Risk-Return Trade-Offs in Real Estate Markets Within and Across Cities

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Abstract

We show that risk-return tradeoffs contribute to spatial variation in residential housing returns across cities and within larger metropolitan areas. For both levels of geography, this occurs because volatility varies with local supply elasticity and propensity for demand shocks. Broader market systematic risk and locally based idiosyncratic risk both contribute to risk-return tradeoffs. At the CBSA level, magnitudes of effects are similar for the two types of risk but within urban areas neighborhood-level risk is more important and contributes to higher equilibrium returns in city centers and in densely developed portions of the city. Our findings indicate that spatial differences in return to residential real estate can persist in equilibrium, complementing persistent spatial variation in price levels.

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1. Introduction

It is well-known that cities can exhibit different rates of house price appreciation over extended periods of time. An example is evident in Figure 1, which plots nominal quality-adjusted home price indexes for San Diego, Milwaukee and Cleveland from 1997 to 2019. Home prices increase at an average annual rate of 5.88 percent in San Diego and just 1.53 percent per year in Cleveland, indicative of the spread between the 20 lowest and highest appreciating cities highlighted in Table 1.[1] Durable, inelastic housing supply in shrinking cities is one reason for these differences, as with Cleveland where declining demand creates downward pressure on price (e.g. Glaeser and Gyourko (2005) and Glaeser, Gyourko, and Saks (2006)). Zoning and other supply constraints that restrict expansion of the housing stock in growing, high-amenity "superstar" cities like San Diego is another, where rising demand creates upward pressure on price (e.g. Gyourko, Mayer and Sinai (2013).

Figure 2 highlights a pattern that is much less well-known. Within cities, systematic spatial variation in house price appreciation is also common. For cities with more than 500,000 people, home price appreciation declines monotonically with distance from the center (Panel A) and, more generally, rises with employment density (Panel B). Cities with 250,000 to 500,000 residents display a similar but more muted pattern, while smaller urban areas (those with fewer than 250,000 people), exhibit little tendency for spatial differences in returns across communities.[2] At first glance, these patterns are surprising. One reason is that within growing cities, profit-seeking developers will tend to direct investment to higher yielding neighborhoods. Resulting supply adjustments should then create pressure for stable relative prices and similar rates of appreciation across communities (e.g. Liu, Nowak and Rosenthal, 2016). Another reason is that demand-side substitution across neighborhoods should also

[1] Twelve-month average price returns in Table 1 range from a low of 1.27% in Youngstown, OH to a high of 7.23% in San Jose, CA. Across all CBSAs in our sample, 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). At the zipcode level, highlighted shortly, the corresponding values are 3.4% and 2.0 percentage points (Appendix B, Table B-1 Panel B).

[2] Estimates in Figure 2 are based on CBSAs in the United States with population over 100,000 and using monthly zipcode-level home price indexes from Zillow Inc. for 1996-2019. The sample is further restricted to zipcodes with employment density greater than 20 workers per square mile and situated within 12 miles of the city center.

create pressure for stable relative prices, as with choice between gentrifying inner-city communities and more outlying locations (e.g. Couture and Handbury, 2020).

This paper emphasizes a different mechanism. We show that risk-return tradeoffs contribute to spatial patterns of home price appreciation both across- and within cities. For both levels of geography, market volatility is modelled as arising from the interaction between the local elasticity of supply and propensity for demand shocks.[3] Framed in this manner, our focus on spatial patterns of housing returns is different from the vast literature that has modelled spatial patterns of home price levels (see reviews in Brueckner (1987) and Duranton and Puga (2015) for within-city patterns and Chen and Rosenthal (2008) for across cities for examples). Our emphasis on risk also differs from prior studies that have confirmed the presence of risk-return tradeoffs in housing markets but without considering spatial patterns. This includes Crone and Voith (1999), Cannon, Miller, and Pandher (2006), and Case, Cotter and Gabriel (2011), all of whom focus on price returns (housing price capital gains). Our paper is also related to a recent set of studies that have emphasized that total returns to housing investment include rent (dividend) payments in addition to price returns (e.g. Jorda et al, 2019; Amaral et al, 2021, Eichholtz et al, 2021; Chambers et al, 2021; Sagi, 2021; Giacoletti, 2021; Gupta et al, 2022).[4]

In the discussion that follows, we consider both price and total returns, in part because they are relevant for different types of behavior. Home price appreciation, for example, affects homeowner net equity and related potential for homeowners to refinance or default on their mortgages. Total returns, in contrast, are preferred when comparing the overall return on housing investment to other assets like stocks and bonds.[5] We also recognize that challenging measurement issues arise when forming estimates

[3] A number of prior studies have demonstrated that differences in zoning restrictions and topographic constraints contribute to differences in the elasticity of housing supply and related volatility in local housing markets. See for example, Glaeser and Gyourko (2005), Glaeser, Gyourko and Saiz (2008), Saiz (2008), Paciorek (2013), Gyourko and Molloy (2015).
[4] Still other studies that focus on the nature of underlying risk as with Sinai and Souleles (2005), Davidoff (2006), Han (2013), Sagi (2021), Giacoletti (2021).
[5] Price 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).

of total returns. Rent, for example, 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. Tax treatment also differs for the rental flow from owner-occupied housing versus rental units (e.g. Glaeser and Gyourko (2010), Han (2013), and many others). These differences introduce error when measuring total returns that we are unable to address directly. This said, an approximation argument in Han (2013), related analysis in Demers and Eisfeldt (2022), and user cost theory discussed in this paper, all suggest that evidence of risk-return tradeoffs is likely to be similar regardless of whether price or total returns are used. Results presented later support that prior.

To establish our results, we utilize monthly home price and rent indexes from Zillow Inc. from 1997 through 2019. Separate indexes are available at the city and zipcode levels and for each location are based on all single-family homes in a geographic market, including owner-occupied and rental. However, whereas the price series are available throughout the 1997-2019 period, the rent series are available only from 2011 to 2019. Partly for this reason, we focus just on the 2011-2019 period when analyzing risk-return tradeoffs. That allows us to compare patterns for price and total returns for a common period. Also, we seek to confirm that *expectations* of market volatility affect returns.[6] To that end, we use lagged measures of market volatility estimated over the 1997-2010 period to explain returns over the 2011-2019 period. In taking this approach, our identifying assumption is that investor expectations of local market risk are positively related to lagged volatility, and that lagged volatility only influences current period returns through effects on current perceptions of risk.

[6] We note here that measurement issues are challenging when forming estimates of total returns. 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. For these and reasons noted earlier (price and total returns address different questions and homeowner behavior), we consider both measures of returns for much of the analysis that follows. This said, 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.

Allowing for the sample design just noted, we begin by documenting that risk-return tradeoffs are present across and within cities. We do this in two ways. First, we regress local average annual housing return over the 2011-2019 period on lagged volatility from 1997-2010 as described above. We then decompose the volatility measure into a proxy for the long-run local supply elasticity and a measure of the propensity for local demand shocks. At the CBSA level, we proxy for the supply elasticity using the Wharton Land Use Regulatory Index (WLURI) developed by Gyourko, Saiz and Summers (2007) and updated in Gyourko, Hartley, and Krimmel (2021).[7] At the zipcode level, we use a zipcode-level measure of the elasticity of supply from Baum-Snow and Han (2024) motivated by the idea that prior development makes new development more difficult (see also Fisher et al, 2022). Subsequent analysis is then designed to confirm that interaction between local supply elasticity and demand shocks is central to risk-return tradeoffs.

We next seek to clarify the nature of risk that drives risk-return tradeoffs. For this part of the analysis, we start by estimating location-specific CAPM models modified to allow for previously documented features of the housing market. Each CAPM regression yields an estimate of beta specific to a given location (CBSA or zipcode). As in the CAPM literature, beta reflects *systematic* risk, the risk associated with returns to a given asset relative to returns to a broader market portfolio of assets. Most applications of CAPM models measure market returns using a broad financial index comprised of many individual assets (e.g. the S&P 500). That approach was also used by 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. We treat the set of CBSAs in the United States as the broader housing

[7] 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/ .

market when we estimate CBSA-level betas, and the CBSA as the broader housing market when we estimate within-CBSA zipcode-level betas.[8]

We measure submarket level risk using two approaches. In the first, we create a term that we refer to as non-systematic risk. This measure is obtained by regressing location-specific volatility of year-over-year returns on a constant and the beta for each 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 a second approach, we follow the finance literature and measure submarket risk as the standard deviation of the squared residuals from the location-specific CAPM regressions. Previous applications of CAPM models 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. Results are nevertheless similar when we use idiosyncratic risk.[9]

Patterns in our data support several conclusions. First, risk-return tradeoffs contribute to differences in housing returns across CBSAs and also across neighborhoods within larger CBSAs. Second, inelastic supply is not sufficient by itself to create price volatility and related exposure to risk. Instead, volatility is amplified by a combination of local demand shocks in conjunction with inelastic supply. Third, at the CBSA level, systematic risk associated with broader shocks to the national housing market are important as are CBSA-specific sources of risk. In contrast, within larger urban areas, neighborhood-level sources of risk are the primary driver of within-city risk-return tradeoffs. Moreover, and fourth, within larger urban areas volatility is positively correlated with density which causes housing returns to decline with distance from the downtown and to be lower in less densely developed

[8] In both cases, we restrict the set of CBSAs in our analysis to those with population over 100,000 in year 2000.
[9] 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.

communities. Fifth, the magnitude of risk-return tradeoffs is large enough to be important at both levels of geography, and last the patterns above mostly all hold for both housing price and total returns.

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 compares distributions of risk and return for CBSA and zipcode levels of geography. Section 4 estimates risk-return tradeoffs across CBSAs while Section 5 repeats the analysis for within-CBSA patterns. Magnitudes of estimated effects for both levels of geography are discussed in Section 6, and Section 7 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, 2022; 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:

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

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,

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

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,

$$R_t \approx [r + (d + m) + p_{tax} - g_t^a] * P_{t-1} + \tau R_t \tag{2.3}$$

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

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.[10]

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:

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

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

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, $\rho_{M,t}^{q}$.[11] 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.[12] The estimating equation is then of the following general form,

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

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 submarket risk, measured as either non-systematic risk or idiosyncratic risk as described in the Introduction. The term x_i includes non-risk based drivers of average return that are discussed in later in the paper.

[11] 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.

[12] 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).

Our ability to identify causal risk-return patterns is based on three modeling assumptions, the first of which is most important. We seek to confirm that *anticipated* volatility drives risk-return tradeoffs. Patterns documented later confirm that at both the CBSA and neighborhood levels, volatility in home prices over the 1997-2010 period is strongly and positively correlated with volatility over the 2011-2019 period. For that reason, in most of the analysis to follow we estimate risk-return tradeoffs over the 2011-2019 period using lagged volatility based on the 1997-2010 period to proxy perceptions of risk.[13] The identifying assumption is that lagged volatility is exogenous and a good indicator of anticipated risk.

A second feature of our modeling approach that helps with identification is that (2.9) is specified in terms of sample horizon average values which smooths away year-to-year short run dynamics (e.g. Danielsson et al, 2013; Glaeser and Nathanson, 2015; DeFusca et al, 2018). This mitigates concerns that investor expectations of future increases or decreases in returns might trigger self-reinforcing short-run movements in asset price that could amplify near-term volatility. This would be the case if self-reinforcing patterns cause price levels to temporarily deviate from sustainable levels, as an example.

Third, when we decompose $\sigma(\rho_{i,t}^{q})$ into β_i and submarket 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 $\bar{\rho}_i^q - \bar{\rho}_f - \beta_i(\bar{\rho}_M^q - \bar{\rho}_f)$). For that reason, 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

[13] A simpler setting would be one for which the variance of return on asset *i* over time is simply exogenous to the average year-over-year return to asset *i* (e.g. $\sigma(\rho_{i,t}^{q})$ is exogenous to $\bar{\rho}_i^q$). That would not, however, allow for the possibility that common unobserved contemporaneous factors could be driving both returns and volatility. Using lagged volatility helps to mitigate that concern and is consistent with many asset pricing models that treat volatility as forecastable.

that a lagged value of $\sigma(\rho_{i,t}^{q})$ is exogenous, $Cov(\tilde{\rho}_i^q, \tilde{\rho}_M^q)$ and $\tilde{\sigma}_M^2$ will be as well.[14]

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.[15] 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 the 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

[14] 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.

[15] 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 .

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.

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.

In some of our models, we also include measures of local housing supply elasticity. For the CBSA-level analysis, we use 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 and increases with the intensity of regulatory restrictions. A larger (more positive) value for this measure indicates that development opportunities are more constrained so that a higher index value implies a lower housing supply elasticity. 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.[16]

For the within-CBSA analysis we use a census tract-level measure of housing supply elasticity developed by Baum-Snow and Han (2024). Baum-Snow and Han experiment with several different measures of neighborhood-level supply elasticity. We use their preferred measure which utilizes distance to the city center and extent of nearby developable land as instruments in an estimation routine designed to measure tract-level supply elasticity. We then aggregate their census tract level measure of elasticity to the zipcode level using an interpolation procedure based on the degree of overlap between census tracts and zipcodes.[17]

A final comment is related to sample composition. 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.[18]

3.2 Risk and return distributions for CBSA and zipcode level measures

This section compares distributions of risk and return measured at the CBSA and zipcode levels pooling locations throughout the sample. Related summary measures that highlight intra- and inter-CBSA patterns are provided in later sections.

We begin with Figure 3 which plots the distributions for the volatility of price returns (Panel A), estimates of beta (Panel B), and estimates of non-systematic risk (Panel C). As is evident in Panel A, the

[16] 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.
[17] We note that because the Baum-Snow and Han measure of local supply elasticity is based in part on distance to the downtown, any further independent effect of distance to the city center (or employment density in other models) in our within-city regressions to follow will tend to capture unobserved location-specific amenities separate from local supply elasticity. We return to this point later in the paper.
[18] To ensure consistency across models, we use the same set of zipcodes when we replace distance to the CBD with zipcode employment density.

distributions of price return volatility across locations has a similar single-peaked shape for the CBSA and zipcode level measures with a well-defined mode and elongated right tails. Also evident is that CBSA-level variation is more limited with a greater share of values concentrated around the mode. In Panel B the reverse is true with a sharply concentrated distribution of beta values close to 1. At the CBSA level, the corresponding distribution is more skewed with the mode clearly less than 1 and once again an elongated right tail. This pattern is suggestive that systematic risk could play a greater role in driving risk-return tradeoffs at the CBSA level as compared to within cities, a point we return to later. The reverse pattern is present in Panel C for non-systematic risk. In this instance non-systematic risk is tightly concentrated around zero for the CBSA-level measures while exhibiting an elongated right tail at the zipcode level; this suggests that non-systematic risk may be an important driver of risk-return tradeoffs within cities.

Figure 4 highlights a different pattern. Recall from Section 2 that price returns, ρ_t^P, should be inversely related to rent R_t since housing 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 less variation in comparison to ρ_t^P. Patterns in Figure 4 support this prior at both the CBSA level (Panel A) and zipcode level (Panel B). In both instances, it is evident that the variance of the rent-to-price distribution is much smaller relative to the distribution of price and total returns. This is consistent with the approximation argument developed by Han (2013) and evidence in Demers and Eisfeldt (2022).

4. Across CBSA risk-return tradeoffs

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 Summary measures

Table 2 reports the 20 CBSAs with the lowest and highest levels of risk as measured by the volatility of price returns. For each CBSA, values are reported for return volatility (σ^P), beta (β^P), non-systematic risk (σ_{NS}^{p}) and year-2000 CBSA population, all rank-ordered by return volatility. Notice that low-risk CBSAs are mostly smaller metropolitan areas with fewer than one million people, as with Wichita and Syracuse, or larger rust-belt metropolitan areas that have lost population, as with Pittsburgh, Buffalo and Rochester. High-volatility CBSAs, in contrast, are larger with populations often well over one million. Many of these cities are also perceived as high-amenity areas and are disproportionately located in California, Arizona and Florida. Detroit is the primary exception as the most prominent among rust-belt urban areas that have lost population since 1950.

Table 3 reports correlations for CBSA-level risk and return measures that are used in the regressions that follow. These include average year-over-year price ($\bar{\rho}^{P}_{2011-19}$) and total ($\bar{\rho}^{Tot}_{2011-19}$) returns, both measured using 2011-2019 data. Also included in the table are the Wharton Land Use Regulatory Index (WLURI), price return volatility measures for the early ($\sigma^{P}_{1997-10}$) and late ($\sigma^{P}_{2011-19}$) periods. Included as well are beta ($\beta^{P}_{1997-10}$), non-systematic ($\sigma^{P}_{NS,1997-10}$) and idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$) based on 1997-2010 data. Both here and in the regressions that follow, as discussed earlier, non-systematic risk is measured as the residual from a cross-sectional regression of log($\sigma^{P}_{1997-10}$) on a constant and $\beta^{P}_{1997-10}$. Idiosyncratic risk is measured as in the broader finance literature as the standard deviation of the residual from the CAPM regression that produces beta for a given location.

Patterns confirm strong correlations between returns, supply restrictions, and the different measures of risk. Note first that correlation between $\sigma^{P}_{1997-10}$ and $\sigma^{P}_{2011-19}$ is 72.4%. The strong correlation supports our identifying assumption in the regressions that follow that lagged price volatility is a good proxy for anticipated volatility. Correlation between lagged volatility $\sigma^{P}_{1997-10}$ and the WLURI index is 30%, affirming prior that supply restrictions are associated with greater price volatility although we note that this does not appear to carry over to total returns, for which the corresponding correlation is close to zero. A more consistent pattern is present for correlation between $\sigma^P_{1997-10}$ and 2011-2019 price and total returns for which the correlations are 59.4% and 30.6%, respectively, suggesting the presence of risk-return tradeoffs. Correlation between 2011-2019 price returns with lagged measures of beta, non-systematic and idiosyncratic risk are 53.6%, 27.6%, and 56.0%, respectively, suggestive that each of these sources of risk may contribute to risk-return tradeoffs. Corresponding correlations with total returns are smaller and especially so for non-systematic risk at just 9.6%. A final pattern to note is that beta and idiosyncratic risk are highly correlated (53.2%) while beta is by construction uncorrelated with non-systematic risk.[19]

4.2 Risk-return tradeoffs

Table 4 presents estimates of the risk-return model with progressively more complete specifications moving from left to right across columns. All regressions are based on price returns from 2011 to 2019 using lagged measures of volatility and risk based on the 1997-2010 period.

Column 1 controls only for return volatility which has a positive and highly significant coefficient. This one control also yields an R-square value of 35.2%. Absent confounding effects, this suggests that risk-return tradeoffs may help to explain variation in price returns across cities.

Columns 2-4 address a different question. In these columns we decompose volatility into proxies for location-specific supply elasticity and propensity for demand shocks. In column 2 we replace volatility with the Wharton land use regulatory index (WLURI). A larger value for WLURI indicates more restrictive local regulations that restrict development opportunities and implies a lower long run housing supply elasticity. The coefficient on WLURI is positive and highly significant as would be expected. This control, however, only explains 3.8% of variability in price returns across CBSAs based on the R-square value.

[19] Some of the locations for which beta was estimated are not included in some of the regressions that follow and were dropped from Table 3. It is for that reason that correlation between beta and non-systematic risk is not exactly equal to zero and instead reported for this part of the sample as 2.4%.

Column 3 adds in the propensity for a location to experience demand shocks over the 1997-2010 period, denoted in the table as D. As discussed earlier, D is obtained as the exponentiated residual from a regression of $\log(\sigma^{P}_{1997-10})$ on WLURI and a constant. Adding D to the model has little effect on the WLURI coefficient. Observe, however, that the coefficient on D is positive, highly significant, and the R-square increases to 32.2%. Column 4 next adds in the interaction between WLURI and D to the model. With this addition, the coefficient on WLURI becomes small, opposite in sign, and is no longer significant. The coefficient on D is mostly unaffected, and the interaction term is positive and highly significant while the R-square value increases to 35.6%, about the same as in column 1 as would be expected given the nature of the decomposition of volatility in the model.

The pattern in column 4 confirms that in the absence of demand shocks – with D equal to zero – inelastic supply is not sufficient to prompt volatility and related risk-return tradeoffs. Instead, it is the combination of inelastic supply coupled with propensity for demand shocks that contributes to volatility and associated potential for risk-return tradeoffs.

Columns 5 and 6 check for robustness and alternative drivers of risk and return. In column 5 we replace the prior measure of volatility with a set of controls that describe the socioeconomic attributes of a CBSA. This includes log population in the CBSA, median income, a measure of population growth if the city grew between 1990 and 2000, and a separate measure of the absolute value of population loss if the CBSA shrank during that period. Also included is a 1-0 dummy variable for whether the CBSA was classified as a superstar city by Gyourko et al (2013).

Among the demand-side controls in column 4, there is evidence that larger and growing cities exhibit higher price returns but overall these controls do not appear to have the same explanatory power as the volatility and risk-related measures. Notice that R-square is just 25.2%. This is also apparent in column 6 which combines the models from columns 5 and 6.

In column 6, notice that the coefficients on all of the socioeconomic controls and superstar status diminish in magnitude. In contrast, the coefficient on D declines by only a modest amount and the coefficients on WLURI and its interaction with D are unaffected. Also, the model R-square increases to

44.6%. Overall, the evidence in Table 4 confirms that risk-return tradeoffs contribute to differences in price returns across CBSAs, and that returns increase with the propensity for demand shocks in conjunction with regulatory restrictions that limit development opportunities. A city's sociodemographic attributes and amenity-related features also contribute to variation in price returns across cities, but to a lesser extent.

Table 4b addresses the nature of risk. All of the models displayed in the table control for the same set of sociodemographic and superstar measures as in Table 4a but those controls are not tabled out to simplify presentation. Panel A of Table 4b focuses on price returns ($\bar{\rho}^{P}_{2011-19}$) while Panel B uses total returns ($\bar{\rho}^{Tot}_{2011-19}$) as the dependent variable, all measured once again at the CBSA level. Column 1 proxies for risk using volatility ($\sigma^{P}_{1997-10}$) while other adjacent columns replace that measure with beta, non-systematic and idiosyncratic risk in different combinations.

Several general patterns are present. First, evidence of risk-return tradeoffs is present once again, including for both price and total returns. Second, systematic risk appears to be an important driver of that risk at the CBSA level. Non-systematic risk has little influence on cross-CBSA variation in housing returns but idiosyncratic risk does further contribute to risk-return tradeoffs beyond that of systematic risk captured by Beta.

These patterns just noted can be seen by comparing estimates across columns 1 to 6 and also for both panels. Notice, for example, that in column 1, volatility has a strong positive effect on returns. Replacing volatility with Beta in column 2, we see that systematic risk has a positive, highly significant effect on returns. That is not the case for non-systematic risk in column 3, however, where we replace Beta with $\sigma^{P}_{NS,1997-10}$. If instead we include idiosyncratic risk as in column 4, that measure is positive and highly significant and these patterns repead in columns 5 and 6 which combine beta first with non-systematic risk (column 5) and then with idiosyncratic risk (column 6).

5. Within CBSA risk-return tradeoffs

This section examines within-CBSA patterns of risk and return using zipcode-level data as the primary geographic unit. The structure of this section mirrors the across-CBSA level analysis with adjustments for the nature of the neighborhood-level data.

5.1 Summary measures

Table 5 reports correlations for within-CBSA level risk and return measures pooling data across all of the zipcodes in our sample. Variables included in the table are the same as for Table 3 (for the CBSA-level patterns) with the exception that the WLURI index is replaced by three measures that are associated with neighborhood-level housing supply restrictions. These include distance to the CBD (in miles), log of zipcode-level employment density, and the zipcode-level measure of housing supply elasticity based on the Baum-Snow and Han measure discussed earlier. For the latter, recall that a more positive value for the supply elasticity indicates more elastic supply and is likely associated with lesser constraints on local development.

Echoing patterns at the CBSA level, values in Table 5 indicate strong correlations between housing returns, supply restrictions, and the different measures of risk. There are also some notable differences from the CBSA-level correlations.

Observe first that correlation between $\sigma^P_{1997-10}$ and $\sigma^P_{2011-19}$ is 55.4%, supporting once again our primary identifying assumption that price volatility from the 1997-2010 period is a good proxy for anticipated volatility during the 2011-2019 period. Correlation between price returns $\bar{\rho}^P_{2011-19}$ and lagged volatility $\sigma^P_{1997-10}$, miles to the CBD, log employment density and supply elasticity are 50.4%, -7.5%, 27.1%, and -31.9%, respectively. These patterns are as anticipated and echo patterns at the CBSA level. They suggest higher returns when volatility and related risk is high, for locations closer to the city center, and in densely developed locations. More generally the correlations also indicate that locations with low (more restrictive) supply elasticities exhibit higher returns. These patterns are also present for total returns.

Correlation between 2011-2019 price returns with lagged measures of beta, non-systematic and idiosyncratic risk are 4.6%, 50.5%, and 2.1%, respectively. These patterns are different from the cross-CBSA patterns considered earlier. They suggest that systematic and idiosyncratic risk are likely only weak drivers of within-city risk-return tradeoffs, but that non-systematic risk may be an important determinant of spatial variation in price returns within individual cities. However, when considering total returns for the 2011-2019 period, correlations suggest that all three measures of risk could be relevant. In this instance, the correlations are 13.1%, 20.6% and 15.1% for beta, non-systematic and idiosyncratic risk, respectively. Also different from the CBSA level patterns, correlation between beta and idiosyncratic risk is just 22.9%, down from 53.2% in Table 3. We return to these comparisons when discussing the regression results that follow.[20]

5.2 Within-city spatial patterns of price returns and risk

Table 6 revisits within-city spatial patterns of price returns highlighted in Figure 2. The table presents estimates from linear regressions of price returns over the full 1997-2019 period pooling data across all zipcodes. Panel A reports estimates of price returns on miles to the CBD while Panel B reports estimates based on a zipcode's log employment density. In both cases, columns 1-3 draw on zipcode-by-month data with roughly 2.8 million observations. Column 1 controls for just miles to the CBD, column 2 adds in controls for CBSA fixed effects, and column 3 adds in further controls for month fixed effects. Estimates confirm once again that within-city price returns are 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 returns

[20] Some of the locations for which beta was estimated are not included in some of the regressions that follow and were dropped from Table 3. It is for that reason that correlation between beta and non-systematic risk is not exactly equal to zero and instead reported for this part of the sample as 2.4%.

across the sample horizon as the dependent variable. In this instance, each zipcode provides one observation while also controlling for CBSA fixed effects. Notice that estimates are nearly the same as for the other columns in the table.

To allow for heterogeneity across urban areas, we also estimated the model in column 3 separately for each CBSA in the sample. This effectively interacts the CBSA fixed effects with the other model controls, including month fixed effects and distance or density depending on the model. Figure 5 plots the distribution of estimated coefficients across CBSAs for 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 500,000, and over 500,000.

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 coefficients 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. For this group of CBSAs, the distribution of distance coefficients (Panel A) is clearly shifted to the left while the distribution of density coefficients (Panel B) is shifted to the right. These patterns indicate that among larger CBSAs, defined here as those with population above 500,000, there is a greater tendency for price returns to be higher closer to the city center and in densely developed neighborhoods.

The different measures of within-CBSA risk also display strong spatial patterns. This is evident in Figures 6a and 6b based on risk measures pooled across CBSAs and limiting the sample to zipcodes within 25 miles of a CBD. Figure 6a has miles to the CBD on the horizontal axis while Figure 6b has log employment density on the horizontal axis. In both cases separate non-parametric plots are provided in Panels A through D for lagged measures of return volatility (Panel A), beta (Panel B), non-systematic risk (Panel C) and idiosyncratic risk (Panel D).

The dominant pattern in Figures 6a and 6b is that risk increases in a nonlinear but roughly monotonic fashion with proximity to city centers and with density of development. This holds for all four indicators of risk although to different degrees across the measures. These patterns echo those highlighted earlier and are suggestive that within CBSAs investor exposure to risk may increase with proximity to central, more densely developed portions of a city.

5.3 Risk-return tradeoffs

Table 7 reports estimates of spatial patterns of housing price and total returns, $\bar{\rho}^{P}_{2011-19}$ and $\bar{\rho}^{Tot}_{2011-19}$, with estimates in columns 1-3 and 4-6, respectively. Panel A includes miles to the CBD as a control while Panel B includes log employment density. Other controls include return volatility $\sigma^{P}_{1997-10}$ and indicators of the socioeconomic status of the zipcode proxied by log population in 2010, growth in zipcode population 2010 to 2020, and average zipcode house value divided by CBSA average housing value as of December 2019. Observe also that column 1 is based on the entire set of CBSAs while column 2 uses only CBSAs with population less than 250,000 and column 3 uses CBSAs with population over 250,000. A corresponding sequence of models for total returns is in columns 4-6.

Three patterns stand out. First and most important, among larger CBSAs (columns 3 and 6), volatility has a clear positive and highly significant effect on returns. That is not the case for small CBSAs for which the corresponding coefficients on volatility are small and not significant (columns 2 and 4). These estimates confirm that risk-return tradeoffs are present within large metropolitan areas but not in smaller urban areas. Second, other controls included in the models are present primarily to soak up possible unobserved confounding factors and are not so easily interpreted. Notice, for example that among larger urban areas, returns increase with proximity to the downtown (Panel A) and density (Panel B). Also, for both city sizes, socioeconomic attributes of a community are sometimes significantly associated with returns. Including these controls helps to ensure that the coefficients on volatility are indicative of risk-return tradeoffs. Third, the patterns just described are present for both price returns (columns 1-3) and total returns (columns 4-6).

Having established that risk-return tradeoffs are present in larger urban areas, Tables 8a and 8b present results from models designed to reveal more about the underlying nature of volatility and risk, mirroring CBSA-level analysis earlier in the paper. Table 8a includes all CBSAs in the sample while Table 8b includes only CBSAs with population above 250,000. We focus on the latter as results based on the full sample of CBSAs are similar. Observe also that all of the models include log employment density rather than distance. We use density as it is a more general measure but this does not affect the coefficients on volatility and risk in any noticeable way. All of the models include the same set of socioeconomic controls as in Table 7, but these are not tabled out to simplify presentation. Finally, columns 1-5 correspond to price returns while columns 6-10 repeat using total returns. We focus on price returns first and then comment on differences that appear with total returns.

Observe in column 1 that once again risk-return tradeoffs contribute to spatial variation of returns within larger metropolitan areas; the coefficient on volatility is positive and significant. Column 2 decomposes volatility into the supply elasticity from Baum-Snow and Han (2024), our measure of the propensity for demand shocks as described earlier, and the interaction of the two. This mirrors the decomposition exercise for the cross-CBSA analysis except that we use the Baum-Snow and Han (2024) measure of supply elasticity in place of the WURLI index. Similar to the CBSA-level results, when demand shocks are absent supply elasticity has no noticeable effect on returns. However, for locations prone to demand shocks, volatility is higher and is amplified by inelastic supply.

Columns 3 replaces the volatility measure with beta while column 4 adds in non-systematic risk and column 5 instead adds in idiosyncratic risk. Comparing estimates across columns 3-5, it is apparent that broader market-level systematic risk (beta) and submarket risk both contribute to within-CBSA risk-return tradeoffs. Observe that the coefficient on beta is positive and significant in all three columns and similar in magnitude across the specifications. These patterns are similar in columns 6-10 when total returns is used as the dependent variable.

The discussion thus far has focused on qualitative patterns, both for spatial variation across CBSAs and within CBSAs. The next section considers magnitudes of the documented relationships.

6. Magnitudes

In this section we compare the magnitude of risk-return tradeoffs and their underlying drivers. Patterns are summarized in Tables 9a and 9b based on a one-standard deviation increase in return volatility, beta, non-systematic risk, and idiosyncratic risk from the most fully specified models in Tables 4b (CBSA level) and 8b (zipcode level) where the latter is based on estimates for CBSAs with population greater than 250,000.

Starting with lagged return volatility, at the CBSA level (Table 9a) volatility has a greater effect on spatial patterns of price returns (Panel A) compared to total returns (Panel B). A one standard deviation increase in return volatility corresponds to a roughly 28.1% increase in price returns relative to the average price return across CBSAs. The same increase in return volatility corresponds to a 5.4% increase in total returns relative to its mean. This pattern is also present within larger urban areas (Table 9b) for which a one standard deviation increase in return volatility has a roughly 10.6% effect on price returns and a 7.6% effect on total returns. These magnitudes are large enough to be important.

Noteworthy patterns are also present when considering the nature of risk, where systematic risk is captured by beta and submarket risk is reflected by non-systematic risk in some models and idiosyncratic risk in others. At the CBSA level for both price and total returns, systematic risk has a larger magnitude effect compared to non-systematic risk. For price returns, the effects are 25.49% versus 11.33% while for total returns the corresponding values are 5.28% and 1.42%. These differences do not, however, persist when we use idiosyncratic risk to capture local exposure. In that instance, the magnitude of estimated effects are nearly the same for systematic and idiosyncratic risk in both panels (for price and total returns).

A different pattern prevails within urban areas with populations above 250,000 (Table 9b). For this level of geography, submarket neighborhood-level risk always has a larger magnitude effect relative to systematic risk and regardless of whether submarket risk is measured using non-systematic or idiosyncratic risk. This pattern is suggestive that localized housing market risk is not so easy to diversify away and adds to spatial patterns of risk and return within urban areas for that reason.

7. 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 submarket), systematic and submarket risk have similar magnitude effects on variation in returns across CBSAs. When considering spatial patterns of returns across neighborhoods within CBSAs, locally based neighborhood-level sources of risk are a more important driver of risk-return tradeoffs compared to CBSA-wide (systematic) risk.

Third, related findings indicate that inelastic supply is not by itself sufficient to general risk-return tradeoffs. Instead, it is the combination of propensity for demand shocks along with inelastic supply that appears to drive volatility in returns and related spatial variation across and within cities. Within larger urban areas, differences in these factors across neighborhoods contribute to higher housing returns closer to the city center and in densely developed neighborhoods.

Our final conclusion is that risk-return tradeoffs are large enough to be important. Increasing volatility by one standard deviation, CBSA-level price returns increase by roughly 29% while total returns increase by roughly 5.5%. At the neighborhood level within larger metropolitan areas the corresponding estimates are roughly 12% to 8% for price and total returns.

A fundamental tenant of urban theory is that equilibrium home price levels differ across and within cities to compensate for differences in amenities and other types of local advantage. This paper provides evidence of a related but less recognized equilibrium phenomena: spatial variation in 1housing returns is also present across and within cities because of locally based risk-return tradeoffs.

References

Amaral, Francisco, Martin Dohmen, Sebatian Kohl and Mortiz Schularick (2021). “Superstar Returns”, Federal Reserve Bank of New York working paper, number 999.

Baum-Snow, Nathaniel, and Lu Han (2024). “The Microgeography of housing supply,” *Journal of Political Economy*, 132(6), 1897-1946.

Board of Governors of the Federal Reserve System (US). 1-year treasury constant maturity rate [dgsi]. (retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS1)

Bodie, Zvi, Alex Kane, Alan Marcus, and Pitabas Mohanty. (2009). *Investments*. McGraw Hill. 8th edition.

Bogin, Alexander N., Doerner, William M. and Larson, William D. (2019). “Local House Price Dynamics: New Indices and Stylized Facts”. *Real* Estate Economics, volume 47, issue 2, pages 365-398

Brueckner, Jan (1987). “The Structure of Urban Equilibria: A Unified Treatment of the Muth-Mills Model,” *in* Handbook of Regional and Urban Economics, Elsevier Inc., Amsterdam, Volume 2, Chapter 20, 821-845.

Cannon, Susanne, Norman Miller, and Gurupdesh Pandher (2006). “Risk and Return in the U.S. Housing Market: A Cross-Sectional Asset-Pricing Approach.” *Real Estate Economics*, Vol. 34, No. 4, pp. 519-552.

Case, Karl, John Cotter, and Stuart A. Gabriel. (2011). “Housing Risk and Return: Evidence from a Housing Asset-Pricing Model,” *The Journal of Portfolio Management*, 37 (5), 89-109.

Chambers, David, Christophe Spaenjers, and Eva Steiner (2021). “The rate of return on real estate: Long-run micro-level evidence,” *Review of Financial Studies*, 34:3572–607.

Chen, Yong, and Stuart S. Rosenthal (2008). “Local amenities and life-cycle migration: Do people move for jobs or fun?” *Journal of Urban Economics*, 64, 519-537.

Crone, Theodore M. and Richard Voith (1998). "Risk and return within the single-family housing market," Working Papers 98-4, Federal Reserve Bank of Philadelphia.

Cotter, John, Stuart A. Gabriel and Richard Roll (2015). “Can Housing Risk Be Diversified? A Cautionary Tale form the Housing Boom and Bust,” *Review of Financial Studies*, 28(3), 913-936.

Couture, Victor, and Jessie Handbury (2020). “Urban revival in America,” *Journal of Urban Economics*, Article 103267.

Davidoff, Thomas “Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors” (2016). *Critical Finance Review*, Vol. 6.

Demers, Andrew and Andrea L. Eisfeldt (2022). “Total Returns to Single Family Rentals”, *Real Estate Economics*, 50(1), 7-32.

Danielsson, Jon, Hyun Song Shin, and Jean-Pierre Zigrand (2013). "Endogenous and Systemic Risk," *in* Quantifying Systematic Risk, Joseph G. Haurbrich and Andrew W. Lo (eds.), University of Chicago Press, ISBN: 0-226-31928-8.

Davidoff, Thomas (2006). "Labor Income, Housing Prices, and Homeownership" *Journal of Urban Economics*, 59(2), 209-235.

DeFusco, Anthony, Wenjie Ding, Fernando Ferreira, and Joseph Gyourko (2018). "The Role of Spillovers in the American Housing Boom," *Journal of Urban Economics*, 108, 72-84.

Duranton, Gilles and Diego Puga (2015). "Urban Land Use," *in* Handbook of Regional and Urban Economics, G. Duranton, J.V. Henderson and W.C. Strange (eds.), Elsevier Inc., Amsterdam. Volume V, Chapter 9, 467-560.

Eichholtz, Piet, Matthijs Korevaar, Thies Lindenthal, and Ronan Tallec (2001). "The Total Return and Risk to Residential Real Estate" *The Review of Financial Studies*, 34, 3608-3646.

Fama, Eugene, and Kenneth French (2004). "The Capital Asset Pricing Model: Theory and Evidence," *Journal of Economic Perspectives*, 18 (3), 25-46.

Fisher, Gregg, Eva Steiner, Sheridan Titman, and Ashvin Viswanathan (2022). "Location Density, Systematic Risk, and Cap Rates: Evidence from REITs," *Real Estate Economics*, 50, 366-400.

Giacoletti, Marco (2021). "Idiosyncratic Risk in Housing Markets," *Review of Financial Studies* 34:3695–741.

Glaeser, Edward and Joseph Gyourko. (2005). "Urban Decline and Durable Housing," *Journal of Political Economy*, 113(2), 345-375.

Glaeser, Edward, Joseph Gyourko, and A. Saiz. (2008). "Housing Supply and Housing Bubbles," *Journal of Urban Economics,* 64 (2), 198-217.

Glaeser, Edward, and Joseph Gyourko (2010). Arbitrage in housing markets. In *Housing and the built environment: Access, finance, policy.* Eds. E. L. Glaeser and J. Quigley. Cambridge, MA: Lincoln Land Institute of Land Policy.

Glaeser, Edward, and Charles Nathanson (2015). "Housing Bubbles," *in* Handbook of Regional and Urban Economics, Elsevier Inc., Amsterdam. Volume V, Chapter 11, 701-751.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, Stijn Van Nieuwerburgh (2022). "Flattening the curve: Pandemic-Induced revaluation of urban real estate," *Journal of Financial Economics*, 146(2), 594-636.

Glaeser, Edward, Joseph Gyourko, (2005). "Urban decline and durable housing." *Journal of Political Economy*, 113, 345-375.

Glaeser, Edward, Joseph Gyourko, Raven Saks, (2006). "Urban growth and housing supply." *Journal of Economic Geography*, 6(1), 71-89.

Gyourko, Joseph, J. Hartley, J. Krimmel (2021). "The local residential land use regulatory environment across U.S. housing markets: Evidence from a new Wharton index," *Journal of Urban Economics*, 124, Article 103337.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai, (2013). "Superstar cities". *American Economic Journal: Economic Policy, American Economic Association*, 5 (4), 167-199.

Gyourko, Joseph, Albert Saiz, and Anita Summers (2008). "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index". *Urban Studies*. 45 (3), 693-729.

Gyourko, Joseph, Raven Molloy (2015). "Regulation and Housing Supply" *in* Handbook of Regional and Urban Economics, G. Duranton, J.V. Henderson and W. Strange, eds., Elsevier Inc. Amsterdam, Ch 19, vol 5, 1289-1337.

Han, Lu (2013). "Understanding the Puzzling Risk-Return Relationship for Housing," *The Review of Financial Studies,* 26(4).

Himmelberg, Charles, Christopher Mayer, and Todd Sinai (2005). "Assessing High House Prices: Bubbles, Fundamentials and Misperceptions," *Journal of Economic Perspectives*, 19(4), 67-92.

Holian, Matthew, and Matthew Kahn (2015). "Household carbon emissions from driving and center city quality of life," *Ecological Economics*, 116, 362-368.

Hryniw, Natalia. "Zillow Home Value Index Methodology, 2019 Revision: Getting Under the Hood". Zillow Research. 2019. https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/ . Accessed Jan 27, 2020.

Jorda, Oscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan Taylor (2019). "The rate of return on everything, 1870–2015," *Quarterly Journal of Economics*, 134:1225–98.

Liu, Hu, Adam Nowak, and Stuart Rosenthal (2016). "Housing price bubble, new supply, and within-city dynamics," *Journal of Urban Economics*, 96, 55-72.

Merton, Robert (1987). "A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance*, 42(3), 483-510.

Paciorek, Andrew (2013). "Supply Constraints and Housing Market Dynamics", *Journal of Urban Economics*, 77, 11-26.

Roback, Jennifer (1982). "Wages, Rents, and the Quality of Life." *Journal of Political Economy*, 90(6), 1257-1278

Rosen, Sherwin (1979). "Wage-Based Indexes of Urban Quality of Life." In *Current Issues of Urban Economics*, edited by Peter Mieszkowski and Mahlon Straszheim, 74-104. Baltimore: John Hopkins University Press.

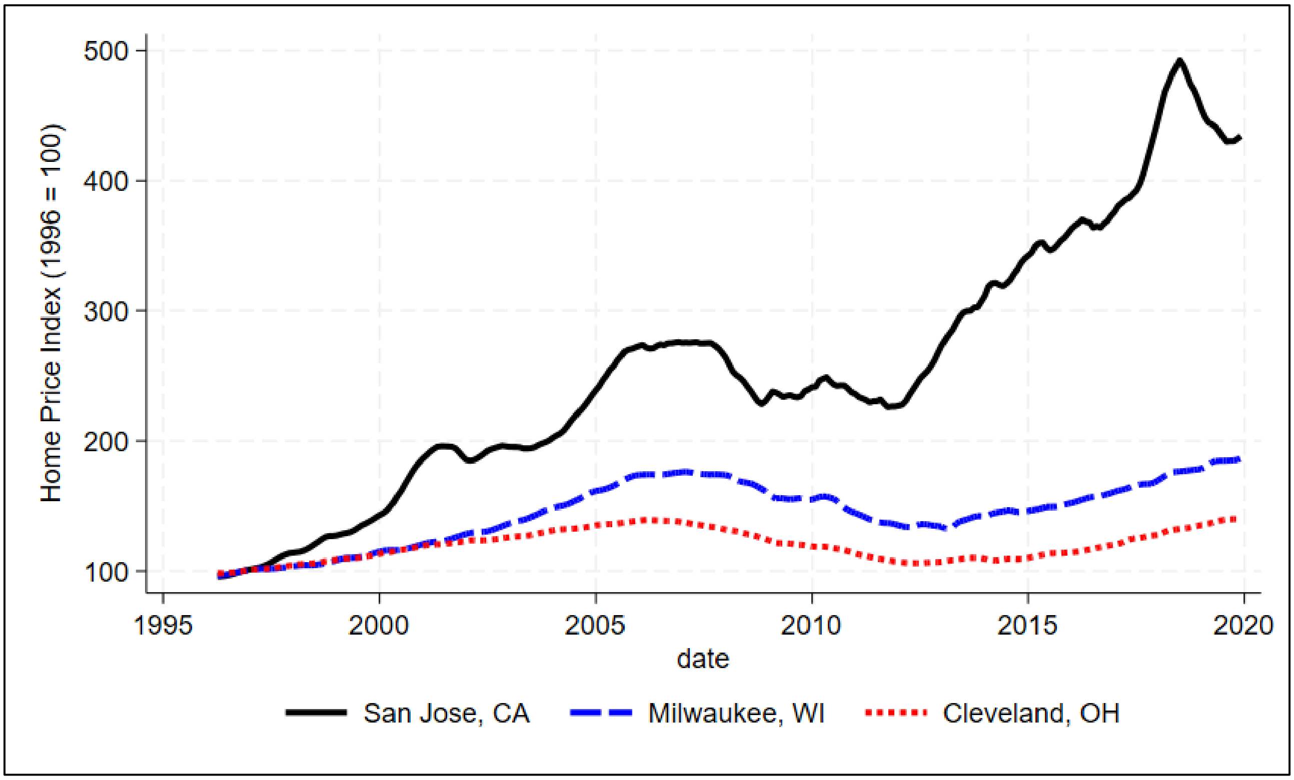
Rosenthal, Stuart S. and William C. Strange (2022). "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," Vol 127, Article 103381.

Sagi, Jacob (2021). "Asset-level risk and return in real estate investments," *Review of Financial Studies* 34:3647–94.

Saiz, Albert (2008). "On Local Housing Supply Elasticity." The Wharton School, University of Pennsylvania Working Paper SSRN No. 1193422.

Sinai, Todd and Nicholas S. Souleles (2005). "Owner Occupied Housing as a Hedge Against Rent Risk." *Quarterly Journal of Economics* 120(2), 763-789.

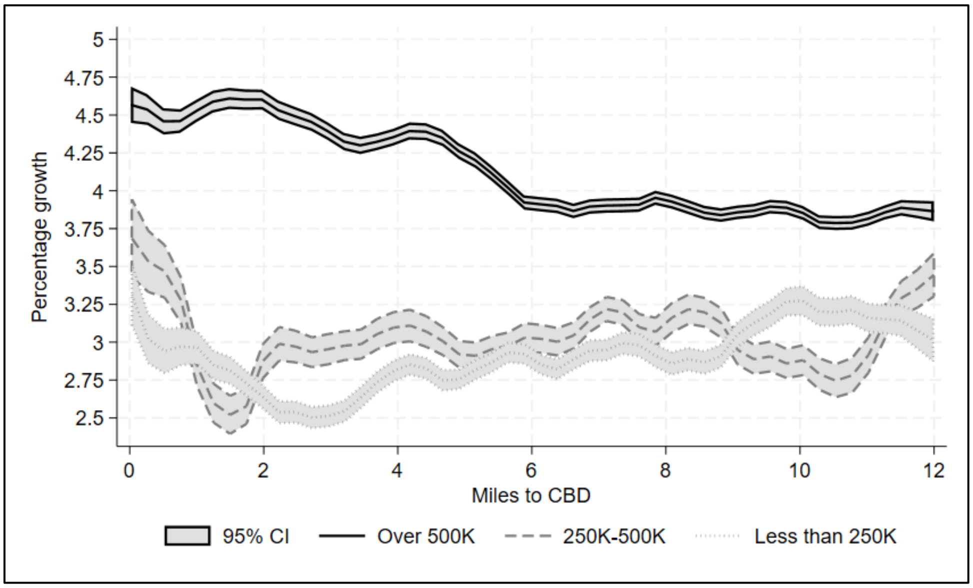
Figure 1: Single-family home value index for select CBSAs[a]



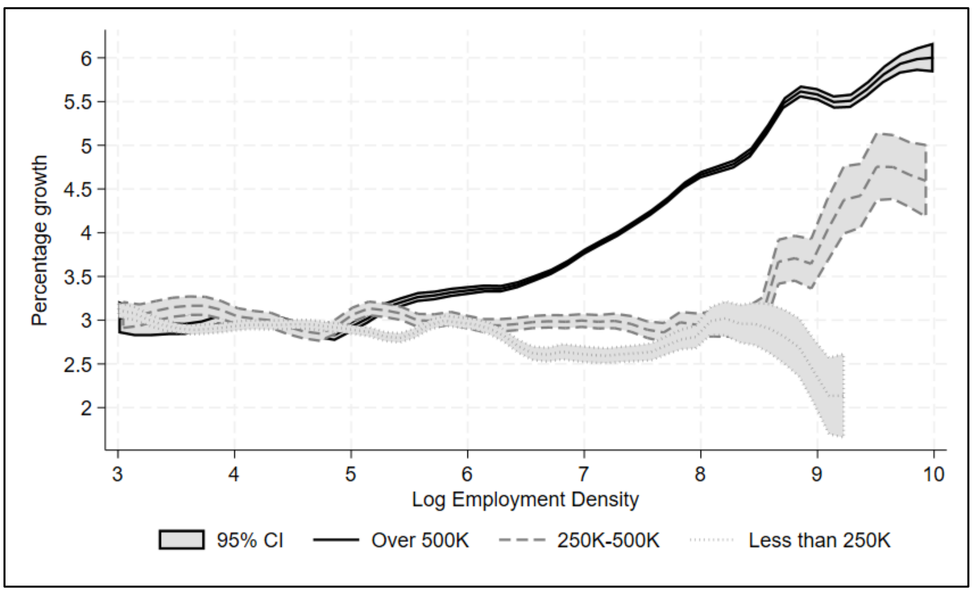
[a] Index data were provided by Zillow Group.

Figure 2: 1997-2019 Year-over-year % growth in zipcode housing price by CBSA population[a]

Panel A: Distance to CBD



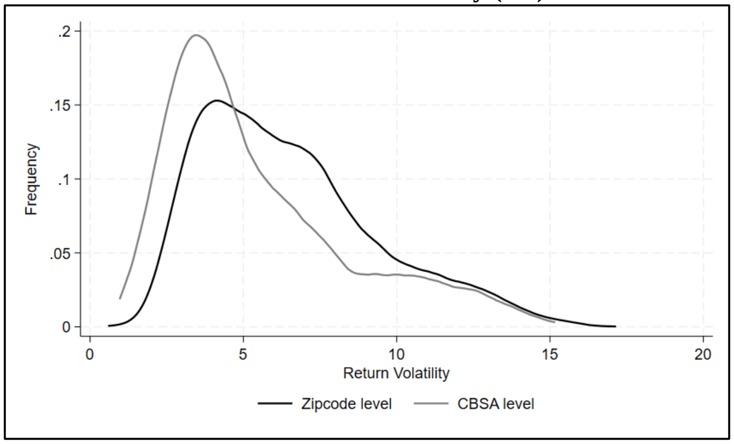
Panel B: Log Employment Density



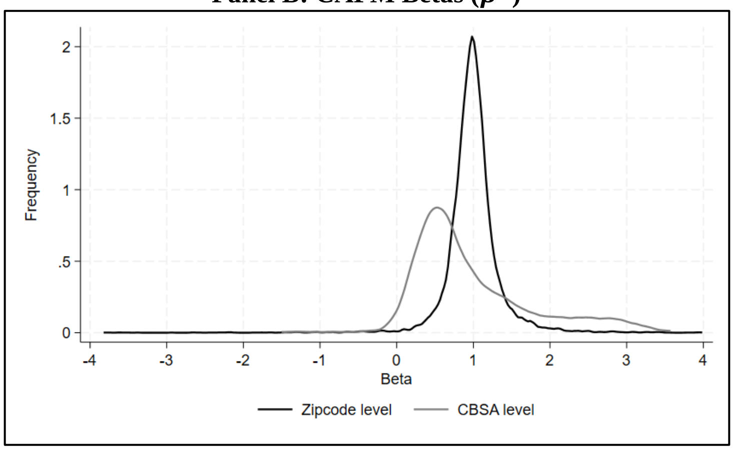
[a] Sample restricted to zipcodes with log employment density greater than 3 (20 workers per square mile) and situated within 12 miles of the CBD. Estimates are based on a local polynomial regression of degree 0 using the epanechnikov kernel and Rule of Thumb bandwidth. Index data were provided by Zillow Group.

Figure 3: 1997-2019 Distribution of Risk Measures at the CBSA and Zipcode Level

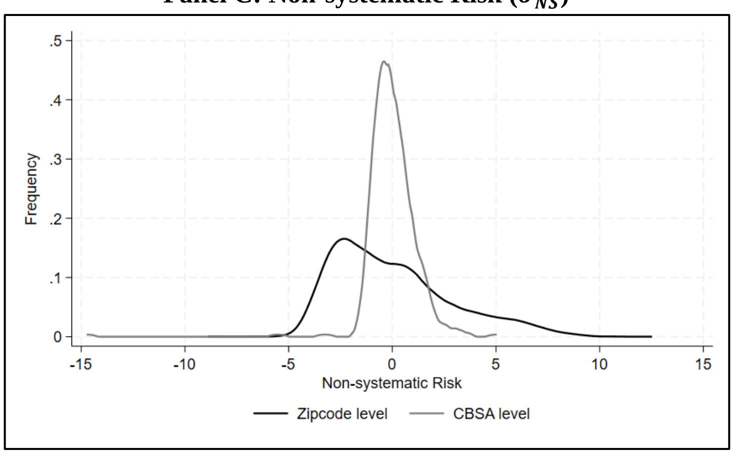
Panel A: Return Volatility (σ^P)



Panel B: CAPM Betas (β^P)



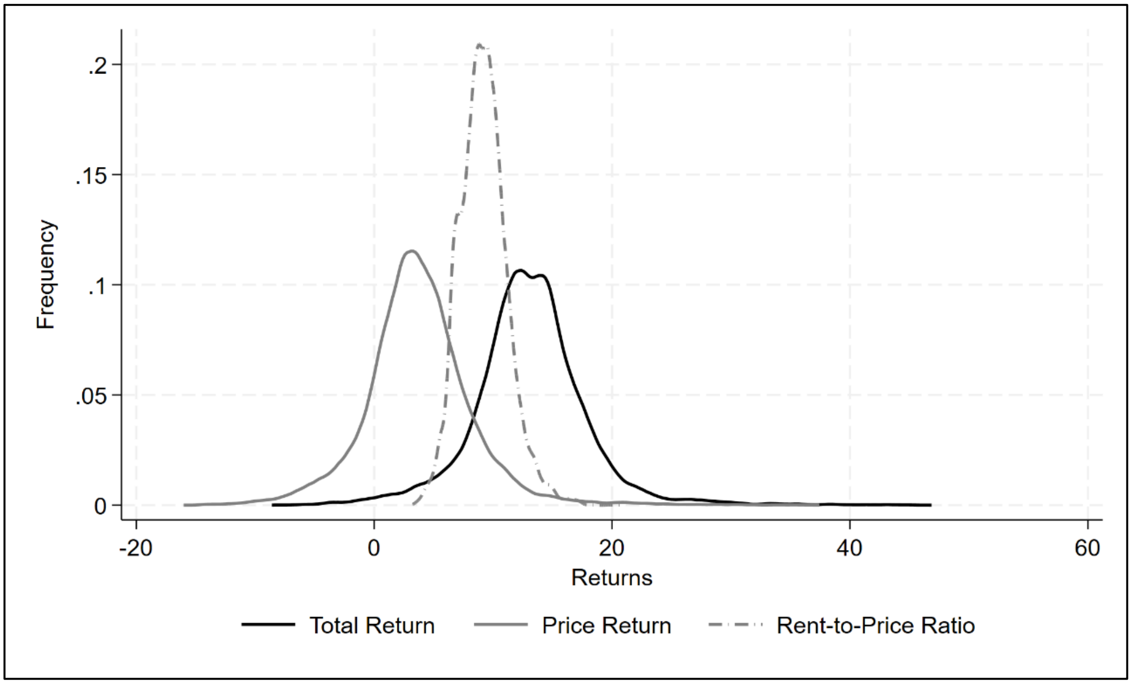
Panel C: Non-systematic Risk (σ^P_{NS})



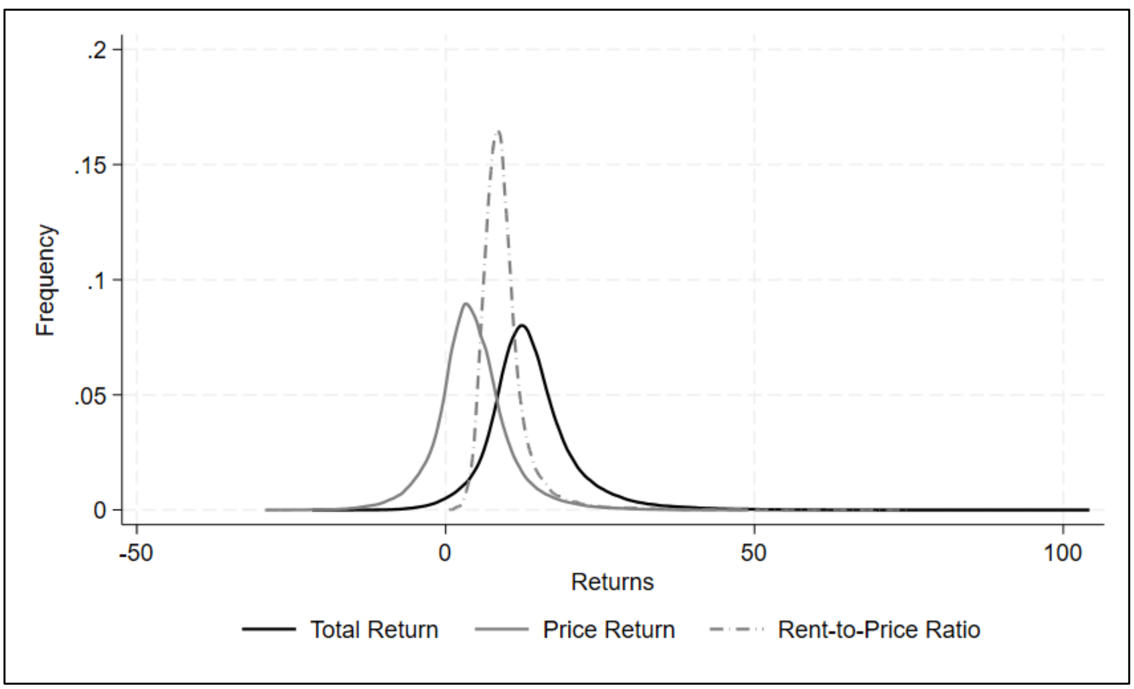
[a] Estimates are based on a kernel density using the epanechnikov kernel and bandwidth determined by the Silverman (1986) optimal bandwidth. Betas beyond -4 and 4 are omitted (44 of 11,644 zipcodes and 1 of 362 CBSAs). Data were provided by Zillow Group.

Figure 4: 2011-2019 Distribution of Total Returns, Price Returns, and Rent-to-Price Ratio[a]

Panel A: CBSA level



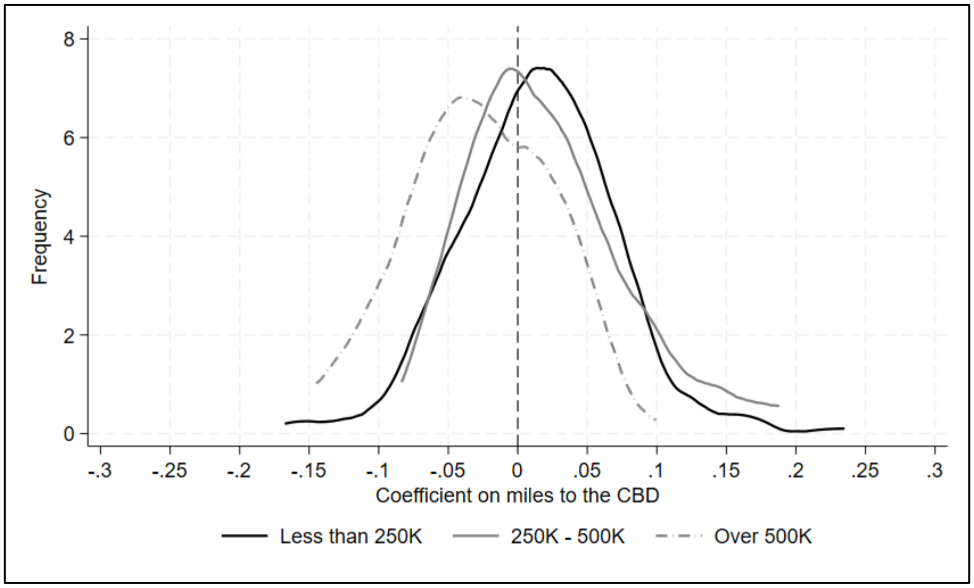
Panel B: Zipcode level



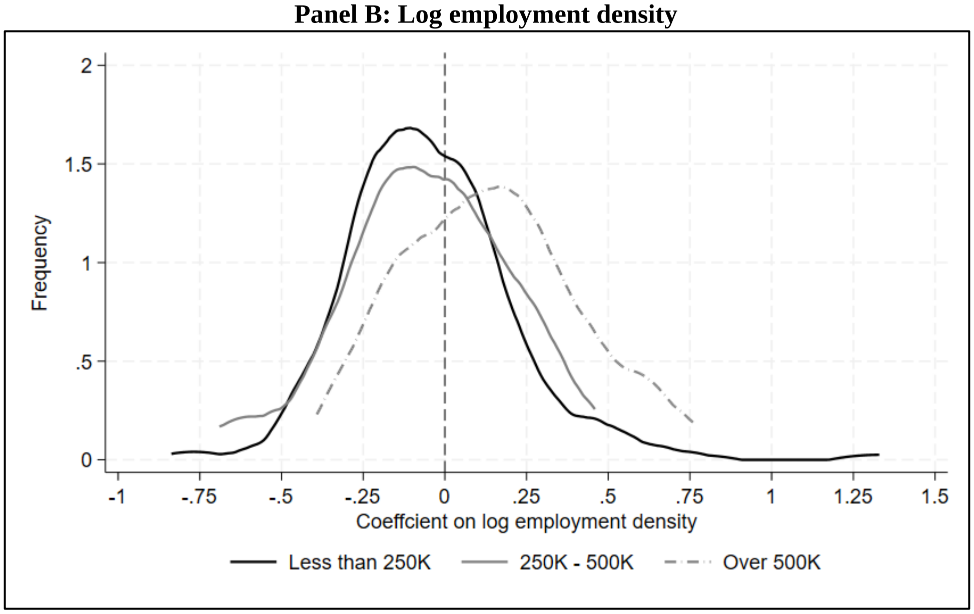
[a] Data were provided by Zillow Group.

Figure 5: 1997-2019 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

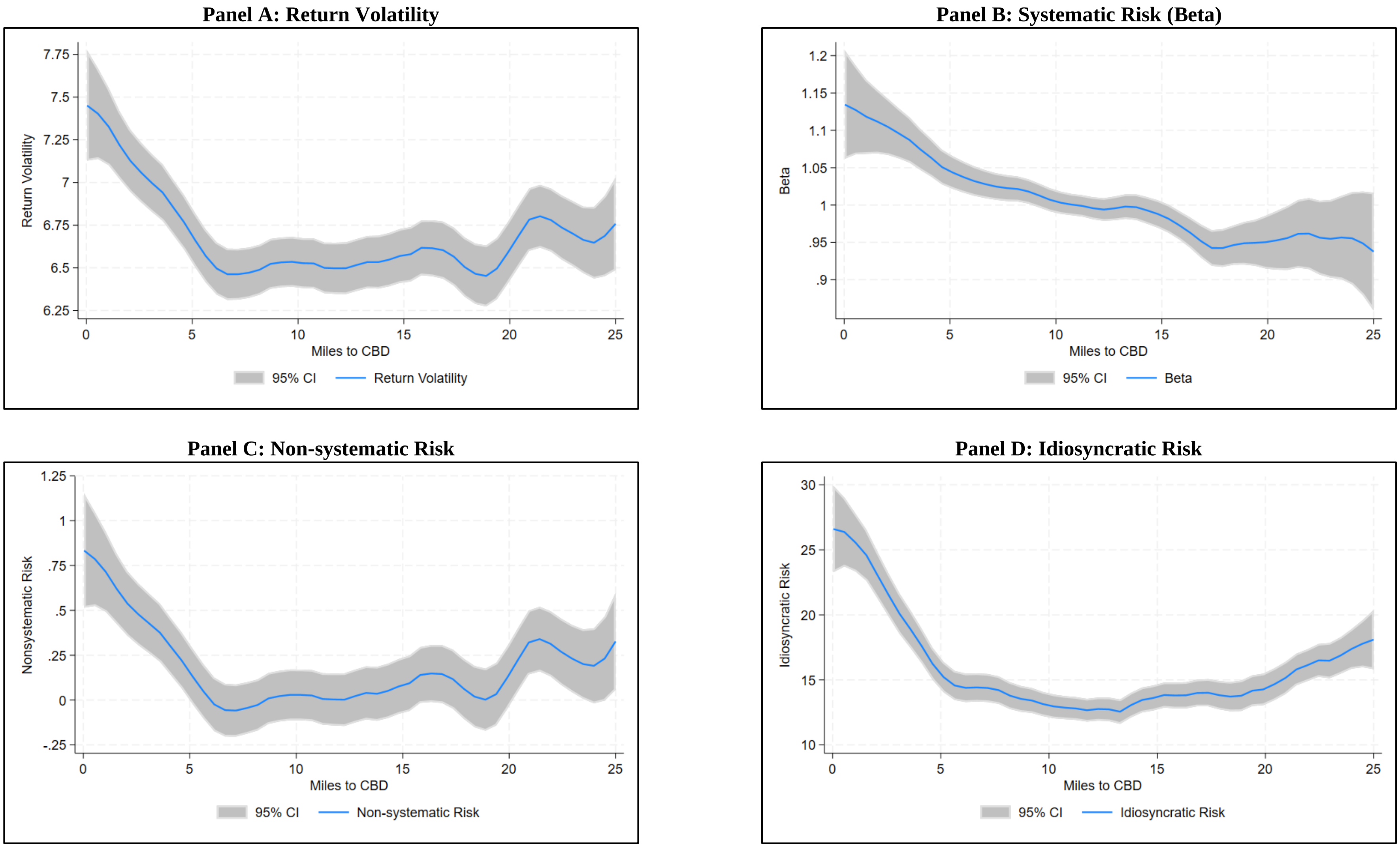


Panel B: Log employment density



[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 6a: 1997-2019 spatial variation in risk based on distance to the CBD[a]

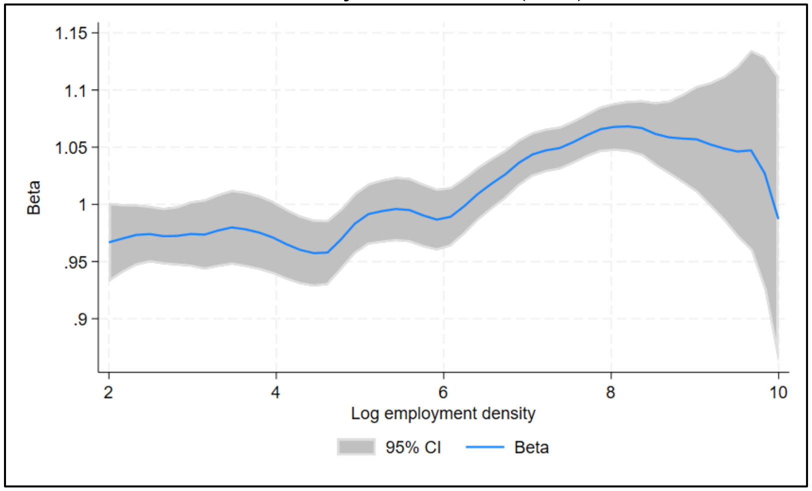


[a] Plotted values are drawn from zipcodes within 25 miles of their CBD and with log employment density between 2 and 10. Plots are smoothed using a local polynomial regression of degree 0 using the epanechnikov kernel and rule of thumb bandwidth selection process. Data were provided by Zillow Group.

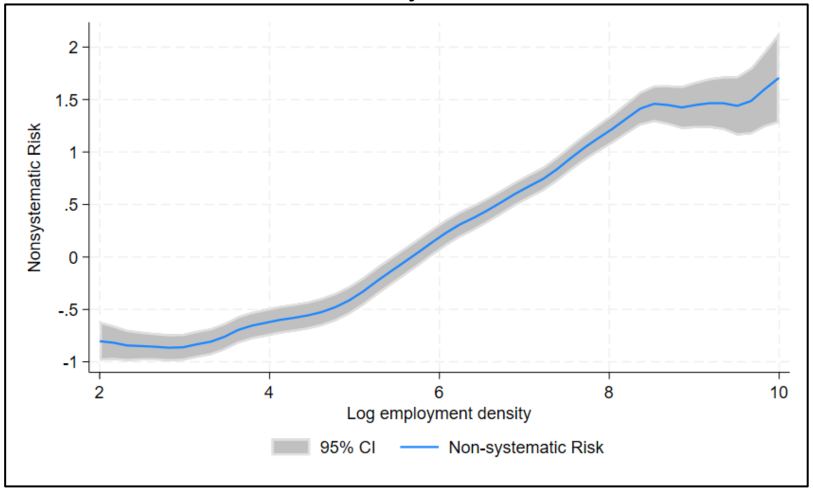
Figure 6b: 1997-2019 spatial variation in risk based on zipcode log employment density[a]

Panel A: Return Volatility

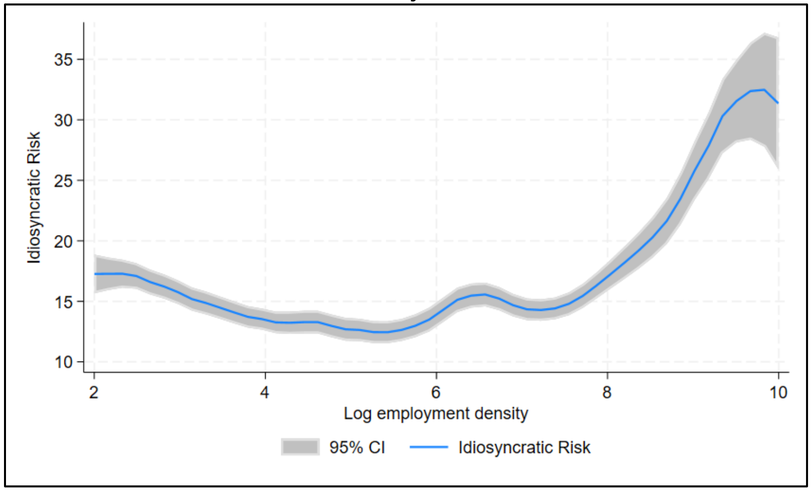
Panel B: Systematic Risk (Beta)



Panel C: Non-systematic Risk



Panel D: Idiosyncratic Risk



[a] Plotted values are drawn from zipcodes within 25 miles of their CBD and with log employment density between 2 and 10. Plots are smoothed using a local polynomial regression of degree 0 using the epanechnikov kernel and rule of thumb bandwidth selection process. 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 over the 1997-2019 period[a]

Bottom 20					Top 20				
	Return Volatility ($\sigma^P_{1997-2019}$)	Beta ($\beta^P_{1997-2019}$)	Non-systematic Risk ($\sigma^P_{NS,1997-10}$)	Year-2000 Population		Return Volatility ($\sigma^P_{1997-2019}$)	Beta ($\beta^P_{1997-2019}$)	Non-systematic Risk ($\sigma^P_{NS,1997-10}$)	Year-2000 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 populations 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 measures of risk and return[a]

	$\bar{\rho}^{P}_{2011-19}$	$\bar{\rho}^{Tot}_{2011-19}$	$\sigma^{P}_{1997-10}$	$\sigma^{P}_{2011-19}$	WLURI	$\beta^{P}_{1997-10}$	$\sigma^{P}_{NS,1997-10}$	$\sigma^{P}_{ID,1997-10}$
Avg yr-over-yr price return 2011-19: $\bar{\rho}^{P}_{2011-19}$	1.000	-	-	-	-	-	-	-
Avg yr-over-yr total return 2011-19: $\bar{\rho}^{Tot}_{2011-19}$	0.757	1.000	-	-	-	-	-	-
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.594	0.306	1.000	-	-	-	-	-
Return volatility 2011-2019: $\sigma^{P}_{2011-19}$	0.706	0.426	0.724	1.000	-	-	-	-
WLURI	0.194	-0.016	0.300	0.326	1.000	-	-	-
Beta 1997-2010: $\beta^{P}_{1997-10}$	0.536	0.294	0.941	0.704	0.268	1.000	-	-
Non-systematic risk 1997-2010: $\sigma^{P}_{NS,1997-10}$	0.276	0.096	0.359	0.200	0.145	0.024	1.000	-
Ideosyncratic risk 1997-2010: $\sigma^{P}_{ID,1997-10}$	0.560	0.323	0.687	0.582	0.289	0.532	0.563	1.000

[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 4a: CBSA-level risk-return tradeoffs based on 2011-2019 average year-over-year price returns ($\bar{\rho}_i^P$) [a]

	Volatility	Land Use Regulation	Demand Shock	Interaction	CBSA Atrb	Risk + CBSA Atrb
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: σ^P	0.3745***	-	-	-	-	-
	(0.027)	-	-	-	-	-
WLURI (W)	-	0.6529***	0.7372***	-0.2084	-	-0.4656
	-	(0.227)	(0.193)	(0.322)	-	(0.305)
Demand Shock (D)	-	-	1.8092***	1.9962***	-	1.6080***
	-	-	(0.149)	(0.142)	-	(0.157)
W by D interaction	-	-	-	0.7808***	-	0.8203***
	-	-	-	(0.231)	-	(0.205)
Log CBSA population 2000	-	-	-	-	0.2417*	0.1617
	-	-	-	-	(0.145)	(0.132)
Median CBSA income 2000 (1,000s)	-	-	-	-	0.2715	-0.1832
	-	-	-	-	(0.577)	(0.485)
|%Δ population| if GROWING	-	-	-	-	0.0431***	0.0292***
1990-2020 (0 otherwise)	-	-	-	-	(0.006)	(0.006)
|%Δ population| if SHRINKING	-	-	-	-	-0.0717	-0.0157
1990-2020 (0 otherwise)	-	-	-	-	(0.073)	(0.068)
Superstar status	-	-	-	-	1.5429	0.9871
	-	-	-	-	(1.217)	(0.993)
Observations	254	254	254	254	254	254
R^2	0.352	0.038	0.322	0.356	0.252	0.446

[a] The dependent variables (average annual price and total returns) are scaled by 100. 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 4b: Alternate measures of CBSA-level risk and returns[a]

Panel A: Price Returns

	Volatility	Beta	Non-sys Risk	Idio Risk	Beta + Non-sys Risk	Beta+ Idio Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: σ^P	0.2989***	-	-	-	-	-
	(0.030)	-	-	-	-	-
Beta: β^P	-	1.0980***	-	-	1.1345***	0.7113***
	-	(0.135)	-	-	(0.153)	(0.169)
Non-systematic risk: σ_{NS}^P	-	-	0.2824	-	0.3426	-
	-	-	(0.305)	-	(0.208)	-
Idiosyncratic risk ($\sigma^q{}_{ID}$)	-	-		0.0622***	-	0.0440***
	-	-		(0.007)	-	(0.008)
Observations	254	254	254	254	254	254
R^2	0.438	0.408	0.273	0.424	0.439	0.475

Panel B: Total Returns

	Volatility	Beta	Non-sys Risk	Idio Risk	Beta + Non-sys Risk	Beta+ Idio Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: σ^P	0.1927***	-	-	-	-	-
	(0.041)	-	-	-	-	-
Beta: β^P	-	0.7522***	-	-	0.7669***	0.4902**
	-	(0.162)	-	-	(0.167)	(0.196)
Non-systematic risk: σ_{NS}^P	-	-	0.0968	-	0.1375	-
	-	-	(0.224)	-	(0.174)	-
Idiosyncratic risk ($\sigma^q{}_{ID}$)	-	-	-	0.0424***	-	0.0298***
	-	-	-	(0.008)	-	(0.009)
Observations	254	254	254	254	254	254
R^2	0.183	0.179	0.115	0.185	0.184	0.207

[a] The dependent variables – average year-over-year price and total returns – are scaled by 100. 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/ . All models include the same set of sociodemographic and amenity controls as in Table 4a.

Table 5: Correlation between zipcode level measures of risk and return[a]

	$\bar{\rho}^{P}_{2011-19}$	$\bar{\rho}^{Tot}_{2011-19}$	$\sigma^{P}_{1997-10}$	$\sigma^{P}_{2011-19}$	Miles to CBD	Log emp density	Supply elasticity	$\beta^{P}_{1997-10}$	$\sigma^{P}_{NS,1997-10}$	$\sigma^{P}_{ID,1997-10}$
Avg year-over-year price return 2011-2019: $\bar{\rho}^{P}_{2011-19}$	1.000	-	-	-	-	-	-	-	-	-
Avg year-over-year total return 2011-2019: $\bar{\rho}^{Tot}_{2011-19}$	0.599	1.000	-	-	-	-	-	-	-	-
Price return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.504	0.223	1.000	-	-	-	-	-	-	-
Price return volatility 2011-2019: $\sigma^{P}_{2011-19}$	0.587	0.592	0.554	1.000	-	-	-	-	-	-
Miles to CBD	-0.075	-0.176	0.026	-0.158	1.000	-	-	-	-	-
Log employment density	0.271	0.166	0.208	0.268	-0.448	1.000	-	-	-	-
Supply elasticity (Baum-Snow and Han)	-0.319	-0.258	-0.286	-0.363	0.267	-0.797	1.000	-	-	-
Beta 1997-2010: $\beta^{P}_{1997-10}$	0.046	0.131	0.186	0.174	-0.110	0.023	-0.077	1.000	-	-
Non-systematic risk 1997-2010: $\sigma^{P}_{NS,1997-10}$	0.505	0.206	0.988	0.535	0.044	0.208	-0.278	0.030	1.000	-
Idiosyncratic risk 1997-2010: $\sigma^{P}_{ID,1997-10}$	0.021	0.151	0.237	0.207	-0.038	-0.019	-0.044	0.076	0.229	1.000

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

Table 6: Zipcode level price returns pooling across CBSAs 1997-2019[a]

Panel A: Miles to the CBD

	Year-over-year home price returns using month by zipcode observations			Average year-over-year price returns 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)
CBSA FE	-	362	362	362
Month FE	-	-	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 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)
CBSA FE	-	362	362	362
Month FE	-	-	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: Risk-return tradeoffs by CBSA size for average 2011-2019 monthly year-over-year home price and total returns[a]

Panel A: Distance to the CBD

	All CBSA Price Return	CBSA Pop < 250K Price Return	CBSA Pop > 250K Price Return	All CBSA Total Return	CBSA Pop < 250K Total Return	CBSA Pop > 250K Total Return
	(1)	(2)	(3)	(4)	(5)	(6)
Return Volatility (σ^P)	0.0983***	0.0114	0.1073**	0.2758***	0.0756	0.2981***
	(0.035)	(0.026)	(0.043)	(0.094)	(0.054)	(0.110)
Miles to CBD	-0.0460***	0.0185***	-0.0613***	-0.1261***	0.0137	-0.1481***
	(0.010)	(0.006)	(0.012)	(0.014)	(0.012)	(0.016)
Log zipcode population 2010	0.0192	-0.0044	0.0538	0.0094	0.0147	0.0645
	(0.033)	(0.024)	(0.044)	(0.082)	(0.064)	(0.093)
Δ zipcode pop 2020 - 2010	-0.3484	-0.2049	-0.3422	-3.6745***	-0.7239	-3.6763***
	(0.253)	(0.302)	(0.297)	(0.524)	(0.781)	(0.548)
Relative home value[a]	0.0630	0.5040***	0.0184	-3.5357***	-5.7000***	-3.3618***
	(0.157)	(0.149)	(0.175)	(0.585)	(0.563)	(0.600)
CBSA FE	361	190	171	355	184	171
Observations	11,094	2,707	8,387	9,228	1,780	7,448
Within R^2	0.054	0.031	0.084	0.344	0.422	0.354

Panel B: Log Employment Density

	All CBSA Price Return	CBSA Pop < 250K Price Return	CBSA Pop > 250K Price Return	All CBSA Total Return	CBSA Pop < 250K Total Return	CBSA Pop > 250K Total Return
	(1)	(2)	(3)	(4)	(5)	(6)
Return Volatility (σ^P)	0.1143***	0.0091	0.1333***	0.3259***	0.0749	0.3652***
	(0.036)	(0.026)	(0.045)	(0.099)	(0.056)	(0.116)
Log Employment Density	0.0555***	-0.0557***	0.0940***	0.3106***	0.0074	0.3646***
	(0.021)	(0.017)	(0.026)	(0.035)	(0.046)	(0.039)
Log zipcode population 2010	0.0678*	0.0009	0.1010**	0.0055	-0.0363	0.0592
	(0.036)	(0.024)	(0.049)	(0.093)	(0.083)	(0.108)
Δ zipcode pop 2020 - 2010	-0.3435	-0.1568	-0.3730	-3.9578***	-0.7618	-4.1012***
	(0.272)	(0.313)	(0.329)	(0.561)	(0.782)	(0.596)
Relative home value[a]	0.0870	0.4765***	0.0431	-3.5193***	-5.7076***	-3.3546***
	(0.163)	(0.144)	(0.184)	(0.614)	(0.567)	(0.638)
CBSA FE	361	190	171	355	184	171
Observations	11,094	2,707	8,387	9,228	1,780	7,448
Within R^2	0.025	0.030	0.041	0.316	0.422	0.317

[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 ratio 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 8a (All CBSA): Alternate measures of zipcode-level risk and return[a]

	Avg 2011-2019 monthly year-over-year price returns: $\bar{\rho}^{P}_{2011-19}$					Avg 2011-2019 monthly year-over-year total returns: $\bar{\rho}^{Tot}_{2011-19}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Return Volatility ($\sigma^{P}_{1997-10}$)	0.1350***	-	-	-	-	0.3136***	-	-	-	-
	(0.048)	-	-	-	-	(0.109)	-	-	-	-
Supply elasticity (S)	-	-0.0138	-	-	-	-	-2.7854***	-	-	-
	-	(0.452)	-	-	-	-	(0.948)	-	-	-
Demand shock (D)	-	1.3610***	-	-	-	-	2.2917**	-	-	-
	-	(0.463)	-	-	-	-	(1.056)	-	-	-
S by D interaction	-	-1.3069***	-	-	-	-	-1.0530	-	-	-
	-	(0.424)	-	-	-	-	(0.934)	-	-	-
Beta ($\beta^{P}_{1997-10}$)	-	-	0.2897***	0.2727***	0.2517***	-	-	0.6252***	0.5848***	0.4972***
	-	-	(0.090)	(0.080)	(0.092)	-	-	(0.185)	(0.164)	(0.176)
Non-systematic risk $\sigma^{P}_{NS,1997-10}$)	-	-	-	0.1203**	-	-	-	-	0.2858**	-
	-	-	-	(0.054)	-	-	-	-	(0.120)	-
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	-	-	0.0185***	-	-	-	-	0.0622***
	-	-	-	-	(0.004)	-	-	-	-	(0.008)
Log employment density	0.0610**	-0.0299	0.0618**	0.0596**	0.0510**	0.3098***	0.0530	0.3125***	0.3073***	0.2762***
	(0.025)	(0.028)	(0.025)	(0.025)	(0.023)	(0.037)	(0.039)	(0.038)	(0.037)	(0.035)
CBSA FE	307	307	307	307	307	307	307	307	307	307
Observations	7,776	7,776	7,776	7,776	7,776	7,776	7,776	7,776	7,776	7,776
Within R^2	0.035	0.045	0.023	0.037	0.052	0.322	0.331	0.309	0.323	0.370
Total R^2	0.248	0.225	0.022	0.236	0.026	0.217	0.225	0.201	0.220	0.221

[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. All models include controls for log zipcode population in 2010, change in zipcode population 2010 to 2010, and relative home value as in Table 8.

Table 8b (CBSA Population > 250,000): Alternate measures of zipcode-level risk and return[a]

	Avg 2011-2019 monthly year-over-year price returns: $\bar{\rho}^{P}_{2011-19}$					Avg 2011-2019 monthly year-over-year total returns: $\bar{\rho}^{Tot}_{2011-19}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Return Volatility ($\sigma^{P}_{1997-10}$)	0.1467***	-	-	-	-	0.3469***	-	-	-	-
	(0.055)	-	-	-	-	(0.126)	-	-	-	-
Supply elasticity (S)	-	0.0098	-	-	-	-	-3.4619***	-	-	-
	-	(0.501)	-	-	-	-	(1.011)	-	-	-
Demand shock (D)	-	1.3625***	-	-	-	-	2.3273**	-	-	-
	-	(0.489)	-	-	-	-	(1.115)	-	-	-
S by D interaction	-	-1.2542***	-	-	-	-	-0.7154	-	-	-
	-	(0.435)	-	-	-	-	(0.939)	-	-	-
Beta ($\beta^{P}_{1997-10}$)	-	-	0.3327***	0.2996***	0.2857**	-	-	0.7717***	0.6929***	0.6169***
	-	-	(0.121)	(0.104)	(0.122)	-	-	(0.244)	(0.207)	(0.228)
Non-systematic risk $\sigma^{P}_{NS,1997-10}$)	-	-	-	0.1308**	-	-	-	-	0.3114**	-
	-	-	-	(0.063)	-	-	-	-	(0.139)	-
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	-	-	0.0209***	-	-	-	-	0.0688***
	-	-	-	-	(0.005)	-	-	-	-	(0.009)
Log employment density	0.0924***	0.0035	0.0928***	0.0900***	0.0770***	0.3539***	0.0602	0.3553***	0.3485***	0.3031***
	(0.028)	(0.036)	(0.028)	(0.028)	(0.027)	(0.041)	(0.049)	(0.043)	(0.041)	(0.040)
CBSA FE	157	157	157	157	157	157	157	157	157	157
Observations	6,492	6,492	6,492	6,492	6,492	6,492	6,492	6,492	6,492	6,492
Within R^2	0.046	0.051	0.033	0.047	0.067	0.321	0.329	0.307	0.322	0.378
Total R^2	0.254	0.229	0.031	0.242	0.032	0.215	0.227	0.200	0.219	0.223

[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. All models include controls for log zipcode population in 2010, change in zipcode population 2010 to 2010, and relative home value as in Table 8.

Table 9a (across CBSAs): Effect on returns from a one standard deviation increase in CBSA-level risk

Panel A: Price Returns (sample mean = 3.99)

Table 4b Column	Risk Measure	Table 4b Coefficient on Risk Measure	Mean of Risk Measure	Std Dev of Risk Measure	Pct Point Change Relative to Mean Total Return	Pct Change Relative to Mean Total Return
Column 1	Return volatility	0.30	6.11	3.73	1.12	28.05%
Column 4	Systematic risk (beta)	1.13	0.98	0.90	1.02	25.49%
	Non-systematic risk	0.34	-0.02	1.33	0.45	11.33%
Column 5	Systematic risk (beta)	0.71	0.98	0.90	0.64	16.02%
	Idiosyncratic risk	0.04	15.4	16.8	0.67	16.84%

Panel B: Total Returns (sample mean = 13.13)

Table 4b Column	Risk Measure	Table 4b Coefficient on Risk Measure	Mean of Risk Measure	Std Dev of Risk Measure	Pct Point Change Relative to Mean Total Return	Pct Change Relative to Mean Total Return
Column 6	Return volatility	0.19	6.11	3.73	0.71	5.40%
Column 9	Systematic risk (beta)	0.77	0.98	0.90	0.69	5.28%
	Non-systematic risk	0.14	-0.02	1.33	0.19	1.42%
Column 10	Systematic risk (beta)	0.49	0.98	0.90	0.44	3.36%
	Idiosyncratic risk	0.03	15.4	16.8	0.50	3.84%

[a] Values obtained by multiplying the coefficient on the specified risk measure by its standard deviation for the sample used in Table 4b.
[b] Values obtained by dividing the percentage point effect by the mean price return (Panel A) and total return (Panel B) as indicated in the panel title for the sample used in Table 4b.

Table 9b (within CBSAs): Effect on returns from a one standard deviation increase in zipcode-level risk

Panel A: Price Returns (sample mean = 4.60)

Table 8b Column	Risk Measure	Table 8b Coefficient on Risk Measure	Mean of Risk Measure	Std Dev of Risk Measure	Pct Point Change Relative to Mean Total Return[a]	Pct Change Relative to Mean Total Return[b]
Column 1	Return volatility	0.14	6.94	3.48	0.49	10.59%
Column 4	Systematic risk (beta)	0.27	0.99	0.54	0.15	3.17%
	Non-systematic risk	0.12	0.00	3.42	0.41	8.92%
Column 5	Systematic risk (beta)	0.25	0.99	0.54	0.14	2.93%
	Idiosyncratic risk	0.02	14.18	17.4	0.35	7.57%

Panel B: Total Returns (sample mean = 14.18)

Table 8b Column	Risk Measure	Table 8b Coefficient on Risk Measure	Mean of Risk Measure	Std Dev of Risk Measure	Pct Point Change Relative to Mean Total Return[a]	Pct Change Relative to Mean Total Return[b]
Column 6	Return volatility	0.31	6.94	3.48	1.08	7.61%
Column 9	Systematic risk (beta)	0.58	0.99	0.54	0.31	2.21%
	Non-systematic risk	0.29	0.00	3.42	0.99	6.99%
Column 10	Systematic risk (beta)	0.50	0.99	0.54	0.27	1.90%
	Idiosyncratic risk	0.06	14.18	17.4	1.04	7.36%

[a] Values obtained by multiplying the coefficient on the specified risk measure by its standard deviation for the sample used in Table 8b.
[b] Values obtained by dividing the percentage point effect by the mean price return (Panel A) and total return (Panel B) as indicated in the panel title for the sample used in Table 8b.

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:

$$a_{h,t} = \frac{z_{h,t} - z_{h,t-1}}{z_{h,t-1}} \quad \text{(A.1)}$$

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.

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

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),

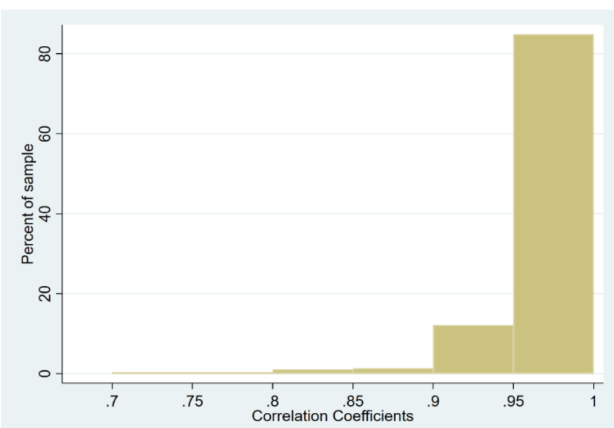
$$ZHVI_{t-1,i} = \frac{ZHVI_{t,i}}{1+A_{t,i}}, \text{for } t = 0, T-1 \quad . \tag{A.3}$$

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.

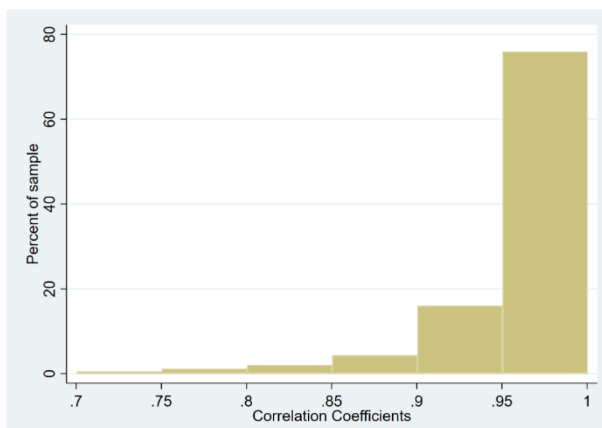
The single-family Zillow Home Value Index (ZHVI) is closely correlated with the single-family Federal Housing Finance Agency's (FHFA) repeat sales Home Price Index (HPI) at the CBSA and zipcode levels (including both sales and appraisals when constructing the FHFA index). Figures A-1 and A-2 display 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: Correlation Between Zillow and FHFA Single Family Home Price Indices

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



Panel 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 95% of CBSAs the correlation between the Zillow and FHFA single-family home price indices is above 0.90.

[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.