towards local stocks. We propose three measures: a mean *distance* between a mutual fund and its holdings, a *fraction of portfolio held locally*, *home bias* measure proposed by Coval and Moskowitz (1999) estimated with all US equity holdings and for the 10 biggest US equity positions.

We use the mean latitude and longitude assigned to each zip-code, in order to match each mutual fund and the headquarters of each US company with the latitude and longitude coordinates. We calculate the *arc* length - the distance $d_{i,j}$ between fund i and company j:

$$d_{i,j} = \arccos(deg_{i,j}) \cdot \frac{2\pi r}{360},$$

[9]See Evans (2010) for more information on incubation bias.

where

$$\begin{aligned} deg_{i,j} &= \cos(lat_i)\cdot\cos(lon_i)\cdot\cos(lat_j)\cdot\cos(lon_j) \\ &\quad +\cos(lat_i)\cdot\sin(lon_i)\cdot\cos(lat_j)\cdot\sin(lon_j) \\ &\quad +\sin(lat_i)\cdot\sin(lat_j). \end{aligned}$$

The latitudes and longitudes of a fund i and a company j are given by lat and lon, and r is the radius of the earth.[10] As our first measure of home bias, we use the distance to compute a mean distance between a mutual fund and its holdings:

$$\text{Distance}_{i,j,t} = \sum_{j=1}^{J} \omega_{i,j,t}\cdot d_{i,j}, \tag{1}$$

where $\omega_{i,j,t}$ is a fraction of mutual fund i's portfolio held in stock j in month t.

A second measure of manager's preferences towards geographically proximate stocks is the fraction of a portfolio held in stocks with headquarters within 100 km radius:

$$\text{Local}_{i,t} = \sum_{j=1}^{J} I_L\cdot\omega_{i,j,t}, \tag{2}$$

where I_L is an indicator variable that is equal to one if a company's headquarters are within 100 km radius away from mutual fund i, and zero otherwise.[11]

Finally, we use a local bias measure constructed by Coval and Moskowitz (1999), which is defined as:

$$\text{Local Bias}_{i,t} = \sum_{j=1}^{J} (m_{i,j,t}-h_{i,j,t})\cdot\frac{d_{i,j}}{d_i^M}, \tag{3}$$

where $m_{i,j,t}$ is a portfolio weight of stock j in the benchmark portfolio, $h_{i,j,t}$ is the fraction of the fund i's portfolio invested in stock j, $d_{i,j}$ is the distance between fund i and stock j, and $d_i^M=\sum_{j=1}^{J} m_{i,j,t}d_{i,j}$. We also use the same local bias measure that assesses manager's preferences towards local stocks within top ten largest holdings.

2.3. Summary statistics

Table 1 presents summary statistics for our home bias proxies that capture mutual fund managers' preferences towards local stocks, where the cities correspond to mutual fund location. An

[10]We use $r \approx 6,374$ kilometers, see Coval and Moskowitz (1999).

[11]Our choice of 100 km for a local threshold is based on Coval and Moskowitz (2001).

average distance between a mutual fund and its holdings varies noticeably by fund location from 482.88 km for funds located in Syracuse, NY to 2865.52 km for funds located in Seattle-Tacoma-Bellevue, WA during the boom period. In the bust period, mean distance ranges from 825.57 km (Syracuse, NY) to 2760.14 (Seattle-Tacoma-Bellevue, WA). In 6 cities (Abilene, Des Moines-West Des Moines, Madison, Santa Fe, Tucson, and Tulsa) mutual funds do not hold any local stocks in either the boom or the bust period. On the other hand, for funds located in cities like Lancaster, Reading, San Francisco-Oakland-Hayward, and Syracuse, local holdings on average constitute more than 5% of a fund portfolio value. During the boom, mutual funds with headquarters in one of 27 cities seem to overweight their portfolios towards geographically proximate stocks (Local Bias > 0), whereas in the bust times, funds located in 33 cities display preferences towards local holdings. Broadly speaking, this evidence is consistent with firms increasing local holdings during economic downturns. Columns 4 and 8 presents mutual fund preferences towards geographically proximate stocks within 10 largest holdings. Mutual funds located in majority of the cities underweight in their portfolio geographically remote assets.

3. Methodology and identification strategy

Our goal is to model average city-level behavior of mutual funds and its relationship to the growth in house prices. Since the main source of variation that we are interested in is at the city-time level, we use a common two-step estimating procedure. In the first-step, we estimate an equation and the fund level to form regression adjusted, city-averages of fund behavior, which form the dependent variable in our second-step. To begin, consider a fund-level model of portfolio choice, $Y_{i,t,m}$, where i indexes fund, m denotes the Core Based Statistical Area (CBSA) in which a given fund is located, and t indexes time:

$$Y_{i,m,t} = D_{i,m} + D_{m,t} + D_{i,t} + D_m + D_i + D_t + \epsilon_{i,m,t}.$$

This specification models mutual fund portfolio choice as a function of city-fund fixed-effects, $D_{i,m}$, city fixed-effects, D_m, fund fixed-effects, D_i, and time fixed-effects, D_t. We also allow for time-varying behavior at the city-level, $D_{m,t}$, and the fund-level $D_{i,t}$. $\epsilon_{i,m,t}$ is an idiosyncratic error term. This specification is, of course, quite general. In order to make headway, we will have to impose some functional form. We begin by working in differences. In particular, we model the changes in fund behavior over the boom (2002-2005) and bust (2006-2009) periods, to arrive at:

$$\Delta Y_{i,m,t} = \Delta D_{m,t} + \Delta D_{i,t} + \Delta D_t + \Delta\epsilon_{i,m,t}. \tag{4}$$

$\Delta Y_{i,m,t}$ captures fund-level changes in behavior in terms of portfolio choice over the boom and bust period. An important feature of our identification strategy is that this specification eliminates all time invariant fund- and city-level characteristics determining portfolio choice through differencing. The term $\Delta D_{m,t}$ captures time varying city-level factors that are common to all funds in city m and $\Delta D_{i,t}$ captures time-varying fund behavior.

We model $\Delta D_{i,t}$ as a linear function of fund style. Thus, we allow fund style to impact portfolio choices in two ways. First, as a fixed-effect that is differenced away. Second, as a fund fixed-factor that has time-varying effects. For example, different fund styles might behave differently over time due to different investment strategies. The ΔD_t term can simply be captured with a period dummy. We model $\Delta D_{m,t}$ as an unrestricted set of city-time dummies, imposing no functional form at this point. In particular, the first-step in our empirical procedure estimates:

$$\Delta Y_{i,m,t} = \alpha_0 + \alpha_1 \cdot \textsc{Bust} + \alpha_2' \cdot \textsc{Style} + \mu_{m,t} + \Delta\epsilon_{i,m,t} \tag{5}$$

In this specification, Bust is an indicator for the (2006-2009) period, and Style is a vector that includes indicators of fund styles.[12] $\mu_{m,t}$ is a vector of coefficients capturing a full set of unrestricted city-period effects. When estimating (5), we use weighted least squares where the weights are equal to the size of the fund in the initial period.[13] From this regression, we extract the estimated coefficient vector $\hat{\mu}_{m,t}$, which we interpret as regression adjusted, weighted city-average changes in portfolio choice. For notational simplicity, we define $\Delta\bar{Y}_{m,t} \equiv \hat{\mu}_{m,t}$.

Our goal is to model city-level fund behavior as a function of changes in house price growth. Thus, the second-step in our empirical procedure estimates an equation of the form:

$$\Delta\bar{Y}_{m,t} = \beta_0 + \beta_1 \cdot \textsc{Bust} + \gamma \cdot \Delta \ln \textsc{House Price}_{m,t} + \Delta\varepsilon_{m,t} \tag{6}$$

The main coefficient of interest in this model is γ, which captures the impact of house price growth on regression adjusted, city-average fund behavior. The $\Delta\varepsilon_{m,t}$ is a new city-level error term. Since our empirical approach already controls for unobservable fixed-factors at the city-level, this term only contains unobserved time-varying city-level factors. OLS estimation of (6) will yield unbiased estimates of γ if shifts in $\varepsilon_{m,t}$ are unrelated to house price growth. In practice, this may not occur because of an omitted time-varying city-level factor that influences both the price of houses and fund portfolio choice, or because of reverse causality or simultaneity bias. We discuss how we address these possibilities below.

Our two-step estimation procedure is common but particularly well suited to our empirical goal. First, since we aim to capture the impact of shifts in house prices on fund behavior at the city-level, our main source of variation is at the city-period level. By working directly at this level of aggregation, we obtain standard errors that already account for clustering.[14] Second, in the

[12]We allow for 9 possible fund styles, capturing small, medium, and large funds of each value, blend and growth types.

[13]In particular, we use as weights the market value of US equity held by a mutual fund at the end of 2001 and 2005 for the first and second period, respectively. We choose to use fixed weights to account for the fact that a fund's market value and portfolio decisions could be jointly determined.

[14]Accounting for clustering is particularly important in our context, as recent literature points out the similarity in investment behavior of mutual fund managers within a city. For example, Hong et al. (2005) document information flows and knowledge spillovers between managers in the same city. Christoffersen and Sarkissian (2009) provide evidence that more skilled managers tend to work in financial centers.

construction of $\Delta \bar{Y}_{m,t}$, we want to take weighted averages to account for the fact that we are dealing with funds of different sizes. This is done by estimating (5) with weighted OLS where we weight by the size of the funds. However, we do not want to impose these same weights while studying city-level responses to changes in house prices as in (6), since this would allow the behavior larger cities to overly influence the parameter estimates due to the fact that some cities are home to larger funds. At the same time, we want to account for fact that $\Delta \bar{Y}_{m,t}$ is estimated more precisely in cities with more funds. To do this, we estimate (6) using weighted OLS, where the weights are number of funds in each city. Finally, our two-step approach allows us to construct $\Delta \bar{Y}_{m,t}$ while taking into account that the composition of fund styles may vary across cities.

Identification of γ so far relies on the assumption that movements in house prices are uncorrelated to changes in the city-level error term of equation (6). While this assumption may be plausible, we aim to establish causality by dealing directly with the potential for an omitted variable or simultaneity regarding fund behavior and house prices.[15] To do this, we exploit the well-known fact that during the housing boom and bust, house price growth was strongly correlated with fixed geographical features of cities. In particular, in a series of papers by Mian and Sufi (2011; 2013; 2014), the authors show that house price growth is strongly influenced by land constraints that limited the elasticity of housing supply: cities where the amount of land available for building is scarce experienced particularly strong growth in house prices while, during the bust, these cities experienced larger falls in housing prices. We apply their insight by using the percentage of land unavailable for building as an instrumental variable for house price growth in a two-stage least squares procedure. In our framework, we allow land unavailability to have differential effects in the boom and bust period. Consider the model for house price growth:

$$\Delta \ln \textsc{House Price}_{m,t} = \delta_0 + \delta_1 \cdot \textsc{Bust} + \delta_2 \cdot \textsc{Unavailable}_m + \delta_3 \cdot \textsc{Bust} \times \textsc{Unavailable}_m + u_{m,t}, \tag{7}$$

where UNAVAILABLE is the Saiz (2010) measure of the fraction of land unavailable for building in city m. Equation (7) constitutes the first-stage of our two-stage least squares procedure for estimating equation (6). Figure 3 shows the variation in topologically constrained housing supply across cities. The variable $\textsc{Unavailable}_m$ takes into account geographical terrain and water features to determine the degree to which the housing supply in different metropolitan areas is constrained. Cities (e.g. San Francisco or San Diego) located near the sea and surrounded by a mountain range are characterized by a high fraction of land that is not available for development, resulting in more constrained housing supply. On the other hand, cities located in flat areas away from major water bodies (e.g. Lincoln in Nebraska or Abilene in Texas) are characterized by highly elastic housing supply.

Our main empirical specification is a first-differenced, two-stage least squares procedure relating changes in city-average fund behavior to house price growth. This identification strategy eliminates

[15] See e.g. Gyourko and Keim (1992), Quan and Titman (1999), and Okunev, Wilson, and Zurbruegg (2000).

time-invariant fund- and city-factors affect shift in fund behavior through differencing, and potential confounding unobservable city-level factors through an instrumental variables framework, where our exclusion restriction is the fixed availability of housing supply due to geographical features of cities. The validity of our exclusion restriction relies on the assumption that changes fund behavior are not directly influenced by the fixed geographical features of cities.

In our baseline analysis, we concentrate on 46 cities located in 33 states across the US. Table 2 reports summary statistics on the distribution of mutual funds across US cities in our sample. There are 727 (1,023) funds in in the boom (bust) period. One fifth of the funds are located in New York, 8% of the funds have their headquarters in San Francisco or Philadelphia, and 6.5% in Chicago. Salt Lake City is the most topographically constrained (71.99%), whereas Dayton in Ohio has the fraction of land available for development (98.96%). In Los Angeles, which has 52.47% land unavailability, the average house price increased by over 250 thousand dollars during boom and fell by almost 175 thousand during bust period. On the other hand in Lincoln (Nebraska), where developable land is abundant, prices for an average house barely increased (decreased) by 12 (2.5) thousand in the boom (bust) period. As we document below, these examples are typical of the relationship between house price growth and land constraints, forming the basis of instrumental variable strategy.

4. Estimation and Results

We design our empirical strategy to estimate the effect of house prices on mutual fund portfolio allocation decision. In order to identify a causal relationship between local house price growth and fund manager investment decisions, we proceed with two stage-least-square (2SLS) analysis. Figure 4 supports the choice of geographical land unavailability measure as an instrument variable for house price growth. Areas with the most topographically constrained housing supply experienced the greatest growth in house prices during the boom, and drop during the bust. Table 3 shows more formally a strong relationship between house prices and land unavailability, which is necessary for the instrumental variable approach. We predict house price changes $\Delta \ln \textsc{House Price}$ by means of geographical land unavailability (Unavailable) measure, bust period dummy variable, and the interaction of those two. A positive Unavailable coefficient implies that CBSAs with topographically constrained housing supply experience higher price growth in the expansion period. However, the estimated coefficient on the interaction term is negative. This indicates that from 2006 to 2009 the house prices dropped more in cities where land availability was scarce. The first stage F-test for excluded instruments yield a F-statistics of 9.82 and a p-value of 0.0000, which suggests that there is a significant relationship between land unavailability in booms/bust and house price growth.

4.1. Tangibles

Investors cash-flows into and out of a mutual fund constitute one of the main reasons why a fund manager alters his portfolio composition. In the first step of our analysis, we investigate whether mutual fund flows vary with local house prices. Table 4 columns 1 and 2 suggest that local house price growth is not associated with mutual fund net-flows. The $\Delta \ln$ HOUSE PRICE coefficients in both OLS and IV regression are insignificant. This result seems reasonable, since mutual funds invest on behalf of investors domiciled in different cities, states, or even countries. Thus changing local economic conditions in one CBSA do not affect liquidity needs of an investor living in another CBSA hundreds kilometres away. Regression estimates in columns 3 – 8 of table 4 further show that fund managers do not noticeably change their portfolio compositions in response to changing local house prices. Indeed, they appear to keep the same fraction of the portfolio in form of equity (columns 3 and 4) or cash (columns 5 and 6). Local house price growth does not affect a fund manager's liquidity preferences (columns 7 and 8). In total, these results suggest that "tangible" attributes of fund behavior do not very with local house market shocks.

4.2. Home bias

Previous studies suggest that localities are strongly related to investors' trading behavior. Engelberg and Parsons (2011) show that geographic variation in the media coverage of information events is associated with magnitude of local trading. Goetzmann, Kim, Kumar, and Wang (2014) relate local weather conditions (cloud coverage) to an institutional investor's mood, which in turn partly determines his trading decision.

Consequently, we focus on the effect of local economic conditions on fund manager's behavioral biases, in particular home bias. Figure 5 relates a fund manager's industry allocation decision to a mean distance between a fund and an industry. We group all stocks into 10 main industries following Kacperczyk, Sialm, and Zheng (2005). We calculate a mean distance between a fund and an industry. Next for each mutual fund we assign each industry into a quintile based on the mean distance to a given fund and estimate a mean fraction of a portfolio held in each industry quintile. In the left panel, we cannot find any observable relationship between a fund's proximity to an industry and a fraction of a portfolio held in that industry. However, the right panel presents a clear pattern in mutual fund preferences towards geographically proximate industries for funds located in cities with little developable land (Land Unavailability > Median). By comparing the 2005 bars with 2009, we can infer that fund managers increase a fraction of their portfolio held in nearby industries (top three quintiles) and decrease the fraction of their holdings invested in distant industries in response to a sharp drop in local house prices.

Next, we investigate this relationship more formally in a regression framework. We use a two stage-least-square regression approach to estimate the effect of local house price growth on fund manager's home bias measures. Regression estimates presented in table 5 suggest that locally changing house prices affect a fund manager's decision regarding investment into local versus distant stocks. According to both OLS and IV regression results, funds with headquarters in the areas, where house prices decreased the most, seem to invest in those stocks that are located more closely. In columns 3 and 4, we use local bias measure proposed by Coval and Moskowitz (1999) and defined in equation 3. Whereas the OLS regression coefficient on change in house prices is negative yet insignificant, IV regression yields a significant result indicating a strong negative relationship between local house price changes and mutual fund home bias. This result suggest that fund managers increase (decrease) their investment in geographically proximate stocks in response to negative (positive) shock to local house market. This effect is even more pronounced, when we look at ten largest holdings (columns 5 – 6). In the areas, where house prices decrease (increase) the most, fund managers even more noticeably select local (distant) stocks for their top ten largest holdings. In the last two columns, we differentiate between a local component of a portfolio and a distant one. A stock is defined as a local holding if the headquarters of a firm are within 100km radius away from a mutual fund. In columns 7 – 8, we regress the fraction of a portfolio held locally (defined in equation 2) on house price changes and other control variables. Especially, the IV regression estimates indicate a strong and negative relationship between local house price growth and fraction of a portfolio held locally. A decrease in a local house prices by 1% is associated with 0.73 percentage point increase in a portfolio share invested in local stocks.

4.3. Quality and safety

In face of deteriorating local economic conditions fund managers may prefer stock with known risks (e.g. local stocks) over unknown. Resent research suggests that uncertainty about the environment affects fund managers' asset-allocation decision and may result in a flight-to-quality.[16] When local economic conditions deteriorate, fund managers may be willing to reduce the undesirable exposure to local risk by shifting their portfolio towards safer and higher quality firms. The reason for this shift in mutual fund manager's preferences arises from a manager's concern that cash-flows of low quality firms can be fairly sensitive the systematic risk.

Consequently, we analyze, how local house price growth affects a mutual fund portfolio composition in terms of quality and safety. For this, we use stock quality and safety measures constructed by Asness et al. (2013).[17] The quality measure captures four dimensions of quality: profitability, growth, safety, and pay. In addition to the quality of the assets in a portfolio, we focus on their safety. We expect a fund manager to increase the quality and safety of his portfolio in response to deterioration in local house prices. Table 6 provides support for our hypothesis. In areas with the greatest drop in house prices, portfolio's quality and safety increase the most. The change in

[16] See e.g. Beber, Brandt, and Kavajecz (2009), Caballero and Krishnamurthy (2008), and Chen, Hope, Li, and Wang (2016).

[17] We thank Lasse Heje Pedersen for sharing this quality measure.

house prices estimated OLS and IV coefficients are negative and statistically significant for both safety and quality regressions (columns 1 – 2 and 7 – 8). In order to isolate a change in a portfolio's quality/safety due to active modification of portfolio composition in terms of holdings, we follow Rzeźnik (2016):

$$\mathrm{AQM}_{i,t} = Quality_{j,t-1} \cdot p_{j,t-1} \cdot \left(\frac{shares_{i,j,t}}{\sum_{j=1}^{J} shares_{i,j,t} \cdot p_{j,t-1}} - \frac{shares_{i,j,t-1}}{\sum_{j=1}^{J} shares_{i,j,t-1} \cdot p_{j,t-1}} \right), \qquad (8)$$

where $\mathrm{AQM}_{i,t}$ is active quality management of fund i in period t, $p_{j,t-1}$ is price of stock j at the end of period $t-1$, $Quality_{j,t-1}$ is quality rank of stock j at the end of period $t-1$, and $shares_{i,j,t}$ is a number of shares of stock j held by fund i at the end of period t.

We separately analyze active quality/safety management of assets purchases and sales. Based on the reported results, fund managers shift their portfolio towards assets of higher quality and safety in response to deterioration in local economic conditions, by purchasing high quality and safe stocks. On the other hand, in the IV regression of active quality/safety management of sales (columns 6 and 12), the estimated coefficient on house price change is positive, yet insignificant. This suggests, that fund managers seem to reduce their position in lower quality and less safe stocks, when they face locally plummeting house prices.

Having established that fund managers exhibit preferences towards local versus distant assets and actively improve portfolio's quality and safety in response to deterioration in local economic conditions, we investigate whether managers employ different portfolio strategies regarding distant and local stocks. Especially, we look at the trading behavior concerning quality and safety. In our analysis we divide holdings into local and distant positions. Local holdings consist of those stocks with headquarters within 100 km radius away from the mutual fund and constitute part of the fund portfolio. Then, we look at a change in a quality/safety of local versus distant component of a portfolio. Table 7 shows the estimation results. Consistent with the previous results, mutual funds located in areas with deteriorating local economic conditions tilt their portfolios towards high quality and safer stocks as the managers of these funds are likely concerned about quality of both local and distant components of a fund's portfolio. Therefore, in the face of falling local house prices, a fund manager increases quality of local and distant holdings. The $\Delta \ln$ House Price estimation coefficients in OLS and IV regressions of a quality change in local (columns 1–2) and distant (columns 3–4) holdings are negative and significant. The coefficient on $\Delta \ln$ House Price in the local quality regression is more than twice as larger as the coefficient in the regression of distant holdings' quality. This may suggest that, while funds shift toward local stocks, they first and foremost choose local stocks of high quality. The last four columns indicate that locally changing house prices are associated with the shift towards/away from safer stocks primarily in the distant component of a portfolio. The coefficient on $\Delta \ln$ House Price in the regression of local holdings' safety (columns 5–6) is negative, yet insignificant.

Our empirical results suggest that mutual fund have preferences towards geographically proximate, safe and high quality stocks when they are located in areas with deteriorating local conditions.

This finding leads to an intriguing question: Where do these preferences originate from? Are they due to a manager's familiarity bias? Or do they result from manager's superior information about geographically proximate assets? We address these questions by looking at mutual fund performance.

4.4. Mutual fund performance

In our analysis, we focus on uncovering the origin of mutual fund preferences towards geographically proximate assets. We proceed in three steps. First, we test the relation between mutual fund returns and local house price growth. The underlying reason behind this test, is to examine whether local house prices are reflected in mutual fund performance.[18] Second, we compare the response of returns on local and distant holdings to the local house price growth. If local informational advantages induce a fund manager to overweight local stock in the period of locally falling house prices, then we expect the performance of local holdings to exceed the performance of distant holdings in face of deterioration in local conditions. Third, we directly look at the impact of shocks to house market on home bias on fund performance. If preferences toward geographically proximate stocks in times of deteriorating local economic conditions arise for informational advantage, then mutual fund performance should increase with local bias.

Table 8 summarizes the result for the first part of mutual fund performance analysis. We regress change in 3- and 6-month future return on instrumented house price growth. We use three measures of mutual fund performance: raw returns, Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) adjusted returns, and market adjusted returns (excess of market return).[19] DGTW returns are constructed by subtracting from each holding's return the return on a portfolio of firms matched on market equity, market-book ratio, and prior one-year return quintiles. The IV regression estimates in the table suggest that deterioration in local economic conditions negatively affect mutual fund performance.[20] One percentage point decrease in house price is associated with a 25 bsp and 51 bsp decrease in future 3- and 6-month DGTW adjusted return, respectively. The analysis of house price growth impact on raw and market adjust returns provides comparable results, indicating that mutual fund performance significantly deteriorates (improves) in areas where house prices decrease (increase) the most.

In sum, the evidence in table 8 show that there is a direct relationship between mutual fund performance and local economic conditions. In the next step, we examine whether this relation can be attributed to a fund's manager asset allocation decision concerning local and distant stocks.

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[18]See Bernile, Korniotis, Kumar, and Wang (2015) for the evidence that local conditions affect liquidity of local companies.

[19]The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[20]The OLS regression coefficients are also positive, yet insignificant.

In table 9, we relate returns on the local and distant components of a portfolio to the local house price growth. In columns 1–6, we regress change in future returns generated by distant and local components a fund's portfolio. We report the regression estimates for DGTW adjusted returns, though the results remain qualitatively and quantitatively the same if we use raw or market adjusted returns instead. The presented results suggest that while future returns on local holdings strongly respond to the local house price growth, returns on distant holdings remain unaffected. A one percentage point decrease in local house prices is associated with 155 bsp drop in a 3-months future return generated by local holdings. Also the difference between returns on local and distant parts of a portfolio significantly decreases in response to a deterioration in local economic conditions. This points out the local part of a portfolio underperforms (outperforms) the distant component in face of a decline (an increase) in local housing market. The regression results for 6-month future return are somewhat weaker. However, the pattern remains the same. At the 10 percent level of significance, a one percentage point decrease in local house price growth is related to 187 bsp drop in a 6-month future return generated by local holdings. The regression results of the difference in local and distant 6-month future returns, though insignificant, suggest that a local portfolio component underperforms (outperforms) the distant one in face of deterioration (improvement) in local economic conditions.

Finally, we focus on a plausible explanation for an underperformance (outperformance) of mutual funds located in the cities experiencing a decline (an increase) in house price growth. In particular, we focus on the response of mutual fund performance to home bias induced by changes in local house prices. In order to examine this relationship, we proceed with 2SLS approach.

When analyzing the impact of fund manager's preferences towards geographically proximate assets on a mutual fund performance, a possible omitted variable problem arises. Unobservable fund's manager attention or time-varying strategy may determine both asset allocation decision and a fund's performance.[21] Thus, we use exogenous variation in Saiz (2010) land unavailability as an instrument for mutual fund preferences towards local stocks.

Table 10 shows first stage regression estimates for four proxies of a mutual fund's home bias: Coval and Moskowitz (1999) measure of local bias for entire portfolio and for the ten largest holdings, mean distance, and a fraction of a portfolio held locally (within 100km radius). In all four first stage regression Unavailable and its interaction with a bust period dummy variable Bust $\times$ Unavailable are strongly significant with F-test for excluded instruments yielding p-values smaller than 0.01. In booms, mutual funds located in areas with scarce developable land become less home bias, increase the distance to their holdings, and hold less local stocks. The situation is, however, reversed in the bust period. They tend to exhibit strong preferences towards geographically proximate assets.

The effect of a mutual fund's local bias measured for the ten largest holdings on a change in

[21] See Lynch and Musto (2003), Kacperczyk et al. (2014), and Kacperczyk et al. (2016).

fund's future performance is presented in table 11, Panel A. Both OLS and IV result suggest that an increase in local bias within top ten holdings is associated with a decrease in a mutual fund performance. The negative impact of local preferences on fund performance monotonically increases with the future return horizon. While OLS coefficients are significant for all reported time periods, IV estimates yield significant results in regressions of 4-, 5-, and 6-month future returns. Panel B presents the regression estimates of the change in mutual fund future returns on the change in the mean distance. The reported results provide a support to the findings in Panel A. A decrease in a mean distance (shift towards more proximate stocks) is associated with a decrease in fund's future returns. According to IV regression estimates, a 100 km decrease in a mean distance is associated with a decrease in future fund performance by 2.9 bsp for 2-month future return and up to 8.1 bsp for 5-month future return. In Panel C, we examine how mutual fund performance is affected by holding local stocks. We regress the change in a mutual fund future performance on a change in the fraction of a portfolio held locally and we find again a negative and significant relationship. This indicates that investing a greater fraction of a portfolio into local stocks is harmful for future fund performance. A one percentage point increase in fraction of local holdings is related to a significant decrease in 2-month (5-month) future fund performance by 27.5 bsp (73.9 bsp). Finally, Panel D relates future fund performance to the measure of local bias for the entire portfolio. Both OLS and IV regression estimates point out that preferences towards geographically proximate stocks have a negative impact on fund performance. While all OLS coefficients remain highly significant, IV estimates are marginally significant, or insignificant.

The results presented in table 11 suggest that the effect of local house price growth on fund manager preferences towards geographically proximate assets is of first-order importance, because it is directly related to mutual fund performance. Based on our four proxies for home bias, we find that a shift in preferences towards local stocks is associated with a mutual fund underperformance. This result eliminate local informational advantage as an origin of fund manager home bias. Next, the symmetry of our results implies that fund managers invest in less known stocks, when house prices increase locally, which makes familiarity hypothesis implausible. Thus, our findings suggest that investors time-varying preferences towards geographically proximate assets originate in previously undocumented behavioral bias.

5. Conclusion

We contribute to the empirical asset pricing literature by investigating a potential source of investor's home bias. While existing research remains divided on the origin of home bias, we argue that funds' time-varying preferences towards local stocks cannot be explained by informational advantages or manager's familiarity.

In this paper, we study how local house market shocks affect a mutual fund asset allocation decision. Specifically, we examine the effect of local house price growth on fund manager's home bias. Our key finding is that deterioration (improvement) in local economic conditions is associated with a shift in fund manager's preferences towards (away from) geographically proximate assets. A one percentage point drop in local house prices is related to a decrease in mean distance between a fund and its holdings by 36 km and increase in a fraction of portfolio held locally by 0.73 percentage point. We find also that in face of locally decreasing house prices, mutual funds put the value of quality and safety before its cost, and actively increase the quality and safety of their portfolio.

Investigating the impact of local economic conditions on a fund manager home bias, allows to set informational advantages and familiarity bias apart as a potential source of home bias. In our analysis, we focus on US equity mutual funds, because they manage money on behalf of their investors domiciled across the world by investing it into companies spread out across US. Therefore, it seems highly unlikely that informational advantages of mutual funds located in a given city are link to a variation in local house price growth.

Using a two stage-least-square estimation approach, we document a series of novel findings. We find that mutual funds located in areas where house prices decrease (increase) the most, shift the composition of their portfolios towards (away from) geographically proximate assets and consequently generate significantly lower (higher) future returns. Deterioration in local economic conditions is also related to underperformance of a local component of a fund's portfolio relative to a distant one. Finally, we find that a shift in a fund's manager preferences towards (away from) local stocks induced by a decrease (increase) in local house prices is associated with significantly lower (higher) future fund returns. Symmetry of our results suggest that fund manager react to positive shocks to local house market by investing in what they *do not* know. All together, these results undermine informational advantage and manager's familiarity as potential explanations for time-varying home bias among mutual funds.

This paper contributes to the literature along a number of dimensions. Our primary contribution is to show that a variation in local economic conditions affect mutual fund managers' preferences towards geographically proximate assets. We also document a strong shift towards safer and higher quality stocks in face of locally decreasing house prices. Last but not least, we argue that our analysis provides evidence of previously undocumented behavioral bias. We find that deterioration in local economic condition induced shift in preferences towards local assets is associated with a significant decrease in a fund's performance. Overall, our evidence highlights the importance of local economic conditions in fund managers' asset allocation decision making.

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6. Tables

Table 1: Mutual fund's bias - summary statistics. This table reports the mean Core Bases Statistical Area (CBSA) characteristics concerning a mutual fund's preferences towards geographically proximate assets. The mean values are displayed separately for boom (2002–2005) and bust (2006–2009) period. DISTANCE (in km) is a value weight distance between a mutual fund and headquarters of its holdings. LOCAL FRACTION (in %) stands for a fraction of a fund's portfolio held in local stocks (within 100 km radius from a mutual fund). LOCAL BIAS is a measure of home bias constructed by Coval and Moskowitz (1999) and defined as: $\sum_{j=1}^{J}(m_{i,j,t} - h_{i,j,t}) \cdot \frac{d_{i,j}}{d_i^M}$, where $m_{i,j,t}$ is a portfolio weight of stock j in the benchmark portfolio, $h_{i,j}$ is the fraction of fund i's portfolio invested in stock j, $d_{i,j}$ is the distance between fund i and stock j, and $d_i^M = \sum_{j=1}^{J} m_{i,j,t} d_{i,j}$. TOP 10 LOCAL BIAS is a local bias measure based on the ten largest holdings in a fund portfolio. The analysis includes equity mutual funds domiciled in US and actively investing in US equity.

	Boom				Bust			
	Distance	Local Fraction	Local Bias	Top 10 Local Bias	Distance	Local Fraction	Local Bias	Top 10 Local Bias
Abilene, TX	1843.3	0	0.02	0.03	1614.38	0	0.09	0.13
Albany-Schenectady-Troy, NY	1242.49	0.13	0.18	0.2	1529.06	0.26	0.09	0.13
Atlanta-Sandy Springs-Roswell, GA	1425.07	1.35	0.01	0.02	1613.63	1.4	-0.07	-0.13
Baltimore-Columbia-Towson, MD	1525.39	1.89	-0.12	-0.13	1578.46	1.85	-0.05	-0.07
Baton Rouge, LA	1610.27	0.09	0.03	-0.05	1617.72	0.24	0.04	0.03
Bloomington, IL	1209.76	0.4	0.08	0.1	1266.74	0.32	0.06	0.15
Boston-Cambridge-Newton, MA-NH	1770.23	0.29	-0.08	-0.1	1787.03	0.36	0	-0.05
Bridgeport-Stamford-Norwalk, CT	1637.36	4.72	-0.11	-0.09	1711.99	4.6	-0.06	-0.08
Chicago-Naperville-Elgin, IL-IN-WI	1361.21	1.39	-0.03	-0.04	1369.51	2.06	0	-0.05
Cincinnati, OH-KY-IN	1191.49	0.18	0.06	0.07	1218.45	0.25	0.09	0.06
Columbus, OH	1402.1	0.18	-0.1	-0.18	1421.82	0.24	-0.04	-0.17
Dallas-Fort Worth-Arlington, TX	1614.39	1.66	0.06	0.07	1577.86	2.74	0.04	0.04
Dayton, OH	1272.84	1.67	-0.01	-0.08	1230.95	1.38	0.09	-0.01
Deltona-Daytona Beach-Ormond Beach, FL	1872.2	0.24	-0.01	-0.03	1863.69	0.22	0.03	0.12
Denver-Aurora-Lakewood, CO	1817.61	0.57	0.05	0.06	1793.99	0.73	0.02	0.01
Des Moines-West Des Moines, IA	1451.59	0	0	0	1437.87	0	-0.01	-0.01
Detroit-Warren-Dearborn, MI	1329.55	0.5	-0.02	-0.12	1388.63	0.34	0.01	-0.07
Hartford-West Hartford-East Hartford, CT	1685.9	1.2	-0.11	-0.15	1807.57	1.41	-0.06	-0.14
Indianapolis-Carmel-Anderson, IN	1225.35	0.15	0.04	0	1276.45	0.21	0.04	-0.05
Kansas City, MO-KS	1485.74	0.37	-0.02	-0.03	1487.49	0.31	-0.03	-0.06
Lancaster, PA	1312.2	5.48	0.09	0.2	1679.6	3.23	-0.11	0.28
Lincoln, NE	1395.21	1.23	0.21	0.34	1444.36	1.42	0.03	0.1
Los Angeles-Long Beach-Anaheim, CA	2554.57	1	0.08	0.09	2584.06	1.31	0.02	0.01
Madison, WI	1366.48	0	0.01	0.01	1370.21	0	0.03	-0.07

	Boom				Bust			
	Distance	Local Fraction	Local Bias	Top 10 Local Bias	Distance	Local Fraction	Local Bias	Top 10 Local Bias
Miami-Fort Lauderdale-West Palm Beach, FL	1760.43	0.28	0.13	0.13	1694.66	1.29	0.19	0.21
Milwaukee-Waukesha-West Allis, WI	1331.45	0.93	0.03	0.02	1357.83	1.13	0.03	0.01
Minneapolis-St. Paul-Bloomington, MN-WI	1500.46	1.87	0.02	-0.01	1466.29	1.9	0.06	0.05
New York-Newark-Jersey City, NY-NJ-PA	1592.78	4.17	-0.12	-0.15	1671.23	4.21	-0.05	-0.08
Omaha-Council Bluffs, NE-IA	1242.68	0.07	0.19	0.18	1142.89	0.15	0.23	0.21
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1558.06	1.34	-0.12	-0.14	1606.19	1.51	-0.04	-0.09
Phoenix-Mesa-Scottsdale, AZ	2305.02	0.35	0.05	0.04	2252.33	0.46	0.02	0.03
Portland-Vancouver-Hillsboro, OR-WA	3111.28	0.09	-0.05	-0.08	3057.9	0.25	-0.08	-0.1
Providence-Warwick, RI-MA	1521.6	0.3	0.02	0.03	1795.5	0.41	0.01	-0.12
Reading, PA	733.18	9.38	0.87	0.88	951.38	4.46	0.65	0.67
Richmond, VA	1204.75	0.85	0.14	0.06	1453.71	0.73	0.04	0.02
Salt Lake City, UT	2002.98	0.12	0.1	0.13	1981.69	0.31	0.08	0.08
San Diego-Carlsbad, CA	2457.06	0.36	0.1	0.09	2544.67	0.89	0.03	0.03
San Francisco-Oakland-Hayward, CA	2772.79	4.26	0.05	0.06	2710.3	5.22	0.02	0.05
Santa Fe, NM	2019.41	0	-0.02	-0.04	1730.14	0	0.09	0.14
Seattle-Tacoma-Bellevue, WA	2865.52	0.91	0.03	0.07	2760.14	0.73	0.03	0.1
St. Louis, MO-IL	1482.79	0.41	-0.1	-0.11	1227.39	0.27	0.1	0.06
Syracuse, NY	482.88	5.04	0.45	0.45	825.57	3.96	0.47	0.55
Tampa-St. Petersburg-Clearwater, FL	1986.48	0.15	-0.03	-0.03	2035.68	0.14	-0.04	-0.09
Tucson, AZ	2519.45	0	-0.02	-0.02	2432.79	0	-0.05	-0.02
Tulsa, OK	1653.85	0	-0.06	-0.16	1490.81	0	0.01	0.08
Washington-Arlington-Alexandria, DC-VA-MD-WV	1431.01	1.54	-0.05	-0.12	1464.27	1.86	0.02	-0.04

Table 2: Mutual fund and housing market - summary statistics. This table reports basic summary statistics for 46 Core Based Statistical Areas (CBSA) included in the analysis. # of funds denotes the number of funds located in each CBSA. Mean TNA (M) is mean mutual fund total net asset represented in millions. Δ in House Price (K) is a change in mean change in house price displayed in thousands. Land Unavailable (%) is a measure constructed by Saiz (2010) and denotes a percentage of undevelopable land within a city. It takes into account geographical terrain and water features to determine the degree to which the housing supply in different metropolitan areas is constrained by topological characteristics.

	# of funds		Mean TNA (M)		Δ in House Price (K)		Land
	2005	2009	2005	2009	2005	2009	Unavailable (%)
Abilene, TX	2	3	11.36	9.07	11.01	5.88	1.95
Albany-Schenectady-Troy, NY	2	6	534.2	118.82	53.32	2.48	23.33
Atlanta-Sandy Springs-Roswell, GA	7	11	802.6	290.77	14.69	-22.09	4.08
Baltimore-Columbia-Towson, MD	46	55	3144.31	1761.5	103.8	-33.74	21.87
Baton Rouge, LA	1	2	78.06	85.28	23.83	15.93	33.52
Bloomington, IL	1	1	188.09	139.87	12.77	6.04	1.4
Boston-Cambridge-Newton, MA-NH	40	60	1817.45	805.31	82.15	-51.28	33.9
Bridgeport-Stamford-Norwalk, CT	17	22	696.2	412.77	129.74	-88.97	45.01
Chicago-Naperville-Elgin, IL-IN-WI	48	67	1014.19	485.73	42.41	-32.29	40.01
Cincinnati, OH-KY-IN	6	10	124.84	54.15	13.73	-11.23	10.3
Columbus, OH	10	16	258.79	94.56	13.77	-9.64	2.5
Dallas-Fort Worth-Arlington, TX	11	19	370.2	549.28	15.88	-9.93	7.03
Dayton, OH	2	2	11.93	9.8	11.94	-9.18	1.04
Deltona-Daytona Beach-Ormond Beach, FL	2	3	30.28	29.72	83.47	-92.11	60.53
Denver-Aurora-Lakewood, CO	36	46	1580.02	1028.63	15.33	-18.7	16.72
Des Moines-West Des Moines, IA	1	1	82.93	27.51	17.92	6.56	6.17
Detroit-Warren-Dearborn, MI	4	4	108.22	60.4	9.49	-53.77	24.52
Hartford-West Hartford-East Hartford, CT	29	44	1330.24	1036.4	64.75	-19.42	23.29
Indianapolis-Carmel-Anderson, IN	5	8	142.66	73.71	0.12	-11.73	1.44
Kansas City, MO-KS	43	56	2050.72	720.67	5.38	7.88	5.82
Lancaster, PA	1	1	163.83	88.45	38.48	3.03	11.9
Lincoln, NE	1	1	60.92	41.52	12.09	-2.62	1.59
Los Angeles-Long Beach-Anaheim, CA	18	30	1008.64	478.96	251.72	-174.34	52.47
Madison, WI	8	8	255.79	60.87	27.5	-2.33	11.34

	# of funds		Mean TNA (M)		Δ in House Price (K)		Land
	2005	2009	2005	2009	2005	2009	Unavailable (%)
Miami-Fort Lauderdale-West Palm Beach, FL	1	1	69.56	59.38	119.2	-130.47	72.12
Milwaukee-Waukesha-West Allis, WI	21	33	732.09	555.64	32.33	-10.94	41.78
Minneapolis-St. Paul-Bloomington, MN-WI	9	15	432.85	254.98	48.5	-42.07	19.23
New York-Newark-Jersey City, NY-NJ-PA	157	205	840.78	609.88	139.92	-65.71	40.42
Omaha-Council Bluffs, NE-IA	1	2	74.28	85.78	12.52	-3.81	3.34
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	58	90	2829.01	2395.79	69.13	-14.01	10.16
Phoenix-Mesa-Scottsdale, AZ	14	29	351.97	396.36	91.07	-98.88	13.95
Portland-Vancouver-Hillsboro, OR-WA	3	4	1001.88	471.44	60.41	-23.73	37.54
Providence-Warwick, RI-MA	4	6	1766.67	810.53	103.19	-58.6	13.87
Reading, PA	1	1	9.64	6.6	34.78	-0.22	16.48
Richmond, VA	1	1	136.48	96.7	48.6	-4.47	8.81
Salt Lake City, UT	6	8	797.31	288.01	13.55	36.14	71.99
San Diego-Carlsbad, CA	2	7	186.66	35.66	215.74	-155.58	63.41
San Francisco-Oakland-Hayward, CA	65	83	1738.03	871.05	229	-168.61	67.4
Santa Fe, NM	2	2	1088.84	1834.02	38.47	101.98	37.22
Seattle-Tacoma-Bellevue, WA	7	8	482.64	1104.1	76.1	-39.3	40.16
St. Louis, MO-IL	1	1	7.56	6.84	25.48	-9.62	11.08
Syracuse, NY	1	1	5.43	3.3	18.28	6.93	17.85
Tampa-St. Petersburg-Clearwater, FL	13	22	456.11	175.79	67.06	-75.47	41.64
Tucson, AZ	3	3	11748.06	10831.97	67.35	-55.78	23.07
Tulsa, OK	1	1	15.65	12.23	6.53	5.5	6.29
Washington-Arlington-Alexandria, DC-VA-MD-WV	15	24	809.65	253.41	172.13	-105.67	13.95

Table 3: First Stage Regression. This table shows coefficient estimates and F-test statistics for excluded instruments from first stage regression of house price growth $\Delta House$ on Saiz (2010) measure of geographically constraint land UNAVAILABLE, its interaction with a bust dummy variable BUST×UNAVAILABLE, and a bust dummy variable BUST, that is equal to one for observations within 2006 and 2009, otherwise zero.

	Unavailable	Bust Unavailable	Bust	Constant	Observations	Adjusted R^2	F-test
Δ House	0.335*	-0.632*	-0.272*	0.214*	92	0.781	9.82
	(3.06)	(-4.41)	(-5.23)	(5.36)			0.000

t statistics in parentheses

* $p < 0.05$

Table 4: OLS and IV regressions of funds' tangibles. This table show regression estimates from OLS and two stage-least-sqaure regressions of funds' tangibles on instrumented house price growth $\Delta \ln$ House Price and a bust dummy variable Bust equal to one for observations within 2006-2009, otherwise zero. The dependent variable in columns 1 and 2 is a change in a percentage net flow between 2002 and 2005, as well as 2006 and 2009. In sepcification 3 and 4 (5 and 6), the dependent variable is a change in a fraction of portfolio value held in form of US equity (cash). In sepcification 7 and 8, the dependent variable is active liquidity management measure, proposed by Rzeźnik (2016), and computed for two periods 2002-2005 and 2006-2009.

	Fund Flows		Equity Holdings		Cash Holdings		Active Liq Mgmt	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln$ House Price	0.539	0.207	-0.0282	0.0388	0.318	-1.168	-0.349	2.334
	(1.63)	(0.27)	(-1.86)	(1.00)	(0.76)	(-1.11)	(-0.51)	(1.37)
Bust	-0.174	-0.330	-0.0400*	-0.00860	0.639*	-0.0590	-2.639*	-1.383
	(-0.97)	(-0.88)	(-4.83)	(-0.46)	(2.80)	(-0.12)	(-7.12)	(-1.68)
Constant	0.115	0.221	0.0170*	-0.00434	-0.202	0.273	1.523*	0.667
	(0.91)	(0.86)	(2.93)	(-0.34)	(-1.26)	(0.78)	(5.84)	(1.18)
Observations	78	78	92	92	84	84	92	92
Adjusted R^2	0.228	0.217	0.315	0.166	0.166	0.037	0.652	0.591

t statistics in parentheses

* $p < 0.05$

Table 5: OLS and IV regression of funds' home bias proxies. This table show regression estimates from OLS and two stage-least-square regression of four home bias proxies on instrumented house price growth $\Delta \ln$ HOUSE PRICE and a bust dummy variable BUST equal to one for observations within 2006-2009, otherwise zero. The dependent variable in columns 1 and 2 is a change in a value-weighted mean distance between a fund and its holdings' headquarters and calculated for two periods: 2002-2005 and 2006-2009. In sepcification 3 and 4 (5 and 6), we use a change Coval and Moskowitz (1999) local bias measure for entire portfolio (top ten largest holdings). LOCAL BIAS meausre is defined as: $\sum_{j=1}^{J}(m_{i,j,t} - h_{i,j,t}) \cdot \frac{d_{i,j}}{d_i^M}$, where $m_{i,j,t}$ is a portfolio weight of stock j in the benchmark portfolio, $h_{i,j}$ is the fraction of fund i's portfolio invested in stock j, $d_{i,j}$ is the distance between fund i and stock j, and $d_i^M = \sum_{j=1}^{J} m_{i,j,t} d_{i,j}$. In specificantion 7 and 8, the dependent variable is a change in fraction of the portfolio held locally (within 100km radius away from a mutual fund).

	Weighted Distance		Local Bias		Local Bias Top 10		Local Holdings	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln$ House Price	0.192*	0.360*	-0.0607	-0.257*	-0.227*	-0.726*	-1.757	-7.349*
	(3.47)	(2.69)	(-1.32)	(-2.22)	(-2.65)	(-3.14)	(-1.93)	(-2.94)
Bust	0.0721*	0.151*	0.00368	-0.0884	-0.0618	-0.295*	-0.157	-2.774*
	(2.40)	(2.33)	(0.15)	(-1.58)	(-1.33)	(-2.64)	(-0.32)	(-2.30)
Constant	-0.0477*	-0.101*	-0.0117	0.0511	0.0432	0.202*	-0.0540	1.729*
	(-2.25)	(-2.28)	(-0.66)	(1.33)	(1.32)	(2.64)	(-0.16)	(2.09)
Observations	92	92	92	92	92	92	92	92
Adjusted R^2	0.111	0.019	0.063	-0.130	0.086	-0.264	0.088	-0.301

t statistics in parentheses

* $p < 0.05$

Table 6: OLS and IV regression of funds' quality and safety management. This table show regression estimates from OLS and two stage-least squared regression of a portfolio's quality and safety management measure on instrumented house price growth $\Delta \ln$ House Price and a bust dummy variable Bust equal to one for observations within 2006-2009, otherwise zero. The dependent variable in columns 1 and 2 (7 and 8) is a change in a portfolios safety (quality) constructed with Asness et al. (2013) safety (quality) measure at a stock level. In columns 3 and 4 (5 and 6), the dependent variable is active safety management measure in terms of purcheses (sales) following Rzeźnik (2016) shift-share analysis and computed for two periods 2002-2005 and 2006-2009. The dependent variable in columns 9 and 10 (11 and 12) is active quality management measure in terms of purcheses (sales) computed in an analogous manner as active safety management measure in columns 3-6.

	Δ Safety Measure		Active Safety Management				Δ Quality Measure		Active Quality Management			
			Purchases		Sales				Purchases		Sales	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln$ House Price	-0.117*	-0.433*	-0.0200*	-0.0279*	0.0130*	0.00652	-0.132*	-0.341*	-0.0269*	-0.0262	0.0166*	0.00976
	(-2.14)	(-2.94)	(-3.31)	(-1.99)	(2.45)	(0.53)	(-2.43)	(-2.52)	(-4.02)	(-1.70)	(2.94)	(0.74)
Bust	0.0769*	-0.0712	-0.0300*	-0.0337*	0.00776*	0.00471	0.0273	-0.0705	-0.0346*	-0.0342*	0.00469	0.00148
	(2.59)	(-1.00)	(-9.12)	(-4.97)	(2.68)	(0.79)	(0.92)	(-1.08)	(-9.49)	(-4.60)	(1.53)	(0.23)
Constant	-0.0125	0.0884	0.0184*	0.0209*	-0.00430*	-0.00222	0.00905	0.0756	0.0220*	0.0217*	-0.00285	-0.000667
	(-0.60)	(1.81)	(7.95)	(4.49)	(-2.11)	(-0.54)	(0.43)	(1.69)	(8.57)	(4.25)	(-1.32)	(-0.15)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.463	0.260	0.639	0.632	0.055	0.039	0.300	0.184	0.630	0.629	0.104	0.089

t statistics in parentheses

* $p < 0.05$

Table 7: OLS and IV regression of funds' quality and safety for local and distant portfolio's components. This table show regression estimates from OLS and two stage-least-square regressions of a portfolio's quality and safety on instrumented house price growth $\Delta \ln$ House Price and a bust dummy variable Bust equal to one for observations within 2006-2009, otherwise zero. A fund's holding is defined as local if it is within 100km radius, otherwise it is considered a distant holding. The depentent variable in columns 1 and 2 (3 and 4) is a change in a local (distant) component of portfolio's quality. The dependent variable in columns 5 and 6 (7 and 8) is a change in a local (distant) component of portfolio's safety. The changes in local and distant components in portfolio's safety and quality are constructed using Asness et al. (2013) quality and safety measures at a stock level. All the changes are calculated for two periods: 2002-2005 and 2006-2009.

	Local Quality		Distant Quality		Local Safety		Distant Safety	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln$ House Price	-0.264	-0.965*	-0.181*	-0.395*	-0.250	-0.358	-0.102	-0.508*
	(-1.58)	(-2.29)	(-3.06)	(-2.71)	(-1.60)	(-1.00)	(-1.65)	(-2.92)
Bust	-0.0868	-0.415*	0.0140	-0.0862	-0.0538	-0.105	0.121*	-0.0692
	(-0.96)	(-2.04)	(0.44)	(-1.22)	(-0.64)	(-0.60)	(3.56)	(-0.82)
Constant	0.0847	0.308*	0.00471	0.0730	0.0494	0.0840	-0.0529*	0.0763
	(1.32)	(2.21)	(0.21)	(1.51)	(0.83)	(0.70)	(-2.22)	(1.32)
Observations	92	92	92	92	92	92	92	92
Adjusted R^2	0.012	-0.183	0.325	0.226	0.029	0.024	0.515	0.283

t statistics in parentheses

* $p < 0.05$

Table 8: OLS and IV regression of fund's future returns on local house price growth. This table show regression estimates from OLS and two stage-least-square regressions of future fund returns on instrumented house price growth $\Delta \ln$ HOUSE PRICE and a bust dummy variable BUST equal to one for obseravtions within 2006-2009, otherwise zero. The dependent variable in a columns 1 to 4 is a change in a future (3- and 6-month) fund's value-weighted raw return. In columns 5 to 8, the dependent variable is a change in a future (3- and 6-month) Daniel et al. (1997) (DGTW) fund's adjusted return. DGTW adjusted returns are constructed by subtracting from each holding's return the return on a portfolio of firms matched on market equity, market-book ratio, and prior one-year return quintiles (overall 125 different portfolios). The dependent variable in columns 9 to 12 is a change in a future (3- and 6-month) fund's excess return over the market return. All the changes are calculated for two periods: 2002-2005 and 2006-2009.

	Raw Returns				DGTW Adj. Returns				Market Adj. Returns			
	3 months		6 months		3 months		6 months		3 months		6 months	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ ln House Price	0.0143	0.0478*	0.0135	0.0620	0.00991	0.0254	0.0122	0.0514*	0.0125	0.0320	0.0143	0.0586*
	(1.46)	(1.99)	(0.70)	(1.35)	(1.59)	(1.71)	(1.34)	(2.22)	(1.72)	(1.83)	(1.33)	(2.17)
Bust	-0.00229	0.0134	-0.00901	0.0137	0.00870*	0.0159*	0.00990*	0.0282*	0.00956*	0.0187*	0.0115	0.0322*
	(-0.43)	(1.16)	(-0.86)	(0.62)	(2.56)	(2.22)	(1.99)	(2.53)	(2.41)	(2.22)	(1.96)	(2.46)
Constant	-0.00165	-0.0123	0.000125	-0.0153	-0.00638*	-0.0113*	-0.00654	-0.0190*	-0.00711*	-0.0133*	-0.00726	-0.0214*
	(-0.44)	(-1.55)	(0.02)	(-1.01)	(-2.67)	(-2.29)	(-1.87)	(-2.48)	(-2.54)	(-2.30)	(-1.76)	(-2.38)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.109	-0.009	0.069	0.003	0.062	-0.002	0.027	-0.173	0.045	-0.032	0.025	-0.160

t statistics in parentheses
* $p < 0.05$

Table 9: OLS and IV regression of fund's future returns generated by local and distant holdings. This table show regression estimates from OLS and two stage-least-sqaure regressions of future Daniel et al. (1997) (DGTW) adjusted fund's returns on instrumented house price growth $\Delta \ln$ HOUSE PRICE and a bust dummy variable BUST equal to one for observations within 2006-2009, otherwise zero. DGTW adjusted returns are constructed by subtracting from each holding's return the return on a portfolio of firms matched on market equity, market-book ratio, and prior one-year return quintiles (overall 125 different portfolios). The dependent variable in columns 1 and 2 (7 and 8) is a change in future 3-month (6-month) DGTW adjusted return generated by a distant component of a fund's portfolio. A fund's holding is defined as local if it is within 100km radius, otherwise it is considered a distant holding. In columns 3 and 4 (9 and 10), the dependent variable is a change in a future 3-month (6-month) DGTW adjusted return generated by a local component of a fund's portfolio. The dependent variable in columns 5 and 6 (11 and 12) is a difference between a change in a future 3-month (6-month) DGTW adjusted returns generated by distant and local components of a fund's portfolio. All the changes are calculated for two periods: 2002-2005 and 2006-2009.

	Three Months						Six Months					
	Distant		Local		Difference		Distant		Local		Difference	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln$ House Price	0.0111	0.0137	-0.0207	0.155*	-0.0317	0.141*	0.00963	0.0311	-0.0539	0.187	-0.0635	0.156
	(1.39)	(0.75)	(-0.85)	(2.19)	(-1.30)	(2.00)	(0.80)	(1.10)	(-1.35)	(1.71)	(-1.62)	(1.49)
Bust	0.0105*	0.0117	0.00234	0.0844*	-0.00812	0.0727*	0.0115	0.0215	-0.00533	0.107*	-0.0168	0.0859
	(2.42)	(1.32)	(0.18)	(2.48)	(-0.61)	(2.14)	(1.75)	(1.58)	(-0.25)	(2.04)	(-0.79)	(1.70)
Constant	-0.00646*	-0.00731	0.00317	-0.0528*	0.00963	-0.0455	-0.00572	-0.0126	0.0138	-0.0630	0.0195	-0.0505
	(-2.12)	(-1.20)	(0.34)	(-2.26)	(1.03)	(-1.95)	(-1.24)	(-1.34)	(0.90)	(-1.74)	(1.30)	(-1.45)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.059	0.057	0.020	-0.550	0.007	-0.548	0.032	-0.003	0.032	-0.363	0.022	-0.322

t statistics in parentheses
* $p < 0.05$

Table 10: First stage regression of home bias measures. This table shows coefficient estimates and F-test statistics for excluded instruments from first stage regressions of a change in a home bias measure on Saiz (2010) measure of geographically constraint land Unavailable, its interaction with a bust dummy variable Bust × Unavailable, and a bust dummy variable Bust, that is equal to one for observations within 2006 and 2009, otherwise zero. The dependent variable in column 1 (4) is a change in Coval and Moskowitz (1999) local bias measure for top ten largest holdings (entire portfolio). In column 2, we use a change in a value-weighted mean distance between a fund and its holdings' headquarters as a home bias meausre. The dependent variable in column 3 is a change in a fraction of the portfolio held locally (within 100km radius away from a mutual fund). All the changes are calculated for two periods: 2002-2005 and 2006-2009.

	Δ Top 10 Local Bias (1)	Δ Distance (2)	Δ Local Fraction (3)	Δ Local Bias (4)
Unavailable	-0.290*	217.2*	-2.143*	-0.171*
	(-3.08)	(2.12)	(-2.17)	(-3.44)
Bust×Unavailable	0.468*	-424.0*	4.584*	0.179*
	(3.80)	(-3.16)	(3.54)	(2.75)
Bust	-0.101*	93.72	-0.757	-0.0240
	(-2.27)	(1.93)	(-1.62)	(-1.02)
Constant	0.0616	-43.70	0.0560	0.0226
	(1.80)	(-1.17)	(0.16)	(1.25)
Observations	92	92	92	92
Adjusted R^2	0.144	0.094	0.164	0.149
F	7.25	5.09	6.63	5.94
P-value	0.001	0.008	0.002	0.004

t statistics in parentheses

* $p < 0.05$

Table 11: OLS and IV regression of fund's future returns on home bias measures. This table show regression estimates from OLS and two stage-least-square regressions of future Daniel et al. (1997) (DGTW) adjusted fund's returns on instrumented home bias measures (Δ Top 10 Local Bias, Δ Distance, Δ Local Fraction, and Δ Home Bias) and a bust dummy variable *Bust* equal to one for observations within 2006-2009, otherwise zero. DGTW adjusted returns are constructed by subtracting from each holding's return the return on a portfolio of firms matched on market equity, market-book ratio, and prior one-year return quintiles (overall 125 different portfolios). In Panel A, we regress a change in a fund's 1- to 6-month future return on a change in Coval and Moskowitz (1999) local bias measure for top ten largest holdings defined as: $\sum_{j=1}^{J}(m_{i,j,t} - h_{i,j,t}) \cdot \frac{d_{i,j}}{d_i^M}$, where $m_{i,j,t}$ is a portfolio weight of stock j in the benchmark portfolio, $h_{i,j}$ is the fraction of fund i's portfolio invested in stock j, $d_{i,j}$ is the distance between fund i and stock j, and $d_i^M = \sum_{j=1}^{J} m_{i,j,t} d_{i,j}$. In Panel B, we use a change in a value-weighted mean distance between a fund and its holdings' headquarters as a home bias measure. Panel C relates changes in future fund returns to changes in a portfolio's fraction held locally (within 100km radius away from a mutual fund). In Panel D, we use a change in Coval and Moskowitz (1999) local bias measure for the entire portfolio. All the changes are calculated for two periods: 2002-2005 and 2006-2009.

PANEL A: Instrumental Variable - Top 10 Local Bias

	1 month		2 months		3 months		4 months		5 months		6 months	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Δ Top 10 Local Bias	-0.007	-0.012	-0.013*	-0.022	-0.016*	-0.032	-0.026*	-0.056*	-0.027*	-0.071*	-0.026*	-0.067*
	(-1.61)	(-1.12)	(-2.21)	(-1.46)	(-2.17)	(-1.61)	(-2.91)	(-2.29)	(-2.88)	(-2.57)	(-2.45)	(-2.22)
Bust	0.002	0.002	0.002	0.003	0.005*	0.005*	0.005*	0.006*	0.005*	0.007*	0.005*	0.007*
	(1.67)	(1.76)	(1.75)	(1.88)	(2.74)	(2.83)	(2.18)	(2.45)	(2.39)	(2.70)	(2.11)	(2.42)
Constant	-0.001	-0.001	-0.002	-0.002*	-0.004*	-0.004*	-0.004*	-0.005*	-0.004*	-0.005*	-0.003	-0.005*
	(-1.05)	(-1.19)	(-1.95)	(-2.07)	(-2.79)	(-2.89)	(-2.30)	(-2.53)	(-2.29)	(-2.58)	(-1.77)	(-2.09)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.027	0.007	0.049	0.019	0.084	0.036	0.092	-0.031	0.097	-0.117	0.070	-0.082

PANEL B: Instrumental Variable - Distance

	1 month		2 months		3 months		4 months		5 months		6 months	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Δ Distance	0.005	0.013	0.011*	0.029	0.016*	0.038	0.025*	0.065*	0.026*	0.081*	0.027*	0.077*
	(1.27)	(1.11)	(2.11)	(1.66)	(2.27)	(1.71)	(3.05)	(2.30)	(3.00)	(2.51)	(2.74)	(2.23)
Bust	0.001	0.002	0.002	0.003	0.005*	0.006*	0.004*	0.006*	0.005*	0.007*	0.005*	0.007*
	(1.56)	(1.72)	(1.66)	(1.89)	(2.70)	(2.80)	(2.11)	(2.35)	(2.32)	(2.53)	(2.09)	(2.34)
Constant	-0.001	-0.001	-0.002	-0.002*	-0.004*	-0.004*	-0.003*	-0.004*	-0.004*	-0.005*	-0.003	-0.004*
	(-0.95)	(-1.15)	(-1.87)	(-2.06)	(-2.74)	(-2.84)	(-2.23)	(-2.41)	(-2.22)	(-2.40)	(-1.74)	(-2.00)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.017	-0.037	0.045	-0.069	0.088	-0.020	0.100	-0.138	0.104	-0.279	0.085	-0.169

PANEL C: Instrumental Variable - Local Fraction

	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Δ Local Fraction	-0.098	-1.199	-0.463	-2.751	-0.336	-3.531	-1.160	-5.940*	-1.167	-7.385*	-0.869	-6.992*
	(-0.25)	(-1.07)	(-0.83)	(-1.66)	(-0.46)	(-1.62)	(-1.33)	(-2.17)	(-1.25)	(-2.37)	(-0.83)	(-2.08)
Bust	0.001	0.002	0.002	0.004*	0.004*	0.006*	0.004	0.007*	0.005*	0.009*	0.005	0.009*
	(1.39)	(1.72)	(1.50)	(1.99)	(2.36)	(2.68)	(1.90)	(2.43)	(2.08)	(2.64)	(1.80)	(2.39)
Constant	-0.001	-0.001	-0.002	-0.003*	-0.003*	-0.005*	-0.004*	-0.007*	-0.004*	-0.008*	-0.003	-0.007*
	(-0.83)	(-1.30)	(-1.76)	(-2.21)	(-2.43)	(-2.73)	(-2.11)	(-2.62)	(-2.08)	(-2.70)	(-1.55)	(-2.27)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	-0.001	-0.088	0.005	-0.182	0.038	-0.172	0.025	-0.304	0.030	-0.450	0.015	-0.360

PANEL D: Instrumental Variable - Local Bias

	1 month		2 months		3 months		4 months		5 months		6 months	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Δ Local Bias	-0.019*	-0.019	-0.025*	-0.014	-0.033*	-0.037	-0.051*	-0.075	-0.056*	-0.098	-0.063*	-0.093
	(-2.50)	(-0.86)	(-2.31)	(-0.46)	(-2.32)	(-0.93)	(-3.04)	(-1.54)	(-3.10)	(-1.86)	(-3.16)	(-1.61)
Bust	0.002*	0.002	0.003	0.002	0.005*	0.005*	0.005*	0.006*	0.006*	0.007*	0.006*	0.007*
	(2.02)	(1.67)	(1.91)	(1.37)	(2.90)	(2.49)	(2.39)	(2.27)	(2.63)	(2.61)	(2.47)	(2.35)
Constant	-0.001	-0.001	-0.002*	-0.002	-0.004*	-0.004*	-0.004*	-0.005*	-0.005*	-0.006*	-0.005*	-0.006*
	(-1.57)	(-1.20)	(-2.27)	(-1.50)	(-3.08)	(-2.45)	(-2.73)	(-2.42)	(-2.75)	(-2.61)	(-2.35)	(-2.15)
Observations	92	92	92	92	92	92	92	92	92	92	92	92
Adjusted R^2	0.065	0.065	0.054	0.044	0.091	0.089	0.099	0.079	0.110	0.054	0.107	0.085

t statistics in parentheses

* $p < 0.05$

7. Figures

Figure 1: Fraction of a fund's portfolio held locally and mean house prices in US. This figure presents a fraction of a fund's portfolio held locally and house price patterns. The US average house price data comes from Zillow Research dataset. The portfolio's local fraction is value-weighted mean of fraction of a portfolio held within 100km radius away from a mutual funds using TNA as weights. The data on holdings of active US funds investing in US equity is provided by Morningstar.

Figure 2: House price growth, home bias and land unavailability. This figure relates house price growth and relative change in mean distance to Saiz (2010) measure of land unavailability for each CBSA included in our sample for both boom (2002-2005) and bust (2006-2009) period. The observations are weighted by the number of mutual funds in each CBSA. The straight lines fit linear regression models.

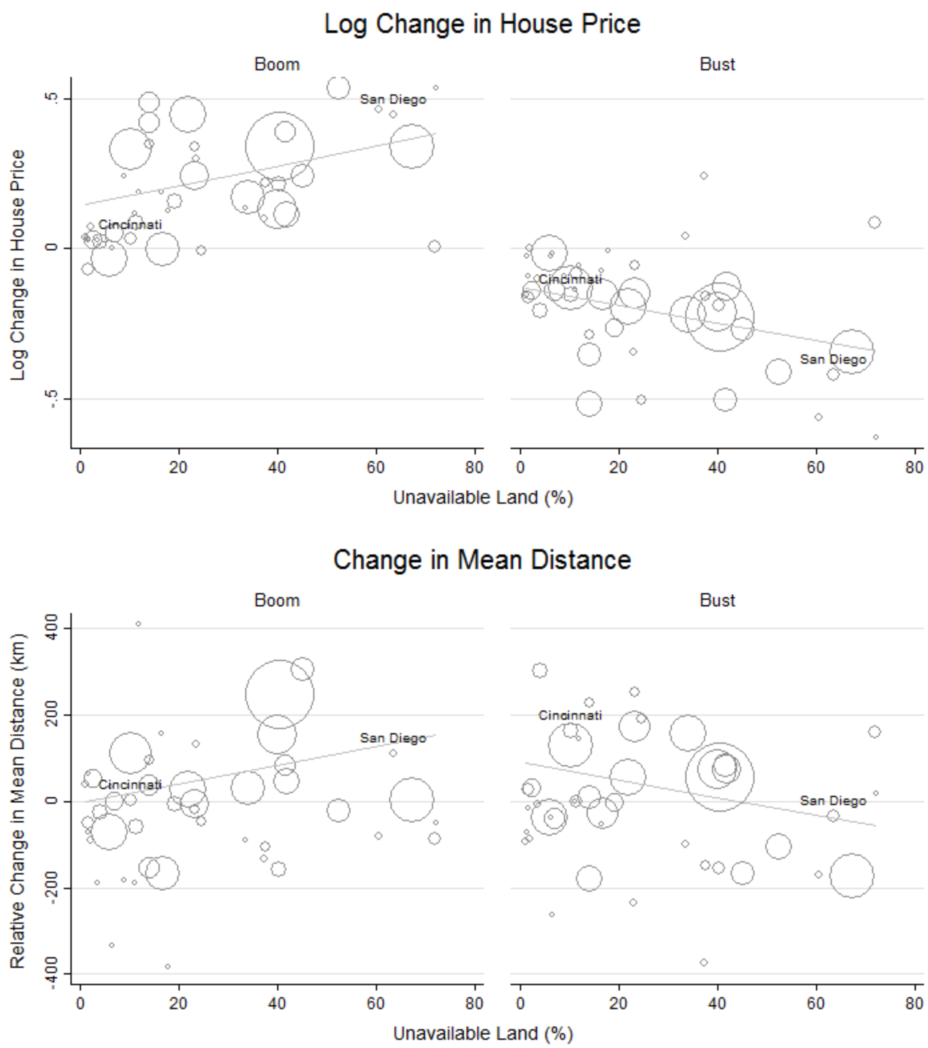

Figure 3: Saiz (2010) measure of land unavailability. This figure presents the variation in topologically constraint land across Core Based Statistical Areas (CBSAs). The measure of land unavailability has been constructed by Saiz (2010) and it takes into account geographical terrain and water features to determine the degree to which urban development is constrained by topological characteristics of the land.

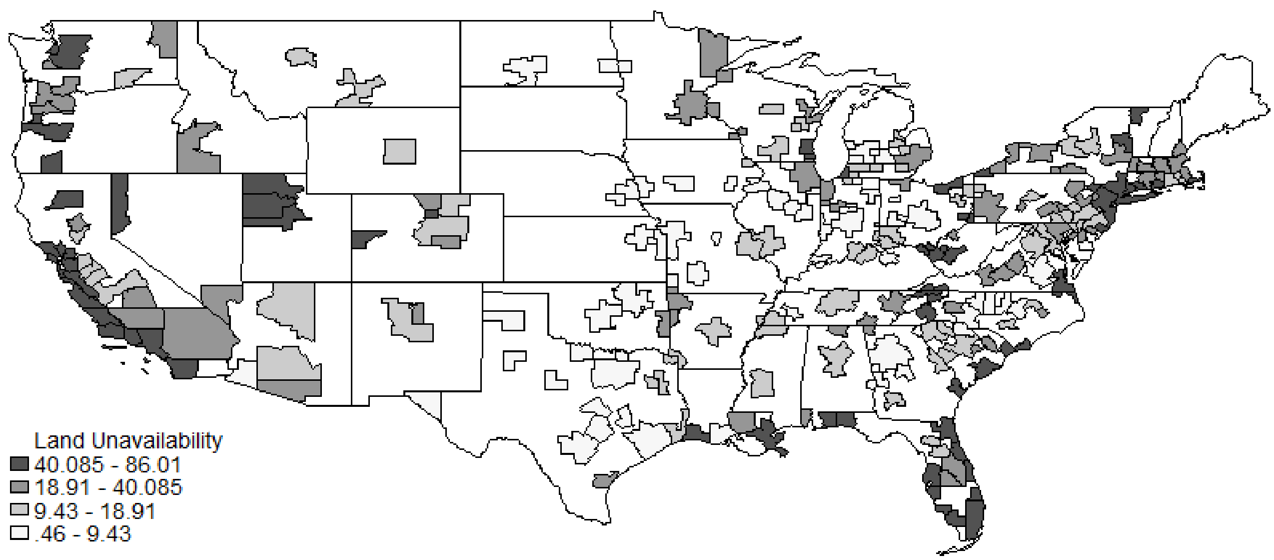

Figure 4: House price growth and land unavailability measure. This figure relates house price growth to Saiz (2010) measure of land unavailability for each CBSA included in our sample for both boom (2002-2005) and bust (2006-2009) period. The observations are weighted by the number of mutual funds in each CBSA. The straight lines fit linear regression models.

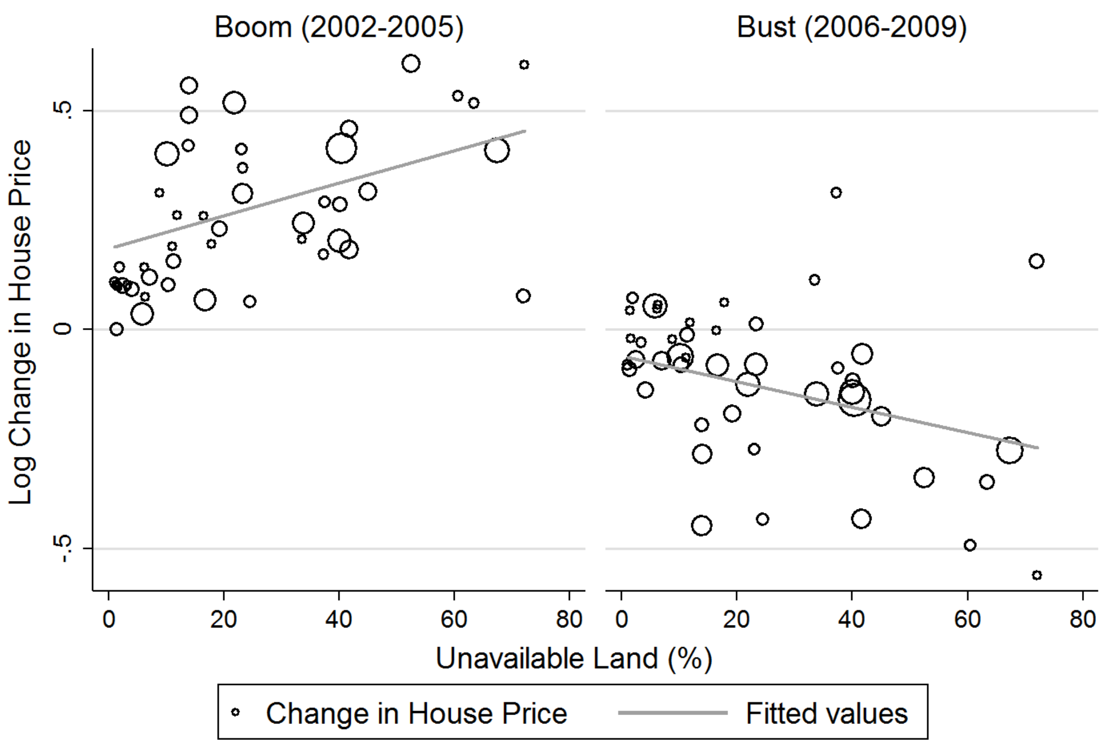

Figure 5: Mutual funds' distance to industries. This figure presents a fraction of a fund's portfolio kept in ten industries divided into five groups based on the distance for the end of the boom (2005) and the bust (2009) periods. We assign mutual fund holdings into ten main industries based on Fama and French (1997) industry classification. The industry clasifiaction is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html`. Industries assigned to *Close* are the nearest and second-nearest industries to a given mutual fund. Industries grouped in *Far* are the most and second most distant industries from a given fund. The left-hand side panel shows mean portfolio percentage invested in each of 5 industry groups for mutual funds located in areas with land unavailability below the median. The right-hand side panel shows mean portfolio percentage invested in each of 5 industry groups for mutual funds located in areas with land unavailability above the median.

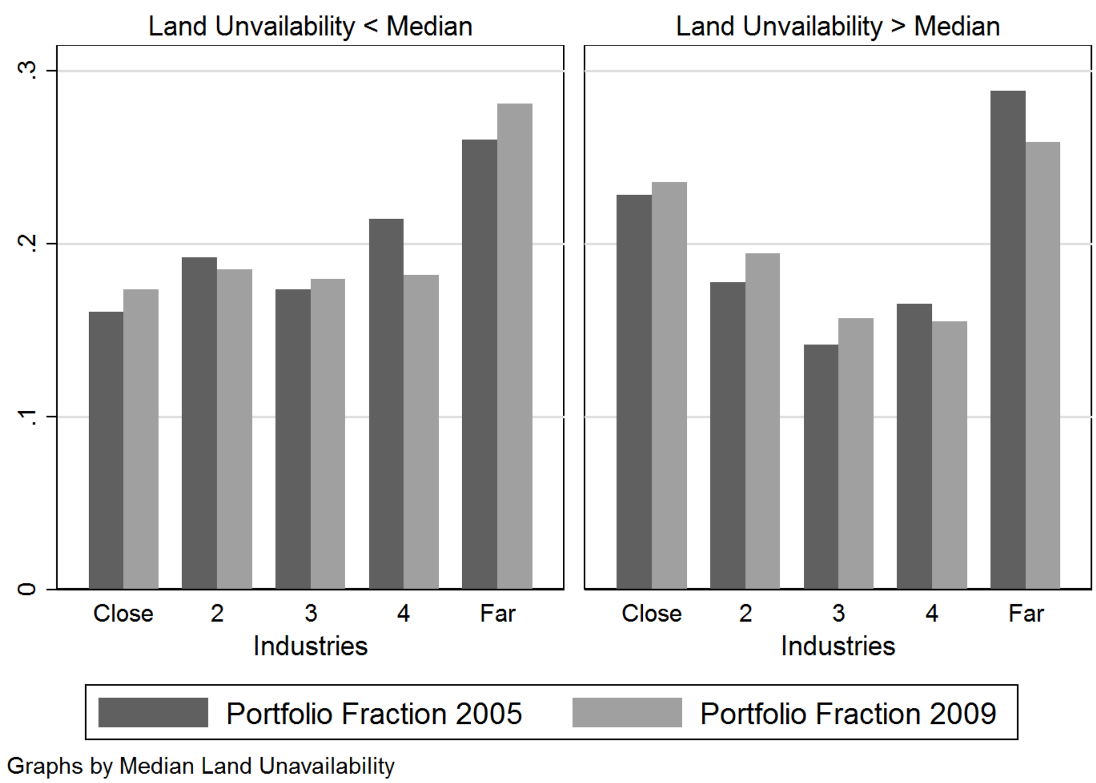

Figure 6: Change in mean distance and land unavailability measure. This figure relates a change in a fund's mean distance from its holdings to Saiz (2010) measure of land unavailability for each CBSA included in our sample for both boom (2002-2005) and bust (2006-2009) period. The observations are weighted by the number of mutual funds in each CBSA. The straight lines fit linear regression models.