Risk-Return Trade-Offs in Real Estate Markets Across and Within 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. At both levels of geography, this occurs because house price volatility varies with local supply elasticity and propensity for demand shocks. Market-wide 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 large urban areas neighborhood-level idiosyncratic risk is more important and contributes to higher average returns in city centers. Our findings indicate that spatial differences in return to residential real estate persist in equilibrium, complementing persistent spatial variation in price levels. As with other assets, higher housing returns are associated with greater exposure to risk.

JEL Codes: R0, G1
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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 in Figure 1, which plots 1997-2019 nominal quality-adjusted home price indexes for San Diego, Milwaukee and Cleveland. Home prices increase at an average annual rate of roughly 6.9%, 2.8%, and 1.5% for the three cities, respectively. Similar differences are present in Table 1 for the 20 lowest and 20 highest appreciating cities over the same period. Durable housing 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 limit development 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 not nearly as well known. Within large 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 among small urban areas (those with fewer than 250,000 people) there is little evidence of spatial differences in returns across communities.[1] At first glance, these patterns are surprising. One reason is that within growing cities, profit-seeking developers should direct investment to higher yielding neighborhoods which creates pressure for stable relative prices and similar rates of price appreciation across communities (e.g. Liu, Nowak and Rosenthal, 2016). Demand-side substitution across neighborhoods should also create pressure for stable relative prices (e.g. Couture and Handbury, 2020).

This paper emphasizes two features of real estate markets that help to explain the patterns above. The first is that risk-return tradeoffs contribute to spatial patterns of housing returns across- and within

[1]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 1997-2019. 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.

cities. This differs from longstanding literature that has modelled spatial patterns of home price *levels* within and across cities. See for example reviews of within-city patterns in Brueckner (1987) and Duranton and Puga (2015) and extensions of Rosen-Roback across-city models in Blomquist, Berger and Hoehn (1988), Gyourko and Tracy (1991), and Chen and Rosenthal (2008). Our emphasis on spatial patterns of housing risk-return tradeoffs also contrasts with previous studies that confirm the presence of such tradeoffs but without considering spatial patterns. This includes Crone and Voith (1999), Cannon, Miller, and Pandher (2006), and Case, Cotter and Gabriel (2011). We note that these studies focus only on housing capital gains or price returns as referred to in the finance literature (e.g. Han, 2010, 2013), which motivates our second line of inquiry.

A recent set of studies have emphasized that the distinction between housing price returns and total returns can be important, where the latter equal price returns plus rent (dividend payment) relative to value, often referred to as the cap rate.[2] Amaral et al (2021) and Demers and Eisfeldt (2022), for example, document an inverse relationship between price returns and cap rates that dampens spatial variation in total housing returns relative to price returns. In a user cost model, we show that this can arise because anticipated capital gains increase price returns while reducing cap rates. Investors in income-generating rental property should, therefore, focus primarily on total returns when comparing housing to alternative assets like stocks and bonds. That does not necessarily carry over to homeowners, however, who comprise roughly two-thirds of the U.S. housing market. For homeowners, housing investment is tied to their residence, exposing the family and the market to housing consumption risk that is sensitive to house price movements. Several studies have considered this.

Sinai and Souleles (2005) model homeownership decisions as being sensitive to tradeoffs between rent risk and house price risk. They emphasize that fewer anticipated years in the home reduces exposure to possible increases in rent while increasing risk associated with house price volatility. In part, that is because homeowner capital gains and losses are realized in lump sum upon moving out of the

[2] See, for example, Bao and Feng (2018), Jorda et al (2019), Amaral et al (2021, 2024) Eichholtz et al (2021), Chambers et al (2021), Sagi (2021), Giacoletti (2021), Demers and Eisfeldt (2022), and Gupta et al (2022).

home and discounting reduces the value of future returns. In related work, Han (2010, 2013) emphasizes that house price volatility exposes homeowners to both financial risk and housing consumption risk. The former supports the usual positive relationship between risk and return and implies that homeowners should enjoy higher average returns in risky, volatile markets. The latter goes in the opposite direction. In this instance, families are willing to accept lower expected financial returns if buying into a volatile market secures their future housing consumption, mitigating risk that they might be unable to afford their preferred level of housing quality in the future.[3] Sinai and Souleles (2005) and Han (2010, 2013) both provide evidence in support of their models.

Although not considered in the studies above, the widespread use of mortgage debt to finance home purchases also contributes to housing consumption risk and sensitivity to house price movements. This became especially apparent following the 2007 housing price crash when vast numbers of homeowners found themselves underwater with negative net equity. These families were mostly unable to refinance into more affordable mortgages despite falling loan rates, and for many, recently obtained ARM loans with teaser rates that had begun to reset up to sharply higher values. Combined with recession-related job and income loss, many underwater homeowners had no choice except to default on their loans, forcing them to move out of their homes.[4] For these and related reasons above, we consider risk-return patterns for both price and total returns in the empirical work that follows.

To establish our results, we utilize monthly home price and rent indexes from Zillow Inc. Separate indexes are available at the city and zipcode levels and for each location. Importantly, our data are based on all single-family homes in a geographic market, including owner-occupied and rental, but we

[3] Han (2013) provides evidence that the housing consumption hedge motive will be especially strong when families operate in positively correlated housing markets. In such instances, rising local home prices generate capital gains that help protect a homeowner's ability to purchase a subsequent home in a correlated market that has experienced similar price increases.

[4] The post-crash sequence of events above reinforces ideas emphasized by Davidoff (2006) who showed that homeownership exposes families to greater risk when their income stream is positively correlated with house price movements, as with individuals employed in construction or other parts of the real estate sector. The description above also reinforces well-known arguments that mortgage default requires negative net equity along with a trigger that prompts a family to move out of their home (e.g. Foote, Gerardi and Willen, 2008), as with job and income loss.

are not able to separate owner-occupiers from pure investors. The price series are available throughout the 1997-2019 period while the rent series are available only from 2011 to 2019. When analyzing drivers of risk-return tradeoffs we focus just on the 2011-2019 period. This allows us to compare patterns for price and total returns for a common period. Focusing on returns in the latter period also allows us to control for lagged local housing market volatility which plays a central role in our empirical strategy.

We seek to identify the impact of *anticipated* volatility on risk-return tradeoffs. To do so, we first smooth away short-term dynamics.[5] This helps to mitigate the effect of possible periodic mispricing that would be followed by a market correction and which could cause short-term volatility to be endogenous. To eliminate that and related concerns, we focus on cross-section regressions in which the dependent variable is a location's average year-over-year housing return based on monthly data over the 2011-2019 period. That measure is then regressed on the location's monthly year-over-year price volatility from the 1997-2010 period, encompassing the beginning and end of the boom-bust cycle experienced by many U.S. cities at that time (as with San Jose in Figure 1). An identifying assumption is that volatility over the 1997-2010 period is exogenous to the one-decade ahead average year-over-year return. Also, that 1997-2010 volatility is a good proxy for investor expectations of 2011-2019 volatility, consistent with evidence shown later.

Patterns confirm that risk-return tradeoffs are present across and within cities and are amplified in locations that have both inelastic supply and a propensity for demand shocks.[6] At the CBSA level, a one standard deviation difference in the volatility of price returns is associated with an increase in price and total returns of roughly 28% and 5.5%, respectively. Within large CBSAs, the corresponding magnitudes at the neighborhood level are 12% and 9%, respectively. The smaller magnitudes based on total returns are consistent with discussion above that higher anticipated price returns reduce equilibrium rent-to-price

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[5] See, for example, Danielsson et al (2013), Glaeser and Nathanson (2015), and DeFusca et al (2018).
[6] A number of studies have demonstrated that zoning and topographic constraints contribute to spatial variation 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).

ratios.[7] The smaller magnitude of price returns within versus across CBSAs likely reflects a lesser scope for within-city variation in supply and demand conditions that drive house price volatility.

We next seek to clarify the nature of risk that drives risk-return tradeoffs. As in the financial literature, we distinguish between market-wide *systematic risk* that affects returns on all assets (as with interest rate shocks) versus *idiosyncratic risk* that is specific to a given asset (as with the quality with which a company is managed). An important tenet from finance is that exposure to idiosyncratic risk can be reduced or even eliminated by forming a sufficiently diversified portfolio of assets. In that event, risk-return tradeoffs would be driven primarily by systematic risk which cannot be diversified away. If investors are unable to form diversified portfolios, idiosyncratic risk would be priced into higher returns.

Extending these ideas to our real estate context, each location's stock of single-family homes in the Zillow data file is treated as a separate asset, where location is sometimes measured at the CBSA level and in other models at the neighborhood level. Focusing once again on lagged measures of risk from 1997-2010, we estimate separate time series CAPM models using monthly data and based on housing returns for each location. This generates a unique estimate of beta for each CBSA and zipcode that drives investor perceptions of risk and their investment decisions. As in the CAPM literature, beta reflects exposure to *systematic* risk for an asset relative to its broader market for which beta is normalized to 1. 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).[8] 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.

[7] Our findings also complement Amaral et al (2024) who calibrate a model designed to highlight the nonlinear effect of declining real interest rates on home price dispersion across cities.

[8] Recent work by Damen et al (2025) also uses lagged stock returns to measure market level returns when evaluating risk-return patterns in the rental market in the Netherlands and also roughly 120,000 loans purchased by Fannie Mae and Freddie Mac. They find that market frictions in the lower tier of the market support higher returns in that market segment but not in a way that is offset by greater exposure to risk.

Seiler and Voicu (2013) make a similar argument while Cotter, Gabriel and Roll (2015) document the degree of housing market integration.

For the reasons above and as in Cotter, Gabriel and Roll (2015), we use only housing returns when measuring market returns in the CAPM model. When we estimate CBSA-level betas, we treat the set of CBSAs in the United States as the broader housing market. In this instance, systematic risk is driven by national shocks like interest rate movements, business cycles, and changes in federal tax policy. Idiosyncratic risk is specific to a given CBSA and could include shocks to a dominant local industry like the technology sector in San Jose or the risk of coastal flooding in New Orleans and New York. When we estimate neighborhood-level betas, we treat the CBSA as the broader housing market. In this instance, systematic risk is driven by national-level events along with CBSA-specific phenomena like those just described. Idiosyncratic shocks are at the neighborhood level and could include flood risk, crime, shifts in community racial composition, or other local shocks that may affect neighborhood price and rent.[9]

Because most housing market investors hold one or at most only a few properties, their portfolios are highly undiversified. This suggests that pricing in housing markets may be sensitive to idiosyncratic risk that is specific to a location (asset). Results support that prior. For both levels of geography, and following the finance literature, idiosyncratic risk is measured as the standard deviation of the squared residuals from the location-specific CAPM regressions (e.g. Merton (1987), Cannon, Miller, and Pandher (2006), Case, Cotter and Gabriel (2011).[10] At the CBSA level, systematic and idiosyncratic risk both contribute to risk-return tradeoffs and with roughly equal magnitude. Across neighborhoods within larger CBSAs, idiosyncratic risk has a notably larger effect on risk-return tradeoffs. Moreover, the magnitude of these effects is large enough to be important.

[9] For both levels of geography, we restrict our analysis to CBSAs with population over 100,000 in year 2000.

[10] Although most housing market studies do not delve into the underlying drivers of housing-specific idiosyncratic risk, two exceptions are Giacoletti (2021) and Sagi (2021). Both of these studies emphasize that illiquidity of real estate investments contributes to a term structure to idiosyncratic risk. Giacoletti (2021) also highlights that limited information on home values can contribute to illiquidity and idiosyncratic risk by increasing uncertainty about market value at the time of sale. In this context low density areas may be subject to greater risk because of fewer sales and reduced information. Partly with this in mind, in the within-city estimation later in the paper, we control for neighborhood density.

To establish our results, Section 2 develops our model while Section 3 describes the data and select summary patterns for the two levels of geography. Sections 4 and 5 present estimates for the across- and within-CBSA analyses, respectively. Magnitudes of estimated effects are discussed in Section 6, and Section 7 concludes.

2. Risk-Return Model

This section has three parts that help guide and interpret the empirical work that follows. The first clarifies the relationship between price and total returns in a simplified setting that does not distinguish between financial versus housing consumption risk or take into account mortgage contract design. The second develops the CAPM model used to estimate beta and idiosyncratic risk. The third summarizes three sets of regressions used to evaluate spatial patterns of returns and risk.

2.1 Returns to real estate investment

As with financial assets like stocks and bonds, total returns ρ_t^{Tot} from owning a home over one period, *t*-1 to *t*, can be expressed as the sum of the one-period capital gain plus the one-period dividend (rent) payment, both normalized by the initial period price of the home (e.g. Gupta et al, 2022; Eichholtz et al, 2021; Sagi, 2021; Chambers et al, 2021; Giacoletti, 2021; and Jorda et al, 2019). The former is referred to as price returns and is given by $\rho_t^P = \frac{P_t - P_{t-1}}{P_{t-1}}$. The latter is written as $\frac{R_t}{P_{t-1}}$ and is the cap rate or yield for income generating (rental) properties. In the discussion below, we assume one-period rental contracts that are set at the start of the period so that $\frac{R_t}{P_{t-1}}$ is known in *t*-1 while ρ_t^P is uncertain and exposes investors to risk.

We decompose ρ_t^P into the sum of unanticipated capital gains g_t^u that have zero expectation over time plus anticipated capital gains g_t^a. The latter includes drivers of price returns that investors know in advance such as the elasticity of supply and population trends. Price returns can then be written as

$$\rho_t^P = g_t^u + g_t^a \quad , \tag{2.1a}$$

where $E[\rho_t^P] = g_t^a$. Substituting, total returns (ρ_t^{Tot}) can be written as

$$\rho_t^{Tot} = \rho_t^P + \frac{R_t}{P_{t-1}} = g_t^u + g_t^a + \frac{R_t}{P_{t-1}} \tag{2.1b}$$

where $E[\rho_t^{Tot}] = g_t^a + \frac{R_t}{P_{t-1}}$.

Suppose now that investors expect real rent to grow at a constant rate θ so that expected rent s periods beyond period t is given by $E(R_{t+s}) = R_t(1+\theta)^s$ for all $t \geq 0$. Price level in any period t can be written as,

$$P_t = \sum_{s=0}^{\infty} \frac{E[R_{t+s}]}{(1+\delta)^s} = R_t \sum_{s=0}^{\infty} \left[\frac{1+\theta}{1+\delta}\right]^s \quad . \tag{2.2}$$

In (2.2), δ is the discount rate with $\theta < \delta$ so that price is finite. Observe also that if real rent is expected to be constant ($\theta = 0$), expression (2.2) yields $\frac{R_t}{P_t} = \delta$ which sets the cap rate equal to the discount rate. Substituting from (2.2) into (2.1a) and treating t-1 as the current period so that P_{t-1} is known, the anticipated one period price return can be written as

$$g_t^a = \frac{E[P_t]}{P_{t-1}} - 1 = \frac{R_t \sum_{s=0}^{\infty}\left[\frac{1+\theta}{1+\delta}\right]^s}{R_{t-1} \sum_{s=0}^{\infty}\left[\frac{1+\theta}{1+\delta}\right]^s} - 1 = \theta \quad , \tag{2.3}$$

with $R_t = (1+\theta)R_{t-1}$. This says that price is expected to grow at the same rate as rent. Also, that g_t^a will be time invariant if real rent is expected to grow at a constant rate θ. We adopt this notation below.

Consider next an alternative perspective on housing rent that is often characterized as the user cost of owning a home, defined as the cost of owning a home for one period, a summary of which is in Himmelberg et al (2005). With competitive markets, the zero-profit condition determines the market rent on a unit which we write as,

$$\begin{aligned} R_t &\approx \left[r_f + (d+m) + p_{tax} - \theta + \phi\right] * P_{t-1} + \tau R_t \\ &= \frac{1}{1-\tau}\left[r_f + (d+m) + p_{tax} - \theta + \phi\right] * P_{t-1} \\ &= \delta * P_{t-1} \end{aligned} \tag{2.4}$$

where $\delta = \frac{1}{1-\tau}\left[r_f + (d+m) + p_{tax} - \theta + \phi\right]$ is the rate at which housing investors discount future rent in (2.2). In this expression the cost of holding a home between *t*-1 and *t* increases with the real risk-free interest rate r_f, the rate at which the home depreciates allowing for maintenance $d + m$, property taxes at rate p_{tax}, and the tax rate on rental income τ.

Adjustments in (2.4) for financial risk and housing consumption risk as described in the Introduction (e.g. Han, 2013) are assumed to occur through two channels. Notice that user cost declines with the expected rate at which the home appreciates θ. This term is determined by events that are known in advance (e.g. announced changes to zoning, regulation, or the arrival of major employers). We also assume that θ is sensitive to market adjustment for risk of unanticipated shocks that could affect future market conditions. Additional risk adjustment occurs through ϕ which is specified as a proportion of the current price level. While θ could be positive or negative allowing for different sources of risk, θ is always positive under the assumption that investors in rental property will charge higher rent in riskier markets for a given price level.[11]

Observe next that apart from P_{t-1}, the terms on the right side of (2.4) are likely to vary little on a year-over-year basis, including τ, r_f, d, m, p_{tax}, θ and ϕ. This is an approximation. Dividing both sides of (2.4) by P_{t-1} gives the rent-to-price ratio or cap rate,

$$\frac{R_t}{P_{t-1}} = \frac{1}{1-\tau}\left[r_f + (d+m) + p_{tax} - \theta + \phi\right] \qquad . \qquad (2.5)$$

Within a given location, this will also vary little from year to year and is approximately equal to one-period net expenses per dollar value of the property.

Except for the real interest rate r_f, the terms in (2.5) all vary across locations, which we index below by *i*. Rearranging (2.5), we can approximate the last two terms in (2.1b) as,

$$\theta_i + \left(\frac{R}{P}\right)_i \approx \left(\frac{1}{1-\tau}\left[r_f + (d+m) + p_{tax} + \phi\right]\right)_i \qquad (2.6)$$

[11] Expression (2.5a) ignores differences in tax treatment for investors in rental property versus homeowners, including deductions for maintenance, tax on realized versus imputed rent, and tax rates on capital gains. This simplifies but does not affect implications from the model.

where the approximation is exact as τ goes to zero as for owner-occupiers for whom rent is not taxed in (2.4). Substituting from (2.6) into (2.1a) and (2.1b), price and total returns vary across time and location and are given by,

$$\rho_{i,t}^{P} = g_{i,t}^{u} + \theta_i \ , \tag{2.7a}$$

$$\rho_{i,t}^{Tot} = g_{i,t}^{u} + \theta_i + \left(\frac{R}{P}\right)_i \quad . \tag{2.7b}$$

In these expressions, unanticipated capital gains $g_{i,t}^{u}$ vary over time as before and can also differ across locations. The other terms vary only across locations, as an approximation. Consistent with (2.5), risk affects housing returns through direct effects of θ_i on price and total returns and a further effect on total returns through the cap rate. Notice however that ϕ_i only affects returns through $\left(\frac{R}{P}\right)_i$ because it is assumed to be proportional to price level and differences out of the ratio $\frac{P_t - P_{t-1}}{P_{t-1}}$.

Our model above has two implications for the empirical work that follows that are worth noting. The first is that expressions (2.5) and (2.7b) suggest that risk-return tradeoffs are likely to be smaller for total returns relative to price returns. To see why, notice that as written above θ_i cancels out of (2.7b) in communities dominated by homeowners for which the tax rate on rent in (2.4) is zero. More generally, the opposite-signed effects of θ_i on price returns and $\left(\frac{R}{P}\right)_i$ contribute to the inverse relationship between price returns and cap rates noted in the Introduction and implicit in (2.6). That tendency will reduce variation in total returns relative to price returns and may reduce sensitivity to risk.

Notice also that the model above suggests that for each location i, the standard deviations of price returns and total returns over time should be approximately equal to the standard deviation of unanticipated capital gains, and therefore equal to each other:

$$\sigma(\rho_i^{P}) = \sigma(\rho_i^{Tot}) = \sigma(g_i^{u}) \quad . \tag{2.8}$$

This suggests that the variances of $\sigma(\rho_i^{P})$ and $\sigma(\rho_i^{Tot})$ across locations i = 1, …, n, should also be equal. Summary measures presented later are consistent with (2.8) and support our strategy of using the variance of $\sigma(\rho_i^P)$ across locations to proxy spatial variation in risk when analyzing both price and total returns.

2.2 CAPM and systematic versus idiosyncratic risk

This section considers the nature of risk to which housing investors are exposed, drawing on the capital asset pricing model (CAPM) and related distinctions between systematic and idiosyncratic risk. 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 so that for each individual asset *i*:

$$\frac{E(\rho_{i,t})-\rho_{f,t}}{Cov(\rho_{i,t},\rho_{M,t})} = \frac{E(\rho_{M,t})-\rho_{f,t}}{\sigma_M^2} \tag{2.9}$$

where $E\left(\rho_{i,t}\right) - \rho_{f,t}$ is the expected return on 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. Rearranging (2.9) yields:

$$E\left(\rho_{i,t}\right) - \rho_{f,t} = \beta_i * [E(\rho_{M,t}) - \rho_{f,t}] \quad , \tag{2.10}$$

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

The CAPM literature recognizes that (2.10) is restrictive in the sense that it allows the return on asset *i* to vary only with the risk-free rate and covariance with the market return (e.g. Fama and French, 2004). To allow for other drivers of $\rho_{i,t}$, it is common to add a constant and an error term to (2.10), α_i and $\varepsilon_{i,t}$, respectively. β_i is then estimated for asset *i* using,

$$\rho_{i,t} - \rho_{f,t} = \alpha_i + \beta_i * \left[\rho_{M,t} - \rho_{f,t}\right] + \varepsilon_{i,t} \quad . \tag{2.11}$$

We estimate (2.11) separately for each local housing market in our sample drawing on time series variation in that market and treating each location as a separate asset *i*. In all instances, we measure $\rho_{M,t}$ using only housing returns for reasons discussed in the Introduction. When we focus on risk-return tradeoffs at the CBSA level, we use the national housing market as the broader market *M* to which each

CBSA belongs (defined as the set of CBSAs in our sample). When we narrow that focus to within-CBSA neighborhood-level patterns, we use the CBSA as the broader market.

Substituting time-varying versions of expressions (2.7a) and (2.7b) into (2.11), the CAPM equations based on price and total housing returns are given by,

$$\rho_{i,t}^{P} - \rho_{f,t} = \alpha_i^P + \beta_i * \left[\rho_{M,t}^{P} - \rho_{f,t}\right] + \varepsilon_{i,t} \tag{2.12a}$$

$$\rho_{i,t}^{Tot} - \rho_{f,t} = \alpha_i^{Tot} + \beta_i * \left[\rho_{M,t}^{Tot} - \rho_{f,t}\right] + \varepsilon_{i,t} \ . \tag{2.12b}$$

Importantly, estimates of beta based on (2.12a) and (2.12b) are the same. In both cases beta reflects the covariance between time-varying unanticipated shocks at the local and market levels, $g_{i,t}^{u}$ and $g_{M,t}^{u}$. This is because, from (2.7a) and (2.7b), price and total returns differ only by time-invariant drivers of returns that are specific to the local housing market and denoted by α_i^P and α_i^{Tot} in (2.12a) and (2.12b).[12] This supports using price returns to measure beta for both price and total returns.

2.3 Estimating spatial patterns of risk-return tradeoffs

In the empirical work that follows, we present three sets of cross-section regressions, the focus of which is to shed light on spatial patterns of housing returns and related risk-return tradeoffs across locations *i* = 1, … n. All of the models are of the following form,

$$\bar{\rho}_i^{q} = \gamma_0 + \gamma_1 Risk_i + \gamma_2 x_i + e_i \ , \qquad \text{for all CBSAs } i = 1, \ldots \text{n} \tag{2.13a}$$

$$\bar{\rho}_i^{q} = \gamma_i + \gamma_1 Risk_i + \gamma_2 x_i + e_i \ , \qquad \text{for all zipcodes } i = 1, \ldots \text{n} \tag{2.13b}$$

where evidence of a positive and significant value for γ_1 is consistent with the presence of risk-return tradeoffs that contribute to spatial variation in returns.

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[12] To clarify, from (2.7b), $\rho_{i,t}^{Tot} = \rho_{i,t}^{P} + \left(\frac{R}{P}\right)_i$ and $\rho_{M,t}^{Tot} = \rho_{M,t}^{P} + \left(\frac{R}{P}\right)_M$. Substituting and rearranging, (2.12b) becomes

$$\rho_{i,t}^{P} - \rho_{f,t} = \tilde{\alpha}_i^{Tot} + \beta_i * \left[\rho_{M,t}^{P} - \rho_{f,t}\right] + \varepsilon_{i,t} \ ,$$

where $\tilde{\alpha}_i^{Tot} = \alpha_i^{Tot} + \beta_i * \left(\frac{R}{P}\right)_M - \left(\frac{R}{P}\right)_i$ and α_i^{Tot} is as in (2.12b).

As discussed in the Introduction, the dependent variables in (2.13a) and (2.13b) are always average year-over-year monthly housing returns over the 2011-2019 period for each location i, measured using both price and total returns with $q = \{P, Tot\}$. The terms γ_0 and γ_i are, respectively, a constant and CBSA fixed effects for the two equations, while x_i includes location-specific attributes not captured by the risk measure. $Risk_i$ is always measured based on variation in price returns, not total returns, for reasons noted in the previous sections. Finally, our measures of $Risk_i$ are based on lagged data from the 1997-2010 period, which encompasses the beginning and end of the boom-bust cycle experienced by many U.S. cities. For reasons outlined in the Introduction, these features help to address possible threats to identification and are supported by conceptual arguments in the previous two sections as well as summary patterns in the data that are presented shortly.

We first estimate (2.13a) and (2.13b) using $\sigma(\rho_i^P)$ as our measure of risk. This is our least restrictive and most robust approach to confirming a relationship between price volatility and returns.

Next, we treat price volatility and risk as arising from the interaction between supply elasticity (S_i) and demand shocks (D_i). Demand shocks contribute to volatility when supply is inelastic but should have limited effect when supply is elastic. Inelastic supply without demand shocks should also have little effect on volatility. Bearing this in mind, we decompose $\sigma\left(\rho_i^P\right)$ into a combination of S_i, D_i and their interaction and include all three terms in the model as our measure of $Risk_i$. Proxies for S_i are obtained from prior studies and are documented shortly. We approximate demand shocks using $D_i \approx e^{\omega_i}$ where ω_i is the residual from a cross-section regression of $\log\left[\sigma\left(\rho_i^P\right)\right]$ on a constant and $\log\left(S_i\right)$ as below,

$$\log\left[\sigma\left(\rho_i^P\right)\right] = a + b \cdot \log\left(S_i\right) + \omega_i \quad . \tag{2.14}$$

The specification in (2.14) treats S_i as time-invariant over our sample horizon. This implies that spatial variation in volatility of price returns is driven by demand shocks and is captured by the residual ω_i.

In our third set of models, we use estimates of beta β_i from the CAPM models in (2.12a) and (2.12b) to measure investor perceptions of systematic risk. As discussed earlier, when investors hold fully diversified portfolios, idiosyncratic risk should be diversified away and will not affect returns. That is not typically feasible however for most investors in the housing market who own only one or at most a few properties. For that reason, we also control for location-specific idiosyncratic risk measured as $\sigma(\varepsilon_i)$, the standard deviation of the residuals in the location-specific CAPM regressions in (2.12a) and (2.12b). Evidence discussed later shows that β_i and $\sigma(\varepsilon_i)$ are correlated. For that reason, we also experiment with an alternate measure that we refer to as non-systematic risk and which is designed to be independent of β_i. This is denoted as $e_{i,NS}$ and is measured as the residual from the regression below,

$$\sigma(\rho_i^P) = c_0 + c_1\beta_i + e_{i,NS} \quad . \tag{2.15}$$

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.[13] We measure house price appreciation using the monthly Zillow Home Value Index (ZHVI) for single-family homes which is available from 1996 through 2019. Important for our measures, for both CBSA and zipcode level geography, the index is seasonally adjusted and designed to measure quality adjusted home price level in the target area as well as home price appreciation. 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. This feature of the ZHVI and its analogue for the rent series discussed below allow us to measure rent-to-price level ratios in addition to returns.

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

[13] 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. 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 .

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%.

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

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.

As discussed earlier, some of our models include measures of local housing supply elasticity. 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.[14] The interpolated values are all positive with smaller values indicating lower supply elasticity.

For the CBSA-level analysis, we proxy for supply elasticity using the updated 2018 Wharton Land Use Regulatory Index (WLURI) index from Gyourko, Hartley, and Krimmel (2021) which we are able to match to 298 of the 362 CBSAs in our sample.[15] This index increases with the intensity of a CBSAs regulatory restrictions including caps on permitting and construction, density restrictions such as minimum lot size and related FAR restrictions, affordable housing requirements, and the tendency for re-zoning permits to be required. The index has mean zero with standard deviation one. We transform the index by reversing its sign and adding in the absolute value of its minimum plus a small amount. The transformed measure is then always positive with smaller values indicating lower supply elasticity.

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 instead take distance to the CBD into account (we use the same set of zipcodes in both cases). Allowing for availability across all datasets, our primary results are based on 254 CBSAs for the CBSA level analysis and 7,776 zipcodes for the neighborhood level analysis.

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[14] 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 effects of unobserved amenities separate from local supply elasticity.
[15] We 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.

3.2 Risk and return distributions for CBSA and zipcode level measures

This section compares the distributions of risk and return measures across locations for CBSA- and zipcode-level geography. We begin with Figure 3 which plots the distributions for the volatility of price returns (Panel A), beta (Panel B), idiosyncratic risk (Panel C), and non-systematic risk (Panel D), where each panel includes plots for both levels of geography. As is evident in Panel A, the 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, variation across CBSAs is more limited with a greater share of values concentrated around the mode. In Panel B the reverse is true. At the zipcode level the distribution of beta values is concentrated around 1 but is more skewed at the CBSA level which also has an elongated right tail. This suggests that systematic risk could play a greater role in driving risk-return tradeoffs across CBSAs as compared to across neighborhoods within cities, a point we return to later. The distributions of idiosyncratic risk in Panel C have similar shape for the two levels of geography. In both cases, there is a sharp mode with many locations in which idiosyncratic risk is small in magnitude, but also an elongated right tail indicating the presence of locations for which idiosyncratic risk is more pronounced. In Panel D, non-systematic risk is tightly concentrated around zero at the CBSA level while exhibiting an elongated right tail at the zipcode level.

Figure 4 plots the distributions of average price returns, total returns and rent-to-price ratios over the 2011-2019 period, with CBSA level plots in Panel A and zipcode-level plots in Panel B. From Section 2, recall that we can approximate average price returns as $\bar{\rho}_i^P \approx g_i^a = \theta_i$ where g_i^a is anticipated capital gains and θ_i is the anticipated rate of real rent growth. From (2.7b), we approximate average total returns as $\bar{\rho}_i^{Tot} \approx \theta_i + \left(\frac{R}{P}\right)_i$. Recall, also from expression (2.5) that $\left(\frac{R}{P}\right)_i$ increases with one-period expenses normalized by house price and decreases with the expected rate of capital gains θ_i.

In Figure 4, the distributions for $\bar{\rho}_i^{Tot}$ are right-shifted relative to $\bar{\rho}_i^P$ because $\left(\frac{R}{P}\right)_i$ is always positive. The tight distributions of $\left(\frac{R}{P}\right)_i$ relative to $\bar{\rho}_i^P$ and $\bar{\rho}_i^{Tot}$ also suggest that high or low values for θ_i

tend to be offset by variation in other factors that affect $\left(\frac{R}{P}\right)_i$ so that the net effect on cap rates is reduced. Locations with high values for θ_i, for example, tend to have high price levels because of past appreciation and many such locations have low property tax rates (as in California).[16] High expected price returns θ_i may also be associated with greater volatility and a larger risk premium ϕ in (2.5). In both examples the effect of high values for θ_i on $\left(\frac{R}{P}\right)_i$ will tend to be at least partially offset by correlated changes in other factors that drive rent-to-price ratios, narrowing the distributions of $\left(\frac{R}{P}\right)_i$ in Figure 4.

Finally, in Appendix B the sample means for the rent-to-price ratio at both the CBSA and zipcode levels are both roughly 9 (see Tables B-1 and B-2). The corresponding sample means for year-over-year total returns and price returns, also in Appendix B, differ by that amount and average roughly 13.5 and 4.5, respectively.

4. Across CBSA risk-return tradeoffs

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 over the 1997-2019 period. For each CBSA, values are reported for return volatility (σ^P), beta (β^P), idiosyncratic risk (σ_{ID}^P), and year-2000 CBSA population, all rank-ordered by return volatility with average values in the bottom row. Notice at the bottom of the table that low-volatility CBSAs have low average beta and low idiosyncratic risk compared to high-volatility cities: 0.44 and 4.84 compared to 2.34 and 37.53, respectively. Also, low-risk CBSAs are mostly smaller urban areas with fewer than one million people, as with Wichita and Syracuse, or large rust-belt metropolitan areas that have lost population, as with Pittsburgh, Buffalo and Rochester. High-volatility CBSAs are larger with populations often well over one million. Many of these cities are also perceived as high-amenity

[16] Property tax rates in the U.S. in 2023 range from 0.1% to 3.0% across counties: see rates reported by the Tax Foundation for 2025 at https://taxfoundation.org/data/all/state/property-taxes-by-state-county/ .

areas in California, Arizona and Florida. Detroit is the primary exception as the largest of the 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. Sample means and standard deviations of these and related measures are in Appendix B, Table B-1.

Note first in the middle of the table that correlation between $\sigma^{P}_{1997-10}$ and $\sigma^{P}_{2011-19}$ is 72.4%. The strong correlation supports our using lagged price volatility as a proxy for anticipated volatility. Correlation between lagged volatility $\sigma^{P}_{1997-10}$ and the transformed WLURI index is -30%, affirming that tighter supply restrictions are associated with greater price volatility. Correlations between $\sigma^{P}_{1997-10}$ and 2011-2019 price and total returns in the fourth row are 59.4% and 30.6%, respectively, suggesting the possibility of risk-return tradeoffs. In the lower portion of the fourth column, correlations between $\sigma^{P}_{1997-10}$ and 1997-2010 measures of beta, idiosyncratic risk, and non-systematic risk are 94.1%, 68.7%, and 33.7%, respectively. This indicates that systematic and submarket risk are closely linked to the volatility of price returns. Finally, beta and idiosyncratic risk are highly correlated (53.2%), a pattern we return to later.

4.2 Risk-return tradeoffs

Table 4 documents relationships between price returns and price return volatility with 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 yields an R-square value of 35.2%. Absent confounding effects, this suggests that risk-return tradeoffs help to explain variation in price returns across cities.

Columns 2-4 decompose volatility into proxies for location-specific supply elasticity and propensity for demand shocks. In column 2 we replace volatility with the transformed Wharton land use regulatory index (WLURI), which we denote as $\widetilde{W}$. The coefficient on $\widetilde{W}$ is negative and highly significant as expected, indicating that tighter restrictions on development (smaller value for $\widetilde{W}$) are associated with higher average price returns. This control, however, only explains 3.8% of variability in price returns across CBSAs based on the R-square value.

Column 3 adds in the propensity for a location to experience demand shocks over the 1997-2010 period, denoted *D*, where *D* is obtained as described in section 2.3. The coefficient on *D* is positive and highly significant. Moreover, adding *D* to the model increases R-square sharply to 33.8%. Column 4 adds in the interaction between $\widetilde{W}$ and *D*. With this addition, the coefficient on $\widetilde{W}$ becomes small, opposite in sign, and not significant. The coefficient on *D* is larger and the interaction term is negative and significant, indicating that more elastic supply (larger $\widetilde{W}$) reduces the positive effect of demand shocks on average price returns. This is as expected.

Columns 5 and 6 check for robustness. In column 5 we omit controls for volatility and instead include a set of controls that describe the socioeconomic attributes of a CBSA. This includes log population in the CBSA, median income, a measure of percent population growth if the city grew between 1990 and 2000, and a separate measure of the absolute value of percent 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). Estimates suggest that larger, growing cities exhibit higher price returns but as a group these controls have less explanatory power compared to volatility. Notice that R-square is just 25.2% compared to 34.9% in column 4.

Column 6 combines the controls from columns 4 and 5. The most notable change is that the coefficient on the interaction between $\widetilde{W}$ and *D* is larger than in column 4 and R-square increases to 0.440, indicating that the two sets of controls from columns 4 and 5 include different information. Overall, the results are robust and confirm that in the absence of demand shocks, supply constraints have little effect on price returns while elastic supply reduces risk associated with demand shocks.

Table 4b addresses the nature of risk. All of the models in the table include the same set of sociodemographic and superstar measures as in column 5 of Table 4a but these are suppressed to simplify presentation. Panel A of Table 4b uses price returns ($\bar{\rho}^{P}_{2011-19}$) as the dependent variable while Panel B uses total returns ($\bar{\rho}^{Tot}_{2011-19}$), both at the CBSA level. Column 1 proxies risk using volatility ($\sigma^{P}_{1997-10}$) while the other columns use different combinations of beta, idiosyncratic risk, and non-systematic.

Evidence of risk-return tradeoffs is present and similar for both price and total returns. Column 1 uses volatility to proxy for risk as in the previous table but this time augmented with additional CBSA controls. Columns 2, 3 and 4 replace volatility with beta, idiosyncratic risk and non-systematic risk, respectively. Column 5 includes both beta and idiosyncratic risk while column 6 includes beta and non-systematic risk. In all instances, the coefficient on beta is positive and highly significant as is the coefficient on idiosyncratic risk. Non-systematic risk has a positive coefficient but is not significant.

Based on column 5, both systematic and idiosyncratic risk are priced into higher average returns. This is consistent with earlier discussion that most housing market investors are highly undiversified, leaving them exposed to location-specific idiosyncratic risk.

5. Within CBSA risk-return tradeoffs

5.1 Summary measures

Table 5 reports correlations for within-CBSA level risk and return measures pooling data across all zipcodes in our sample. Variables included in the table are the same as in Table 3 except that the transformed WLURI index is replaced with the Baum-Snow and Han neighborhood-level measure of supply elasticity. Zipcode distance and employment density are also included. Sample means and related summary measures for these and related variables are in Appendix B, Table B-2.

The patterns in Table 5 mostly echo those for the cross-CBSA data although there are also some differences. Observe first in the fifth row that the correlation between $\sigma^{P}_{1997-10}$ and $\sigma^{P}_{2011-19}$ is 55.4%, once again supporting our assumption that price volatility from the 1997-2010 period is a good proxy for anticipated volatility during the 2011-2019 period. In the second column, correlation between 2011-2019 price returns $\bar{\rho}^P_{2011-19}$ with lagged volatility $\sigma^P_{1997-10}$, miles to the CBD, log employment density and supply elasticity are, respectively, 50.4%, -7.5%, 27.1%, and -31.9%, respectively. These patterns are as anticipated and are similar to those at the CBSA level. They indicate that returns are higher when volatility and risk is high, and in locations closer to the city center and/or in densely developed locations. Broadly, the correlations suggest that locations with low (more restrictive) supply elasticities exhibit higher returns. These patterns are also present for total returns in column 3.

Correlation between 2011-2019 price returns with 1997-2010 measures of beta, idiosyncratic risk, and non-systematic risk are 4.6%, 2.1%, and 50.4%, respectively (see the lower portion of the second column). The correlations with beta and idiosyncratic risk are much weaker than corresponding values for cross-CBSA patterns in Table 3, while the correlation with non-systematic risk is larger. A similar pattern of differences is also present for total returns. Perhaps most striking, the correlation between beta and idiosyncratic risk at the neighborhood level in the lower right of Table 5 is just 7.6%, down from 53.2% at the CBSA level in Table 3. Both within-CBSA measures of submarket risk are therefore mostly or fully independent of systematic risk. On the other hand, correlation between idiosyncratic and non-systematic risk is just 22.7%, indicating that the two measures still contain quite different information.

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 regressions of price returns over the full 1997-2019 period pooling data across all zipcodes. Panel A reports estimates for which miles to the CBD is the primary control of interest while Panel B replaces that measure with log employment density in the zipcode. Observations in columns 1-3 are zipcode-by-month with roughly 2.8 million records. Column 1 controls for just the location measure (distance or density), column 2 adds in controls for CBSA fixed effects, and column 3 adds in additional controls for month fixed effects. For both panels, estimates confirm that within-city price returns are higher closer to the center of the CBD and in high density locations. This is also true in column 4 which uses zipcode average year-over-year price returns 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. On average, returns are roughly 3% lower with each mile further away from the CBD, while the elasticity of price returns with respect to density is roughly 5%.

To allow for additional heterogeneity across urban areas, we estimated the model in column 3 of both panels separately for each CBSA. The distribution of distance and density coefficients across urban areas are plotted in Figure 5 for three size groupings of CBSAs based on year-2000 population including those with population below 250,000, between 250,000 to 500,000, and over 500,000. Estimates based on distance are in Panel A and those based on density are in Panel B.

In Panel A (distance), observe 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. A different pattern is present in the larger CBSAs. For this group, the distribution of distance coefficients (Panel A) is shifted to the left and for most urban areas price returns decline with distance. The plots in Panel B based on density mirror those based on distance. Among larger CBSA, for example, higher density is most often associated with higher price returns. Together, the two sets of plots indicate that among larger CBSAs, there is a clear tendency for price returns to be higher close to the city center and in densely developed neighborhoods. The patterns are more varied for smaller CBSAs.

Figures 6a and 6b confirm that within-CBSA measures of risk also exhibit strong spatial patterns. The figures plot zipcode-level risk measures pooled across all 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 in Panels A through D for 1997-2010 measures of return volatility (Panel A), beta (Panel B), idiosyncratic risk (Panel C), and non-systematic 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. This holds for all four indicators of risk although to different degrees across the measures. These patterns echo those highlighted earlier and suggest that within CBSAs exposure to risk tends to be higher in central, more densely developed areas.

5.3 Risk-return tradeoffs

Tables 7a and 7b repeat the cross-CBSA models in Table 4a only in this instance based on within-CBSA variation. To simplify, both here and for the remaining within-city analysis in the paper, we group CBSAs into two size categories for those with population less than 250,000 and those with population above 250,000.[17] As in Table 4a, estimates in Tables 7a and 7b (small and large CBSAs, respectively) focus just on the relationship between price returns and volatility. All of the models include CBSA fixed effects. Observe also that in the latter columns, zipcode-level sociodemographic and amenity controls include log employment density, log zipcode population in 2010, the change in log zipcode population between 2010 and 2022, and relative home value in 2019, measured as the zipcode's median home value divided by median home value in the CBSA. Estimates are similar when density is replaced with distance and are not reported to save space.

In Table 7a, the dominant pattern is that there is little evidence of a systematic relationship between price returns and volatility within small CBSAs. Almost all the volatility controls have small and insignificant coefficients and especially so after adding in controls for employment density and other zipcode-level socioeconomic controls. In the final column, notice that price returns are lower in high-density locations and higher in locations with comparatively expensive housing, suggestive of nicer local

[17] When separate regressions were run for CBSAs with population between 250,000 to 500,000, estimates were more similar to those based just on CBSAs with population over 500,000 as compared to CBSAs with population below 250,000. For that reason, we divided the CBSAs into those with population below and above 250,000.

amenities.[18] But the coefficients on supply elasticity, demand shocks and their interaction are small and not significant.

A different pattern is present for larger CBSAs in Table 7b where estimates echo those from the cross-CBSA models in Table 4a. In column 1, there is a positive and significant relationship between volatility and price returns. Progressing to column 4, as with the cross-CBSA models, price returns are higher in neighborhoods with inelastic housing supply that are also subject to demand shocks. In column 4, observe that the direct effect of supply elasticity is small and not significant while demand shocks and the interaction term have significant positive and negative effects, respectively. Moreover, these estimates hardly change when density and socioeconomic attributes are added in column 6. The same is not true, however, for density. In column 5, which includes only density and the socioeconomic controls, the elasticity of price returns with respect to density is 1 and is highly significant. When controls for supply elasticity and demand shocks are included in column 6, the estimated density elasticity shrinks to just 0.3% indicating that it has no role independent role after taking the other controls into account.

Tables 8a and 8b consider the nature of risk and are structured as in Table 4b from the cross-CBSA analysis. For both Tables 8a and 8b, notice that the upper panels consider price returns while the lower panels focus on total returns. As above, the sample in Table 8a is restricted to zipcodes in CBSAs with fewer than 250,000 people while the sample in Table 8b is based on CBSAs with population over 250,000. All models in both tables include CBSA fixed effects and the same set of zipcode-level socioeconomic controls and log employment density as in columns 5 and 6 of Tables 7a and 7b.

Note first in Table 8a that once again, there is no evidence of a risk-return relationship within smaller CBSAs. Both for price returns (Panel A) and total returns (Panel B) all the coefficients on volatility, beta, idiosyncratic risk, nonsystematic risk, and combinations of (in columns 5 and 6) are small and not significant.

[18] Higher price returns in low-density neighborhoods could also reflect a liquidity premium if investors expect it to be difficult to sell their homes in lightly developed locations (e.g. Giacoletti (2021) and Sagi (2021)).

The pattern is different for larger CBSAs in Table 8b where evidence of risk-return tradeoffs is present and robust. For both price and total returns, the coefficient on volatility (column 1) is positive and highly significant. Replacing this measure with beta (column 2), here too beta is positive and highly significant. The same is true when beta is replaced with idiosyncratic risk (column 3) and nonsystematic risk (column 4), both of which are only weakly correlated with beta as shown in Table 5. Consistent with these patterns, it is not surprising that when beta and idiosyncratic risk are included together in column 5, both are positive and highly significant and an analogous result is present in column 6 when beta and nonsystematic risk are included in the models.[19]

Overall, the estimates in Table 8b confirm that within larger CBSAs, variation across neighborhoods in systematic risk (beta) and idiosyncratic risk both contribute to within-CBSA risk-return tradeoffs. This echoes patterns for the cross-CBSA analysis. The importance of idiosyncratic risk is also once again consistent with the observation that most investors in the housing market hold undiversified portfolios which should contribute to idiosyncratic risk being priced.

6. Magnitudes

The discussion thus far has focused on qualitative patterns. This section considers magnitudes of the documented risk-return tradeoffs. Patterns are summarized in Tables 9a and 9b for the cross-CBSA and within-CBSA level analyses. In both cases we simulate the effect of a one-standard deviation increase in return volatility, beta, idiosyncratic risk and non-systematic risk using coefficient estimates from the most fully specified models. For the cross-CBSA analysis, these are drawn from Table 4b. For the within-CBSA analysis, we focus only on larger CBSAs (those with population over 250,000) and compute one-

[19] We also ran the regression in Table 8b omitting the socioeconomic and density controls, mirroring the structure of Table 7b. As before, omitting those controls had little effect on the risk coefficients when price returns was used as the dependent variable (Panel A). When total returns was used as the dependent variable (Panel B), the qualitative pattern was robust with highly significant coefficients on the different risk measures. Also, the magnitude of the coefficients on beta and the R-square values were reduced by roughly half, while the coefficients on idiosyncratic and non-systematic risk were largely unaffected.

standard deviations based just on that sample and draw on coefficients from Table 8b. In both Tables 9a (across CBSAs) and 9b (within-CBSAs), Panel A reports estimates based on price returns and Panel B reports estimates based on total returns.

Starting with 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 28.5% increase in price returns relative to the average price return across CBSAs. The same increase in return volatility corresponds to a 5.6% increase in total returns relative to its mean. Analogous estimates based on variation within larger urban areas (Table 9b) are 12.05% for price returns and 9.2% for total returns. These magnitudes suggest that risk-return tradeoffs are an important contributor to both across- and within-CBSA variation in spatial variation in housing returns.

Noteworthy patterns are also present when considering the nature of risk. At the CBSA level (Table 9a) we focus here on only models with idiosyncratic risk given earlier results that non-systematic risk does not have a significant effect. For both price and total returns, observe that systematic risk and idiosyncratic risk have similar magnitude effects on returns. For the two measures respectively, a one standard deviation increase causes price returns to increase by roughly 16.4% and 17.2%, while corresponding values for total returns are 3.4% and 3.9%.

The patterns differ within urban areas with population over 250,000 (Table 9b). In this instance, a one standard deviation increase in systematic risk has a notably smaller effect than a one standard deviation increase in idiosyncratic risk. For price returns (Panel A), the estimates are 2.9% versus 7.3% while for total returns the estimates are 2.0% and 7.8%. A similar but noisier pattern is present for non-systematic risk. These estimates further reinforce the idea that local idiosyncratic housing market risk cannot be diversified away and is priced into higher returns.

7. Conclusion

A fundamental tenet of urban theory is that equilibrium home price levels differ across and within cities to compensate for differences in amenities and other local advantages. This paper provides evidence of a related but less well-known phenomenon: systematic spatial variation in risk-return tradeoffs contributes to differences in housing returns across cities and across neighborhoods within larger urban areas. In both cases, this arises because of spatial variation in supply constraints and propensity for demand shocks that drive differences in house price volatility and risk. In small urban areas, evidence of such patterns is absent, likely because there is insufficient scale to allow for persistent within-city differences in market conditions needed to support neighborhood-level variation in risk and returns.

We also shed light on the nature of housing market risk. Because most housing market investors hold highly undiversified portfolios with only one or at most a few properties, it should be difficult for owners of residential property to diversify away exposure to local idiosyncratic risk. Evidence supports this view. Across CBSAs and across neighborhoods within larger CBSAs, systematic and local idiosyncratic risk are both priced into higher housing returns.

Finally, estimates indicate 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 5.6%. At the neighborhood level within larger metropolitan areas the corresponding estimates are roughly 12% and 9%.

A widely held policy view is that homeownership is an effective way for families to build wealth. While that may be true in some instances, this paper shows that locations with higher average housing returns expose homeowners and other housing investors to greater price volatility and risk. As with financial assets, higher expected housing returns come with potential costs.

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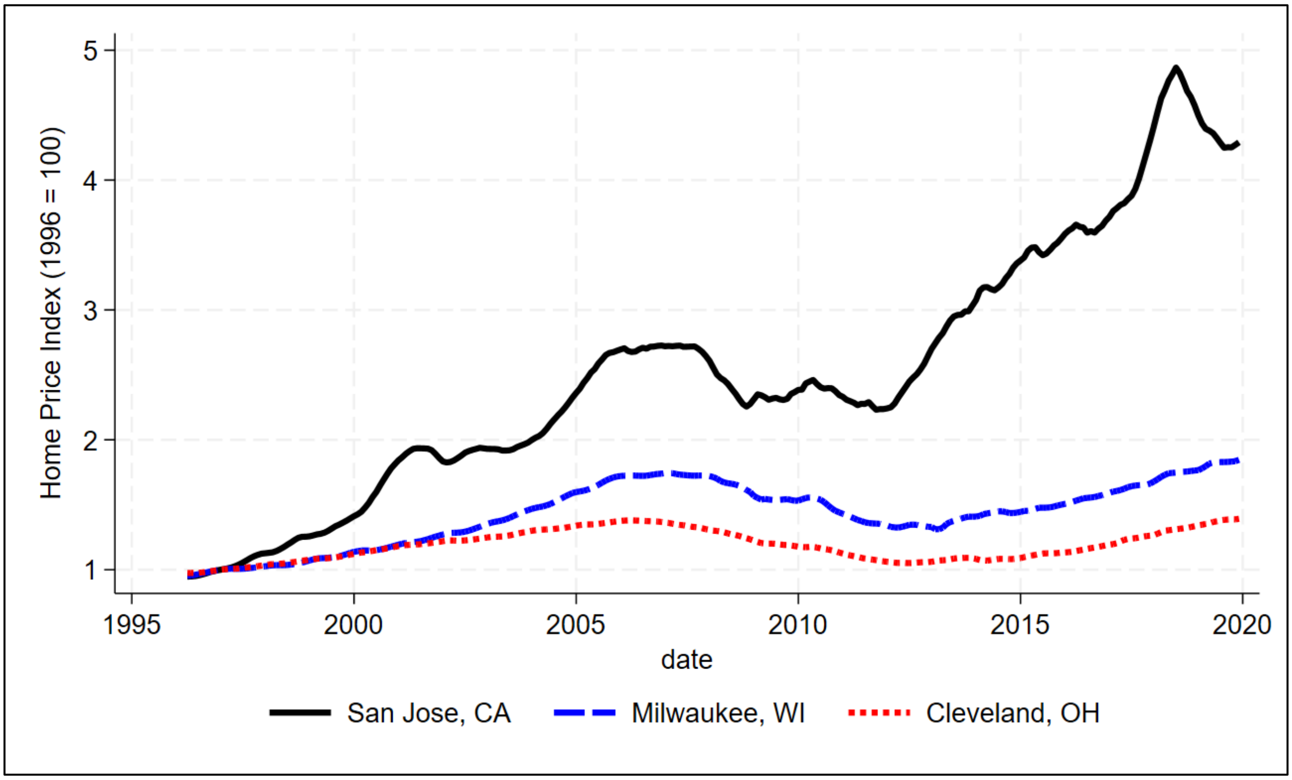
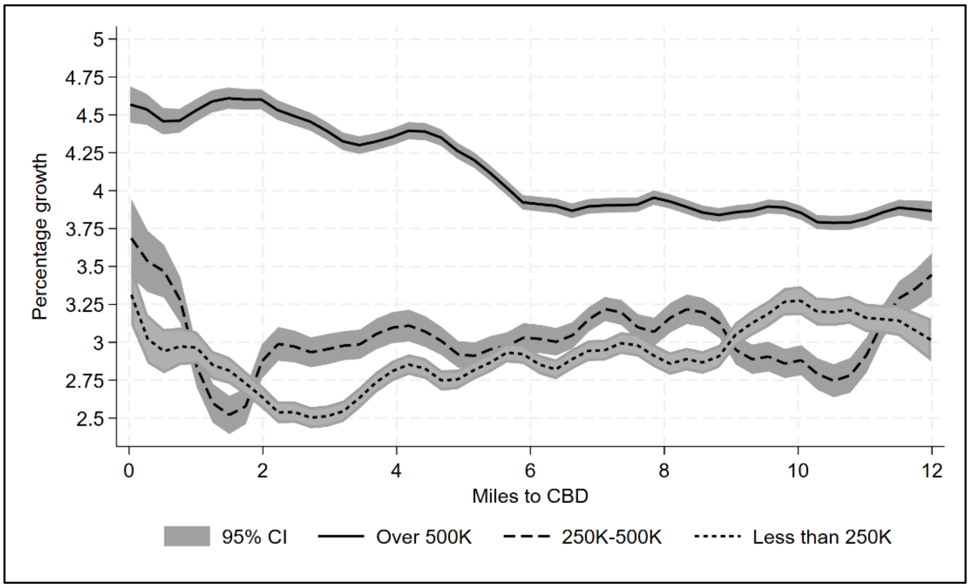
Figure 1: Single-family home value index for select CBSAs (January 1997 through December 2019)[a]



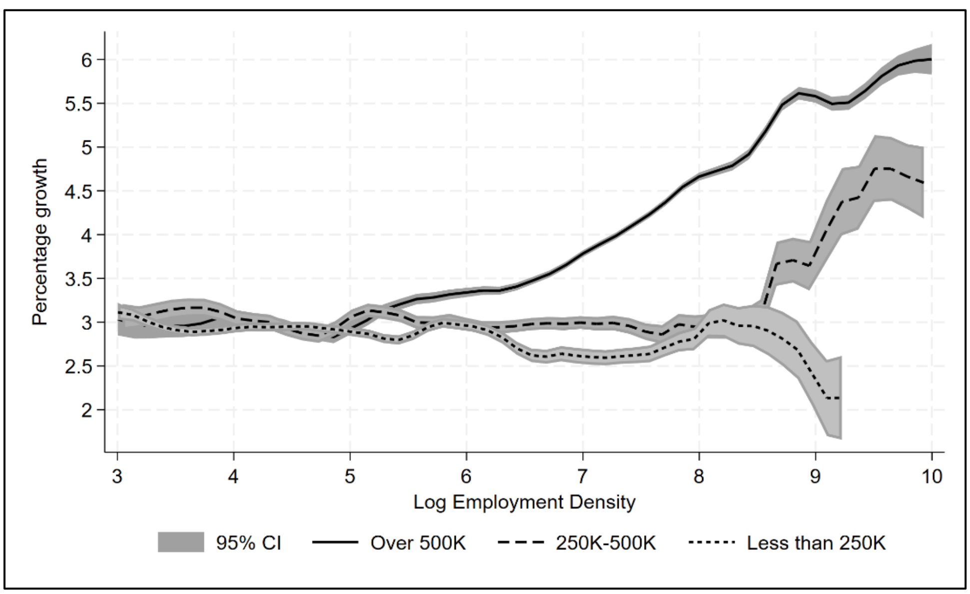
[a] Index data were provided by Zillow Group.

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

Panel A: Distance to CBD

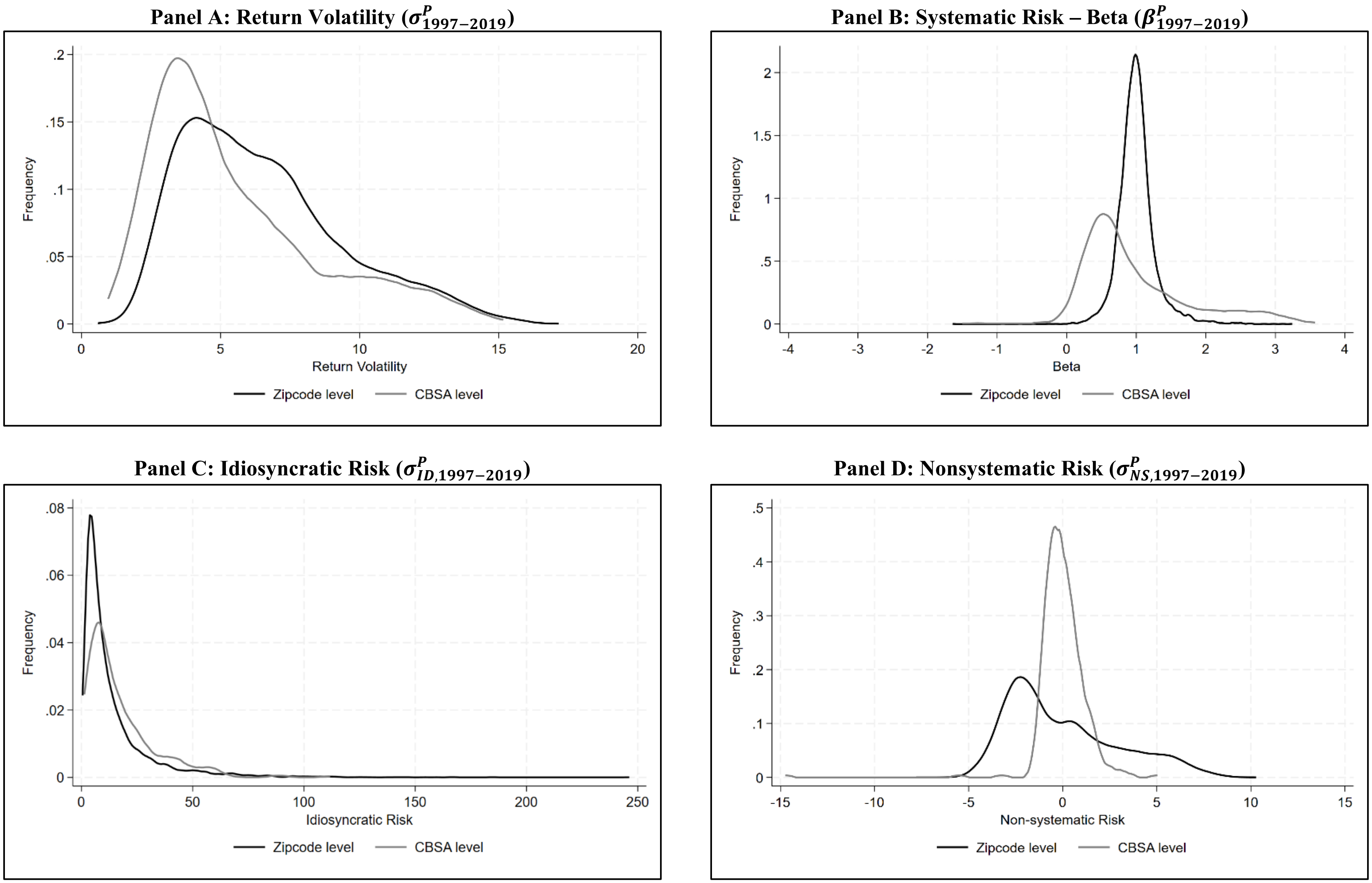


Panel B: Log Employment Density



[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.

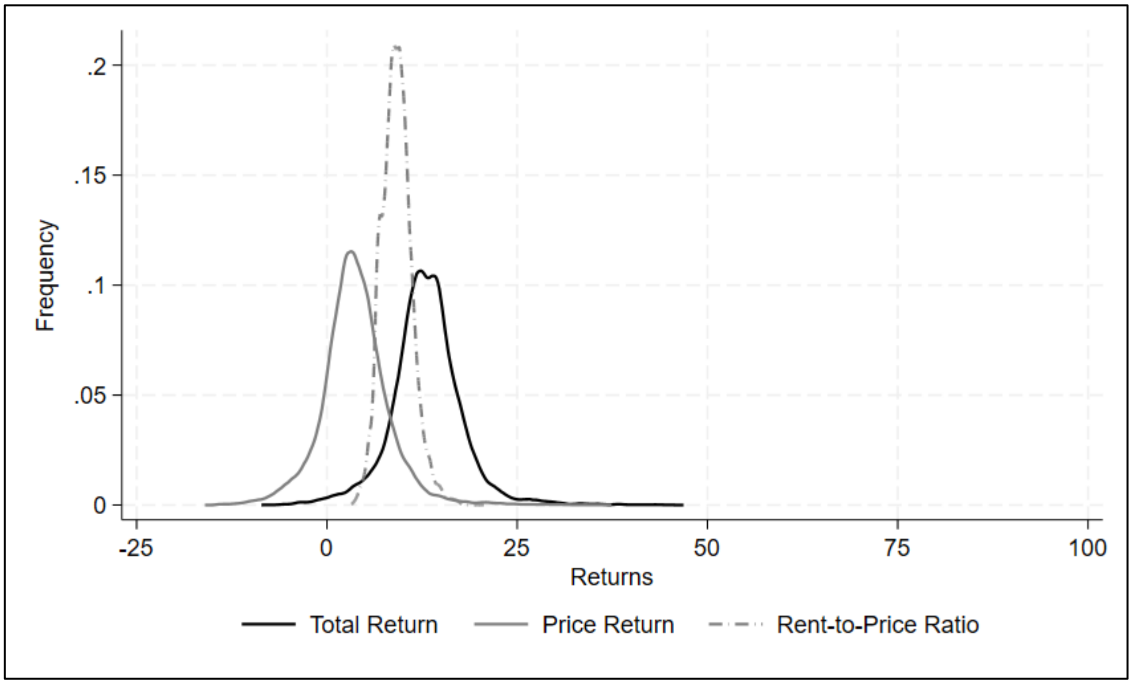
Figure 3: 1997-2019 Distribution of Risk Measures at the CBSA and Zipcode Level



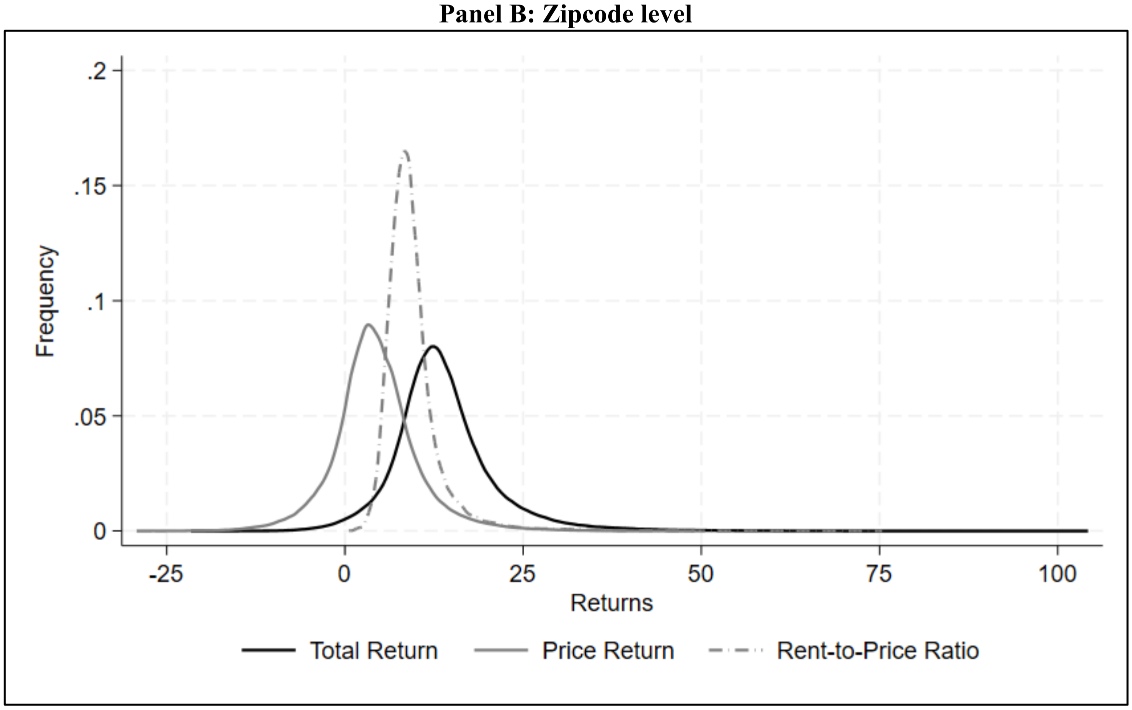
[a] Plotted values are drawn from zipcodes within 25 miles of their CBD and with log employment density between 2 and 10. Plots are smoothed using a local polynomial regression of degree 0 using the epanechnikov kernel and rule of thumb bandwidth selection process. Data were provided by Zillow Group.

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

Panel A: CBSA level



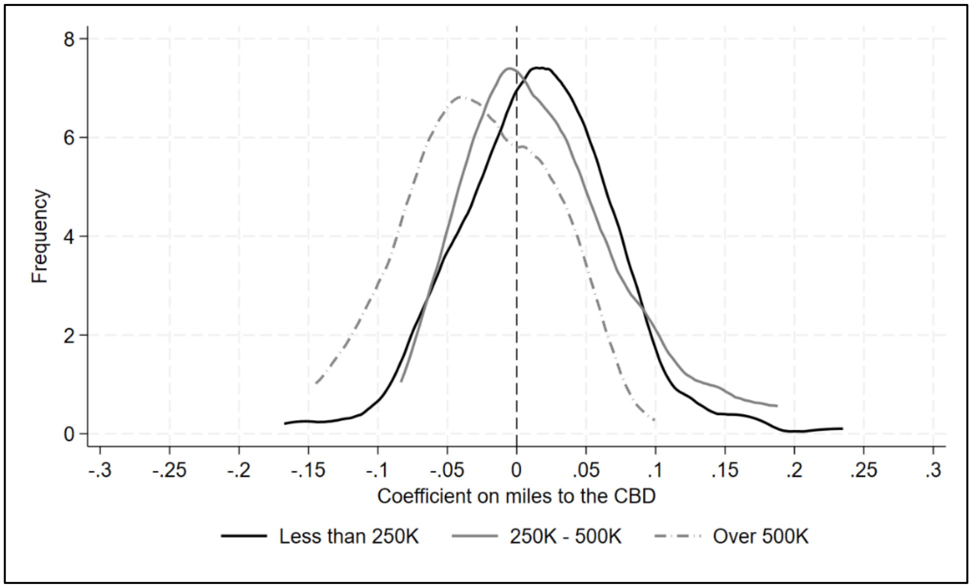
Panel B: Zipcode level



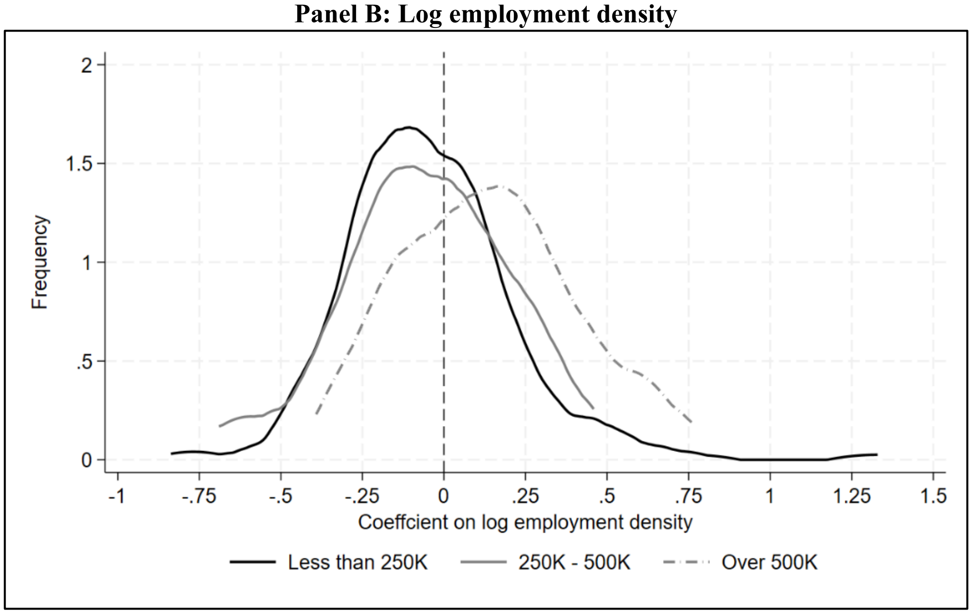
[a] Data were provided by Zillow Group.

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



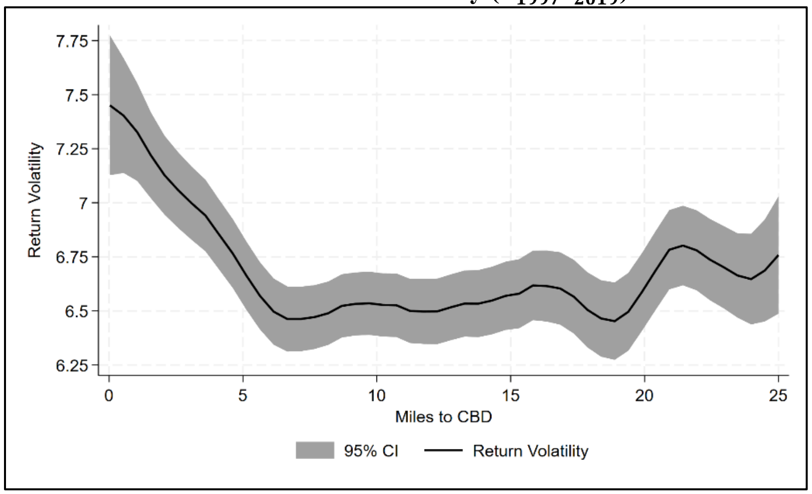
Panel B: Log employment density



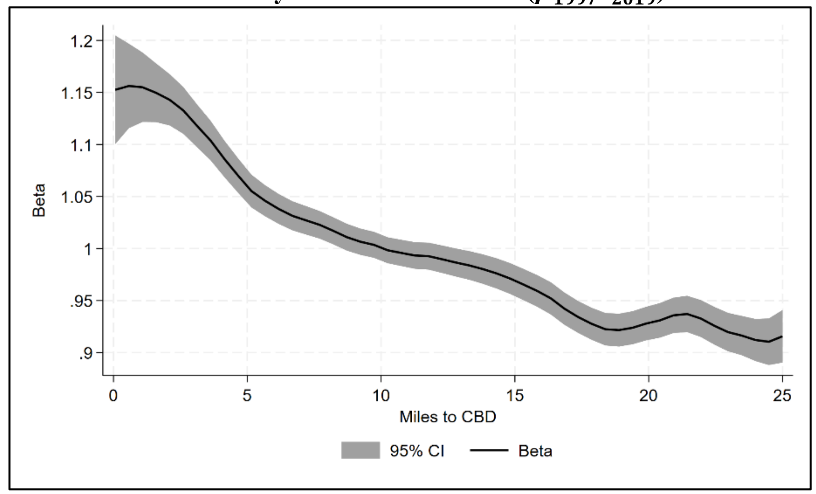
[a] Separate zipcode level regressions were first run for each CBSA based on $\rho_{it}^{P} = a_c + a_{i,c}x_i + Month\ FE + e_{it}$, where ρ_{it}^{P} is year-over-year percent growth in home prices in zipcode *i* for month *t*. Subscript *c* denotes individual CBSAs and *x* is distance to the CBD or 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]

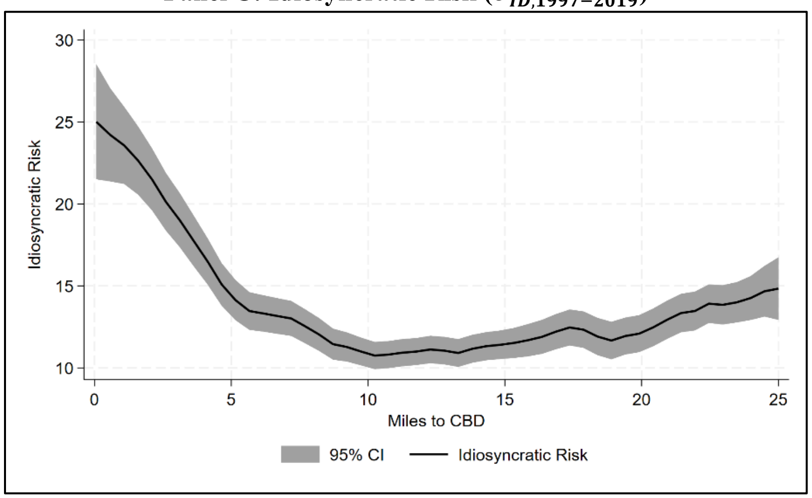
Panel A: Return Volatility ($\sigma^{P}_{1997-2019}$)



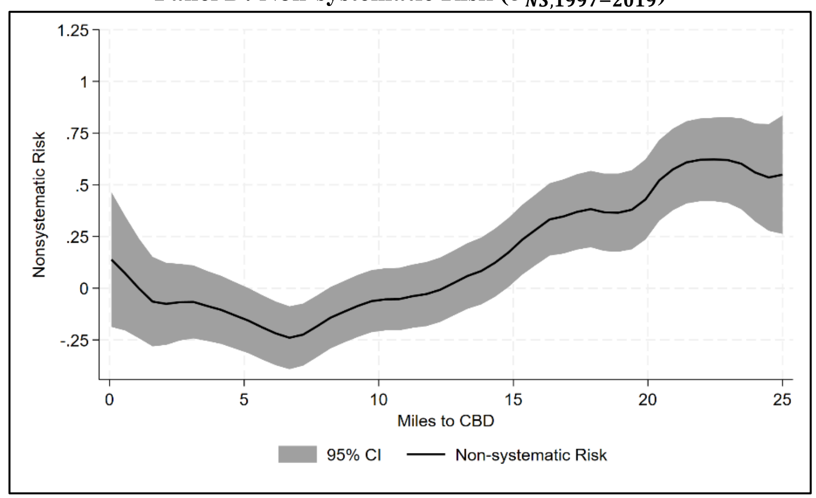
Panel B: Systematic Risk – Beta ($\beta^{P}_{1997-2019}$)



Panel C: Idiosyncratic Risk ($\sigma^{P}_{ID,1997-2019}$)

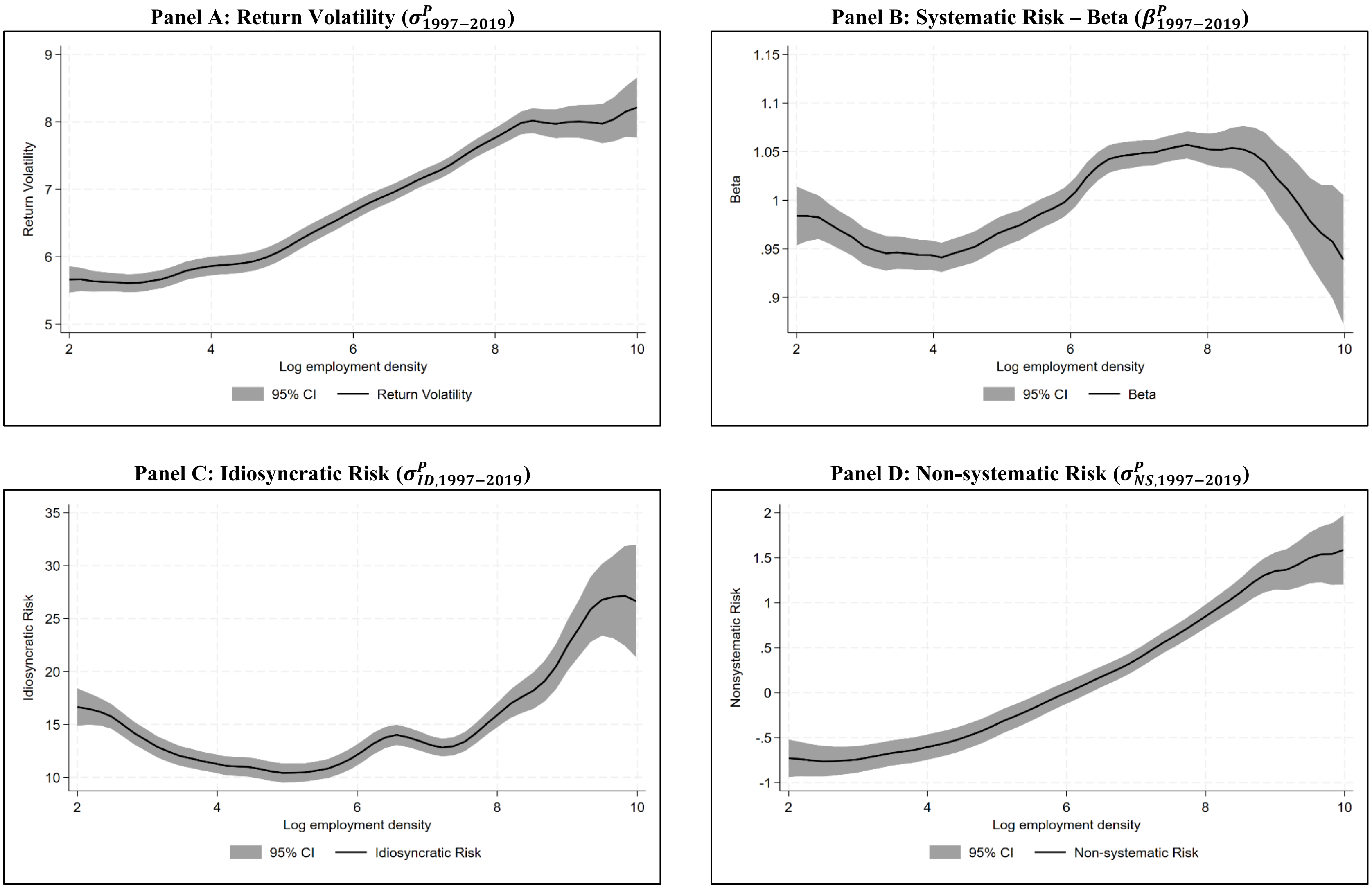


Panel D: Non-systematic Risk ($\sigma^{P}_{NS,1997-2019}$)



[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]



[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]

	Return Volatility ($\sigma^P_{1997-2019}$)	Beta ($\beta^P_{1997-2019}$)	Idiosyncratic Risk ($\sigma^P_{ID,1997-2019}$)	Year-2000 Population		Return Volatility ($\sigma^P_{1997-2019}$)	Beta ($\beta^P_{1997-2019}$)	Idiosyncratic Risk ($\sigma^P_{ID,1997-2019}$)	Year-2000 Population
Pittsburgh, PA	1.90	0.37	4.45	2,431,087	Providence, RI	7.89	1.66	26.28	1,582,997
Oklahoma City, OK	2.03	0.33	1.92	1,095,421	Jacksonville, FL	8.13	1.84	12.93	1,122,750
Little Rock, AR	2.41	0.39	1.85	610,518	Seattle, WA	8.17	1.64	15.08	3,043,878
Wichita, KS	2.44	0.22	5.20	571,166	Washington, DC	8.58	1.86	14.82	4,849,948
Rochester, NY	2.46	0.43	8.82	1,062,452	Tucson, AZ	8.75	1.97	24.76	843,746
Tulsa, OK	2.51	0.28	3.43	859,532	Detroit, MI	9.44	1.80	40.72	4,452,557
Buffalo, NY	2.58	0.44	9.48	1,170,111	San Jose, CA	9.87	1.28	90.60	1,735,819
McAllen, TX	2.75	0.39	7.55	569,463	San Francisco, CA	10.02	1.98	44.14	4,123,740
Syracuse, NY	2.84	0.47	7.07	650,154	San Diego, CA	10.17	2.11	31.98	2,813,833
Des Moines, IA	2.93	0.60	4.53	518,607	Tampa, FL	10.48	2.49	13.85	2,395,997
Greenville, SC	2.94	0.43	5.01	725,680	Los Angeles, CA	10.54	2.36	21.24	12,365,627
Harrisburg, PA	2.96	0.47	3.00	509,074	North Port, FL	11.57	2.62	35.76	589,959
Columbia, SC	2.97	0.43	2.99	647,158	Miami, FL	11.80	2.79	16.91	5,007,564
Winston-Salem, NC	3.02	0.39	3.50	569,207	Orlando, FL	11.92	2.67	43.86	1,644,561
Louisville, KY	3.02	0.48	4.79	1,090,024	Sacramento, CA	12.28	2.83	37.92	1,796,857
Greensboro, NC	3.16	0.45	4.44	643,430	Fresno, CA	12.72	3.06	13.33	799,407
Raleigh, NC	3.18	0.53	4.04	797,071	Phoenix, AZ	12.87	2.60	111.77	3,251,876
Omaha, NE	3.22	0.58	7.81	767,041	Bakersfield, CA	13.12	3.03	25.43	661,645
Augusta, GA	3.29	0.49	4.10	508,032	Riverside, CA	13.49	3.08	42.34	3,254,821
Knoxville, TN	3.30	0.57	2.81	727,600	Stockton, CA	14.90	3.25	86.87	563,598
Mean	**2.80**	**0.44**	**4.84**	**826,141**	**Mean**	**10.84**	**2.34**	**37.53**	**2,845,059**

[a] CBSAs shown here are limited to those with populations greater than 500 thousand in 2000. 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]

		$(\bar{R}/\bar{P})_{2011-19}$	$\bar{\rho}^{P}_{2011-19}$	$\bar{\rho}^{Tot}_{2011-19}$	$\sigma^{P}_{1997-10}$	$\sigma^{P}_{2011-19}$	$\widetilde{W}$	$\beta^{P}_{1997-10}$	$\sigma^{P}_{ID,1997-10}$	$\sigma^{P}_{NS,1997-10}$
Avg rent-to-price ratio 2011-2019	$(\bar{R}/\bar{P})_{2011-19}$	1.000	-	-	-	-	-	-	-	-
Avg yr-over-yr price return 2011-19	$\bar{\rho}^{P}_{2011-19}$	-0.353	1.000	-	-	-	-	-	-	-
Avg yr-over-yr total return 2011-19	$\bar{\rho}^{Tot}_{2011-19}$	0.339	0.757	1.000	-	-	-	-	-	-
Price return volatility 1997-2010	$\sigma^{P}_{1997-10}$	-0.426	0.594	0.306	1.000	-	-	-	-	-
Price return volatility 2011-2019	$\sigma^{P}_{2011-19}$	-0.418	0.706	0.426	0.724	1.000	-	-	-	-
Transformed WLURI	$\widetilde{W}$	0.317	-0.194	0.016	-0.300	-0.326	1.000	-	-	-
Beta 1997-2010	$\beta^{P}_{1997-10}$	-0.365	0.536	0.294	0.941	0.704	-0.268	1.000	-	-
Idiosyncratic risk 1997-2010	$\sigma^{P}_{ID,1997-10}$	-0.356	0.560	0.323	0.687	0.582	-0.289	0.532	1.000	-
Non-systematic risk 1997-2010	$\sigma^{P}_{NS,1997-10}$	-0.245	0.263	0.089	0.337	0.183	-0.139	0.000	0.551	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	Interaction + CBSA Atrb
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^P_{1997-10}$	0.3745***	-	-	-	-	-
	(0.027)	-	-	-	-	-
Transformed WLURI ($\widetilde{W}$)	-	-0.6529***	-0.4596**	0.0782	-	0.3807
	-	(0.227)	(0.194)	(0.361)	-	(0.357)
Demand Shock (D)	-	-	1.7877***	3.2711***	-	3.3076***
	-	-	(0.150)	(0.749)	-	(0.756)
$\widetilde{W}$ by D interaction	-	-	-	-0.4647*	-	-0.6068**
	-	-	-	(0.242)	-	(0.244)
Log CBSA population 2000	-	-	-	-	0.2417*	0.1476
	-	-	-	-	(0.145)	(0.133)
Median CBSA income 2000 (1,000s)	-	-	-	-	0.2715	-0.2566
	-	-	-	-	(0.577)	(0.488)
|%Δ population| if GROWING	-	-	-	-	0.0431***	0.0296***
1990-2020 (0 otherwise)	-	-	-	-	(0.006)	(0.006)
|%Δ population| if SHRINKING	-	-	-	-	-0.0717	-0.0163
1990-2020 (0 otherwise)	-	-	-	-	(0.073)	(0.067)
Superstar status	-	-	-	-	1.5429	1.0142
	-	-	-	-	(1.217)	(1.012)
Observations	254	254	254	254	254	254
R-square	0.352	0.038	0.338	0.349	0.252	0.440

[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 ($\bar{\rho}^{P}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.2989***	-	-	-	-	-
	(0.030)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	1.0980***	-	-	0.7113***	1.1458***
	-	(0.135)	-	-	(0.169)	(0.149)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	0.0622***	-	0.0440***	-
	-	-	(0.007)	-	(0.008)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.2632	-	0.3426
	-	-	-	(0.302)	-	(0.206)
Observations	254	254	254	254	254	254
R^2	0.438	0.408	0.424	0.270	0.475	0.439

Panel B: Total Returns ($\bar{\rho}^{Tot}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.1927***	-	-	-	-	-
	(0.041)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	0.7522***	-	-	0.4902**	0.7714***
	-	(0.162)	-	-	(0.196)	(0.166)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	0.0424***	-	0.0298***	-
	-	-	(0.008)	-	(0.009)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.0840	-	0.1375
	-	-	-	(0.221)	-	(0.174)
Observations	254	254	254	254	254	254
R-square	0.183	0.179	0.185	0.114	0.207	0.184

[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. All models include the same set of sociodemographic and amenity controls as in column 5 of Table 4a.

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

		$(\bar{R}/\bar{P})_{11-19}$	$\bar{\rho}^{P}_{11-19}$	$\bar{\rho}^{Tot}_{11-19}$	σ^{P}_{97-10}	σ^{P}_{11-19}	Miles to CBD	Log emp density	Supply elasticity	β^{P}_{97-10}	$\sigma^{P}_{ID,97-10}$	$\sigma^{P}_{NS,97-10}$
Avg rent-to-price ratio 2011-2019	$(\bar{R}/\bar{P})_{11-19}$	1.000	-	-	-	-	-	-	-	-	-	-
Avg yr-over-yr price return 2011-2019	$\bar{\rho}^{P}_{11-19}$	-0.124	1.000	-	-	-	-	-	-	-	-	-
Avg yr-over-yr total return 2011-2019	$\bar{\rho}^{Tot}_{11-19}$	0.718	0.599	1.000	-	-	-	-	-	-	-	-
Price return volatility 1997-2010	σ^{P}_{97-10}	-0.168	0.504	0.223	1.000	-	-	-	-	-	-	-
Price return volatility 2011-2019	σ^{P}_{11-19}	0.218	0.587	0.592	0.554	1.000	-	-	-	-	-	-
Miles to CBD	-	-0.151	-0.075	-0.176	0.026	-0.158	1.000	-	-	-	-	-
Log employment density	-	-0.037	0.271	0.166	0.208	0.268	-0.448	1.000	-	-	-	-
Supply elasticity (Baum-Snow/Han)	S	-0.035	-0.319	-0.258	-0.286	-0.363	0.267	-0.797	1.000	-	-	-
Beta 1997-2010	β^{P}_{97-10}	0.123	0.046	0.131	0.186	0.174	-0.110	0.023	-0.077	1.000	-	-
Idiosyncratic risk 1997-2010	$\sigma^{P}_{ID,97-10}$	0.167	0.021	0.151	0.237	0.207	-0.038	-0.019	-0.044	0.076	1.000	-
Non-systematic risk 1997-2010	$\sigma^{P}_{NS,97-10}$	-0.195	0.504	0.202	0.983	0.530	0.047	0.207	-0.276	-0.000	0.227	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 ($\rho^P_{i,t}$)			Avg year-over-year price returns1997-2019 ($\bar{\rho}^P_{i,1997-19}$)
	(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
Within R-square	0.0003	0.0003	0.402	0.006
Overall R-square				

Panel B: Log Employment Density

	Year-over-year home price returns using month-by-zipcode observations ($\rho^P_{i,t}$)			Avg year-over-year price returns1997-2019 ($\bar{\rho}^P_{i,1997-19}$)
	(1)	(2)	(3)	(4)
Log employment density	0.2217***	0.0530***	0.0368**	0.0481***
	(0.0433)	(0.0141)	(0.0153)	(0.0137)
CBSA FE	-	362	362	362
Month FE	-	-	273	-
Observations	2,790,418	2,790,418	2,790,418	11,644
Within R-square	0.0054	0.0054	0.403	0.078
Overall R-square				

[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 7a (CBSA Population < 250,000): Lagged zipcode level volatility and Average 2011-2019 monthly year-over-year home price returns ($\bar{\rho}^{P}_{2011-19}$)[a]

	Volatility	Supply Elasticity	Demand Shock	Interaction	Zipcode Atrb	Interaction + Zipcode Atrb
	(1)	(2)	(3)	(4)	(5)	(6)
Return Volatility ($\sigma^{P}_{1997-10}$)	0.0210	-	-	-	-	-
	(0.037)	-	-	-	-	-
Supply elasticity (S)	-	0.6364**	-	1.0289*	-	0.1675
	-	(0.262)	-	(0.562)	-	(0.632)
Demand shock (D)	-	-	0.1488	0.5109	-	0.4314
	-	-	(0.192)	(0.582)	-	(0.627)
S by D interaction	-	-	-	-0.5271	-	-0.4168
	-	-	-	(0.572)	-	(0.615)
Log Employment Density	-	-	-	-	-0.0888***	-0.0955***
	-	-	-	-	(0.026)	(0.028)
Log zipcode population 2010	-	-	-	-	0.0644	0.0759
	-	-	-	-	(0.047)	(0.047)
Δ log zipcode pop 2020 - 2010	-	-	-	-	-0.4205	-0.4210
	-	-	-	-	(0.418)	(0.425)
Relative home value in 2019[a]	-	-	-	-	0.5008**	0.5193**
	-	-	-	-	(0.192)	(0.205)
CBSA FE	150	150	150	150	150	150
Observations	1,284	1,284	1,284	1,284	1,284	1,284
Within R-square	0.001	0.010	0.002	0.013	0.048	0.050
Overall R-square	0.092	0.001	0.094	0.024	0.002	0.013

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

Table 7b (CBSA Population > 250,000): Lagged zipcode level volatility and Average 2011-2019 monthly year-over-year home price returns ($\bar{\rho}^{P}_{2011-19}$)[a]

	Volatility	Supply Elasticity	Demand Shock	Interaction	Zipcode Atrb	Interaction + Zipcode Atrb
	(1)	(2)	(3)	(4)	(5)	(6)
Return Volatility ($\sigma^{P}_{1997-10}$)	0.1478**	-	-	-	-	-
	(0.059)	-	-	-	-	-
Supply elasticity (S)	-	-1.2591***	-	-0.1736	-	0.0098
	-	(0.219)	-	(0.430)	-	(0.501)
Demand shock (D)	-	-	0.2086	1.3628**	-	1.3625***
	-	-	(0.272)	(0.528)	-	(0.489)
S by D interaction	-	-	-	-1.2884***	-	-1.2542***
	-	-	-	(0.446)	-	(0.435)
Log Employment Density	-	-	-	-	0.1004***	0.0035
	-	-	-	-	(0.028)	(0.036)
Log zipcode population 2010	-	-	-	-	0.0735	0.0969
	-	-	-	-	(0.064)	(0.059)
Δ log zipcode pop 2020 - 2010	-	-	-	-	-0.9789***	-0.7337**
	-	-	-	-	(0.350)	(0.370)
Relative home value in 2019[a]	-	-	-	-	-0.1221	0.0273
	-	-	-	-	(0.264)	(0.260)
CBSA FE	157	157	157	157	157	157
Observations	6,492	6,492	6,492	6,492	6,492	6,492
Within R^2	0.023	0.025	0.001	0.046	0.024	0.051
Total R^2	0.258	0.092	0.174	0.243	0.035	0.229

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

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

Panel A: Price Returns ($\bar{\rho}^{P}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.0195	-	-	-	-	-
	(0.041)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	0.0167	-	-	0.0207	0.0270
	-	(0.075)	-	-	(0.074)	(0.082)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	-0.0043	-	-0.0044	-
	-	-	(0.003)	-	(0.003)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.0174	-	0.0196
	-	-	-	(0.041)	-	(0.043)
CBSA FE	150	150	150	150	150	150
Observations	1,284	1,284	1,284	1,284	1,284	1,284
Within R^2	0.048	0.048	0.051	0.048	0.051	0.048
Total R^2	0.016	0.002	0.003	0.013	0.003	0.016

Panel B: Total Returns ($\bar{\rho}^{Tot}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.0545	-	-	-	-	-
	(0.070)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	-0.0553	-	-	-0.0548	-0.0189
	-	(0.195)	-	-	(0.194)	(0.195)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	-0.0006	-	-0.0005	-
	-	-	(0.005)	-	(0.005)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.0840	-	0.1375
	-	-	-	(0.221)	-	(0.174)
CBSA FE	150	150	150	150	150	150
Observations	1,284	1,284	1,284	1,284	1,284	1,284
Within R^2	0.433	0.432	0.431	0.433	0.432	0.433
Total R^2	0.205	0.209	0.208	0.205	0.209	0.205

[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. All models include the same set of sociodemographic and amenity controls as in column 5 of Tables 7a and 7b.

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

Panel A: Price Returns ($\bar{\rho}^{P}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.1467***	-	-	-	-	-
	(0.055)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	0.3327***	-	-	0.2857**	0.3288***
	-	(0.121)	-	-	(0.122)	(0.103)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	-	-	0.0215***	-	0.0209***	-
	-	-	(0.005)	-	(0.005)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.1317**	-	0.1308**
	-	-	-	(0.062)	-	(0.063)
CBSA FE	157	157	157	157	157	157
Observations	6,492	6,492	6,492	6,492	6,492	6,492
Within R^2	0.046	0.033	0.061	0.039	0.067	0.047
Total R^2	0.254	0.031	0.033	0.248	0.032	0.242

Panel B: Total Returns ($\bar{\rho}^{Tot}_{2011-19}$)

	Volatility	Beta	Idiosyncratic Risk	Non-sys Risk	Beta + Idio Risk	Beta + Non-sys Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Return volatility 1997-2010: $\sigma^{P}_{1997-10}$	0.3469***	-	-	-	-	-
	(0.126)	-	-	-	-	-
Beta: $\beta^{P}_{1997-10}$	-	0.7717***	-	-	0.6169***	0.7625***
	-	(0.244)	-	-	(0.228)	(0.210)
Idiosyncratic risk ($\sigma^{P}_{ID,1997-10}$)	--	-	0.0702***	-	0.0688***	-
	-	-	(0.009)	-	(0.009)	-
Non-systematic risk: $\sigma^{P}_{NS,1997-10}$	-	-	-	0.3135**	-	0.3114**
	-	-	-	(0.136)	-	(0.139)
CBSA FE	157	157	157	157	157	157
Observations	6,492	6,492	6,492	6,492	6,492	6,492
Within R^2	0.321	0.307	0.373	0.314	0.378	0.322
Total R^2	0.215	0.120	0.219	0.213	0.223	0.219

[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. All models include the same set of sociodemographic and amenity controls as in column 5 of Table 4a.

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

Panel A: Price Returns (sample mean = 3.99)

Table 4b Model	Risk Measure	Sample Mean of Risk Measure	Sample Std Dev of Risk Measure	Percent Change Relative to Sample Mean Price Return[a]	
				Estimate	± 95% Confidence
Column 1	Return volatility	6.28	3.81	28.54	5.61
Column 5	Systematic risk (beta)	1.03	0.92	16.40	0.76
	Idiosyncratic risk	15.57	17.14	17.18	6.74
Column 6	Systematic risk (beta)	1.03	0.92	26.42	6.73
	Non-systematic risk	0.00	1.29	11.08	13.05

Panel B: Total Returns (sample mean = 13.13)

Table 4b Model	Risk Measure	Sample Mean of Risk Measure	Sample Std Dev of Risk Measure	Percent Change Relative to Sample Mean Total Return[a]	
				Estimate	± 95% Confidence
Column 1	Return volatility	6.28	3.81	5.59	2.33
Column 5	Systematic risk (beta)	1.03	0.92	3.43	2.69
	Idiosyncratic risk	15.57	17.14	3.89	2.30
Column 6	Systematic risk (beta)	1.03	0.92	5.41	2.28
	Non-systematic risk	0.00	1.29	1.35	3.35

[a] Values were obtained using the coefficient on the specified risk measure in the highlighted column from Table 4b along with its 95% confidence band. For each percent change reported, the corresponding coefficient was multiplied by the sample standard deviation of the risk measure divided by its sample mean.

Table 9b (within CBSAs with population > 250,000): Effect on returns from a one standard deviation increase in CBSA-level risk measures

Panel A: Price Returns (sample mean = 4.60)

				Percent Change Relative to Sample Mean Price Return[a]	
Table 8b Model	**Risk Measure**	**Sample Mean of Risk Measure**	**Sample Std Dev of Risk Measure**	**Estimate**	**± 95% Confidence**
Column 1	Return volatility	7.34	3.78	12.05	8.86
Column 4	Systematic risk (beta)	1.01	0.47	2.92	2.44
	Idiosyncratic risk	12.58	16.13	7.33	3.44
Column 5	Systematic risk (beta)	1.01	0.47	3.36	2.06
	Non-systematic risk	0.28	3.71	10.56	9.97

Panel B: Total Returns (sample mean = 14.18)

				Percent Change Relative to Sample Mean Total Return[a]	
Table 4b Model	**Risk Measure**	**Sample Mean of Risk Measure**	**Sample Std Dev of Risk Measure**	**Estimate**	**± 95% Confidence**
Column 6	Return volatility	7.34	3.78	9.24	6.58
Column 9	Systematic risk (beta)	1.01	0.47	2.04	1.48
	Idiosyncratic risk	12.58	16.13	7.82	2.01
Column 10	Systematic risk (beta)	1.01	0.47	2.53	1.36
	Non-systematic risk	0.28	3.71	8.16	7.14

[a] Values were obtained using the coefficient on the specified risk measure in the highlighted column from Table 8b along with its 95% confidence band. For each percent change reported, the corresponding coefficient was multiplied by the sample standard deviation of the risk measure divided by its sample mean.

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:

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

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.

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

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),

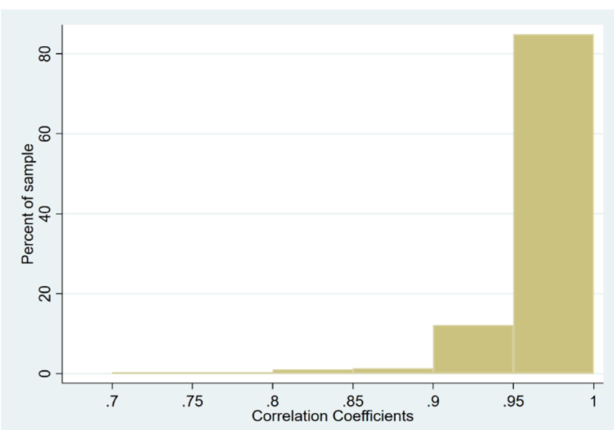
$$ZHVI_{t-1,i} = \frac{ZHVI_{t,i}}{1+A_{t,i}}, \text{for } t = 0, T-1 \quad . \tag{A.3}$$

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.

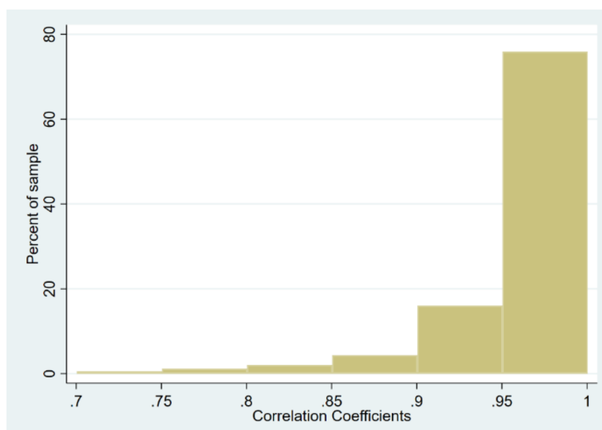
The single-family Zillow Home Value Index (ZHVI) is closely correlated with the single-family Federal Housing Finance Agency's (FHFA) repeat sales Home Price Index (HPI) at the CBSA and zipcode levels (including both sales and appraisals when constructing the FHFA index). Figures A-1 and A-2 display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

Appendix B: Supplemental Summary Statistics

Table B-1: Summary Statistics for CBSA-Level Measures Used in Table 4b

Variable		Obs	Mean	Std. Dev.	Min	Max
Avg total return 2011−2019	$\bar{\rho}^{TR}_{2011-19}$	254	13.131	2.521	7.111	20.297
Avg rent-to-price 2011−2019	$\bar{\rho}^{R/P}_{2011-19}$	254	9.089	1.778	4.266	14.946
Avg price return 2011−2019	$\bar{\rho}^{P}_{2011-19}$	254	3.992	2.406	-0.599	10.538
Avg price return 1997-2010	$\bar{\rho}^{P}_{1997-10}$	254	2.562	1.997	-9.935	6.899
Total return volatility 2011-2019	$\sigma^{TR}_{2011-19}$	254	3.761	1.912	0.626	11.480
Price return volatility 2011-2019	$\sigma^{P}_{2011-19}$	254	3.661	1.798	0.983	10.907
Difference in volatility 2011-2019	$\sigma^{TR}_{2011-19} - \sigma^{P}_{2011-19}$	254	0.099	0.318	-0.913	0.973
Price return volatility 1997-2010	$\sigma^{P}_{1997-10}$	254	6.288	3.814	0.109	17.903
Beta 1997-2010	$\beta^{P}_{1997-10}$	254	1.029	0.923	-0.344	4.601
Idiosyncratic Risk 1997-2010	$\sigma^{P}_{ID,1997-10}$	254	15.568	17.138	0.000	104.241
Non-systematic Risk 1997-2010	$\sigma^{P}_{NS,1997-10}$	254	0.000	1.286	-11.312	3.879
Transformed WRLURI18	$\widetilde{W}$	254	3.003	0.715	0.018	4.936
Demand Shock:	D	254	1.197	0.710	0.024	3.341

Table B-2: Summary Statistics for Zipcode-Level Measures Used in Table 8b

Variable		Obs	Mean	Std. Dev.	Min	Max
Avg total return 2011−2019	$\bar{\rho}^{TR}_{2011-19}$	6,492	14.373	4.696	4.405	54.807
Avg rent-to-price 2011−2019	$\bar{\rho}^{R/P}_{2011-19}$	6,492	9.441	3.841	0.711	49.499
Avg price return 2011−2019	$\bar{\rho}^{P}_{2011-19}$	6,492	4.835	3.104	-6.626	20.559
Avg price return 1997-2010	$\bar{\rho}^{P}_{1997-10}$	6,492	2.682	2.771	-24.975	14.653
Total return volatility 2011-2019	$\sigma^{TR}_{2011-19}$	6,492	5.071	2.473	0.858	19.365
Price return volatility 2011-2019	$\sigma^{P}_{2011-19}$	6,492	4.835	2.319	0.800	19.806
Difference in volatility 2011-2019	$\sigma^{TR}_{2011-19} - \sigma^{P}_{2011-19}$	6,492	0.236	0.426	-3.146	4.684
Price return volatility 1997-2010	$\sigma^{P}_{1997-10}$	6,492	7.339	3.779	0.010	18.783
Beta 1997-2010	$\beta^{P}_{1997-10}$	6,492	1.005	0.470	-12.253	11.057
Idiosyncratic Risk 1997-2010	$\sigma^{P}_{ID,1997-10}$	6,492	12.584	16.125	0.000	309.587
Non-systematic Risk 1997-2010	$\sigma^{P}_{NS,1997-10}$	6,492	0.282	3.714	-16.383	15.697
Transformed WRLURI18	$\widetilde{W}$	6,492	0.490	0.279	0.002	1.155
Demand Shock:	D	6,492	1.167	0.600	0.002	3.395