Why Do Home Prices Appreciate Faster in City Centers? The Role of Risk-Return Trade-Offs in Real Estate Markets

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Abstract

In large urban areas, home prices appreciate faster in city centers, in part because of risk-return tradeoffs that vary in response to differences in housing supply constraints and volatility. This echoes a similar pattern across cities. Within urban areas, location-specific risk is most important, while across cities, systematic risk dominates. A one standard deviation increase in the dominant source of risk increases total housing returns by 22.7% and 12.2% within and across cities, respectively. It is well-known that home price levels vary spatially. Our findings indicate that spatial differences in home price appreciation rates can also persist in equilibrium.

JEL Codes: R0, G1
Key words: Risk-Return tradeoff, Home price appreciation, Supply constraints, Spatial patterns

1. Introduction

This paper establishes a new stylized fact that helps to highlight market mechanisms that drive spatial patterns of housing capital gains and related returns. Pooling across cities, year-over-year neighborhood level single-family home price appreciation rates decline almost monotonically with distance to the closest city center (Figure 1a) and as employment density declines (Figure 1b).[1] Controlling for city and neighborhood attributes, we show later that this pattern is especially robust in large urban areas. In some respects, this echoes more widely recognized tendencies for metropolitan level home price appreciation rates to vary across cities, as is evident in Table 1. Gyourko et al (2013), for example, suggest that for highly attractive, supply constrained "superstar" cities, cross-metro differences in price appreciation can be sustained if a growing population of high-income households is drawn to such locations.

The superstar city argument helps to explain higher appreciation rates for supply-constrained, amenity rich cities like San Jose relative to less sought-after locations like Milwaukee or Cleveland, as in Figure 2. It does not, however, explain differences in appreciation rates among cities with similar appeal (e.g. New York and Los Angeles based on amenity valuations in Chen and Rosenthal, 2008). A different explanation is also needed for within-city variation in appreciation rates. If developers direct investment to higher yielding neighborhoods, supply adjustments create pressure for stable relative prices and similar rates of appreciation across communities (e.g. Liu et al, 2016). The same is true if households view different neighborhoods as close substitutes, as with choice between gentrifying inner-city communities and more outlying locations (e.g. Couture and Handbury, 2020), in which case demand-side pressure should also contribute to stable relative prices.

We draw on risk-return principles to provide a simple but unified explanation for spatial patterns in home price appreciation rates at both the macro (cross-city) and micro (within-city) levels of

[1] Estimates in Figures 1a and 1b are based on all CBSAs in the United States with population over 100,000 using monthly zipcode-level home price indexes from Zillow Inc. for the period 1996-2019. Additional detail will be provided later in the paper.

geography. In doing so, we build on prior studies of risk-return tradeoffs in the housing market. This includes early studies that confirm the presence of such tradeoffs (e.g., Crone and Voith, 1999; Cannon, Miller, and Pandher 2006; Case, Cotter and Gabriel, 2011), and more recent studies that emphasize the role of rent (dividend) payments when measuring returns (e.g. Jorda et al, 2019; Amaral et al, 2021). It also includes studies that use long timeseries that mitigate confounding effects of short-run dynamics (e.g. Eichholtz et al, 2021; Chambers et al, 2021), and still other studies that focus on the nature of underlying risk (e.g. Sinai and Souleles, 2005; Davidoff, 2006; Han, 2013; Sagi, 2021; Giacoletti, 2021).

Different from the papers above, our focus is on spatial patterns of risk-return tradeoffs within and across cities. We show that spatial patterns of housing capital gains (price returns) and total returns can persist in equilibrium. This is possible because of well-known cross-sectional differences in housing supply constraints that amplify local market volatility and investor exposure to risk (e.g. Glaeser and Gyourko, 2005; Glaeser, Gyourko and Saiz, 2008; Saiz, 2008; Paciorek, 2013; Gyourko and Molloy, 2015). This focus – spatial patterns of risk-return tradeoffs – is in contrast to extensive previous literature that has modelled spatial patterns of home price levels in response to local advantages, but without considering the potential for spatial variation in returns (see reviews in Brueckner (1987) and Duranton and Puga (2015)).

To establish our results, we first make a set of decisions that govern how risk and return are measured. Beginning with the former, we treat investor exposure to risk as given by the volatility of year-over-year housing returns over our sample horizon for a given location. In some models, that measure is then decomposed into systematic risk driven by shocks to the broader market and a term that we refer to as non-systematic risk that is specific to the local housing market.

In measuring systematic risk, we use beta from a location-specific capital asset pricing model (CAPM), modified to focus on housing market returns. Most applications of CAPM models measure market returns using a broad financial index comprised of many individual assets (e.g. the S&P 500). This includes early studies of risk-return tradeoffs in housing markets (e.g. Crone and Voith, 1999; Cannon, Miller and Pandher, 2006). Case, Cotter and Gabriel (2011), however, point out that local housing returns are only weakly correlated with financial indexes but covary with returns to the broader housing market to which the local area belongs. Voicu and Seiler (2013) make a similar argument while Cotter, Gabriel and Roll (2015) document the degree of housing market integration. Following these studies, we use only housing returns when measuring market returns in the CAPM model, treating the set of CBSAs in the United States as the broader housing market when we estimate CBSA-level betas, and the CBSA as the broader housing market when we estimate within-CBSA zipcode-level betas.[2]

To measure non-systematic risk, we regress location-specific volatility of year-over-year returns on the beta for that location. By construction, the residual from this regression is uncorrelated with systematic risk and includes sources of risk that might arise from shocks that are specific to the local area. This could include shocks to an important local industry (e.g. the auto industry in Detroit), flood risk, or the potential for a neighborhood to gentrify, for example. We use that residual as our measure of non-systematic risk. In robustness checks, we instead use the standard deviation of the squared residuals from the location-specific CAPM regressions. Previous applications of CAPM models typically refer to this measure as idiosyncratic risk (e.g. Merton (1987), Cannon, Miller, and Pandher (2006), Case, Cotter and Gabriel (2011) and related studies). We show later that idiosyncratic risk is correlated with beta and prefer non-systematic risk for that reason since it is orthogonal to beta by construction. Results are nevertheless similar when we use idiosyncratic risk.[3]

We measure housing returns as year-over-year percent gain using monthly data. Two approaches are used, each of which has advantages and disadvantages. The first is based only on house price appreciation (price returns), while the second takes both price returns and rent (dividend) payments into account.

Focusing on price returns complements extensive work in the urban literature that models spatial patterns of home price levels (e.g. the reviews by Brueckner (1987) and Duranton and Puga (2015)). Price

[2] In both cases, we restrict the set of CBSAs in our analysis to those with population over 100,000 in year 2000.
[3] Although most studies do not delve into the underlying drivers of idiosyncratic risk, two recent exceptions are Giacoletti (2021) and Sagi (2021) both of which emphasize the role of illiquidity of real estate investments and show that this contributes to a term structure to idiosyncratic risk.

returns are also the focus of many papers that consider exposure to housing market risk, as with Case, Cotter and Gabriel (2011), Han (2013) and Cotter, Gabriel and Roll (2015), in addition to a broader literature on asset-pricing (see Fama and French (2004) for a review). On the other hand, a burst of recent studies has emphasized that rent contributes to total housing returns, and for that reason, is part of the calculus when considering potential for risk-return tradeoffs. This includes Gupta et al (forthcoming), Amaral et al (2021), Eichholtz et al (2021), Sagi (2021), Chambers et al (2021), Giacoletti (2021) and Jorda et al (2019).

We use Zillow home price and rent indexes for single family homes to measure returns. These data are available for different time periods which affects when price and total returns can be measured. Price series are available on a monthly basis at both the CBSA and zipcode levels of geography from 1996 to 2019. This allows us to compare patterns of price returns before and after the housing market boom-bust episode that took place in the first half of the sample period, which is appealing. The rent series, however, is available only from 2010-2019, which restricts the period over which total returns can be measured.

Additional measurement issues arise because of the nature of rent. The home price and rent data are based on all single-family homes in a geographic market, including owner-occupied and rental. Rent, however, is imputed for owner-occupied homes but realized as a cash flow for owners of rental property. For this reason, owner-occupiers may place less weight on rental flow when considering return on investment. Also, as noted by Glaeser and Gyourko (2010), Han (2013), and many others, tax treatment differs for the rental flow from owner-occupied housing versus rental units. These differences introduce error when measuring total returns but in a manner that is difficult to model in the empirical work.

Given the considerations above, we initially estimate our models using just price returns over our entire sample horizon, 1996-2019. Additional estimates then compare price return models from the early period (1996-2010) to the later period (2010-2019), and for the later period, estimates based on price returns to those based on total returns. An approximation argument in Han (2013), related analysis in Demers and Eisfeldt (2022), and user cost theory discussed in this paper suggest that evidence of risk-return tradeoffs is likely to be similar regardless of whether price or total returns are used. Results presented later mostly confirm that prior although some differences do arise.

Patterns in our data confirm that spatial variation in housing supply restrictions contribute to spatial variation in home price volatility and risk. For the cross-metro analysis, we proxy for CBSA level housing supply elasticities using the Wharton Land Use Regulatory Index (WLURI) developed by Gyourko, Saiz and Summers (2007) and updated in Gyourko, Hartley, and Krimmel (2021).[4] We find a strong, positive correlation of 0.31 between the WLURI and housing return volatility. For the within-CBSA analysis, neighborhood level housing supply constraints are proxied using distance from the CBD and local employment density, motivated by the idea that prior development makes new development more difficult (e.g. Baum-Snow and Han, 2019; Fisher et al, 2022). Patterns indicate that home price volatility declines with distance from the CBD and is 13% lower for zipcodes 10 miles away from the center. Analogous results are obtained based on zipcode employment density.

Most important, there is compelling evidence that increased exposure to housing market risk contributes to spatial patterns of risk-return tradeoffs and related spatial variation in housing returns. The pattern is especially robust for within-city variation among the 48 largest urban areas, those with over one million people in 2000, and when considering variation across CBSAs.

Decomposing risk into its systematic and non-systematic components is also revealing. For models that use total returns, at the CBSA level, a 1-unit increase in beta is about equal to its interquartile range across cities. Controlling for non-risk measures (e.g. proxies for local supply restrictions, demand, and amenity appeal), that change is associated with a 1.60 percentage point increase in housing returns, about equal to 12.2% of the mean return. A corresponding 25th-75th percentile change in non-systematic risk has a much smaller effect on returns, just 0.36 percentage points. Strikingly, when looking across neighborhoods within large CBSAs, the relative magnitudes are reversed. For the 48 largest urban areas, a change in beta from the 25th to the 75th percentile increases returns by 0.54 percentage points, while a

[4] The WLURI index can be downloaded from the following site noted in the Gyourko, Hartley, and Krimmel (2021) paper, http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/ .

corresponding change in non-systematic risk increases returns by 3.3 percentage points, equivalent to 22.7% of the mean return. Our modelling framework suggests that this reversal arises because of differences in the intensity of unobserved shocks at different levels of geography, along with local variation in housing supply constraints, which drive spatial patterns of investor exposure to risk.

To establish these and related results, we proceed as follows. Section 2 describes our model including conceptual framework, estimating model, and our primary identifying assumptions. Section 3 describes the data and summary measures, both for across and within-CBSA patterns. Section 4 estimates risk-return tradeoffs across CBSAs. Section 5 repeats the analysis for within-CBSA risk-return tradeoffs, and Section 6 concludes.

2. Risk-Return Model

2.1 Returns to real estate investment

As with a financial asset, total returns from owning a home over one period, *t*-1 to *t*, can be expressed as the sum of the one period capital gain and the one-period dividend payment, normalized by the initial period price of the home (Gupta et al, forthcoming; Eichholtz et al, 2021; Sagi, 2021; Chambers et al, 2021; Giacoletti, 2021; and Jorda et al, 2019). Capital gains are given by the change in price between periods, $P_t - P_{t-1}$, while the dividend is the rent earned over the period, R_t. Collecting terms and dividing by P_{t-1}, this can be written as:

$$\rho_t^{Tot} = \frac{P_t - P_{t-1}}{P_{t-1}} + \frac{R_t}{P_{t-1}} \tag{2.1}$$

where, as in the literature, we often refer to the first term in (2.1) as price returns which we express as $\rho_t^P = \frac{P_t - P_{t-1}}{P_{t-1}}$.

Also helpful for the discussion below, we decompose ρ_t^P into capital gains that were anticipated at the start of the period and those that were unanticipated, g_t^a and g_t^u, respectively, where $\rho_t^P = g_t^a + g_t^u$, and the one period ahead expectation of g_t^u is zero. Expression (2.1) can then be written as,

$$\rho_t^{Tot} = g_t^u + g_t^a + \frac{R_t}{P_{t-1}} \tag{2.2}$$

Assuming a one-period rental contract, $\frac{R_t}{P_{t-1}}$ is also known in period *t*-1. As of period *t*-1, therefore, uncertainty about the one-period ahead return on the asset is driven primarily by g_t^u. We return to this point shortly.

Consider now an alternative perspective on housing rent that is often characterized as the user cost of owning, a summary of which is in Himmelberg et al (2005). In this case an accounting approach is typically used to summarize the cost of owning and holding a home for one period. With competitive markets, the zero-profit condition determines the market rent on the unit. A complicating factor is that income tax treatment differs for rental versus owner-occupied homes because of different provisions for what can be deducted and whether rental income is taxed. Those differences however do not affect the central points below provided income tax rates do not change very much from one year to the next. Bearing that in mind, we approximate user cost as,

$$\begin{aligned} R_t &\approx [r + (d + m) + p_{tax} - g_t^a] * P_{t-1} + \tau R_t \\ &= \frac{1}{1-\tau}[r + (d + m) + p_{tax} - g_t^a] * P_{t-1} \quad . \end{aligned} \tag{2.3}$$

In this expression the cost of holding a home between *t*-1 and *t* increases with the tax paid on rental income. For owner-occupiers this is zero while for investors it is positive. We treat τ as the income tax rate for the marginal investor without specifying that individual's identity. Other terms in (2.3) include the interest rate *r*, the rate at which the home depreciates *d*, maintenance *m*, and property taxes at rate p_{tax}. User cost declines with the anticipated rate at which the home appreciates, g_t^a.

Rearranging terms,

$$\frac{1}{1-\tau}[r + (d + m) + p_{tax}] \approx \frac{1}{1-\tau} g_t^a + \frac{R_t}{P_{t-1}} \quad . \tag{2.4}$$

Notice that the left side of equation (2.4) is comprised of terms that typically change little from one year to the next. Substituting into expression (2.2),

$$\rho_t^{Tot} \approx g_t^u + \alpha \quad , \tag{2.5}$$

where from (2.4), $\alpha = \frac{1}{1-\tau} g_t^a + \frac{R_t}{P_{t-1}}$. Note that α will tend to not change very much from one year to the next and is equal to the one-period ahead expected return on investment given that E(g_t^u) = 0.

Expression (2.5) has implications for our measures of housing returns and risk. One implication is that $\Delta g_t^a \approx -\Delta \frac{R_t}{P_{t-1}}(1-\tau)$, where Δ denotes a one period ahead change. This indicates that an increase in expected capital gains across periods is approximately offset by a corresponding decline in the equilibrium rent-to-price ratio. This occurs because higher expected capital gains lower user cost in expression (2.3) and are capitalized into higher current prices in anticipation of future returns. This also suggests that variance of the rent-to-price ratio $var(\frac{R_t}{P_{t-1}})$ should be small, both in absolute terms and relative to $var(\rho_t^P)$, and that the variance of total returns is approximately equal to the variance of unanticipated capital gains, $var(\rho_t^{Tot}) \approx var(g_t^u)$. This implies that most of the variation in total returns over time is likely to come from changes in capital gains in response to unanticipated shocks, and not from changes in rent-to-price ratios. That principle lies behind the approximation argument in Han (2013) and helps to explain why our alternate measures of housing returns described earlier – capital gains versus total returns – yield similar evidence of risk-return tradeoffs.

2.2 Risk in real estate markets

As indicated in the Introduction, we treat the overall level of risk to which an investor is exposed as equal to the standard deviation of housing returns in a local market across a given sample horizon. This is denoted as $\sigma(\rho_{i,t}^q)$, where $\rho_{i,t}^q$ is the year-over-year percent return to housing investment in market *i* as of period *t*. Also noted earlier, in some applications we measure $\sigma(\rho_{i,t}^q)$ using just price returns or capital gains, referenced by *q* = *P*, while in other applications we use total returns, $q = Tot$. In our more fully specified models, we also decompose $\sigma(\rho_{i,t}^q)$ into the sum of systematic and non-systematic risk, where the former is given by the beta from a CAPM model, modified to target the housing market, and the latter is the residual from a regression of $\sigma(\rho_{i,t}^{q})$ on beta and a constant.[5]

For reasons described earlier, we use only housing returns when measuring systematic risk from the CAPM models, with separate betas computed for each local area drawing on location specific time series variation. For betas measured at the CBSA level, we use the national housing market (defined by all CBSAs in our sample) as the broader market to which the CBSA belongs. For betas measured at the zipcode level, we use the CBSA in which a zipcode is located as the broader market.

Bearing the above in mind, under the simplest CAPM assumptions (Fama and French, 2004; Bodie, Kane, and Mohanty, 2009) all investments offer the same reward-to-risk ratio in equilibrium, and we can write:

$$\frac{E\left(\rho_{i,t}^{q}\right)-\rho_{f,t}}{Cov(\rho_{i,t}^{q},\rho_{M,t})} = \frac{E(\rho_{M,t}^{q})-\rho_{f,t}}{\sigma_M^2} \tag{2.6}$$

where $E\left(\rho_{i,t}^{q}\right) - \rho_{f,t}$ is the expected return of asset *i* in excess of the risk-free rate of return, $\rho_{f,t}$, and σ_M^2 is the variance of the market portfolio which is comprised of a balanced portfolio of individual assets (in this case, local housing markets). Rearranging yields:

$$E\left(\rho_{i,t}^{q}\right) - \rho_{f,t} = \beta_i * [E(\rho_{M,t}^{q}) - \rho_{f,t}] \quad , \tag{2.7}$$

where $\beta_i = \frac{Cov(\tilde{\rho}_i^q,\tilde{\rho}_M^q)}{\tilde{\sigma}_M^2}$ where the tilda notation indicates that ρ_f is taken into account.

In practice, the large literature built around the CAPM model recognizes that (2.6) is restrictive in the sense that the return on asset *i* varies only with the risk-free rate and its covariance with the market return (e.g. Fama and French, 2004). To allow for other drivers of asset *i* return, we add a constant and an error term to (2.7), denoted as α_i and $\varepsilon_{i,t}$, respectively. β_i is then estimated using separate time series CAPM regressions for each location:

[5] Our measure of non-systematic risk will also capture any effects of model misspecification associated with a one-factor CAPM model.

$$\rho_{i,t}^{q} - \rho_{f,t} = \alpha_i + \beta_i * [\rho_{M,t}^{q} - \rho_{f,t}] + \varepsilon_{i,t} \text{ , for all } i = 1,\ldots, \text{I}. \tag{2.8}$$

In (2.8), α_i captures the effect of time invariant drivers of returns that are specific to the local housing market. This includes terms from the user cost expression in (2.5) like maintenance and depreciation that vary across locations but have similar expected value over time. β_i, in contrast, captures time varying risk that is systematically related to shocks that affect the market return, $\rho_{M,t}^{q}$.[6] Examples include market-level shocks such as changes in interest rates and other macroeconomic conditions, the effect of which differs across local housing markets with city and neighborhood-specific differences in housing supply elasticity.

2.3 Estimating risk-return tradeoffs and identifying assumptions

In all of the risk-return regression models that follow, we use cross-section regressions that draw on sample horizon average values for both the dependent variable and the control measures. This has advantages that we comment on below.[7] The estimating equation is then of the following general form,

$$\bar{\rho}_i^{q} = \gamma_0 + \gamma_1 Risk_i + \gamma_2 x_i + e_i \ . \tag{2.9}$$

where $\bar{\rho}_i^{q}$ is the average year-over-year return in housing market *i* over a specified sample period. $Risk_i$ includes different combinations of the risk measures discussed above, with each always estimated over the same sample horizon as returns. This includes $\sigma(\rho_{i,t}^{q})$, β_i and non-systematic risk. The term x_i includes non-risk based drivers of average return that are discussed in detail later in the paper. These include proxies for local housing supply elasticity, amenities, and potential for demand shocks, for example.

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[6] A beta equal to 1 indicates that asset *i* and market returns move together, in both the same direction and magnitude. In that instance, asset *i* is risk neutral relative to the market portfolio, whereas a beta greater than 1 indicates that investors in asset *i* are exposed to greater risk; a beta equal to 1.2, for example, indicates that asset *i* is 20% more volatile in response to a market-level shock than that of the market return.

[7] Using sample averages also limits some of the questions that can be addressed. As an example, it precludes analysis of term structure of non-systematic risk documented by Giacoletti (2021).

When we regress $\bar{\rho}_i^q$ on $\sigma(\rho_{i,t}^q)$, the identifying assumption is that the variance of return on asset *i* over time is exogenous to the average year-over-year return to asset *i*. This is characteristic of two-parameter distributions as with the joint normal.[8] Specifying (2.9) to depend on sample horizon average values also mitigates possible concerns that might arise from year-to-year short run dynamics (e.g. Danielsson et al, 2013; Glaeser and Nathanson, 2015; DeFusca et al, 2018). As an example, if investor expectations of future increases or decreases in returns create self-reinforcing movements in asset price, that could amplify volatility in coming periods. This would be the case if self-reinforcing patterns cause price levels to temporarily deviate from sustainable levels, in which case market fundamentals would prompt a correction. This sort of argument has been used to help explain the dramatic boom and bust in home prices between roughly 2003 and 2009, for example.

When we decompose $\sigma(\rho_{i,t}^q)$ into β_i and non-systematic risk, we allow for the possibility that risk-return tradeoffs differ depending on whether the source of risk is market level or local in nature. The identifying assumption in this case is that β_i is exogenous. This is also plausible. Notice, for example, that expression (2.8) is a simple one variable regression. As such, the constant term captures the average difference over time between excess returns in location *i* and its broader geographic market *M* (given by $\bar{\rho}_i^q - \bar{\rho}_f - \beta_i(\bar{\rho}_M^q - \bar{\rho}_f)$) so that the least squares measure of β_i is $\frac{Cov(\tilde{\rho}_i^q, \tilde{\rho}_M^q)}{\tilde{\sigma}_M^2}$, where the tilda notation denotes excess returns over the risk free rate as in expression (2.7). Mirroring the assumption that $\sigma(\rho_{i,t}^q)$ is exogenous, $Cov(\tilde{\rho}_i^q, \tilde{\rho}_M^q)$ and $\tilde{\sigma}_M^2$ are assumed to be as well. We also note that because many local housing markets are used to measure $\rho_{M,t}$, any potential for a mechanical relationship between $\rho_{i,t}^q$ and $\rho_{M,t}^q$ when measuring $Cov(\tilde{\rho}_i^q, \tilde{\rho}_M^q)$ shrinks away.

[8] A one-parameter distribution like the exponential instead sets mean equal to variance. That would be an unusual assumption when modeling asset returns which are widely characterized based on two parameter models like the normal distribution or sometimes three parameter distributions, as with the generalized error distribution or GED.

3. Data and Summary Measures of Risk and Return

3.1 Data

Our primary data are single family home price and rent indexes from Zillow.[9] We measure house price appreciation using the monthly Zillow Home Value Index (ZHVI) for single-family homes which is available from 1996 through 2019. For both CBSA and zipcode levels of geography, the index is seasonally adjusted and designed to measure quality adjusted home price appreciation in the target area. The index values are scaled so that the index value for December 2019 is equal to the average home value in the target area in that month. In this way, the ZHVI captures home price appreciation while facilitating comparison of home price levels across locations. In the analysis to follow, house price appreciation in location *i* is calculated based on the growth of ZHVI between periods (e.g. year-over-year appreciation). Appendix A provides additional discussion on construction of the ZHVI. Also in the appendix are summary measures of location-specific correlations between the ZHVI over time and an analogous repeat sales index produced by the Federal Housing Finance Agency (FHFA). At both the CBSA and zipcode levels, for almost all locations common to the ZHVI and FHFA indexes, correlation is above 90%.

When we measure total returns, we include rent as described in the previous section, where the rent series is also obtained from Zillow. The Zillow Rent Indices (ZRI) for single-family housing at the CBSA and zipcode level are dollar-valued indexes that are designed to capture the typical market rent for a given location. ZRI is calculated as the mean of the middle quintile of Zillow's rent estimates for the universe of single-family homes in a given location, weighted by the 5-year American Community Survey (ACS) counts of renter-occupied housing units by decade built. The ZRI is available from 2010 to 2019 and covers a slightly smaller set of CBSAs and zipcodes relative to the price series: 309 CBSAs and 9,510 zipcodes compared to 362 CBSA and 11,644 zipcodes for the price series.

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[9] Zillow periodically updates its methodologies used to measure the home and rent indexes. It also recently renamed the rent index from ZRI to ZORI, reflecting a change in methodology. Zillow policy does not allow us to share the ZHVI and ZRI data. However, the current indexes can be downloaded from https://www.zillow.com/research/data/ . For this paper, we downloaded the data in 2020, at which time the indexes were developed using Zillow's 2019 methodology. A home price index from FHFA is compared to the ZHVI in Appendix A and is available at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx .

At the time our data was downloaded the core-based statistical area (CBSA) definition used by Zillow was the September 2018 US Census definition of CBSAs in the United States. We use this definition when assigning zipcodes to different CBSAs and also when constructing CBSA population counts for 1990, 2000, and 2010. For both the CBSA and zipcode level analyses, we limit our sample to the 364 CBSAs with population greater than a hundred thousand in 2000.

For the within-CBSA analysis, we also need to define the location of the city center, referred to going forward as the central business district or CBD. This allows us to evaluate the effect of distance from the center on housing returns. For 321 CBSAs, we adopt the latitude and longitude coordinates of the CBD as reported by Holian and Kahn (2015) and based on information they procured from Google Earth. Following their same procedure, we also determined CBD location for the 41 remaining CBSAs included in our estimating samples. For the within-CBSA analysis that instead considers employment density, we calculate zipcode level employment density using employment counts and land areas from 2010 zipcode tabulation areas (ZCTAs) as obtained from the NHGIS site at www.IPUMS.org.

For the within-CBSA (neighborhood-level) analysis, we restrict our sample to zipcodes within 25 miles of the Central Business District (CBD) of the primary city associated with the CBSA. This mitigates possible effects from population subcenters when we estimate models that take distance to the CBD into account. To ensure consistency across models, we use the same set of zipcodes when we replace distance to the CBD with zipcode employment density as our proxy for prior development and supply constraints.

A final important data item is the Wharton Land Use Regulatory Index (WLURI). This index is based on the intensity of the local regulatory environment for an urban area including caps on permitting and construction, density restrictions such as minimum lot size restrictions, affordable housing requirements, and the tendency for re-zoning permits to be required. The index has mean zero with standard deviation one. It is also normalized so that urban areas in the lowest quartile are the least supply constrained while those in the top quartile are the most supply constrained. We use the updated 2018 index from Gyourko, Hartley, and Krimmel (2021) and are able to match the index to 298 of the 362 CBSAs in our sample.[10]

3.2 Summary measures

There is considerable spatial variation in housing price returns across locations over our sample horizon. At the CBSA level, Table 1 highlights the 20 CBSAs with the largest and smallest average annual price returns over the 1997-2019 period. For each area, the average price return and year-2000 CBSA population are reported. Twelve-month average price returns range from a low of 1.27% in Youngstown, OH to a high of 7.23% in San Jose, CA. Across the entire sample of CBSAs, year-over-year nominal price returns average 3.1%, with a standard deviation of 1.4 percentage points (Appendix B, Table B-1 Panel A). In comparison, at the zipcode level, the corresponding values are 3.4% and 2.0 percentage points (Appendix B, Table B-1 Panel B). As would be expected, average price returns are similar for the two levels of geography and variance is greater at the narrower level of geography.

For both levels of geography, Figure 3 plots the distributions across locations for price return volatility (Panel A), beta (Panel B), and non-systematic risk (Panel C). Additional tabular detail is in Appendix B, Tables B-2 and B-3. As is evident from Panel A of the figure, at both the CBSA and zipcode levels the distributions of return volatility exhibit elongated right tails and considerable variance. Also notable, in Panel B the distribution for beta is much tighter within cities as compared to across cities, while the reverse is true in Panel C for non-systematic risk. These differences mirror patterns that will follow latter in the paper when we consider differences in the nature of risk that drives spatial patterns of returns within and across cities.[11]

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[10] We also considered using the Saiz (2008) housing supply elasticities to proxy for supply restrictions. Those measures could only be matched to 82 CBSAs versus 298 using the WLURI index and were not used for that reason.
[11] Additional detail on these distributions is in Appendix B, Tables B-2 and B3. For beta, the mean, standard deviation, and interquartile range are 0.98, 0.82, and 0.86 at the CBSA level, respectively, and 1.00, 0.57, and 0.27 at the zipcode level. In both cases, the mean is approximately equal to 1 because the market portfolio is an aggregation of the local assets (markets). For non-systematic risk, at the CBSA level, the standard deviation is 1.25

A last feature of the data to highlight is in Figure 4. Recall from Section 2, price returns, ρ_t^P, should be inversely related to rent R_t since capital gains reduce the cost of providing rental services. Also, higher ρ_t^P is capitalized into higher values for P_{t-1}. For these reasons, we expect $\frac{R_t}{P_{t-1}}$ to display relatively little variation in comparison to ρ_t^P. This is confirmed in Panel A of Figure 4 at the CBSA level and again in Panel B at the zipcode level. In both instances, the variance of the rent-to-price distribution is small relative to the distribution of returns. This is consistent with the approximation argument developed by Han (2013) and evidence in Demers and Eisfeldt (2022).

4. Risk and Return Across CBSAs

In this section, we examine evidence of risk-return tradeoffs at the CBSA level and their effect on cross-CBSA differences in housing returns. We begin with additional CBSA-level summary measures.

4.1 CBSA summary measures

Table 2 reports the 20 CBSAs with the lowest and highest levels of risk as measured based on the volatility of price returns. For each CBSA, values are reported for return volatility, beta, non-systematic risk and CBSA population, all rank ordered based on return volatility. It is worth noting that CBSAs with especially low risk are typically relatively small, less sought-after metropolitan areas that are not growing rapidly, an example of which is Syracuse, NY. CBSAs with especially high investor exposure to risk exhibit more heterogeneity. Some are rapidly growing, high-amenity cities, as with San Francisco. Other cities experienced dramatic housing price boom-bust patterns between 1997-2010, as with Phoenix and Las Vegas. Still other urban areas have suffered substantial population loss in recent decades, with Detroit

while at the zipcode level the corresponding value is 2.86. In this instance, the sample mean is always zero by construction.

being the most prominent example (see Glaeser and Gyourko (2005) for related discussion of price dynamics in shrinking cities).

Table 3 reports correlations between CBSA average year-over-year returns, the Wharton Land Use Regulatory Index (WLURI), beta, and non-systematic risk. In this table, returns and risk are measured based on price appreciation as opposed to total returns. Patterns confirm strong correlations between returns, supply restrictiveness, and risk. For return volatility, correlations with price returns and the WLURI index are 67.4% and 30.6%, respectively, consistent with our prior that housing supply restrictions will be associated with greater price volatility and that risk-return tradeoffs contribute to higher housing capital gains. Correlations between return volatility with beta and non-systematic risk are 90.9% and 43.7%, respectively. This indicates that both sources of risk contribute to volatility of housing returns, but the relationship is stronger for systematic shocks as measured by the CAPM beta.

4.2 Risk-return tradeoffs

Table 4 presents estimates of the risk-return model with more fully specified models in columns to the right. In all cases, price returns are used to measure risk and returns, and the sample period is from 1997 to 2019.

In column 1, the WLURI index of land use constraints is the only control and has a positive, significant effect on price returns: a one standard deviation increase in the WLURI is associated with a 0.53 percentage point increase in year-over-year capital gains. This confirms that home prices appreciate more rapidly in more supply constrained cities. In column 2, we replace the WLURI measure with return volatility, σ^P. Return volatility explains 45% of the variation in price returns across CBSAs, much more than the WLURI in column 1. The coefficient on σ^P indicates that a 1 unit increase in return volatility is associated with 0.302 percentage point higher capital gains, roughly 10 percent of the sample mean value for ρ^P. To put this in further perspective, σ^P increases 3.6 units with a shift from the 25th to 75th

percentile CBSA. The estimate in column 2 suggests that this would translate into 1.08 percentage point higher average year-over-year price returns.

In column 3 we control for both return volatility and the WLURI index in addition to several proxies for potential demand-side shocks. The coefficient on WLURI shrinks sharply and is no longer significant while the coefficient on return volatility is nearly unchanged from that in column 2. This suggests that return volatility largely captures any effect of supply restrictiveness on housing returns, a conclusion that is robust to the remaining specifications in the table.

Also worth noting, among the demand-side controls in column 3, only population loss among shrinking cities has a significant effect on price returns, with a negative sign as anticipated. Other demand side controls include income, population size, population growth among growing cities, and superstar status in 2000 as designated by Gyourko et at (2013). These other controls are all insignificant, suggesting that risk-return tradeoffs play a dominant role in driving spatial patterns of price returns.

In column 4 we decompose return volatility into systematic (beta) and non-systematic risk while retaining the other controls from column 3. Both beta and non-systematic risk have positive, strongly significant coefficients. This suggests that investors at the CBSA level of geography are sensitive to both market (national-level) drivers of risk and CBSA-specific sources of risk.

The magnitude of the risk coefficients is also important. The coefficient on beta in column 4 is 0.87. This suggests that doubling CBSA sensitivity to national-level shocks increases CBSA-level price returns by roughly 0.87 percentage points. Alternatively, a shift from the 25th to the 75th percentile CBSA with respect to beta would increase capital gains by roughly 0.75 percentage points, roughly 24% of the average annual capital gains rate across CBSAs. In contrast, the coefficient on non-systematic risk is smaller, just 0.33. In this instance, a shift from the 25th to the 75th percentile CBSA with respect to non-systematic risk would increase price returns by roughly 0.4 percentage points or 13% of the national average.

In columns 5 and 6 we repeat the estimation but with a more limited sample of just 222 CBSAs for which the Chen and Rosenthal (2008) quality of life index can be matched to the rest of our data.[12] That measure is then included in the column 6 specification. Repeating the model without the quality-of-life index in column 5 allows us to hold sample composition constant. Notice that estimates are very similar in columns 4 and 5, confirming that sample composition has little effect. In column 6, however, the coefficient on the quality-of-life index is positive and significant as are the coefficients on the risk-related measures. The risk coefficients also hardly change from column 5 where the quality-of-life index is omitted. These results suggest that amenity-based and risk-return mechanisms have largely independent effects on differences in housing returns across CBSAs. Also, both systematic and non-systematic risk elevate equilibrium housing returns at the CBSA level.

4.3 Alternate specifications

The estimates discussed above are based on price returns with model coefficients restricted to be alike throughout the entire 1997-2019 period and using non-systematic risk to capture risk exposure that differs from systematic risk. In Table 5 we consider how these design features affect estimates from column 6 of Table 4, the most fully specified model in the table.

Notice that Table 5 reports separate estimates for price returns in 1997-2010 (column 1) and price returns in 2011-2019 (column 2), before and after the boom-bust episode that mostly ended by 2010. Separate estimates are also provided for the 2011-2019 period using rent-to-price ratio (column 3) and total housing returns (column 4) as dependent variables. Panel A uses non-systematic risk to capture investor concerns that differ from systematic risk. Panel B replaces non-systematic risk with idiosyncratic risk as a further check on the stability of our estimates.

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[12] This quality-of-life index measures the amount of real wage workers forgo to live in a CBSA relative to other urban areas. As such, it is an indicator of the amenity appeal of the urban area, as in Rosen-Roback. The index is normalized to have mean zero across urban areas in Chen and Rosenthal (2008).

Three primary results are present in Table 5. The first is that risk has a larger effect on price returns in the 2011-2019 as compared to 1997-2010. This is evident from comparison of estimates in columns 1 and 2, both in Panel A (with non-systematic risk) and Panel B (with idiosyncratic risk). In both panels, the coefficients on systematic risk (beta) are notably larger in the later period, as are the coefficients on non-systematic risk and idiosyncratic risk. This pattern suggests that investor sensitivity to the different types of risk may have increased following the boom-bust episode of the earlier period. The primary caveat to this interpretation is that price returns do not allow for change in rent as a driver of rent-to-price ratios and total returns (e.g. Amaral et al, 2021). However, rent series are typically less volatile than price (e.g. Demers and Eisfeldt, 2022), and a wealth of anecdotal evidence suggests that investors became keenly aware of real estate price risk following the 2007 crash in housing prices that triggered widespread mortgage defaults.

A second pattern is that results are robust to whether we include non-systematic risk or idiosyncratic risk, both qualitatively and with respect to the magnitude of effects. The standard deviation of idiosyncratic risk is roughly 12 times higher than the corresponding value for non-systematic risk (Appendix B, Table B-2). Nevertheless, the coefficients on WRLURI and beta in Panels A and B are very similar. The coefficients on non-systematic risk (Panel A) are also of the same sign and mostly the same statistical significance as for idiosyncratic risk (Panel B). Moreover, a one standard deviation increase in non-systematic risk has a similar magnitude effect on returns as a one standard deviation change in idiosyncratic risk. Although both measures yield similar results, we still treat non-systematic risk as the preferred measure given that idiosyncratic risk is correlated with beta whereas non-systematic risk is not (see Appendix B, Table B-5).

Our third primary finding in Table 5 concerns use of price returns versus total returns. Once again, the qualitative patterns are robust. Both panels indicate that risk-return tradeoffs are positive and contribute to higher returns in higher risk markets. Notice also, that the coefficients on beta are similar in magnitude regardless of whether returns are measured using price returns or total returns in columns 2 and 4. This reflects the patterns in Figure 4 discussed earlier, with the tight distribution (low variance) for the rent-to-price ratio.

The magnitude of the estimated risk-return patterns is also important.[13] Focusing on the total return model in Panel A of column 4, recall that at the CBSA level a 1-unit increase in beta is close to its interquartile range across cities. Conditioning on the other model controls, that change is associated with a 1.60 percentage point increase in housing returns. In comparison, an increase in non-systematic risk from the 25th to 75th percentile across cities is associated with a 0.36 percentage point increase in total returns. Relative to the average annual total return across cities over the 2010-2019 sample horizon, which equals 13.1%, these estimates translate into increases of 12.2% and 2.7%, respectively.

5. Risk and Return Within CBSAs

This section repeats the analysis for within-CBSA patterns using zipcodes as the primary geographic unit. Recall that in this instance we proxy for housing supply constraints using distance to the CBD and zipcode employment density as alternate measures. In our more fully specified regression models, neighborhood amenities and related appeal is proxied by the price of housing in the zipcode relative to its CBSA. As above, we begin with additional summary measures. This is followed by model estimates using price returns and then total returns.

5.1 Within-CBSA summary measures

Recall that Figure 1 plots raw zipcode-level price returns against distance to the CBD (Panel A) and employment density (Panel B), pooling data across CBSAs. Table 6 revisits those patterns using

[13] When considering the magnitude of the risk coefficients in Table 5, it is helpful to note related summary measures in Appendix B. Those measures indicate that for the 2011-2019 period, risk measures based on price and total returns exhibit little difference in the mean and variance of the risk measures. That is consistent with the theory from Section 2.

linear regressions. In this instance, columns 1-3 use zipcode-by-month observations rather than zipcode average values over the sample horizon. Column 1 controls for only miles to the CBD in Panel A and year-2010 zipcode employment density in Panel B. Column 2 adds in controls for CBSA fixed effects and column 3 adds in further controls for month fixed effects. Estimates mirror those in Figure 1, with price returns higher closer to the CBD and in high density locations. This is also true in column 4 which uses zipcode average year-over-year price return across the sample horizon as the dependent variable. In this instance, each zipcode provides one observation. The model also includes CBSA fixed effects. Notice that estimates are nearly the same as for the other columns in the table.

To allow for further heterogeneity the distance and log employment density models were estimated separately for each CBSA using the specification in column 3 of Table 6. This interacts the CBSA fixed effect with the other controls in the model, including the month fixed effects. Figure 5 plots the distribution of estimated coefficients across CBSAs for both miles to CBD (Panel A) and zipcode employment density (Panel B). This is done for three different size categories of CBSAs based on year-2000 population, including those with fewer than 250,000 people, 250,000 to 1 million, and over 1 million.

In Figure 5, for both Panels A (distance) and B (employment density), notice that for small and mid-size CBSAs the coefficient distributions are single-peaked, centered close to zero, and include many cities with positive and many with negative coefficients. This indicates the presence of considerable heterogeneity of spatial patterns in the raw data for these size categories. A different pattern is present in the larger CBSAs. Among the 48 CBSAs with year-2000 population over 1 million, 42 have both negative distance coefficients and positive density coefficients, indicating that housing capital gains decline with distance from central, densely developed locations.[14]

[14] Note that Cleveland, Louisville, Oklahoma City, and Rochester, NY all have positive distance coefficients and negative density coefficients. In addition, Baltimore has a positive distance coefficient and Houston has a negative density coefficient.

The different measures of within-CBSA risk also display strong spatial patterns. This is evident in Figure 6 based on raw data pooled across CBSAs and limiting the sample to zipcodes within 25 miles of a CBD. Panel A reports non-parametric plots of return volatility, beta, and non-systematic risk against distance to the CBD, while Panel B has employment density on the horizontal axes.

The dominant pattern in Figure 6 is that for each of the six plots, risk increases roughly monotonically with proximity to city centers and/or densely developed neighborhoods. This echoes the patterns in Figure 1 and is suggestive that within CBSAs, investor exposure to risk may increase with proximity to central, more densely developed portions of a city.

It is also helpful to confirm the degree to which the different risk measures capture similar or different information, as we did for the across-CBSA analysis. Table 7 reports correlations between several key measures for the within-CBSA analysis that follows. These include zipcode-level average price returns over the 1997-2019 sample horizon, miles to CBD, log employment density, return volatility, beta, and non-systematic risk.

Two patterns stand out in Table 7. First, the correlation between price returns and return volatility is 48.7%, a bit lower than at the CBSA level in Table 3 (67.4%), but still quite large. Second, return volatility is much more strongly correlated with non-systematic risk as opposed to beta, with respective correlations of 98.7% and 16.3%. In comparison, the corresponding values at the CBSA level in Table 3 are 43.7% and 90.9%. These patterns suggest that non-systematic risk may play an important role in driving risk-return tradeoffs within CBSAs, consistent with estimates that follow.[15]

5.2 Risk-return tradeoffs

Table 8 reports estimates of spatial patterns of risk and return within CBSAs. In all cases, price appreciation is used to measure returns and risk. In Panel A, housing supply restrictions and spatial

[15] Notice also in Table 7 that the correlations between price growth with distance to CBD and employment density are -6.8% and 27.9%, respectively. These correlations echo the patterns highlighted in Figure 1.

patterns are captured by miles to the CBD, while in Panel B we use zipcode log employment density. These measures may also partly proxy for differences in amenity appeal across neighborhoods (e.g. Davidoff, 2016). In the more fully specified models, neighborhood-level amenity appeal is also proxied by the relative economic status of the zipcode. This is measured using the zipcode's year-2019 mean home value relative to the year-2019 mean home value in the CBSA. Risk measures in the regressions are as previously described. Notice also that the models in Table 8 are based on pooled samples of zipcodes across all CBSAs. CBSA fixed effects are included to allow for cross-CBSA heterogeneity. Stratified sample regressions by CBSA size groupings are in Table 9 and are discussed shortly.

In Table 8, column 1 controls for only distance (Panel A) or employment density (Panel B). Column 2 adds in a control for return volatility σ^P. Column 3 adds in relative home value, and column 4 separates σ^P into its systematic (beta) and non-systematic components.

Several patterns are evident. First, comparing estimates in the two panels, it mostly does not matter whether we control for distance to the CBD or density. In both cases, the coefficients on the other model controls are similar. Similarly, the coefficients on distance and density diminish only slightly when other controls are added. Nevertheless, density is likely a sharper proxy for housing supply constraints as it allows for dense suburban employment centers that are present in some CBSAs and which are not captured by distance (see Rosenthal and Strange (2022) for related discussion).

Second, non-systematic risk has a clear, positive effect on house price returns. In column 4 of Panel B, the coefficient on non-systematic risk is 0.0843. For a shift from the 25^{th} to the 75^{th} percentile zipcode with respect to non-systematic risk (equal to 3.9 units in Table C-2 of the appendix), that translates into a 0.33 percentage point increase in price returns, or roughly 10% of the mean return for the entire sample. The effect of systematic risk, in contrast, is small and not significant, consistent with the much lesser correlation with price returns in Table 7. In this case, a shift from the 25^{th} to 75^{th} percentile zipcode with respect to beta increases price returns by just 0.5% of the sample mean.

One possible explanation for why beta has little effect in Table 8 could be CBSA size. Many CBSAs may be too small to allow for differences in supply elasticities across neighborhoods that could amplify broader market shocks, including shocks at the national level as well as those specific to the CBSA. This would reduce any tendency for systematic risk to drive spatial patterns of price returns within a CBSA. To consider that possibility, Table 9 stratifies the models in Table 8 into three size groupings of CBSAs. Moving from left to right, these include CBSAs with under 250,000 population, 250,000 to 1 million, and over 1 million (all based on year 2000 population). Several patterns stand out.

Notice first in Table 9 that the coefficients on distance (Panel A) and density (Panel B) are smaller in the small and mid-size CBSAs, and notably larger in the large CBSAs. This confirms that spatial patterns in price returns are more pronounced in the larger cities even after conditioning on neighborhood appeal and amenity value (as proxied by zipcode relative home price). This may reflect that larger CBSAs have greater potential for differences in supply restrictions across communities that contribute to within-CBSA spatial variation in price returns. Smaller cities, in contrast, may exhibit a comparatively greater degree of demand and supply substitution between neighborhoods, forces that would stabilize relative prices between communities and cause price returns to be similar (see Liu et al (2016) for related discussion and evidence).

Also evident among large CBSAs is that the coefficient on density shrinks roughly 20% when other controls are added to the model. This can be seen in columns 5-7 of Panel B. In column 5, the density coefficient is 0.157 compared to 0.126 when other controls are added to the model. An analogous but smaller change in magnitude is also present for the distance coefficients in Panel A. These patterns indicate that a portion of the spatial pattern in price returns is accounted for by spatial patterns in neighborhood amenities and risk-return tradeoffs. However, most of the spatial pattern remains which suggests that something else beyond our controls for risk and local amenities is contributing to variation in price returns. We return to this point in the following section.

Most important, spatial variation in risk-return tradeoffs is clearly present in large CBSAs. For CBSAs with population over 1 million, the coefficient on return volatility in column 6 (Panel B) is 0.1207 and highly significant. Moreover, the coefficient is roughly three times larger in magnitude compared to estimates in small and mid-size CBSAs. The general pattern for large CBSAs is also robust to further specifications that follow shortly, as is the absence of evidence of risk-return tradeoffs in small CBSAs. Among mid-size cities, other specifications to follow suggest that risk-return tradeoffs are present although this is not so obvious in Table 9.

A final pattern in Table 9 is that for large CBSAs, upon decomposing return volatility into systematic and non-systematic risk, non-systematic risk is the more dominant driver of returns. In Panel B, which controls for density, the coefficient on beta has a t-ratio of just 0.65. The coefficient on non-systematic risk, in contrast, is 0.122 with a t-ratio of 2.8. This suggests that neighborhood specific sources of risk are an important driver of spatial variation in risk-return tradeoffs within large urban areas.

5.3 Alternate specifications

The estimates above are based on price returns over the full sample period, 1997-2019. In Table 10 we consider how these design features affect estimates from the more fully specified models in Table 9 that decompose return volatility into systematic and non-systematic risk. As before, models that control for distance to the CBD are in Panel A, while models that control for density are in Panel B. In both panels, and for each of the size groupings of CBSAs from Table 9, separate models are reported using price returns for 1997-2010 and 2011-2019, and total returns in 2011-2019. Several conclusions emerge.

Among small CBSAs, evidence of within-city spatial patterns is not robust. Using price returns, the signs on the distance and density coefficients are as anticipated in the early period but reversed in the later period. For total returns, the distance and density coefficients are not significant and of conflicting signs relative to priors. Evidence of risk-return tradeoffs is also mixed. In the earlier period using price returns, non-systematic risk is positive and significant, and in the later period using total returns, systematic risk is positive and marginally significant. The other risk coefficients are smaller and not significant. We conclude that small CBSAs do not exhibit robust spatial patterns of risk-return tradeoffs.

Among mid-size CBSAs, distance and density have the anticipated signs and are significant in the early period using price returns, and the later period using total returns. For the later period using price returns the corresponding coefficients are much smaller and not significant. The risk coefficients are all positive as anticipated, with non-systematic risk significant in the early period (using price returns) and both systematic and non-systematic risk significant in the later period when using total returns. Overall, there does appear to be a spatial pattern to housing returns in mid-size CBSAs, a portion of which is driven by risk-return tradeoffs.

For large CBSAs, the distance and density measures always have the anticipated sign and are significant in the later period regardless of whether price returns or total returns are used. The risk coefficients also are always of the anticipated sign and are always significant except for systematic risk in the early period. Affirming evidence from Table 9, these patterns indicate that spatial variation in housing returns is present within large CBSAs and, as with mid-sized cities, a portion of that variation is driven by risk-return tradeoffs. Moreover, comparing price returns in the early versus the later period (in columns 1 and 2), evidence of risk-return tradeoffs is more pronounced in the later period with significant and larger coefficients on beta. This is suggestive that house market investors may have become more sensitive to systematic risk following the dramatic boom-bust episode of the previous decade.[16]

A final point concerns magnitude. For price returns in column 8, average annual return among zipcodes in the 48 largest CBSAs is 5.15% whereas average annual total return is 14.6%, indicating a rent-to-price ratio of roughly 9.5 percentage points (Appendix B, Table B-4). Consider now a change in magnitude for each risk measure (systematic and non-systematic) from its 25th to the 75th percentile zipcode. Recall also that these values differ depending on whether they are measured using price versus total returns. Bearing this in mind, for price returns a change from the 25th to 75th percentile values for systematic and non-systematic risk would increase capital gains by roughly 5% and 20% relative to the sample mean. For total returns, the analogous values are nearly identical, 4% and 23%.

Two messages follow from the exercise above. First, the magnitude of risk-return tradeoffs appears to be similar when using price and total returns provided these are scaled by the respective mean

[16] Table B-6 in Appendix B reports estimates when we replace non-systematic risk with idiosyncratic risk, with both constructed as described earlier in the paper. Results are robust and are not discussed for that reason.

values. Second, as with the across-CBSA analysis, risk-return tradeoffs within large urban areas are large enough to drive noteworthy within-city spatial variation. In this case, however, most of that effect arises from non-systematic, neighborhood-level sources of risk.

6. Conclusion

Three broad conclusions follow from our analysis. The first is that risk-return tradeoffs contribute to spatial variation in housing returns, in part because of spatial variation in supply constraints that amplify the effect of unobserved shocks on housing market volatility (e.g. Glaeser and Gyourko, 2005; Glaeser, Gyourko and Saiz, 2008; Saiz, 2008; Paciorek, 2013; Gyourko and Molloy, 2015). This occurs across cities and within large CBSAs. We do not see compelling evidence of spatial variation in risk-return patterns within small CBSAs, possibly because small cities have insufficient scale to allow for substantive variation in neighborhood-level shocks and supply constraints.

Our second conclusion is that the dominant source of risk that drives spatial variation in returns differs with the level of geography. For a one standard deviation change for a given type of risk (non-systematic and systematic), and allowing for the estimated model coefficients, systematic risk is the dominant driver of variation in returns across CBSAs. Our modelling framework suggests that this pattern arises because housing markets in supply-constrained cities experience more volatility in response to national-level as opposed to city-specific shocks. When looking within large CBSAs, neighborhood level non-systematic risk is the dominant driver of spatial variation in risk-return tradeoffs. Given the manner in which within-city patterns are modelled, if city-wide shocks were the only driver of risk-return tradeoffs, systematic risk would dominate. Instead, our finding that non-systematic risk dominates suggests that the intensity of neighborhood-level shocks also varies within large urban areas, contributing to the more substantive role of locally based (non-systematic) risk as a driver of within-city spatial variation in returns.

Our third and final broad conclusion is that risk-return tradeoffs are large enough to be important. Increasing the dominant source of risk by one standard deviation, total housing returns increase 12.2% when looking across cities and by 22.7% within large urban areas. Absent an explanation such as risk-return tradeoffs, these differences would not be sustainable. Instead, our study shows that differences in home price appreciation rates and related housing returns can persist in equilibrium across and within cities because of spatial variation in investor exposure to risk.

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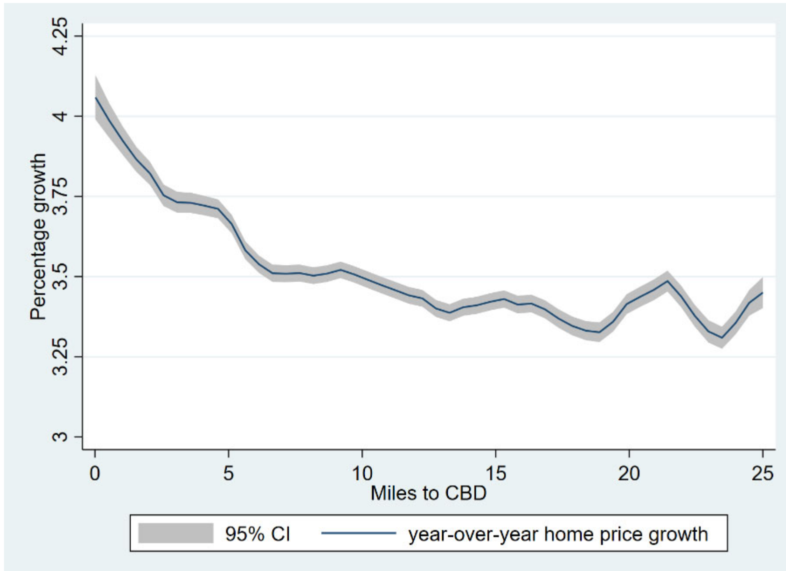
Figure 1: Year-over-year % growth in zipcode housing price[a]

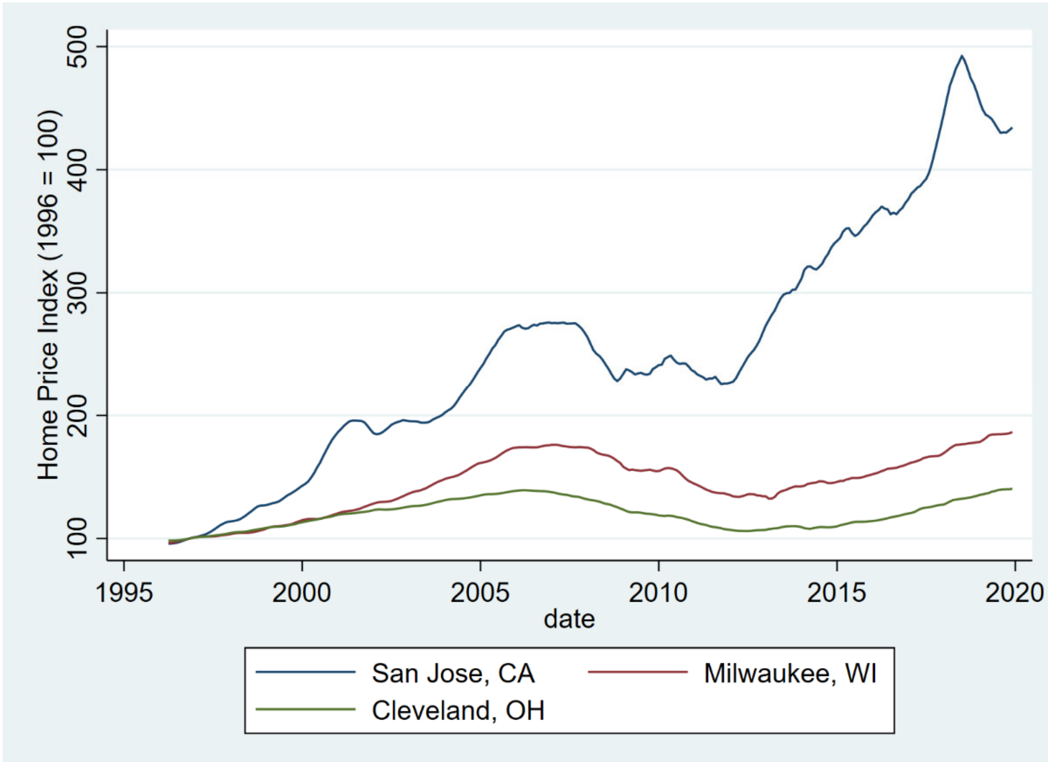
Panel A: Distance to CBD



Panel B: Log Employment Density

[a] Sample restricted to zipcodes with residential units within 25 miles of a CBD with employment density above 1. Estimates are based on a local polynomial regression of degree 0 using the epanechnikov kernel and Rule of Thumb bandwidth. In Panel B the figure is cut at log 10 after which estimates are imprecise. Index data were provided by Zillow Group.

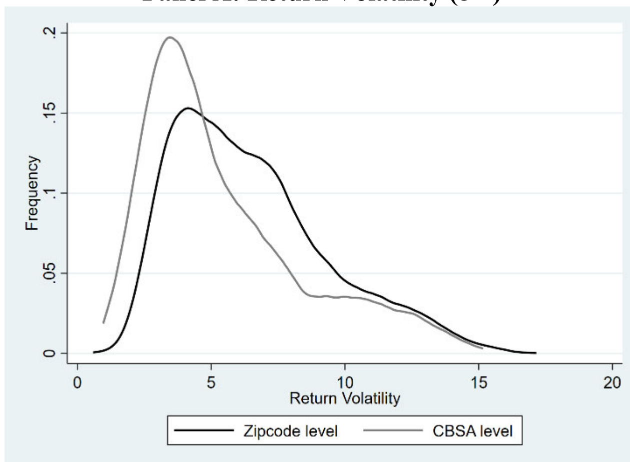
Figure 2: Single-family home value index for select CBSAs[a]



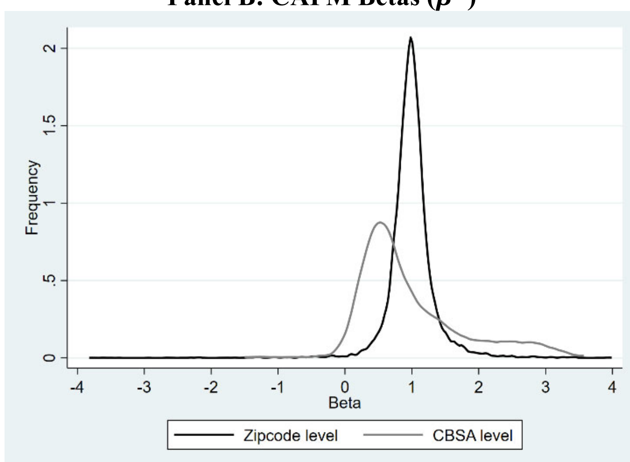
[a] Index data were provided by Zillow Group.

Figure 3: Distribution of Risk Measures at the CBSA and Zipcode Level

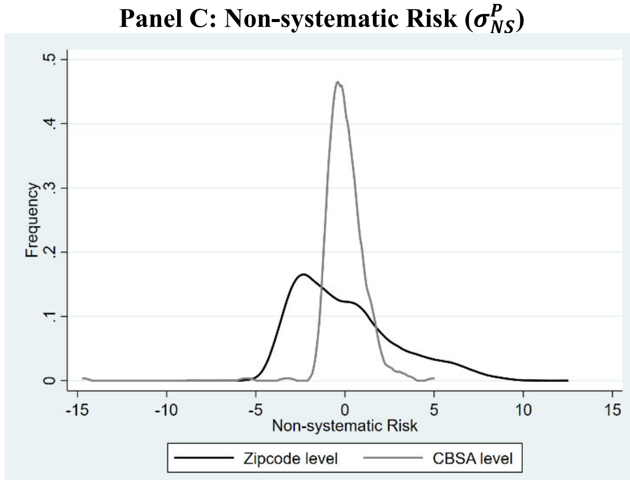
Panel A: Return Volatility (σ^P)



Panel B: CAPM Betas (β^P)



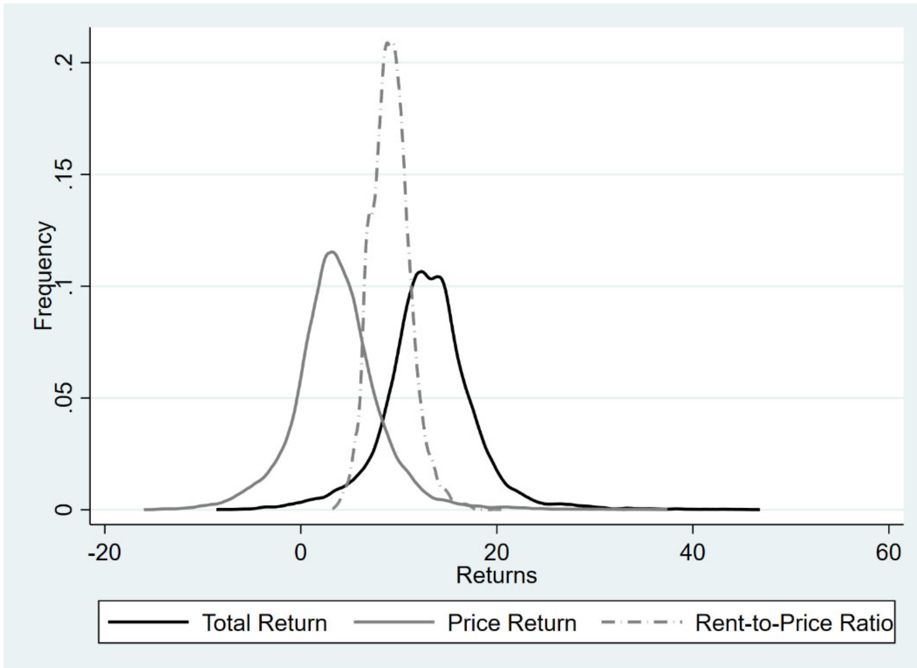
Panel C: Non-systematic Risk (σ^P_{NS})



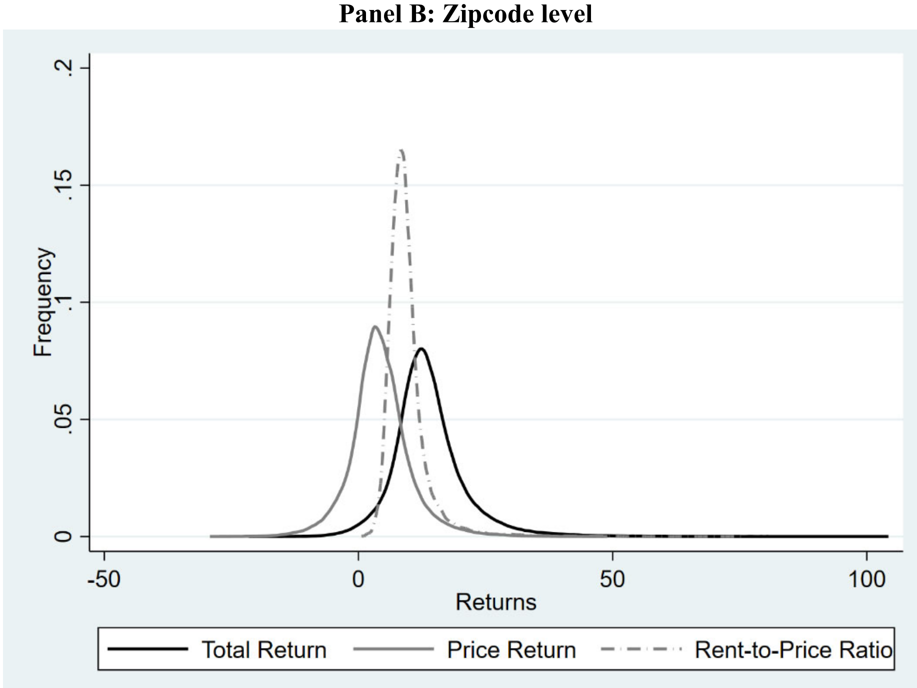
[a] Estimates are based on a kernel density using the epanechnikov kernel and bandwidth determined by the Silverman (1986) optimal bandwidth. Betas beyond -4 and 4 are omitted (44 of 11,644 zipcodes and 1 of 362 CBSAs). Data were provided by Zillow Group.

Figure 4: Distribution of Total Returns, Price Returns, and Rent-to-Price Ratio[a]

Panel A: CBSA level



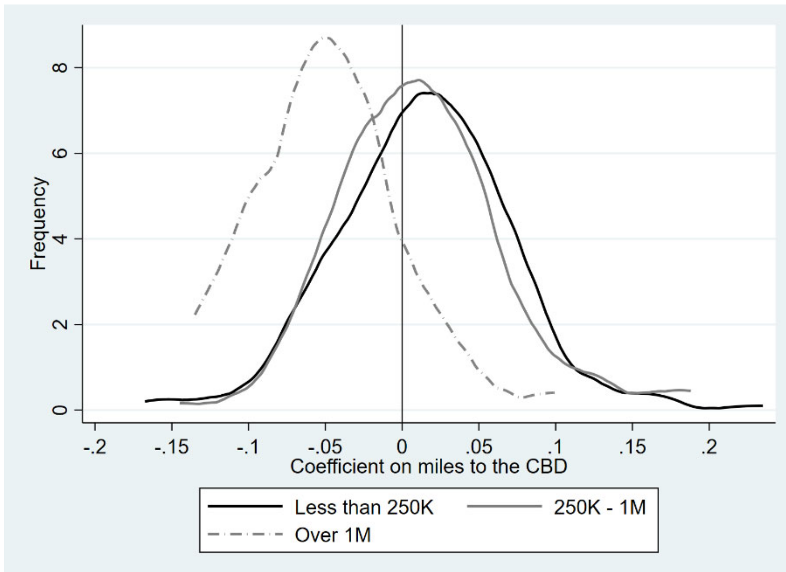
Panel B: Zipcode level



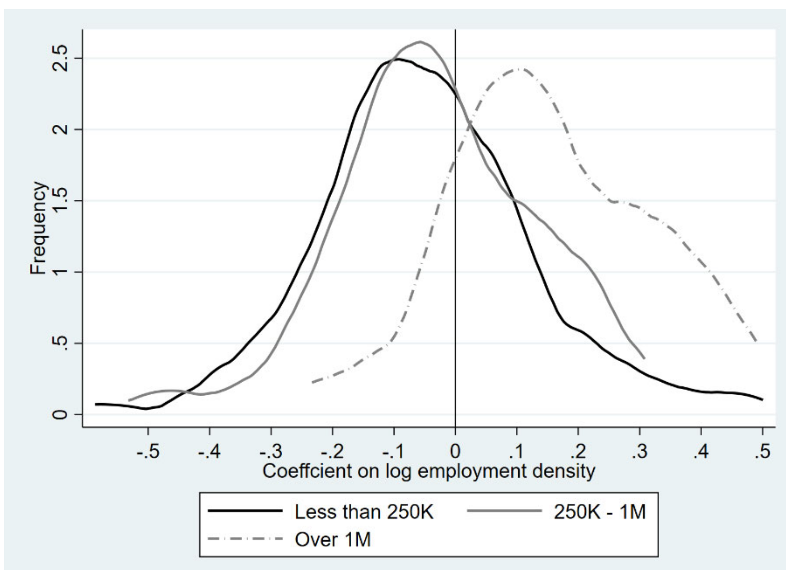
[a] Data were provided by Zillow Group.

Figure 5: Distribution of coefficients on Distance to CBD and Density from CBSA-by-CBSA regressions of zipcode level home price growth (ρ_{it}^{P}) [a]

Panel A: Miles to CBD



Panel B: Log employment density

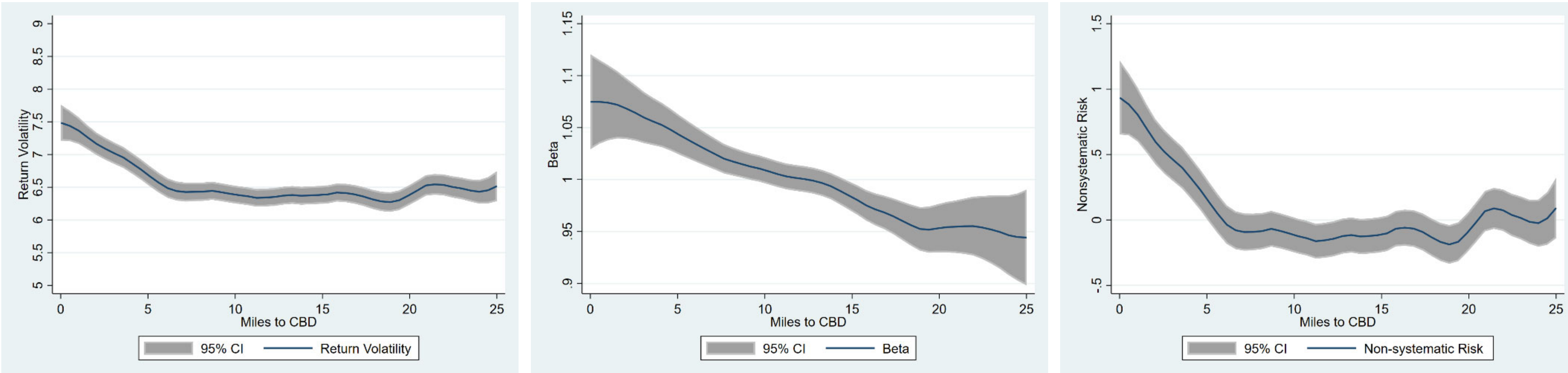


[a] Separate zipcode level regressions were first run for each CBSA based on $\rho_{it}^{P} = a_c + a_{i,c}x_i + Month\ FE + e_{it}$, where ρ_{it}^{P} is year-over-year percent growth in home prices in zipcode *i* for month *t*. Subscript *c* denotes individual CBSAs and *x* is distance to the CBD or log employment density for Panels A and B, respectively. The distribution of estimated a_c across regressions was then smoothed and plotted using the epanechnikov kernel with optimal Silverman (1986) bandwidth. Data were provided by Zillow Group.

Figure 6: Spatial variation in risk measures within CBSAs (return volatility (σ^P), systematic risk (β^P), and non-systematic risk (σ^P_{NS}))

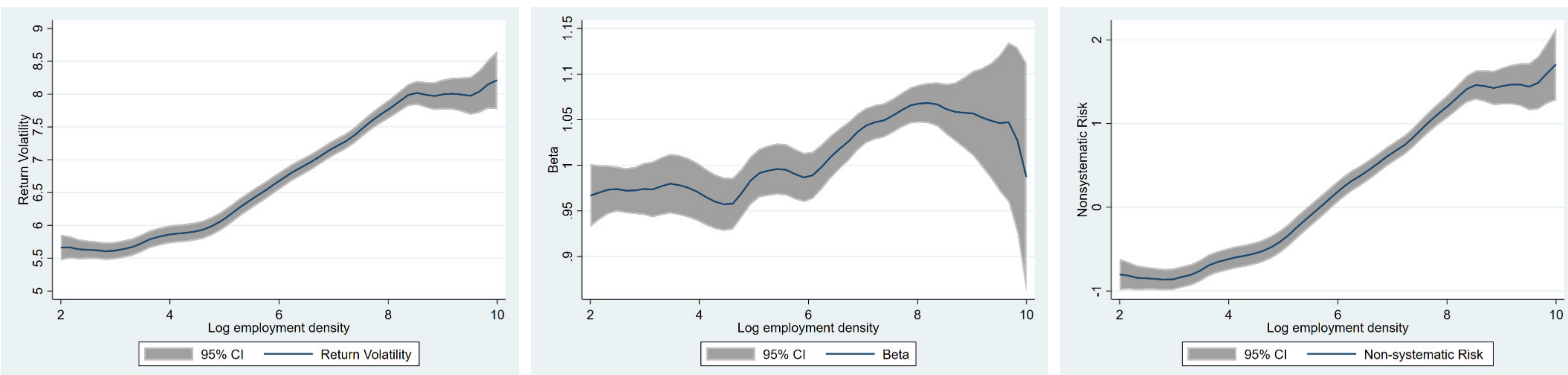
Panel A: Miles to the CBD

Return Volatility | Beta | Non-systematic Risk



Panel B: Log Employment Density

Return Volatility | Beta | Non-systematic Risk



[a]Sample restricted to zipcodes with residential units within 25 miles of a CBD with employment density above 1. Estimates are based on a local polynomial regression of degree 0 using the epanechnikov kernel and Rule of Thumb bandwidth selection process. In Panel B the observations are limited to zipcodes with employment density greater than natural log 2 (approximately 8 workers per square mile) and less than natural log 10 (approximately 22,000 workers per square mile). Data were provided by Zillow Group.

Table 1: Single-family home price index growth for bottom and top 20 CBSAs: 1997-2019 [a]

Bottom 20			Top 20		
	Average one-year growth	Population in 2000		Average one-year growth	Population in 2000
Youngstown, OH	1.27	602,964	Washington, DC	4.30	4,849,948
Dayton, OH	1.43	805,816	New York, NY	4.36	18,323,002
Cleveland, OH	1.53	2,148,143	North Port, FL	4.43	589,959
Memphis, TN	1.75	1,205,204	Orlando, FL	4.45	1,644,561
Akron, OH	1.84	694,960	Phoenix, AZ	4.57	3,251,876
Jackson, MS	1.93	546,955	Tampa, FL	4.66	2,395,997
Birmingham, AL	1.94	981,525	Portland, OR	4.71	1,927,881
Scranton, PA	1.95	560,625	Boston, MA	4.77	4,391,344
Toledo, OH	1.96	659,188	Urban Honolulu, HI	4.79	876,156
Chicago, IL	1.98	9,098,316	Fresno, CA	4.84	799,407
Greensboro, NC	1.99	643,430	Denver, CO	4.94	2,157,756
El Paso, TX	2.00	682,966	Miami, FL	5.17	5,007,564
Indianapolis, IN	2.05	1,658,462	Seattle, WA	5.35	3,043,878
Columbia, SC	2.08	647,158	Sacramento, CA	5.48	1,796,857
Rochester, NY	2.20	1,062,452	San Diego, CA	5.88	2,813,833
Albuquerque, NM	2.23	729,649	Riverside, CA	6.17	3,254,821
Wichita, KS	2.23	571,166	Los Angeles, CA	6.33	12,365,627
Cincinnati, OH	2.29	2,016,981	Stockton, CA	6.57	563,598
Winston-Salem, NC	2.29	569,207	San Francisco, CA	7.22	4,123,740
Baton Rouge, LA	2.38	729,361	San Jose, CA	7.23	1,735,819

[a] CBSAs in this this table are limited to those with population greater than 500,000 in 2000. The name of each CBSA is limited to its primary city. Price growth measures were calculated using data provided by Zillow Group.

Table 2: CBSAs with the highest and lowest risk sorted by return volatility[a]

Bottom 20					Top 20				
	Return Volatility (σ^P)	Beta (β^P)	Non-systematic Risk (σ^p_{NS})	Population		Return Volatility (σ^P)	Beta (β^P)	Non-systematic Risk (σ^p_{NS})	Population
Pittsburgh, PA*	1.901	0.371	-1.539	2,431,087	Jacksonville, FL	8.132	1.844	-0.223	1,122,750
Oklahoma City, OK	2.026	0.327	-1.267	1,095,421	Seattle, WA	8.172	1.637	0.510	3,043,878
Little Rock, AR	2.414	0.388	-1.082	610,518	Washington, DC	8.577	1.857	0.180	4,849,948
Wichita, KS	2.443	0.219	-0.488	571,166	Tucson, AZ	8.751	1.971	-0.026	843,746
Rochester, NY	2.461	0.429	-1.172	1,062,452	Detroit, MI	9.442	1.800	1.233	4,452,557
Tulsa, OK	2.513	0.279	-0.620	859,532	San Jose, CA	9.874	1.277	3.411	1,735,819
Buffalo, NY*	2.582	0.440	-1.089	1,170,111	San Francisco, CA	10.016	1.975	1.223	4,123,740
McAllen, TX	2.751	0.385	-0.734	569,463	San Diego, CA	10.172	2.106	0.942	2,813,833
Syracuse, NY	2.843	0.468	-0.921	650,154	Tampa, FL	10.477	2.487	-0.023	2,395,997
Des Moines, IA	2.928	0.595	-1.259	518,607	Los Angeles, CA	10.539	2.363	0.452	12,365,627
Greenville, SC	2.939	0.427	-0.688	725,680	North Port, FL	11.574	2.619	0.632	589,959
Harrisburg, PA	2.963	0.470	-0.806	509,074	Miami, FL	11.802	2.791	0.287	5,007,564
Columbia, SC	2.967	0.426	-0.655	647,158	Orlando, FL	11.916	2.672	0.798	1,644,561
Winston-Salem, NC	3.017	0.393	-0.496	569,207	Sacramento, CA	12.282	2.826	0.649	1,796,857
Louisville, KY	3.020	0.482	-0.789	1,090,024	Fresno, CA	12.715	3.055	0.318	799,407
Greensboro, NC	3.164	0.450	-0.538	643,430	Phoenix, AZ	12.868	2.596	2.003	3,251,876
Raleigh, NC	3.180	0.526	-0.776	797,071	Bakersfield, CA	13.119	3.026	0.820	661,645
Omaha, NE	3.221	0.580	-0.916	767,041	Riverside, CA	13.489	3.080	1.011	3,254,821
Augusta, GA	3.292	0.493	-0.553	508,032	Las Vegas, NV	13.932	3.216	0.998	1,375,765
Knoxville, TN	3.295	0.573	-0.819	727,600	Stockton, CA	14.904	3.249	1.861	563,598

[a] CBSAs shown here are limited to those with population greater than 500 thousand in 2000. Stars indicate CBSAs with population loss between 1990 and 2010. The North Port, FL CBSA contains Sarasota. Return volatility measures were calculated using data provided by Zillow Group.

Table 3: Correlation between CBSA level 1997-2019 average year-over-year home price returns and alternate measures of risk[a]

	Average year-over-year return ($\bar{\rho}^P$)	WLURI	Return volatility (σ^P)	Beta (β^P)	Non-systematic risk (σ_{NS}^P)
Average year-over-year return ($\bar{\rho}^P$)	1.0	-	-	-	-
WLURI	0.286	1.0	-	-	-
Return volatility (σ^P)	0.674	0.306	1.0	-	-
Beta (β^P)	0.591	0.226	0.909	1.0	-
Non-systematic risk (σ_{NS}^P)	0.340	0.246	0.437	0.022	1.0

[a] Return and volatility measures were calculated using data provided by Zillow Group. WLURI was obtained from Gyourko, Hartley, and Krimmel (2021), http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/ .

Table 4: CBSA level 1997-2019 average price returns $\bar{\rho}_i^P$ (scaled by 100)[a]

	(1)	(2)	(3)	(4)	(5)	(6)
WRLURI	0.5345***	-	0.1397	0.1232	0.1710	0.0092
	(0.1257)	-	(0.0872)	(0.0892)	(0.1049)	(0.0958)
Return volatility: σ^P	-	0.3018***	0.2723***	-	-	-
	-	(0.0187)	(0.0212)	-	-	-
Beta: β^P	-	-	-	0.8726***	0.8749***	0.7889***
	-	-	-	(0.0726)	(0.0787)	(0.0806)
Non-systematic risk: σ_{NS}^P	-	-	-	0.3286***	0.2927***	0.2442***
	-	-	-	(0.0502)	(0.0497)	(0.0518)
Log CBSA population 2000	-	-	0.0457	0.0575	0.1029	0.2509***
	-	-	(0.0678)	(0.0680)	(0.0820)	(0.0762)
Median CBSA income 2000 (1,000s)	-	-	0.0414	0.0325	0.2250	0.1111
	-	-	(0.2022)	(0.2005)	(0.2258)	(0.2195)
|%Δ population| if GROWING 1990-2020 (0 otherwise)	-	-	0.0011	0.0008	0.0016	-0.0014
	-	-	(0.0023)	(0.0023)	(0.0026)	(0.0024)
|%Δ population| if SHRINKING 1990-2020 (0 otherwise)	-	-	-0.0992**	-0.1046**	-0.0998*	-0.0793
	-	-	(0.0403)	(0.0423)	(0.0530)	(0.0482)
Superstar status	-	-	0.4883	0.4452	0.382	0.1362
	-	-	(0.5061)	(0.4952)	(0.4888)	(0.2486)
Quality of Life Index (x 1,000)	-	-	-	-	-	0.2464***
	-	-	-	-	-	(0.0379)
Observations	298	298	298	298	222	222
R^2	0.0817	0.4538	0.4807	0.4837	0.5216	0.6034

[a] The dependent variable has a mean of 3.1, indicating that CBSA-level home prices increase 3.1% on average year-over-year over our sample horizon. Standard errors are in parentheses. Significance is indicated as: * p<0.1, ** p<0.05, *** p<0.01. Return and volatility measures were calculated using data provided by Zillow Group. WLURI was obtained from Gyourko, Hartley, and Krimmel (2021), http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/ .

Table 5: CBSA price and total returns with non-systematic versus idiosyncratic risk[a]

	Price Returns 1997-2010	Price Returns 2011-2019	Rent-to-Price 2011-2019	Total Returns 2011-2019
Panel A: Non-systematic risk	(1)	(2)	(3)	(4)
WRLURI	0.1686	-0.1825	-0.1873	-0.5285**
	(0.1677)	(0.1631)	(0.1447)	(0.2567)
Beta (β^q)	0.3423*	1.5888***	-0.3279**	1.8709***
	(0.1992)	(0.2077)	(0.1355)	(0.1947)
Non-systematic risk (σ^q_{NS})	0.4146	0.7411***	-0.1394	0.3351*
	(0.2811)	(0.1816)	(0.1017)	(0.1838)
Observations	220	222	197	197
R2	0.3308	0.6453	0.5359	0.3929
Panel B: Idiosyncratic risk				
WRLURI	0.2166	-0.1301	-0.0018	-0.5640**
	(0.1626)	(0.1838)	(0.0014)	(0.2519)
Beta (β^q)	0.2753	1.2242***	-0.2646*	1.5595***
	(0.3993)	(0.3720)	(0.1415)	(0.2182)
Idiosyncratic risk ($\sigma^q{}_{ID}$)	0.0005	0.0523***	-0.0105	0.0428***
	(0.0105)	(0.0100)	(0.0070)	(0.0107)
Observations	220	222	197	197
R2	0.2588	0.6245	0.5356	0.4141

[a] Standard errors are in parentheses. Significance is denoted as: * p<0.1, ** p<0.05, *** p<0.01. Controls include all measures in column 6 of Table 4 with the coefficients on proxies for demand and CBSA amenity appeal suppressed (population level and growth, median income, superstar status and quality of life index). Measures of risk and return are based on price returns in columns 1-3 ($q = p$) and total returns in column 4 ($q = Tot$). Return and volatility measures were calculated using data provided by Zillow Group. WLURI was obtained from Gyourko, Hartley, and Krimmel (2021), http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/ .

Table 6: Zipcode level price returns pooling across CBSAs[a]

Panel A: Miles to the CBD

	Year-over-year home price returns using month by zipcode observations			Average year-over-year price returns over 1997-2019
	(1)	(2)	(3)	(4)
Miles to CBD	-0.0204***	-0.0286***	-0.0240***	-0.0290***
	(0.0057)	(0.0053)	(0.0059)	(0.0054)
Fixed Effects				
CBSA	-	362	362	362
Month	-	-	273	-
Observations	2,790,418	2,790,418	2,790,418	11,644
R^2	0.0030	0.0384	0.4352	0.554

Panel B: Log Employment Density

	Year-over-year home price returns using month by zipcode observations			Average year-over-year price returns over 1997-2019
	(1)	(2)	(3)	(4)
Log employment density	0.2217***	0.0530***	0.0368**	0.0481***
	(0.0433)	(0.0141)	(0.0153)	(0.0139)
Fixed Effects				
CBSA	-	362	362	362
Month	-	-	273	-
Observations	2,790,418	2,790,418	2,790,418	11,644
R^2	0.0054	0.0380	0.435	0.548

[a] Standard errors are in parentheses and are clustered at the CBSA. Significance is denoted as follows: * p<0.1, ** p<0.05, *** p<0.01. Return measures were calculated using data provided by Zillow Group.

Table 7: Correlation between zipcode level 1997-2019 average year-over-year home price returns and alternate measures of within-CBSA location and risk[a]

	Average year-over-year return ($\bar{\rho}^P$)	Miles to CBD	Log employment density	Return volatility (σ^P)	Beta (β^P)	Non-systematic risk (σ^P_{NS})
Average year-over-year return ($\bar{\rho}^P$)	1.0	-	-	-	-	-
Miles to CBD	-0.0685	1.0	-	-	-	-
Log employment density	0.2798	-0.4618	1.0	-	-	-
Return volatility (σ^P)	0.4871	-0.0580	0.2716	1.0	-	-
Beta (β^P)	0.0123	-0.0710	0.0340	0.1635	1.0	-
Non-systematic risk (σ^P_{NS})	0.4918	-0.0474	0.2698	0.9874	0.0051	1.0

[a]Return and volatility measures were calculated using data provided by Zillow Group.

Table 8: Zipcode level 1997-2019 average monthly year-over-year percent home price (scaled by 100)[a]

Panel A: Distance to the CBD

	(1)	(2)	(3)	(4)
Miles to CBD	-0.0290***	-0.0283***	-0.0263***	-0.0263***
	(0.0053)	(0.0053)	(0.0049)	(0.0050)
Return Volatility (σ^P)	-	0.022	0.0660***	-
	-	(0.0247)	(0.0232)	-
Beta (β^P)	-	-	-	0.0419
	-	-	-	(0.0960)
Non-systematic risk (σ_{NS}^P)	-	-	-	0.0677**
	-	-	-	(0.0268)
Relative home value[a]	-	-	0.4183***	0.4178***
	-	-	(0.1176)	(0.1172)
CBSA FE	362	362	362	362
Observations	11,644	11,644	11,644	11,644
Within R2	0.0187	0.0192	0.0381	0.0381

Panel B: Log Employment Density

	(1)	(2)	(3)	(4)
Log Employment Density	0.0481***	0.0471***	0.0410***	0.0411***
	(0.0137)	(0.0136)	(0.0126)	(0.0127)
Return Volatility (σ^P)	-	0.0383	0.0829***	-
	-	(0.0257)	(0.0235)	-
Beta (β^P)	-	-	-	0.0577
	-	-	-	(0.0958)
Non-systematic risk (σ_{NS}^P)	-	-	-	0.0843***
	-	-	-	(0.0274)
Relative home value[a]	-	-	0.4334***	0.4330***
	-	-	(0.1141)	(0.1136)
CBSA FE	362	362	362	362
Observations	11,644	11,644	11,644	11,644
Within R2	0.0044	0.0061	0.0264	0.0265

[a] Standard errors are in parentheses and are clustered at the CBSA. Significance is indicated as * p<0.1, ** p<0.05, *** p<0.01. Relative home value is measured at the ration of zipcode level home value to average home value in a zipcodes's market at the final period (December 2019). Home value, return and volatility measures were calculated using data provided by Zillow Group.

Table 9: Zipcode level 1997-2019 average monthly year-over-year home price returns by CBSA population bins[a]

Panel A: Distance to the CBD

	100,000 < 250,000		250,000 to 1 Million		Above 1 Million		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Miles to CBD	0.0046	0.0045	-0.0034	-0.003	-0.0667***	-0.0610***	-0.0610***
	(0.0055)	(0.0055)	(0.0050)	(0.0053)	(0.0075)	(0.0082)	(0.0082)
Return Volatility (σ^P)	0.0034	-	0.0364	-	-	0.055	-
	(0.0403)	-	(0.0351)	-	-	(0.0373)	-
Beta (β^P)	-	-0.0736	-	0.081	-	-	0.0416
	-	(0.1831)	-	(0.1930)	-	-	(0.1328)
Non-systematic risk (σ^P_{NS})	-	0.0172	-	0.0298	-	-	0.0555
	-	(0.0490)	-	(0.0370)	-	-	(0.0426)
Relative home value[a]	0.5598***	0.5634***	0.6964***	0.6979***	-	0.2428	0.2426
	(0.1150)	(0.1169)	(0.1078)	(0.1078)	-	(0.1548)	(0.1534)
CBSA FE	191	191	123	123	48	48	48
Observations	2,952	2,952	3,726	3,726	4,966	4,966	4,966
Within R2	0.0214	0.0223	0.0394	0.0398	0.0856	0.0939	0.0939

Panel B: Log Employment Density

	100,000 < 250,000		250,000 to 1 Million		Above 1 Million		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Employment Density	-0.0102	-0.0102	0.0089	0.0079	0.1570***	0.1261***	0.1261***
	(0.0170)	(0.0170)	(0.0149)	(0.0151)	(0.0272)	(0.0254)	(0.0255)
Return Volatility (σ^P)	0.0042	-	0.0372	-	-	0.1207***	-
	(0.0404)	-	(0.0350)	-	-	(0.0374)	-
Beta (β^P)	-	-0.0746	-	0.0824	-	-	0.0876
	-	(0.1833)	-	(0.1916)	-	-	(0.1344)
Non-systematic risk (σ^P_{NS})	-	0.018	-	0.0304	-	-	0.1221***
	-	(0.0490)	-	(0.0371)	-	-	(0.0430)
Relative home value[a]	0.5557***	0.5594***	0.6949***	0.6965***	-	0.2990*	0.2990*
	(0.1141)	(0.1160)	(0.1094)	(0.1093)	-	(0.1490)	(0.1490)
CBSA FE	191	191	123	123	48	48	48
Observations	2,952	2,952	3,726	3,726	4,966	4,966	4,966
Within R2	0.0212	0.0221	0.0393	0.0398	0.0296	0.0496	0.0496

[a] Standard errors are in parentheses and are clustered at the CBSA. Significance is indicated as * p<0.1, ** p<0.05, *** p<0.01. Relative home value is measured at the ration of zipcode level home value to average home value in a zipcodes's market at the final period (December 2019). Home value, return and volatility measures were calculated using data provided by Zillow Group.

Table 10: Zipcode level average monthly returns by period for price versus total returns[a]

	100,000 < 250,000			250,000 to 1 Million			Above 1 Million		
	Price Returns 1997-2010	Price Returns 2011-2019	Total Returns 2011-2019	Price Returns 1997-2010	Price Returns 2011-2019	Total Returns 2011-2019	Price Returns 1997-2010	Price Returns 2011-2019	Total Returns 2011-2019
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Distance to CBD									
Miles to CBD	-0.0279**	0.0163**	0.0085	-0.0195***	0.0046	-0.0472***	0.0153	-0.0846***	-0.1350***
	(0.0107)	(0.0064)	(0.0111)	(0.0073)	(0.0064)	(0.0123)	(0.0125)	(0.0147)	(0.0222)
Beta (β^q)	0.1985	-0.0310	0.6652*	0.1596	0.0442	0.5763**	0.2902	0.5395***	1.2566***
	(0.1873)	(0.2706)	(0.3534)	(0.2237)	(0.0912)	(0.2442)	(0.2340)	(0.1540)	(0.2036)
Non-systematic risk (σ_{NS}^q)	0.6892***	-0.0530	0.1100	0.5720***	0.0541	0.8857***	0.5144***	0.3611***	1.1418***
	(0.0687)	(0.0759)	(0.1386)	(0.0958)	(0.0410)	(0.1171)	(0.1377)	(0.0738)	(0.0973)
Relative home value	1.4731***	0.3715*	-5.7233***	2.0260***	0.0915	-4.2754***	1.4608***	0.2888	-2.4663***
	(0.2625)	(0.1962)	(0.5069)	(0.2141)	(0.1650)	(0.3848)	(0.3066)	(0.2469)	(0.5846)
CBSA FE	191	191	191	123	123	123	48	48	48
Observations	1780	1877	1877	3038	3117	3117	4410	4516	4516
Within R2	0.2601	0.0213	0.4363	0.2382	0.0027	0.508	0.2369	0.2649	0.4637
Panel B: Log employment density									
Log Employment Density	0.1101***	-0.0392**	0.0403	0.0486**	-0.0163	0.1865***	0.0306	0.1860***	0.1929***
	(0.0296)	(0.0193)	(0.0358)	(0.0222)	(0.0207)	(0.0358)	(0.0445)	(0.0442)	(0.0637)
Beta (β^q)	0.2305	-0.0462	0.6744*	0.1752	0.0429	0.5830**	0.2588	0.6173***	1.4701***
	(0.1868)	(0.2688)	(0.3451)	(0.2249)	(0.0896)	(0.2442)	(0.2412)	(0.1682)	(0.2237)
Non-systematic risk (σ_{NS}^q)	0.6959***	-0.0503	0.1284	0.5737***	0.0526	0.8961***	0.5039***	0.4485***	1.2840***
	(0.0699)	(0.0759)	(0.1374)	(0.0955)	(0.0415)	(0.1176)	(0.1373)	(0.0773)	(0.1024)
Relative home value	1.5407***	0.3475*	-5.6788***	2.0088***	0.0915	-4.2754***	1.4512***	0.3615	-2.2815***
	(0.2703)	(0.1957)	(0.5074)	(0.2138)	(0.1652)	(0.3794)	(0.3093)	(0.2543)	(0.5861)
CBSA FE	191	191	191	123	123	123	48	48	48
Observations	1,780	1,877	1,877	3,038	3,117	3,117	4,410	4,516	4,516
Within R2	0.2638	0.0182	0.4368	0.2367	0.0028	0.511	0.2353	0.2204	0.4387

[a] Standard errors are in parentheses and are clustered at the CBSA. Significance is indicated as * p<0.1, ** p<0.05, *** p<0.01. Relative home value is measured as the ratio of zipcode level home value to average home value in a zipcodes's market at the final period of a sample (December 2010 or 2019). Measures of risk and return are based on price returns in columns 1,2, 4, 5, 7, and 8 ($q = P$) and total returns in columns 3, 6, and 9 ($q = Tot$). Home value, return and volatility measures were calculated using data provided by Zillow Group.

Appendix A: Zillow Home Value Index

This appendix provides additional detail on how the Zillow Home Value Index (ZHVI) is constructed. We also compare the Zillow index to the FHFA repeat sales index for similar locations. In all cases, Zillow data were provided by the Zillow Group.

The Zillow index is designed to measure the change in aggregate home values within a given location, holding constant the stock of homes between adjacent periods. The index is constructed from Zillow's estimates of individual home values. Zillow estimates home values, designed to capture fair market value, for over 110 million homes in the United States. While the specific process by which Zillow estimates these values is proprietary, we know that estimates are based on home attributes, comparable sales in the neighborhood, tax assessments, and on-market data when available such as listing price, description, and days on the market. Any noise in the estimates of individual home values is likely to average away in the aggregate.

Building on the estimate of individual home values, the index is calculated in three steps (Hryniw, 2019). First the appreciation rate between periods is calculated for each property. Let z_{ht} be Zillow's estimate of the price of home h in time *t*. Define $a_{h,t}$ to be the appreciation in z_h from one period prior:

$$a_{h,t} = \frac{z_{h,t} - z_{h,t-1}}{z_{h,t-1}} \tag{A.1}$$

Next, the home value appreciation, $A_{i,t}$, for location i in period t is calculated as the average of individual home price appreciation rates weighted by the value of each home.

$$A_{i,t} = \sum_{h \in i} w_{h,t} a_{h,t}, \text{ where } w_{h,t} = \frac{z_{h,t}}{\sum_{h \in i} z_{h,t}} \tag{A.2}$$

More valuable homes contribute more to the overall appreciation and represent a larger share of the market. When calculating appreciation from time *t* to *t+1* the basket of homes is kept constant to those available in time *t*. If a new home is constructed in time *t+1*, it will be included in the growth calculation from *t +1* to *t+2*.

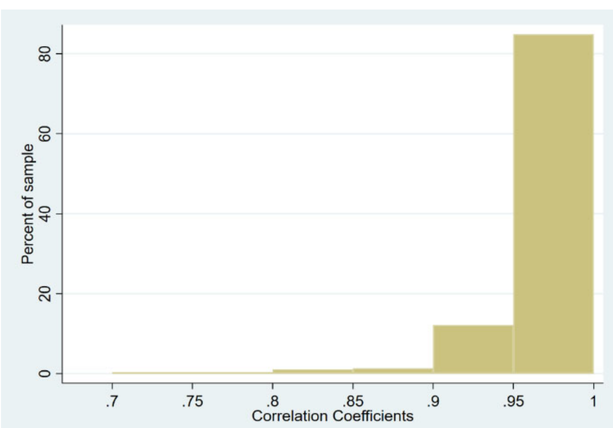
In the last step, the index is benchmarked to the mean home value at the final period for that location, $ZHVI_{T,i}$ (the mean value estimate for period T and location i),

$$ZHVI_{t-1,i} = \frac{ZHVI_{t,i}}{1+A_{t,i}}, \text{for } t = 0, T-1 \quad . \tag{A.3}$$

By anchoring the index to the mean home value in the final period, the ZHVI captures home price growth between periods while allowing for value comparisons across locations.

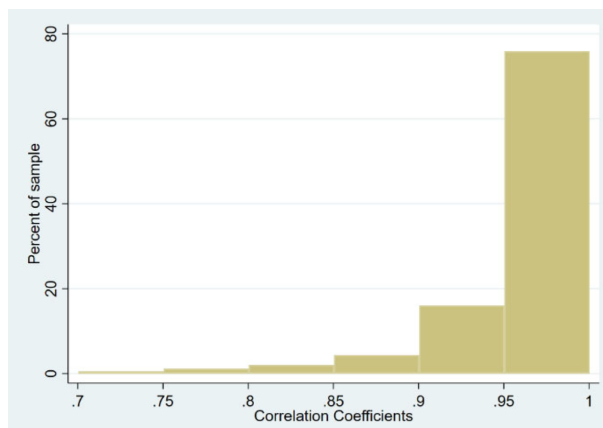
The single-family Zillow Home Value Index (ZHVI) is closely correlated with the single-family Federal Housing Finance Agency's (FHFA) repeat sales Home Price Index (HPI) at the CBSA and zipcode levels (including both sales and appraisals when constructing the FHFA index). Figures A-1 and A-2 display histograms of the correlation coefficients that summarize correlation between the FHFA and Zillow indexes for each CBSA (Figure A-1) and zipcode (Figure A-2). As is evident, the degree of correlation is quite high for both levels of geography and exceeds 90% for most CBSAs and zipcodes.

Figure A-1: Histogram of Correlation Coefficients for the CBSA Level Zillow and FHFA SF Home Price Indices[a]



[a] The bin-width is set to 0.05. For 95% of CBSAs the correlation between the Zillow and FHFA single-family home price indices is above 0.90.

Figure A-2: Histogram of Correlation Coefficients for the Zipcode Level Zillow and FHFA SF Home Price Indices[a]



[a] The bin-width is set to 0.05. For 91% of zipcodes the correlation between the Zillow and FHFA single-family home price indices is above 0.9. The 95 zipcodes with correlation coefficients below .7 have been omitted from this figure for visual clarity. They make up 1.5% of the comparable sample.

Appendix B: Supplemental Tables[a]

Table B-1: Summary Statistics for Average Housing Price Returns, Total Returns and Rent-to-Price Ratio

Panel A: CBSA Level

	Price Returns 1997-2019	Price Returns 1997-2010	Price Returns 2011-2019	Rent-Price Ratio 2011-2019	Total Returns 2011-2019
Mean	3.144	2.535	3.748	9.192	13.094
Standard Dev	1.395	2.074	2.288	1.886	2.491
75^{th} Percentile	3.993	3.767	5.125	10.278	14.497
25^{th} Percentile	2.230	1.601	2.185	7.856	11.383
Observations	362	355	362	309	309

Panel B: Zipcode Level

	Price Returns 1997-2019	Price Returns 1997-2010	Price Returns 2011-2019	Rent-Price Ratio 2011-2019	Total Returns 2011-2019
Mean	3.375	2.518	4.082	9.572	13.915
Standard Dev	2.019	2.929	3.000	4.229	5.060
75^{th} Percentile	4.388	4.254	5.761	10.594	15.699
25^{th} Percentile	2.250	1.377	2.071	7.306	10.802
Observations	11,644	11,101	11,644	9,510	9,510

[a] Data were provided by the Zillow Group.

Table B-2: CBSA Level Summary Statistics for Alternate Measures of Housing Risk[a]

Panel A: 1997-2019

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	5.474	0.981	0.000	0.000	-	-	-	-
Standard Dev	3.001	0.817	1.253	15.692	-	-	-	-
75th Percentile	6.854	1.300	0.595	5.294	-	-	-	-
25th Percentile	3.276	0.437	-0.620	-10.697	-	-	-	-
Observations	362	362	362	362	-	-	-	-

Panel B: 1997-2010

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	6.050	0.960	0.000	0.000	-	-	-	-
Standard Dev	3.646	0.880	1.333	16.601	-	-	-	-
75th Percentile	7.819	1.406	0.632	5.859	-	-	-	-
25th Percentile	3.439	0.350	-0.685	-11.308	-	-	-	-
Observations	355	355	355	355	-	-	-	-

Panel C: 2011-2019

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	3.565	0.998	0.000	0.000	3.662	0.981	0.000	0.000
Standard Dev	1.767	0.808	0.995	12.345	1.886	0.740	0.970	12.151
75th Percentile	4.589	1.364	0.344	0.809	4.643	1.303	0.479	1.0400
25th Percentile	2.298	0.456	-0.612	-6.619	2.290	0.448	-0.617	-6.547
Observations	362	362	362	362	309	309	309	309

[a] Data were provided by the Zillow Group.

Table B-3: Zipcode Level Summary Statistics for Alternate Measures of Housing Risk[a]

Panel A: 1997-2019

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	6.502	1.003	0.000	0.000	-	-	-	-
Standard Dev	2.902	0.569	2.864	19.657	-	-	-	-
75th Percentile	8.134	1.125	1.607	3.543	-	-	-	-
25th Percentile	4.221	0.851	-2.253	-11.767	-	-	-	-
Observations	11,644	11,644	11,644	11,644	-	-	-	-

Panel B: 1997-2010

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	6.940	0.995	0.000	0.000	-	-	-	-
Standard Dev	3.477	0.540	3.417	17.350	-	-	-	-
75th Percentile	8.884	1.143	1.898	3.231	-	-	-	-
25th Percentile	4.194	0.838	-2.699	-10.217	-	-	-	-
Observations	11,097	11,097	11,097	11,097	-	-	-	-

Panel C: 2011-2019

	Based on Price Returns				Based on Total Returns			
	Return Volatility (σ_r^P)	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Idio Risk (σ_{ID}^P)	Return Volatility (σ_r^{Tot})	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})	Idio Risk (σ_{ID}^{Tot})
Mean	4.573	1.004	0.000	0.000	4.830	0.999	0.000	0.000
Standard Dev	2.200	0.671	2.078	17.014	2.400	0.589	2.235	19.279
75th Percentile	5.763	1.202	1.035	0.387	6.102	1.175	1.095	-0.509
25th Percentile	2.950	0.748	-1.464	-8.413	3.076	0.757	-1.540	-8.403
Observations	11,644	11,644	11,644	11,644	9,510	9,510	9,510	9,510

[a] Data were provided by the Zillow Group.

Table B-4: Zipcode Level Summary Statistics Stratified by CBSA Population[a]

Panel A: Large CBSAs

	Price Returns: 1997-2011			Price Returns: 1997-2010			Price Returns: 2011-2019			Total Returns: 2011-2019		
	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})
Mean	4.127	0.996	0.977	3.201	0.993	0.998	5.150	1.000	0.615	14.606	0.996	0.631
Standard Dev	2.098	0.649	2.977	2.888	0.495	3.550	3.282	0.740	2.259	5.808	0.649	2.355
Interquartile Range	2.412	0.269	4.151	3.154	0.272	5.126	4.498	0.449	2.888	5.665	0.431	2.903
Observations	4,966	4,966	4,966	4,825	4,824	4,824	4,966	4,966	4,966	4,516	4,516	4,516

Panel B: Medium CBSAs

	Price Returns: 1997-2011			Price Returns: 1997-2010			Price Returns: 2011-2019			Total Returns: 2011-2019		
	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})
Mean	2.866	1.006	-0.479	2.125	0.988	-0.460	3.400	1.005	-0.323	13.388	0.994	-0.371
Standard Dev	1.731	0.525	2.767	2.686	0.534	3.235	2.696	0.646	1.883	4.455	0.538	2.044
Interquartile Range	1.697	0.269	3.271	2.269	0.310	3.806	2.963	0.453	2.009	4.205	0.412	2.043
Observations	3,726	3,726	3,726	3,566	3,564	3,564	3,726	3,726	3,726	3,117	3,117	3,117

Panel C: Small CBSAs

	Price Returns: 1997-2011			Price Returns: 1997-2010			Price Returns: 2011-2019			Total Returns: 2011-2019		
	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^P)	Non-sys Risk (σ_{NS}^P)	Price Returns	Beta (β^{Tot})	Non-sys Risk (σ_{NS}^{Tot})
Mean	2.752	1.013	-1.040	1.819	1.008	-1.172	3.146	1.008	-0.628	13.129	1.012	-0.903
Standard Dev	1.798	0.472	2.193	3.045	0.620	2.862	2.197	0.572	1.676	3.664	0.513	1.740
Interquartile Range	2.117	0.295	2.906	3.506	0.369	3.592	2.564	0.456	2.278	3.987	0.408	2.408
Observations	2,952	2,952	2,952	2,710	2,709	2,709	2,952	2,952	2,952	1,877	1,877	1,877

[a] Data were provided by the Zillow Group.

Table B-5: Correlation Between Alternate Measures of Risk for Beta ($\boldsymbol{\beta^q}$), Non-Systematic Risk ($\boldsymbol{\sigma^q_{NS}}$) and Idiosyncratic Risk ($\boldsymbol{\sigma^q_{ID}}$)[a]

Panel A: CBSA Level

	Price Returns 1997-2019	Price Returns 1997-2010	Price Returns 2011-2019	Total Returns 2011-2019
Correlations between:	(1)	(2)	(3)	(4)
β^q *and* σ^q_{NS}	0.000	0.000	0.000	0.000
β^q *and* σ^q_{ID}	0.611	0.532	0.505	0.472
σ^q_{NS} *and* σ^q_{ID}	0.473	0.562	0.674	0.698

Panel B: Zipcode Level

	Price Returns 1997-2019	Price Returns 1997-2010	Price Returns 2011-2019	Total Returns 2011-2019
Correlations between:	(1)	(2)	(3)	(4)
β^q *and* σ^q_{NS}	0.000	0.000	0.000	0.000
β^q *and* σ^q_{ID}	0.0124	0.0380	0.0812	0.0780
σ^q_{NS} *and* σ^q_{ID}	0.309	0.236	0.590	0.576

[a] Data and samples used in each column are as in the earlier tables for the specified periods. In columns 1-3 measure or return and risk are based on price returns ($q = P$), in column 4 they are based on total returns ($q = Tot$). Data were provided by the Zillow Group.

Table B-6: Zipcode level returns with non-systematic risk versus idiosyncratic risk[a]

	Price Returns 1997-2010		Price Returns 2011-2019		Total Returns 2011-2019	
Panel A: Above 1 Million	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β^q)	0.3785*	0.4363***	0.5568***	0.4721**	1.4701***	1.0578***
	(0.2093)	(0.1538)	(0.1518)	(0.1774)	(0.2237)	(0.2694)
Non-systematic risk (σ_{NS}^q)	0.4661***	-	0.3890***	-	1.2840***	-
	(0.1366)	-	(0.0697)	-	(0.1024)	-
Idiosyncratic risk (σ_{ID}^q)	-	-0.0049	-	0.0200***	-	1.0578***
	-	(0.0045)	-	(0.0050)	-	(0.2694)
CBSA FE	48	48	48	48	48	48
Observations	4,824	4,824	4,966	4,966	4,516	4,516
Within R2	0.1781	0.0582	0.1794	0.118	0.4387	0.4295
Panel B: 250,000 to 1 Million	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β^q)	0.2376	0.2638	0.0335	0.0369	0.5830**	0.3739
	(0.1810)	(0.1950)	(0.1305)	(0.1318)	(0.2442)	(0.2334)
Non-systematic risk (σ_{NS}^q)	0.5216***	-	0.0215	-	0.8961***	-
	(0.0814)	-	(0.0399)	-	(0.1176)	-
Idiosyncratic risk (σ_{ID}^q)	-	0.0005	-	-0.0034	-	0.0738***
	-	(0.0033)	-	(0.0036)	-	(0.0081)
CBSA FE	123	123	123	123	123	123
Observations	3,564	3,564	3,726	3,726	3,117	3,117
Within R2	0.1934	0.0761	0.0019	0.0027	0.511	0.5207
Panel A: 100,000 < 250,000	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β^q)	0.1717	-0.0039	-0.0067	0.0115	0.6744*	0.6312*
	(0.1392)	(0.1486)	(0.1416)	(0.1407)	(0.3451)	(0.3675)
Non-systematic risk (σ_{NS}^q)	0.6012***	-	-0.1022**	-	0.1284	-
	(0.0613)	-	(0.0454)	-	(0.1374)	-
Idiosyncratic risk (σ_{ID}^q)	-	0.0115***	-	-0.0093***	-	0.0107
	-	(0.0043)	-	(0.0036)	-	(0.0094)
CBSA FE	191	191	191	191	191	191
Observations	2,709	2,709	2,952	2,952	1,877	1,877
Within R2	0.202	0.0339	0.0258	0.0263	0.4368	0.4365

[a] Standard errors are in parentheses. Significance is denoted as: * p<0.1, ** p<0.05, *** p<0.01. All models include controls for zipcode log employment density and relative home value as in Panel B of Table 9; coefficients on those measures are not reported. Data were provided by the Zillow Group.