The Cross-Section of Housing Returns*

PRELIMINARY AND INCOMPLETE - PLEASE DO NOT CITE (YET)

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Abstract

We document large systematic variations in the return to property within U.S. metropolitan areas. Areas with low income, low credit scores or high shares of non-white residents have higher yields and therefore higher returns. The spreads between low credit areas and high credit areas widened considerably during a period when credit availability was low. We argue that this is evidence for segmented housing markets where local discount rates price different local assets.

*The views in this paper are those of the authors' and do not reflect the opinions of the Federal Reserve Bank of Boston, the Federal Reserve Bank of Cleveland, or the Federal Reserve System.

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1 Introduction

Housing investments tend to be lumpy and geographically differentiated. Different households sort into different houses and locations, meaning that the marginal household that "prices" housing in one part of the market may vary from the marginal household in another part of the market. If households have heterogeneous intertemporal marginal rates of substitution (IMRS, or equivalently heterogeneous wedges in their Euler equations perhaps due to borrowing constraints), then the return to holding a house can vary within a market for reasons other than risk. This heterogeneity, at the household level, is at the core of many models of housing choice (e.g. Rios-Rull and Sanchez-Marcos (2008), Landvoigt et al. (2015) and Piazzesi and Schneider (2016)). In this paper, we show that household heterogeneity in IMRSs translates into predictable differences in the returns to housing, one of the most important household assets.

Specifically, we show that the returns to holding single family real estate vary considerably and predictably even within a single market. Ex-ante differences in neighborhood demographics and economic characteristics, such as the median income of a neighborhood, average credit scores and racial composition, predict future returns mainly by predicting yields. Areas with ex-ante lower median income or credit scores or a larger non-white population have higher yields.

We argue that the return difference is evidence of segmented housing markets: different households are pricing housing in different parts of the market. The factors we use seem intuitively correlated with households' opportunity cost of funds or discount rates. And historical periods in our data when borrowing constraints exogenously tightened led to increased spreads in measured returns and yields across segments in the market. In other words, the correlation between our factors and ex-post returns is higher (in absolute value) during the historical periods when there were likely larger differences in discount rates within our markets.

In sample, there is no equivalent correlation between the riskiness of housing, measured in various ways, and these economic and demographic factors. Moreover, as we discuss further below, under the hypothesis of different discount rates pricing different assets, canonical measures like Sharpe Ratios and coefficients from CAPM regressions are no longer necessarily straightforward to interpret.

Estimating the returns to single-family housing is complicated: data on rents are scarce; the gross dividend for owner-occupied housing (under some assumptions, the implied rent) is not observed in any data set; data on the costs of owning a home (maintenance, depreciation, taxes, etc...) may be limited; houses are traded infrequently, which means values are not always observed.

We contribute to the growing literature that estimates and analyzes returns to property at granular levels by: Estimating the rental price and for-sale value of most single-family housing within 20 U.S. CBSAs using hedonic methods. These allow us to estimate the contribution of each of structure and location in both rents and prices. We can then estimate the return to holding the property and examine how structure and location contribute to the return. Our results confirm that a house is a depreciating asset on top of an appreciating one.

More importantly, there is substantial variation in returns across locations within an CBSA to owning the same structure. Systematic variation in returns across location comes entirely from variation in the net yield to land. Simply put, a high average rent-to-price ratio in a particular location within a CBSA relative to other locations within the CBSA predicts higher returns in that location relative to other locations in that CBSA (and not lower capital gains).

We show that a location's average yield and return are highly correlated with many ex-ante area economic and demographic characteristics. Within CBSAs, land yields and our demographic/economic factors are generally all statistically significantly correlated in the same direction. All 20 of the CBSAs in our sample have higher yields in low-income zip codes, in zip codes with a higher non-white population, and with lower average credit scores.

The systematic relationship between capital gains and the income, race and credit score in an area is less clear. It is clear that the relationship between yields and the economic factors is not counterbalanced by capital gains; zip code with higher yields do not have lower capital gains. If anything, most but not all of the point estimates have the same sign as their counterparts for yields; zip codes with higher yields often have higher average capital gains in sample.

Putting these two results together, the relationships between our factors and total returns across zips is very strong; nearly all 20 CBSAs have statistically and economically significant relationships for all three factors (besides vacancy). A zip code with double the median income or a 100 point higher average credit score than another within the same CBSA can expect anywhere between roughly 1 and 6 percent lower returns on their property. The results on non-white population share are similarly striking. Areas with high shares of non-whites pay higher rents relative to prices so that an area with a 10 percent higher non-white share has roughly between 0.5 and 3 percentage point higher returns.

When we run a multivariate "horserace" with all economic factors, credit scores by far are the most important.

Measures of risk that we can compute with out data, such as average capital gains, rental volatility or CAPM Betas are uncorrelated with these same return predictors. The higher returns in some locations does not appear to be compensation for bearing additional risk. However, measures of risk are very noisy in our short sample.

Instead we argue that the large spread in returns across locations could be due to spreads in discount rates. In Section 2 we show how different discount rates may price different houses within the same housing market, even if there exists a deep pocketed landlord with the lowest discount rate. Even though landlords may have a low opportunity cost of funds, they may be inefficient relative to owner-occupiers at converting a house into housing services.

We do not directly observe discount rates in our data, but the link between, e.g. credit scores, and the opportunity cost of borrowing is straightforward. We do document that many of the yield spreads across locations that we estimate in the data widened significantly during the post-Great Recession years, when access to funds for low credit borrowers dried up.

Our results have many potentially important implications both economically and econometrically. Higher returns in low income areas may imply that owner-occupancy in these areas is a potent way to build wealth. Also, if the high cost of borrowing for certain households suppresses prices for the types of houses that these households live in, this could lower the incentive for developers to develop these houses. If different areas respond differently to changes in the cost and access to credit, then the effects of monetary policy may have important intra-urban heterogeneity. And the response of house prices to changes in monetary policy may vary within markets as well.

Econometrically, our results imply that different houses can have different long-run expected returns. Time-series studies that follow Campbell-Shiller decompositions should be wary of estimating models where the return to all housing is restricted in the long-run to be the same.

More importantly, when markets are segmented, the same factor can be both a risk-factor and a discount-rate factor. This can lead to invalid conclusions based on widely used measures.

To see this in the case of real estate, consider a stylized version of our setting. Suppose there are two sub-markets within a market, A and B. They each contain the same houses but in A, all households have a lower IMRS than the households in B. This may be because households in A have a better credit score and are thus not borrowing constrained. Thus, houses in A should have a lower expected return than houses in B. Further suppose that households in A are less directly affected by changes in the way, e.g., credit scores map into mortgage rates. For example, suppose A households always strictly prefer to buy with all-cash (as an extreme example).

Now suppose borrowing constraints tighten exogenously (perhaps a change in government policy) in such a way that the IMRS of households in A are unaffected but the IMRS of households in B goes up. Absent other effects, expected returns and prices in A will remain unchanged but expected returns in B will go up and prices in B will go down. Ex-post, realized price and return volatility in B will be higher than A. Ex-ante, B will have more exposure to this credit risk-factor. This will lead it to having still higher returns, *ceterus paribus*. Meanwhile, in-sample (and possibly out of sample) Sharpe Ratios for property in B may be either lower or higher property in A. In our CAPM regressions and Sharpe Ratios results, these are exactly the results we find.

1.1 Related Literature

There is a growing literature that finds dispersion of housing returns (variously measured) within metropolitan areas ("markets") and attempts to explain it by using differences in risk (variously measured). Housing is both an asset and a consumption good and so the relationship between expected returns and risk may be non-trivial. For example, Sinai and Souleles (2005) finds a positive relationship between price-to-rent ratio and risk across markets. Han (2013) finds a positive relationship between housing returns (measured using only capital gains) and risk within some markets and a negative within others. Giacoletti (2021) finds that idiosyncratic capital gains risk is a significant part of housing risk, particularly over short horizons. Demers and Eisfeldt (2021) finds that yields and, thus, returns are higher in the lowest priced zip codes within markets and that price appreciation is more correlated with city-level risk in these same zip codes. Plazzi et al. (2010) studies risk and return among CRE properties using Campbell-Shiller decompositions.

A huge literature looks at the time-varying relationship between risk and returns in the housing markets, with an eye to understanding the market or macro level factors that may be driving them (see Goetzmann et al. (2021) for a recent summary). We view the cross-sectional facts that we document here as contributing to this literature for several reasons. For one, structural dynamic models of housing and home ownership (e.g. Landvoigt et al. (2015), Kaplan et al. (2020)) often feature binding borrowing constraints that affect the equilibrium price of housing. Our results are consistent with that model mechanism. For another, these theories and our empirical results both point to there being likely dispersions in the long-run expected returns of houses within (and perhaps across) markets. This means that time-series econometric tests that rely on a common long-run expected return need to be adjusted. Measuring returns for real estate, particularly single-family residential housing, is complicated because many components of cash flows are not observed in most data sets. For this reason, historically, many studies of risk and return in housing focus on capital gains. We show yields contain a lot of important information on the cross-section of returns.

2 Returns in a two sector model

Time is discrete. Each property is vector of characteristics $z^\varepsilon \in Z^\varepsilon$ a compact, convext subset of $\mathbb{R}^{n_\varepsilon}$. These characteristics may or may not be observable to the econometrician. Examples of characteristics include location, lot size, floor space, etc... Households and landlords are a vector of characteristics (state variables) $s \in S$. For convenience we assume that we can partition the state such that for households there is a set of household states, $S^h = \{s_h, 0\}$ and for similarly for landlords $S^l = \{0, s_l\}$. Examples of household characteristics that may be in S are income, martial and family status, age, etc.... Examples of landlord characteristics could include measures of managerial ability, location of headquarters, etc.... As with property characteristics, household and landlord characteristics may or may not be observable to the econometrician.

Define the flow value (in non-durable consumption units) from an owner in state s of a property of type z^ε given the price function P as $U(z^\varepsilon, s)$. Assume maintenance costs (including property taxes) are $c(z^\varepsilon, s)P(z^\varepsilon)$ and the opportunity cost of capital is $r(s)$.[1] To simplify notation below, we assume maintenance costs are paid at the end of each time period. Let $g(z^\varepsilon, s)$ be the expected after-tax capital gains.

We assume that the willingness to pay to own a property z^ε by an owner in state s is given by

$$\pi(z^\varepsilon; s, P, R) = U(z^\varepsilon, s) - \frac{c(z^\varepsilon, s)P(z^\varepsilon)}{1 + r\,(z^\varepsilon, s)} + \frac{(1 + g(z^\varepsilon, s))\,P(z^\varepsilon)}{1 + r(z^\varepsilon, s)}. \tag{1}$$

Thus, the willingness to pay equals the current net utility flow plus the discounted expected future value of the property.[2][3]

We assume that in equilibrium there is a correspondence mapping properties to owners $T : Z^\varepsilon \rightrightarrows S$. If, given the set of equilibrium (state-dependent) prices and rents, $s \in T(z)$, then agents at state s weakly prefer z^ε to any other in Z^ε. Note that an equilibrium correspondence T implies two correspondences $T_h : Z^\varepsilon \rightrightarrows S^h$ and $T_l : Z^\varepsilon \rightrightarrows S^l$ which describe the sets of households and landlords, respectively, that own properties z^ε given prices and rents.

In equilibrium, if an agent in state s buys a property z^ε then $\pi(z^\varepsilon; T(z^\varepsilon), P, R) = P(z^\varepsilon)$.[4]

[1] The functions themselves may be time-dependent (i.e. dependent on some macro-state variables). Likewise owners may change states over time. We suppress time-dependent notation for ease of reading.

[2] A similar expression can be found in Piazzesi and Schneider (2016). There the focus is only on the equilibrium price using the characteristics of the marginal owner, whereas here we characterize the willingness to pay of any potential owner.

[3] We can readily extend the model to include features like adjustment costs for properties switching between owners. See Halket et al. (2020) for an example.

[4] See, e.g. Nesheim (2006) for formal proof for the general hedonic case.

Equation (1) can be rewritten as

$$U(z^\varepsilon, T(z^\varepsilon)) = \left[\frac{c(z^\varepsilon, T(z^\varepsilon)) + r(T(z^\varepsilon)) - g(z^\varepsilon, T(z^\varepsilon))}{1 + r(T(z^\varepsilon))}\right] P(z^\varepsilon) \tag{2}$$

$$\approx [c(z^\varepsilon, T(z^\varepsilon)) + r(T(z^\varepsilon)) - g(z^\varepsilon, T(z^\varepsilon))] P(z^\varepsilon) \tag{3}$$

The approximation becomes exact as the duration of the time period shrinks. For a competitive landlord, rents, R, equals the gross flow value of occupancy so that in equilibrium, $R(z^\varepsilon) = U(z^\varepsilon, T_l^*(z^\varepsilon))$ as long as $T_l^*(z^\varepsilon)$ is non-empty. Equation 3 reveals a user-cost $uc : Z^\varepsilon \times T(Z^\varepsilon) \to \mathbb{R}$ for properties that is both property and agent dependent:

$$uc(z^\varepsilon, T(z^\varepsilon)) = \frac{R(z^\varepsilon)}{P(z^\varepsilon)} = c(z^\varepsilon, T(z^\varepsilon)) + r(T(z^\varepsilon)) - g(z^\varepsilon, T(z^\varepsilon)) \tag{4}$$

Properties with characteristics z^ε may be both renter and owner-occupied, $s^h \in T(z^\varepsilon)$ and $s^l \in T(z^\varepsilon)$, even if the owner-occupier is borrowing constrained and has a higher effective discount rate $r(s^h) > r(s^l)$, if, for instance, a landlord has sufficiently higher maintenance costs for the property than an owner-occupier, $c(z^\varepsilon, s^l) > c(z^\varepsilon, s^h)$.

If we assume that both rents and prices are well-approximated by a semi-log specification where z is a vector of observable characteristics in $Z \subset Z^\varepsilon$:

$$\log R(z) = \alpha z + \varepsilon_r \tag{5}$$

$$\log P(z) = \beta z + \varepsilon_p \tag{6}$$

with $\varepsilon_r \sim N(0, \sigma_r^2)$ and $\varepsilon_p \sim N(0, \sigma_p^2)$ then:

$$\log uc(z, T(z)) = (\alpha - \beta) z + \varepsilon_r - \varepsilon_p \tag{7}$$

$$\frac{R(z)}{P(z)} = \exp\left((\alpha - \beta) z + \frac{\sigma_r^2}{2} + \frac{\sigma_p^2}{2} + cov(\varepsilon_r, \varepsilon_p)\right) \tag{8}$$

Note, using (5), (6) and (8), if we assume we can partition z into elements which are "structure," z_s, and elements which are location, z_l, then predicted yields (or user-costs) are the product of three components: $\exp((\alpha_s - \beta_s) z_s)$, $\exp((\alpha_l - \beta_l) z_l)$, and the Jensen inequality terms.

3 Data

Our data on rents and prices comes from the CoreLogic Multiple Listing Service (MLS) data, which is collected from participating regional boards of realtors that contribute their data to a centralized database. Over 90 boards participate, providing coverage for approximately 56 percent of all active listings nationwide. The data includes both listing and closing prices and rents, as well as property information including street address, square footage of living space, number of bedrooms, bathrooms, and the square footage of the plot of land. Our main dataset is the full set of closed sale and rental listings on single family homes and condos.

In addition, we identify a set of properties for which we there is both a rental and sale transaction within one year of each other. This provides a direct measure of property-level yields. We use this to adjust our measure of yields for our full sample and as a robustness check. We find matching sale prices for about 21 percent of rental listings from MLS. There are no significant differences in rental rates between properties for which we did and did not find a match.

Historical coverage in the data varies by market. Our main analysis is limited to CBSAs for which we have at least 500 rent transactions without missing information in each year between 2009 and 2021 and for which we also have a matched sample of property-level yields. Within each CBSA, we only consider a balanced panel of zip codes, and drop zip codes for which the standard deviation of the log sale price or rental rate is greater than one. Finally, we only consider CBSAs for which we have a balanced panel of at least 23 zip codes. This leaves us with a sample of 21 CBSAs.

We perform some data cleaning. We cap the number of bedrooms and bathrooms at 5 and remove any properties for which the comments indicate either are an accessory dwelling, or contain an accessory dwelling. The distributions of building and land square footage contain some outliers. We winsorize the distributions of building square footage at 300 square feet at the lower end and 15,000 at the higher end, and similarly at 500 square feet and 500,000 square feet for land parcel sizes.

Our main measure of property-level rent is the annual rental income net of property taxes. The MLS data often includes information on property taxes in the listing. In addition, Corelogic has matched the MLS data with data collected from local tax assessors. Whenever possible, we net out the actual dollar amount of property taxes associated with a given property from the annual rental income. For properties for which we do not have property tax information, we estimate property taxes using the average implied property tax rate in that county.

Properties only transact intermittently. Both to reduce noise and to reduce concerns related to sample selection, we expand our sample of sale prices by using estimated sale prices for properties in years in which they did not transact. We do this in two ways. First, we interpolate sale prices for any properties that transact more than once. Second, we estimate sale prices for properties that only transact once, or for years outside the first and last transaction of a property that transacts more than once using annual tract-level house prices indices from the FHFA.

We also use a variety of other data sources. We obtain information about the credit scores of people in a given zip code from the New York Consumer Credit Panel, which is a representative panel of households with Equifax credit reports. Information on LTVs and credit scores on newly originated mortgages comes from Black Knight Analytics. Demographic information, such as race, age, and income comes from Decennial Census and American Community Survey. We also use a measure of the housing vacancy rate based on USPS administrative data and made available by the US Department of Housing and Urban Development (HUD).[5]

4 Estimating Returns to Land

We estimate yields, capital gains, and total returns to land in each zip code for each CBSA in our sample using a hedonic approach and our full sample of sale prices and rents. Our methodology builds on that of Kuminoff and Pope (2012), who use the market values of properties to estimate values of the underlying land and structure.

This approach has number of benefits relative to other approaches. For example, one could estimate the capital gains from land from the sales of empty land parcels. However, the sample size of empty land parcels is small and not random in the sense that they may only be available for sale in certain parts of each city. Furthermore, there is no available rent data for land parcels that we are aware of, which would preclude us from estimating yields and total returns. Another approach is to estimate structure values from the replacement cost and then attribute the remainder of the market value of the house to land. However, again, this approach would not provide the rental values of land or structure.

We run the following regression year-by-year using our sample of sale and rental transactions:

$$\begin{aligned}\ln(\text{price}_{ijkt}) = {} & \beta_{0,k,t} + \beta_{1,k,t}\text{Sq. Ft.}_i + \beta_{2,k,t}\text{Sq. Ft.}_i^2 + \beta_{3,k,t}\text{Bedrooms}_i \\ & + \beta_{4,k,t}\text{Bathrooms}_i + \beta_{5,k,t}\text{Building Age}_{i,k,t} + \beta_{6,k,t}\text{Building Age}_{i,t}^2 \\ & + \beta_{7,k,t}\text{Land Sq. Ft.}_i + \gamma_{jt}\text{Land Sq. Ft.}_i + \delta_{jt} + \epsilon_{ijkt}, \end{aligned} \tag{9}$$

where i, j, k, t indexes the property, the zip code, the CBSA and the year, respectively and the dependent variable is either the log of the transaction price in the case of a sale or

[5] Available here: `https://www.huduser.gov/portal/datasets/usps.html`

the log of the annual net rent for rental transactions. The $\gamma_{j,t}$ are separate coefficients on Land Sq. Ft. for each zip code j. The $\delta_{j,t}$ are zip code fixed effects.

We then calculate the market value of each plot of land assuming a constant-characteristic, constant-price house. We calculate the predicted value both in- and out-of-sample (that is, we predict sale prices for rental properties and rental rates for owner-occupied properties) assuming that each house is a two bedroom, two bath, 2,000 square foot, 10 year old house on a 2,000 square foot plot of land, with the values for β_1–β_6 equal to those estimated using Equation (9) for the year 2015.

This gives us one predicted value for the $\ln(\text{price}_L)$ and $\ln(\text{rent}_L)$ for each zip code in each year. While the levels of these prices also contain the values of the constant-characteristic, constant-price structure, differences in these values are attributable to location. In other words, strictly speaking, what we call "land value" (or rents) here is not the value of a parcel of vacant land. Rather it the value of (or rent of) a property in a certain location with a certain structure on it.

We can compare how our estimates of the value of land per square foot to the estimates in Davis et al. (2021), who estimate land values for land used for single family residential purposes using appraisal data from the GSEs. Their approach is to calculate the value of land as the value of the house minus a depreciated replacement cost for the structure. The results of our comparison are in Figure A.2 in the appendix. Our measure of land value is not strictly land but also includes a constant structure. Due to the difference in measurement, the two measures will differ in levels. But, as can be seen in the figures, the correlation is extremely high; the median CBSA has a correlation of 0.81 between our zip code level measure of location value and the land value measure in Davis et al. (2021).

Using the net rents and the values over time for each location, we can then form a panel of returns of properties with the same structure characteristics but different locations. The estimated level of the returns may be biased slightly because we do not have a good measure of certain costs, like maintenance. However, since we do observe property taxes, most of the poorly measured (or unobserved costs) likely vary with structure. So though the level of returns may be biased, the variation in returns (and its components) across locations is hopefully not.

The bottom panel of Figure 1 shows that, within CBSAs, higher income areas have considerably higher land shares: Higher income areas have higher structure values and higher land values, but the latter grows with income more. As we will discuss further later, structure and land tend to have different gross yields and different capital gains. Structure requires more periodic maintenance (which in equilibrium raises gross yields) and tends to depreciate (due to age effects), whereas land tends to appreciate. Differences in land share within CBSAs could bias any inference on the causes of differences in returns at the property level.

This is another reason why for much of the remainder of the paper we focus on the returns to land, holding structure constant.

We calculate the capital gains to land as the annual log difference in predicted price.

$$\text{Capital Gains}_{L,j,t} = \ln(\text{price}_{L,j,t}) - \ln(\text{price}_{L,j,t-1}). \tag{10}$$

We calculate the predicted yield of each zip code using the following equation:

$$\text{yield}_{j,t} = \exp\left\{\ln(\widehat{\text{rent}_{j,t}}) - \ln(\widehat{\text{price}_{j,t}}) + \frac{\sigma^2_{r,k,t} + \sigma^2_{p,k,t} - 2\text{cov}_k(\epsilon_r, \epsilon_p)}{2}\right\} \tag{11}$$

where $\text{cov}_k(\epsilon_r, \epsilon_p)$ is the covariance of the residuals from a single simultaneous regression system using our full sample of properties with matched prices and rents, where both regressions take the form of Equation (9), and $\sigma_{r,k,t}$ and $\sigma_{p,k,t}$ are the standard deviations of the residuals from the full-sample regression for CBSA k, and year t.

The total return to land is calculated as:

$$\text{Total Return}_{L,t} = \text{Yield}_{L,t-1} + \text{Capital Gains}_{L,t}.$$

We estimate yields, capital gains and total returns to structures by CBSA by holding land values constant across time, but allowing the estimated value of the structure to vary. Specifically, we take the estimated land price or rent of the zip code with the highest number of housing units in each CBSA. The price or rental value of a structure in any year is then the price or rental value of land in that zip code plus the estimated value based on coefficients $\beta_1, ..., \beta_6$ from our annual rent and price regressions and the same constant characteristics used in our land estimates. Similar to our estimates of land value, the levels of these values are not solely attributed to the structure, but any differences are solely attributable to the structure.

Last, we estimate yields, capital gains, and total returns to housing (both structure and land) by taking the average predicted value from our rent and price regressions, holding characteristics constant.

We perform a check to validate our methodology. We compare our estimated land yields to the implied zip code-level land yields from our matched sample of property-level rent-price ratios. The yield estimates from the matched sample are from a single regression of the sample specification as in Equation 9, but with property-level yields as the dependent variable. The estimated value holding all characteristics constant as described above are the estimated land-yields. The results are in Figure A.1 in the appendix. While the levels of the two yield estimates are different, the pattern across areas within each city are very similar.

5 Cross-Sectional Variation in the Returns to Land

Average land yields, capital gains, and total returns for each of the 21 CBSAs in our sample are in Table 1. The unconditional standard deviation of each is calculated as the average time-series standard deviation across zip codes:

$$\sigma_{x,k} = \frac{\sum_j \left(\sqrt{\sum_t (x_{j,t} - \mu_j)^2 / N}\right)}{M}$$

where N the number observations for each zip code and is always equal to 11 (unless otherwise specified) since we limit to our analysis to 2010–2020, M is the number of zip codes in the CBSA, and μ_i is the average value over time in zip code i.[6] Similar summary statistics for housing and structure returns are in Tables 2 and 3 respectively. Information on the variation in structure and land returns across CBSAs are in Table 4.

The tables validate some priors. Markets in the sunbelt have seen higher capital gains on average, while other cities (for example, St. Louis and Chicago) saw lower average capital gains. Variation also exists in yields, but we have fewer priors on what to expect.

We can also look at our yield estimates over time for single cities. In Figure 2, we plot yields, capital gains, and net total returns (net of the market return) across zip codes with different median incomes for Phoenix. The data for Phoenix goes back to 2000, allowing us to observe the time series of our estimates over the vast majority of the last two decades. During the early 2000s, yields in Phoenix declined and capital gains rose, consistent with the house price boom that occurred during this period (Begley et al. 2022). This pattern subsequently reversed.

Almost always, yields for low income zip codes in Phoenix are higher than higher income zip codes. There is no such pattern for capital gains. A low correlation with the market return is evident as well. The spread in yields by local income widens around the start of the Great Recession before narrowing eventually.

5.1 Land returns within cities

Our main goal is to ascertain determinants of within-city variation in land returns. To this end, in Figures 3, 4, and 5 we include binned scatter plots of the zip code-level average of each of capital gains, yields and total returns to land respectively against 2010 median household income for 21 CBSAs in our sample individually[7]. The binned scatter plots are weighted by the number of households living in single unit housing units in according to the

[6] Since we use the lagged yield value, the earliest dates for which we have yields and total returns for our 21 CBSAs is 2010.

[7] For space reasons, we omitted St. Louis

2011 5-year American Community Survey.

These graphs illustrate a striking pattern. The majority of CBSAs see little variation in capital gains to land across space. However, yields, and consequently total returns, do vary across zip codes within CBSAs. Specifically, they are higher in low-income zip codes. This is not just true by income. In Figure 6 we produce a similar set of graphs with the average Equifax Risk Score (a credit score) of the residents on the x-axis. Yields are higher in low-credit score zip codes.

To more formally explore the correlations between land returns and local demographic factors, we run a series of univariate regressions of yields, capital gains, and total returns on a series of zip code-level demographic measures including the log of median household income, the share of the population that is non-white, the share of of properties that are vacant and the average credit score of the resident population. All of these right-hand-side variables are measured as of 2010.

The results are in Tables 5 (yields), 6 (capital gains), and 7 (total returns). These indicate that across CBSAs land yields and our demographic/economic factors are generally all statistically significantly correlated in the same direction. Of the 21 CBSAs in our sample, lower income implies significantly higher returns in 13 CBSAs, higher non-white population implies higher returns in 16 CBSAs, and 20 CBSA have higher returns in zips with lower average credit scores. No CBSA has a significant relationship with these factors in the opposite direction. By contrast, far fewer than half of the CBSAs show significantly higher yields in zip codes with higher vacancy rates.[8]

The systematic relationship between capital gains and the income, race and credit score in an area is less clear. It is clear that the relationship between yields and the economic factors is not counterbalanced by capital gains; zip code with higher yields do not have lower capital gains. If anything, most but not all of the point estimates have the same sign as their counterparts for yields; zip codes with higher yields often have higher average capital gains in sample.

Putting these two results together, the relationships between our factors and total returns across zips is very strong; nearly all 21 CBSAs have statistically and economically significant relationships for all three factors (besides vacancy).[9] A zip code with double the median income or a 100 point higher average credit score than another within the same CBSA can expect anywhere between roughly 1 and 6 percent lower returns on their property. The results on non-white population share are similarly striking. Areas with high shares of non-

[8]This is not surprising as in short samples, it can be difficult to detect vacancy patterns. For one, there is likely a lot of measurement error in our vacancy rates. For another, in the "short-run" there may be a negative relationship between yields and vacancies, while in the "long-run" there may be a positive rate (higher average vacancy rates could be compensated for with higher yields gross of vacancy as in Halket and Pignatti Morano di Custoza (2015).)

[9]Due to its capital gains patterns, Detroit is a strong outlier here.

whites pay higher rents relative to prices so that an area with a 10 percentage point higher non-white share has roughly between 0.5 and 3.5 percentage point higher returns.

Of course, area income, credit and race are all correlated. So we run a series of horse races in Tables 8 (yields), 9 (capital gains), and 10 (total returns). Credit score remains a very strong predictor of yields in 17 out of the 21 CBSAs even after controlling for income, race and vacancy. Income and race become far less important after controlling for credit and vacancy, though in two of the CBSAs (Miami and Tampa, FL) where higher credit does not significantly predict lower yields, race and/or income do. Results for total returns are similar, albeit noisier.

5.1.1 Leverage

The strong pattern in unlevered returns to land is not undone by leverage: households in high-income or high credit areas are less levered (have lower LTV mortgage loans) than households in low-income neighborhoods.

Figure 7 is a plot of the average FICO score of first-lien purchase mortgage originated in 2010 against the average LTV of those loans in that zip code. Higher FICO score neighborhoods have lower LTV loans on average. This is large part because of the presence of the Federal Housing Administration (FHA), which insures the credit risk of low-down payment loans for low-income households with the express purpose of increasing access to homeownership.

5.2 Risk and Returns

We calculate several measures to see if differences in returns across zip codes might be arising from differences in risk. We have a wide panel of returns but a relatively short one. This makes time-series standard deviations of returns, which themselves are fitted from estimates, quite noisy. Nevertheless we can discern some patterns in our results. In Table 11 we show results of univariate regressions of these measures on credit score. Results using income and race are similar.

The two measures of risk are the standard deviations in the year-on-year log differences in land yields and in capital gains. Point estimates indicate that for most CBSAs there were slightly higher realized volatilities in areas with low credit scores. For seven CBSAs, this relationship is significant at the five percent level. San Francisco has significantly higher rent volatility in higher credit areas. The relationship between capital gains volatility and credit scores is clearer: all CBSAs have negative estimates of the effect of credit on volatility; 20 out of 21 are significant at the five percent level.

So higher credit areas within CBSAs tend to have lower returns but less volatile rents and capital gains. This leads to no discernible pattern between Sharpe Ratios and credit.

These results are consistent with changes in the way credit affects expected returns over time, particularly in low credit areas, leading to higher realized volatility low credit areas (with indeterminate effects on Sharpe Ratios). We develop this further below after first looking at the risk-return relationship through the lens of a standard CAPM regression.

5.2.1 CAPM

To understand how much land returns in each CBSA vary with market returns and risk, we run the following regression separately for each CBSA:

$$
\begin{aligned}
\text{Total Return}_{L,i,t} = & \beta_0 + \beta_1 R_m - R_f + \beta_2 \text{Credit Score}_{i,2010} \\
& + \beta_3 (R_m - R_f) \times \text{Credit Score}_{i,2010} + \beta_4 \text{CBSA Return}_{L,t} \\
& + \beta_5 \text{CBSA Return}_{L,t} \times \text{Credit Score}_{i,2010} + \epsilon_{i,t}
\end{aligned} \tag{12}
$$

where Total Return$_{L,i,t}$ is the total return to land in zip code i in year t. The net market return $(R_m - R_f)$ is from the Fama-French data library.[10] The CBSA return is the residual of the average total return to land in the CBSA regressed on national house price growth. It is conventional to include metro area housing returns in CAPM regressions of local returns. We remove national housing returns from the metro return measure so as not to confound the detection of a relationship between credit and returns if changes in the relationship between credit and expected returns are national (thereby causing a national downturn in house values).

The results are in Table 12. β_2 measures whether ex-ante area credit scores can be used to predict average returns to land, after controlling for potential differences in risk (i.e. "alpha"). Using the point estimate, credit score negatively affects "alpha" in 19 out of 21 CBSAs.[11] In nine of these CBSAs the relationship is significant at the five percent (or better) level. In these, a one standard deviation higher average local credit score implies 0.6 to 1.6 percentage points in returns.

Meanwhile market betas are low and mostly insignificant, as expected from the right panel of Figure 2. The betas on CBSA net returns are much higher and universally significant, with (in most CBSAs) zip codes with lower credit having higher betas.

[10] Available here.

[11] The alphas are anyway significantly different from zero.

5.3 Changes in credit and risk and returns

Our hypothesis is that differences in the discount rates caused perhaps by differences in borrowing costs can explain the differences in land returns and yields within markets. Our best proxy (or perhaps instrument) for borrowing costs is lagged credit score. Historically, particularly in the last 20 years, the relationship between credit score and borrowing costs has varied a lot over time. During the boom period prior to the Great Recession, the relationship may have been weak whereas, in the period leading to the Great Recession and after the recession, credit standards tightened Goodman et al. (2018).

In Figure 8 we plot the time-series profile of the univariate relationship between land yields and credit scores for CBSAs with data prior to 2009. In most CBSAs, The relationship hovers near 0 in the mid 2000s (when lending standards were lax) and then starts to become increasing negative around the Great Recession (with differences in timing of the dip across CBSAs). By 2016, in most cases the marginal effect of credit score on land yields had recovered from the trough of the Great Recession.

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	Average			Std. Dev.		
	Yield	Cap Gains	Tot Return	Yield	Cap Gains	Tot Return
Atlanta, GA	7.73	5.11	12.84	1.65	8.08	8.54
Boston, MA-NH	6.17	3.77	9.93	0.87	4.86	13.00
Bridgeport, CT	4.90	0.90	5.80	0.54	4.70	4.39
Charlotte, NC-SC	7.22	5.70	12.92	1.67	4.98	6.72
Chicago, IL-IN-WI	5.64	0.90	6.54	1.03	5.29	5.20
Dallas, TX	7.59	6.39	13.98	1.06	4.03	4.40
Detroit, MI	6.66	3.44	10.10	1.15	8.08	7.98
Hartford, CT	5.67	1.37	7.05	0.98	3.59	4.02
Houston, TX	6.91	5.11	12.02	0.80	3.49	3.32
Jacksonville, FL	5.96	3.61	9.58	0.93	6.80	6.31
Los Angeles, CA	3.77	4.23	8.00	0.39	5.50	4.83
Miami, FL	6.73	3.71	10.44	1.44	10.22	10.07
Orlando, FL	6.68	3.10	9.78	1.20	9.14	9.12
Phoenix, AZ	5.57	4.95	10.52	0.63	8.02	7.64
Riverside, CA	5.81	3.91	9.72	0.83	7.12	6.75
San Diego, CA	5.38	4.29	9.67	0.55	4.63	4.31
San Francisco, CA	3.38	3.37	6.75	0.46	6.33	6.11
St. Louis, MO-IL	6.29	2.60	8.89	1.13	3.43	2.03
Tampa, FL	8.31	3.67	11.98	2.28	7.04	4.77
Tucson, AZ	4.91	3.15	8.07	1.01	5.93	5.46
Virginia Beach, VA-NC	6.21	2.22	8.43	0.45	3.49	1.98

Table 1: Summary Statistics for Land Returns by CBSA. *Note:* Values are weighted averages of the average and standard deviation (over time) of zip code-level yields, capital gains, and total returns between 2009 and 2021, where the weights are the number of households that are living in single-unit structures. *Source:* Corelogic MLS and the American Community Survey.

	Average			Std. Dev.		
	Yield	Cap Gains	Tot Return	Yield	Cap Gains	Tot Return
Atlanta, GA	7.22	3.08	10.30	1.16	6.80	6.79
Boston, MA-NH	5.89	2.99	8.89	0.97	4.81	13.67
Bridgeport, CT	4.91	0.13	5.04	0.59	4.84	4.06
Charlotte, NC-SC	6.67	3.50	10.17	1.06	4.77	5.45
Chicago, IL-IN-WI	5.94	0.32	6.26	1.21	4.98	4.81
Dallas, TX	6.77	4.57	11.34	0.91	3.84	4.16
Detroit, MI	7.90	2.79	10.68	1.66	8.12	8.36
Hartford, CT	5.25	0.51	5.76	0.78	3.72	3.61
Houston, TX	7.02	3.47	10.49	0.80	3.59	3.39
Jacksonville, FL	6.23	1.95	8.18	0.76	5.73	5.02
Los Angeles, CA	3.95	3.31	7.26	0.28	4.99	4.16
Miami, FL	6.53	2.29	8.82	1.08	8.51	6.86
Orlando, FL	6.00	1.81	7.81	0.88	8.14	7.51
Phoenix, AZ	5.43	3.14	8.57	0.56	8.34	7.92
Riverside, CA	5.47	3.15	8.63	0.70	6.83	5.34
San Diego, CA	4.89	3.23	8.12	0.47	4.61	4.22
San Francisco, CA	3.71	2.78	6.49	0.49	6.69	6.44
St. Louis, MO-IL	6.91	1.86	8.77	0.84	3.27	1.94
Tampa, FL	6.52	2.50	9.02	1.13	6.83	6.50
Tucson, AZ	5.50	1.60	7.10	0.80	5.46	4.76
Virginia Beach, VA-NC	6.40	1.29	7.69	0.53	3.32	1.99

Table 2: Summary Statistics for Housing Returns by CBSA. *Note:* Values are weighted averages of the average and standard deviation (over time) of zip code-level yields, capital gains, and total returns between 2009 and 2021, where the weights are the number of households that are living in single-unit structures. *Source:* Corelogic MLS and the American Community Survey.

	Average			Std. Dev.		
	Yield	Cap Gains	Tot Return	Yield	Cap Gains	Tot Return
Atlanta, GA	7.77	–2.03	5.74	0.53	1.96	2.16
Boston, MA-NH	6.30	–0.77	5.53	0.84	0.39	0.80
Bridgeport, CT	3.51	–0.77	2.74	0.30	0.67	0.79
Charlotte, NC-SC	6.95	–2.20	4.74	0.65	1.35	1.86
Chicago, IL-IN-WI	5.18	–0.58	4.60	0.35	0.53	0.68
Dallas, TX	7.33	–1.82	5.51	0.49	0.90	1.01
Detroit, MI	9.64	–0.65	8.99	1.23	0.79	1.52
Hartford, CT	5.36	–0.87	4.49	0.85	0.69	0.93
Houston, TX	7.64	–1.64	6.01	0.27	1.33	1.34
Jacksonville, FL	7.44	–1.66	5.78	0.90	1.67	2.34
Los Angeles, CA	4.50	–0.92	3.58	0.29	0.95	1.11
Miami, FL	6.84	–1.42	5.42	0.48	2.26	2.47
Orlando, FL	5.52	–1.29	4.22	0.61	1.88	2.17
Phoenix, AZ	5.07	–1.81	3.26	0.28	0.89	0.85
Riverside, CA	5.57	–0.75	4.82	1.34	0.53	2.44
San Diego, CA	5.36	–1.06	4.30	0.55	0.84	.
San Francisco, CA	5.59	–0.59	5.00	0.48	1.13	1.23
St. Louis, MO-IL	7.66	–0.74	6.92	1.42	0.58	1.70
Tampa, FL	6.47	–1.17	5.30	1.30	1.36	1.76
Tucson, AZ	6.27	–1.55	4.71	1.98	1.19	2.24
Virginia Beach, VA-NC	6.44	–0.93	5.51	0.36	0.62	0.81

Table 3: Summary Statistics for Structure Returns by CBSA. *Note:* Values are weighted averages of the average and standard deviation (over time) of zip code-level yields, capital gains, and total returns between 2009 and 2021, where the weights are the number of households that are living in single-unit structures. *Source:* Corelogic MLS and the American Community Survey.

	Mean	Std. Dev.	Min	Max
Capital Gains...				
Structure	–0.01	0.01	–0.02	–0.01
Land	0.04	0.01	0.01	0.06
Yields...				
Structure	–2.83	0.22	–3.39	–2.39
Land	–2.89	0.21	–3.44	–2.58
Jensen	0.04	0.03	–0.00	0.11

Table 4: Variation in Structure and Land Returns Across CBSAs. *Note:* Values are summary statistics for CBSA-level average structure and land capital gains and yields. *Source:* Authors' calculations using MLS data.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score
Atlanta, GA	-0.0128***	0.000299***	0.00198***	-0.000186***
	(0.00311)	(0.0000512)	(0.000511)	(0.0000182)
Boston, MA	-0.0200***	0.000530	-0.000148	-0.000306***
	(0.00379)	(0.000414)	(0.000909)	(0.0000373)
Bridgeport, CT	-0.0162***	0.000587***	0.00231	-0.000202***
	(0.00244)	(0.000113)	(0.00146)	(0.0000301)
Charlotte, NC	-0.00598	0.000278***	-0.00141	-0.000200***
	(0.00739)	(0.000101)	(0.00120)	(0.0000521)
Chicago, IL	-0.00520**	0.000183*	-0.000903**	-0.000135***
	(0.00233)	(0.000101)	(0.000444)	(0.0000204)
Dallas, TX	0.00165	0.000210***	-0.000673**	-0.0000948***
	(0.00174)	(0.0000463)	(0.000334)	(0.0000191)
Detroit, MI	-0.0258***	0.000274***	0.00115***	-0.000234***
	(0.00223)	(0.0000315)	(0.000155)	(0.0000157)
Hartford, CT	-0.0133***	0.000334***	0.000108	-0.000170***
	(0.00370)	(0.000114)	(0.000778)	(0.0000290)
Houston, TX	-0.00590***	0.000215***	-0.000189	-0.000156***
	(0.00204)	(0.0000502)	(0.000331)	(0.0000183)
Jacksonville, FL	-0.00865**	0.000288***	0.00124***	-0.000133***
	(0.00417)	(0.0000676)	(0.000440)	(0.0000317)
Los Angeles, CA	-0.00760***	0.000953***	-0.000455	-0.000114***
	(0.00147)	(0.000235)	(0.000466)	(0.0000170)
Miami, FL	-0.00151	0.000116**	0.0000349	0.00000671
	(0.00234)	(0.0000561)	(0.000245)	(0.0000260)
Orlando, FL	-0.00665	0.000572***	-0.000924**	-0.000128***
	(0.00411)	(0.000149)	(0.000379)	(0.0000288)
Phoenix, AZ	-0.00493***	0.000490***	0.0000766	-0.0000593***
	(0.00132)	(0.000127)	(0.000122)	(0.00000958)
Riverside, CA	-0.00589*	0.0000174	0.000127	-0.0000959***
	(0.00307)	(0.000281)	(0.000212)	(0.0000333)
St. Louis, MO	-0.00660	-0.000382	-0.00248***	-0.000208***
	(0.00734)	(0.000523)	(0.000760)	(0.0000686)
San Diego, CA	-0.0122***	0.00150***	-0.000664	-0.000155***
	(0.00285)	(0.000357)	(0.000919)	(0.0000276)
San Francisco, CA	-0.0156***	0.000870***	0.00312***	-0.000165***
	(0.00216)	(0.000118)	(0.000926)	(0.0000145)
Tampa, FL	-0.00617	0.000638***	-0.00143***	-0.000217***
	(0.00477)	(0.000225)	(0.000244)	(0.0000462)
Tucson, AZ	-0.00238	0.000916*	-0.000229	-0.000107***
	(0.00290)	(0.000544)	(0.000246)	(0.0000255)
Virginia Beach, VA	-0.0109***	0.000316***	0.00195***	-0.000114***
	(0.00378)	(0.0000415)	(0.000614)	(0.0000323)

Table 5: Univariate determinants of Yields. *Note:* Coefficient estimates of univariate regressions of land yields on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score
Atlanta, GA	-0.0176***	0.000536***	0.00403***	-0.000239***
	(0.00573)	(0.0000901)	(0.000875)	(0.0000413)
Boston, MA	-0.0140***	0.00180***	0.0000215	-0.000147***
	(0.00429)	(0.000348)	(0.000918)	(0.0000525)
Bridgeport, CT	-0.0138***	0.000596***	0.00555***	-0.000192***
	(0.00368)	(0.000147)	(0.00150)	(0.0000430)
Charlotte, NC	-0.0177***	0.000349***	0.00305***	-0.000165***
	(0.00423)	(0.0000502)	(0.000675)	(0.0000326)
Chicago, IL	0.000219	0.000245*	-0.0000981	0.00000452
	(0.00324)	(0.000138)	(0.000614)	(0.0000324)
Dallas, TX	-0.00838***	0.000320***	0.00126***	-0.000168***
	(0.00210)	(0.0000567)	(0.000415)	(0.0000223)
Detroit, MI	0.0750***	-0.00125***	-0.00818***	0.000801***
	(0.0163)	(0.000183)	(0.000631)	(0.000125)
Hartford, CT	-0.00741	0.000102	0.00524***	-0.0000699
	(0.00848)	(0.000248)	(0.000862)	(0.0000851)
Houston, TX	-0.00847***	0.000129***	0.000282	-0.0000806***
	(0.00178)	(0.0000473)	(0.000301)	(0.0000193)
Jacksonville, FL	0.00263	0.000132	-0.000220	-0.00000511
	(0.00662)	(0.000126)	(0.000737)	(0.0000599)
Los Angeles, CA	-0.00892***	0.00103**	-0.00143	-0.000198***
	(0.00304)	(0.000477)	(0.000894)	(0.0000342)
Miami, FL	-0.00409	0.000112	0.000708*	0.0000709*
	(0.00354)	(0.0000865)	(0.000364)	(0.0000388)
Orlando, FL	-0.0125*	0.000396	-0.000719	-0.0000908
	(0.00712)	(0.000297)	(0.000698)	(0.0000598)
Phoenix, AZ	-0.00654***	0.000763***	-0.00000830	-0.0000649***
	(0.00249)	(0.000236)	(0.000223)	(0.0000195)
Riverside, CA	-0.000539	0.000333	-0.000121	-0.000132***
	(0.00413)	(0.000355)	(0.000273)	(0.0000418)
St. Louis, MO	-0.00397	0.0000140	-0.00110***	-0.0000976***
	(0.00356)	(0.000259)	(0.000388)	(0.0000342)
San Diego, CA	-0.0133***	0.00203***	-0.000970	-0.000196***
	(0.00460)	(0.000530)	(0.00132)	(0.0000441)
San Francisco, CA	-0.0294***	0.00184***	0.00655**	-0.000337***
	(0.00727)	(0.000380)	(0.00261)	(0.0000577)
Tampa, FL	-0.0106***	-0.000484***	0.000523***	0.0000331
	(0.00304)	(0.000152)	(0.000195)	(0.0000363)
Tucson, AZ	-0.00789**	0.00138**	0.000266	-0.000166***
	(0.00326)	(0.000656)	(0.000306)	(0.0000241)
Virginia Beach, VA	0.000974	0.0000418	-0.000571	-0.0000407
	(0.00293)	(0.0000453)	(0.000477)	(0.0000253)

Table 6: UNIVARIATE DETERMINANTS OF CAPITAL GAINS. *Note:* Coefficient estimates of univariate regressions of land capital gains on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score
Atlanta, GA	-0.0304***	0.000834***	0.00601***	-0.000425***
	(0.00764)	(0.000116)	(0.00118)	(0.0000482)
Boston, MA	-0.0340***	0.00233***	-0.000127	-0.000453***
	(0.00494)	(0.000522)	(0.00132)	(0.0000526)
Bridgeport, CT	-0.0299***	0.00118***	0.00786***	-0.000394***
	(0.00485)	(0.000206)	(0.00255)	(0.0000557)
Charlotte, NC	-0.0237***	0.000628***	0.00164	-0.000365***
	(0.00879)	(0.0000988)	(0.00155)	(0.0000521)
Chicago, IL	-0.00498	0.000428***	-0.00100*	-0.000131***
	(0.00308)	(0.000128)	(0.000583)	(0.0000288)
Dallas, TX	-0.00673**	0.000531***	0.000585	-0.000262***
	(0.00316)	(0.0000799)	(0.000618)	(0.0000315)
Detroit, MI	0.0492***	-0.000974***	-0.00703***	0.000567***
	(0.0167)	(0.000192)	(0.000713)	(0.000132)
Hartford, CT	-0.0207**	0.000436*	0.00535***	-0.000239***
	(0.00836)	(0.000257)	(0.00106)	(0.0000795)
Houston, TX	-0.0144***	0.000343***	0.0000932	-0.000237***
	(0.00261)	(0.0000670)	(0.000453)	(0.0000236)
Jacksonville, FL	-0.00603	0.000419***	0.00102	-0.000138**
	(0.00655)	(0.000101)	(0.000714)	(0.0000541)
Los Angeles, CA	-0.0165***	0.00199***	-0.00189*	-0.000312***
	(0.00342)	(0.000547)	(0.00106)	(0.0000359)
Miami, FL	-0.00560	0.000228**	0.000743*	0.0000776*
	(0.00427)	(0.000103)	(0.000443)	(0.0000470)
Orlando, FL	-0.0192**	0.000968***	-0.00164*	-0.000219***
	(0.00868)	(0.000346)	(0.000841)	(0.0000682)
Phoenix, AZ	-0.0115***	0.00125***	0.0000683	-0.000124***
	(0.00267)	(0.000251)	(0.000251)	(0.0000196)
Riverside, CA	-0.00643	0.000351	0.00000661	-0.000228***
	(0.00605)	(0.000532)	(0.000407)	(0.0000588)
St. Louis, MO	-0.0106	-0.000368	-0.00359***	-0.000306***
	(0.00930)	(0.000675)	(0.000905)	(0.0000817)
San Diego, CA	-0.0255***	0.00353***	-0.00163	-0.000351***
	(0.00696)	(0.000819)	(0.00213)	(0.0000654)
San Francisco, CA	-0.0450***	0.00271***	0.00967***	-0.000502***
	(0.00825)	(0.000426)	(0.00317)	(0.0000598)
Tampa, FL	-0.0168***	0.000154	-0.000907***	-0.000184***
	(0.00526)	(0.000278)	(0.000333)	(0.0000581)
Tucson, AZ	-0.0103*	0.00230**	0.0000371	-0.000273***
	(0.00559)	(0.00107)	(0.000510)	(0.0000393)
Virginia Beach, VA	-0.00995*	0.000358***	0.00138	-0.000155***
	(0.00522)	(0.0000637)	(0.000874)	(0.0000420)

Table 7: Univariate determinants of Total Returns. *Note:* Coefficient estimates of univariate regressions of land total returns on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score	Constant
Atlanta, GA	0.0130***	-0.0000420	0.000205	-0.000277***	0.119***
	(0.00354)	(0.0000563)	(0.000456)	(0.0000346)	(0.0340)
Boston, MA	0.000488	-0.000702**	-0.00168***	-0.000375***	0.333***
	(0.00623)	(0.000311)	(0.000623)	(0.0000688)	(0.0427)
Bridgeport, CT	-0.00399	-0.0000667	-0.00342***	-0.000243	0.278***
	(0.00715)	(0.000293)	(0.00121)	(0.000152)	(0.0593)
Charlotte, NC	0.0262*	-0.000234	-0.00212	-0.000543***	0.163*
	(0.0135)	(0.000210)	(0.00157)	(0.000149)	(0.0940)
Chicago, IL	0.00162	-0.0000694	-0.00211***	-0.000199***	0.185***
	(0.00287)	(0.0000926)	(0.000429)	(0.0000274)	(0.0263)
Dallas, TX	0.0152***	-0.0000151	-0.000294	-0.000236***	0.0664***
	(0.00257)	(0.0000525)	(0.000350)	(0.0000312)	(0.0209)
Detroit, MI	0.00410	-0.0000787	-0.000895***	-0.000422***	0.315***
	(0.00449)	(0.0000558)	(0.000208)	(0.0000605)	(0.0273)
Hartford, CT	0.00518	-0.0000239	-0.000743	-0.000234**	0.169***
	(0.00874)	(0.000147)	(0.000524)	(0.000103)	(0.0401)
Houston, TX	0.0191***	-0.000136***	-0.000107	-0.000362***	0.104***
	(0.00286)	(0.0000504)	(0.000267)	(0.0000333)	(0.0213)
Jacksonville, FL	0.0169***	0.0000704	0.00128***	-0.000186***	-0.00655
	(0.00585)	(0.000112)	(0.000423)	(0.0000683)	(0.0500)
Los Angeles, CA	-0.00155	0.000453**	-0.000447	-0.0000852***	0.116***
	(0.00221)	(0.000230)	(0.000410)	(0.0000271)	(0.0172)
Miami, FL	-0.00458	0.000200***	-0.000544*	0.0000830**	0.0596**
	(0.00311)	(0.0000695)	(0.000315)	(0.0000381)	(0.0277)
Orlando, FL	0.00837	0.000251	-0.000203	-0.000140**	0.0646
	(0.00563)	(0.000185)	(0.000390)	(0.0000585)	(0.0425)
Phoenix, AZ	-0.00424**	-0.0000380	-0.000201	-0.0000497***	0.137***
	(0.00182)	(0.000162)	(0.000146)	(0.0000142)	(0.0198)
Riverside, CA	0.00247	-0.000496	0.000334	-0.000164***	0.143***
	(0.00442)	(0.000337)	(0.000292)	(0.0000522)	(0.0383)
St. Louis, MO	0.00339	-0.000146	-0.00155	-0.000198	0.173**
	(0.0120)	(0.000543)	(0.00123)	(0.000143)	(0.0744)
San Diego, CA	-0.00570	0.0000397	-0.00166**	-0.000121**	0.207***
	(0.00354)	(0.000460)	(0.000664)	(0.0000484)	(0.0380)
San Francisco, CA	-0.00356	0.000143	-0.0000888	-0.000121***	0.162***
	(0.00302)	(0.000185)	(0.000639)	(0.0000415)	(0.0246)
Tampa, FL	-0.0176***	-0.00000964	-0.00180***	-0.0000926*	0.344***
	(0.00403)	(0.000229)	(0.000241)	(0.0000552)	(0.0429)
Tucson, AZ	0.00752	0.000388	-0.000174	-0.000163***	0.0830**
	(0.00486)	(0.000486)	(0.000294)	(0.0000384)	(0.0403)
Virginia Beach, VA	0.00779	0.000487***	0.000874	0.0000894*	-0.101*
	(0.00544)	(0.0000693)	(0.000642)	(0.0000486)	(0.0516)

Table 8: Multivariate determinants of Yields. *Note:* Coefficient estimates of multivariate regressions of land yields on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score	Constant
Atlanta, GA	0.0182**	0.000298**	0.00275***	-0.000169**	-0.0447
	(0.00802)	(0.000127)	(0.00103)	(0.0000784)	(0.0769)
Boston, MA	-0.00566	0.00153***	-0.000157	-0.00000499	0.100*
	(0.00839)	(0.000419)	(0.000839)	(0.0000926)	(0.0575)
Bridgeport, CT	0.00318	-0.0000716	0.00240	-0.000201	0.115
	(0.0114)	(0.000468)	(0.00194)	(0.000242)	(0.0947)
Charlotte, NC	-0.00236	0.000381***	0.00109	0.0000682	0.0270
	(0.00912)	(0.000142)	(0.00106)	(0.000101)	(0.0637)
Chicago, IL	-0.00134	0.000374**	-0.000465	0.0000500	-0.0137
	(0.00517)	(0.000167)	(0.000772)	(0.0000493)	(0.0474)
Dallas, TX	0.00632*	0.0000823	0.000788*	-0.000182***	0.118***
	(0.00349)	(0.0000712)	(0.000473)	(0.0000423)	(0.0283)
Detroit, MI	-0.00920	0.000349	-0.0139***	-0.000668*	0.658***
	(0.0259)	(0.000322)	(0.00120)	(0.000349)	(0.157)
Hartford, CT	0.0121	0.0000416	0.00572***	-0.0000598	-0.0862
	(0.0163)	(0.000274)	(0.000976)	(0.000192)	(0.0747)
Houston, TX	-0.00905***	0.0000344	-0.000354	0.00000198	0.153***
	(0.00350)	(0.0000615)	(0.000326)	(0.0000407)	(0.0261)
Jacksonville, FL	0.00361	0.000432*	-0.000296	0.000130	-0.0947
	(0.0129)	(0.000247)	(0.000931)	(0.000150)	(0.110)
Los Angeles, CA	0.00647	0.000166	-0.000918	-0.000252***	0.151***
	(0.00445)	(0.000464)	(0.000826)	(0.0000547)	(0.0346)
Miami, FL	-0.0108**	0.000225**	-0.000297	0.000183***	0.0332
	(0.00458)	(0.000102)	(0.000464)	(0.0000561)	(0.0408)
Orlando, FL	-0.0171	0.000264	-0.000982	0.0000806	0.172*
	(0.0122)	(0.000401)	(0.000848)	(0.000127)	(0.0924)
Phoenix, AZ	-0.00883**	0.000392	-0.000534*	-0.0000180	0.162***
	(0.00367)	(0.000326)	(0.000295)	(0.0000286)	(0.0400)
Riverside, CA	0.0135**	-0.000523	0.000656*	-0.000266***	0.0660
	(0.00543)	(0.000413)	(0.000358)	(0.0000641)	(0.0470)
St. Louis, MO	-0.00140	0.000238	-0.00119*	-0.0000434	0.0754**
	(0.00612)	(0.000278)	(0.000630)	(0.0000729)	(0.0380)
San Diego, CA	-0.00242	0.000393	-0.00191*	-0.000167**	0.194***
	(0.00604)	(0.000785)	(0.00113)	(0.0000825)	(0.0648)
San Francisco, CA	-0.000785	0.000360	0.000277	-0.000278*	0.248**
	(0.0122)	(0.000747)	(0.00258)	(0.000168)	(0.0993)
Tampa, FL	-0.00778**	-0.000534**	0.000152	-0.0000379	0.153***
	(0.00372)	(0.000212)	(0.000223)	(0.0000510)	(0.0397)
Tucson, AZ	0.0112**	-0.000106	0.000470	-0.000243***	0.0790*
	(0.00514)	(0.000514)	(0.000311)	(0.0000406)	(0.0426)
Virginia Beach, VA	0.0109*	-0.0000119	-0.000935	-0.000158***	0.0126
	(0.00573)	(0.0000729)	(0.000676)	(0.0000511)	(0.0543)

Table 9: Multivariate determinants of Capital Gains. *Note:* Coefficient estimates of multivariate regressions of land capital gains on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	ln(Median Income)	Share Non-White (%)	Share Vacant (%)	Average Credit Score	Constant
Atlanta, GA	0.0313***	0.000256*	0.00296**	-0.000446***	0.0747
	(0.00925)	(0.000147)	(0.00119)	(0.0000904)	(0.0886)
Boston, MA	-0.00517	0.000831*	-0.00184**	-0.000380***	0.433***
	(0.00884)	(0.000441)	(0.000884)	(0.0000975)	(0.0605)
Bridgeport, CT	-0.000811	-0.000138	-0.00102	-0.000444	0.393***
	(0.0152)	(0.000621)	(0.00257)	(0.000321)	(0.126)
Charlotte, NC	0.0238	0.000147	-0.00103	-0.000474***	0.190*
	(0.0157)	(0.000244)	(0.00182)	(0.000173)	(0.109)
Chicago, IL	0.000282	0.000304**	-0.00258***	-0.000149***	0.171***
	(0.00428)	(0.000138)	(0.000639)	(0.0000408)	(0.0392)
Dallas, TX	0.0216***	0.0000671	0.000495	-0.000419***	0.185***
	(0.00456)	(0.0000931)	(0.000620)	(0.0000553)	(0.0370)
Detroit, MI	-0.00510	0.000270	-0.0148***	-0.00109***	0.974***
	(0.0270)	(0.000335)	(0.00125)	(0.000363)	(0.164)
Hartford, CT	0.0172	0.0000177	0.00498***	-0.000294	0.0823
	(0.0171)	(0.000289)	(0.00103)	(0.000202)	(0.0787)
Houston, TX	0.0100**	-0.000102	-0.000461	-0.000360***	0.256***
	(0.00420)	(0.0000738)	(0.000392)	(0.0000489)	(0.0313)
Jacksonville, FL	0.0205**	0.000502***	0.000984	-0.0000559	-0.101
	(0.00981)	(0.000188)	(0.000710)	(0.000115)	(0.0839)
Los Angeles, CA	0.00492	0.000618	-0.00137	-0.000337***	0.267***
	(0.00463)	(0.000483)	(0.000861)	(0.0000569)	(0.0360)
Miami, FL	-0.0154***	0.000425***	-0.000841	0.000266***	0.0928**
	(0.00531)	(0.000119)	(0.000538)	(0.0000651)	(0.0473)
Orlando, FL	-0.00877	0.000515	-0.00118	-0.0000592	0.236**
	(0.0140)	(0.000457)	(0.000968)	(0.000145)	(0.105)
Phoenix, AZ	-0.0131***	0.000354	-0.000734**	-0.0000677**	0.300***
	(0.00358)	(0.000318)	(0.000288)	(0.0000279)	(0.0390)
Riverside, CA	0.0160**	-0.00102*	0.000989**	-0.000430***	0.209***
	(0.00749)	(0.000570)	(0.000493)	(0.0000884)	(0.0649)
St. Louis, MO	0.00199	0.0000920	-0.00274**	-0.000241	0.248***
	(0.0131)	(0.000595)	(0.00135)	(0.000156)	(0.0815)
San Diego, CA	-0.00812	0.000433	-0.00357**	-0.000288**	0.401***
	(0.00863)	(0.00112)	(0.00162)	(0.000118)	(0.0926)
San Francisco, CA	-0.00434	0.000503	0.000188	-0.000400**	0.410***
	(0.0126)	(0.000774)	(0.00267)	(0.000173)	(0.103)
Tampa, FL	-0.0254***	-0.000543*	-0.00165***	-0.000131*	0.498***
	(0.00550)	(0.000313)	(0.000329)	(0.0000753)	(0.0586)
Tucson, AZ	0.0187**	0.000282	0.000296	-0.000407***	0.162***
	(0.00746)	(0.000746)	(0.000451)	(0.0000589)	(0.0619)
Virginia Beach, VA	0.0187**	0.000475***	-0.0000611	-0.0000689	-0.0880
	(0.00874)	(0.000111)	(0.00103)	(0.0000780)	(0.0829)

Table 10: MULTIVARIATE DETERMINANTS OF TOTAL RETURNS. *Note:* Coefficient estimates of multivariate regressions of land total returns on factors. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the decennial census, HUD vacancy rates, and the New York Consumer Credit Panel.

	Land Sharpe Ratio	Land Rent Volatility	Land Cap Gains Volatility
Atlanta, GA	0.00284***	-0.000277	-0.000465***
	(0.000766)	(0.000223)	(0.0000455)
Boston, MA	-0.0498***	0.000204	-0.000208
	(0.00917)	(0.000325)	(0.000199)
Bridgeport, CT	-0.000317	-0.000295	-0.000308***
	(0.00128)	(0.000281)	(0.0000598)
Charlotte, NC	-0.00180*	-0.0000259	-0.000201***
	(0.00102)	(0.000377)	(0.0000254)
Chicago, IL	0.000636	-0.000843**	-0.000288***
	(0.00175)	(0.000355)	(0.0000382)
Dallas, TX	0.00230*	-0.000527***	-0.000143***
	(0.00122)	(0.000151)	(0.0000201)
Detroit, MI	0.00472***	-0.00177***	-0.000710***
	(0.000545)	(0.000205)	(0.0000712)
Houston, TX	0.00447*	-0.000398**	-0.000142***
	(0.00258)	(0.000172)	(0.0000343)
Jacksonville, FL	0.00755***	-0.000590**	-0.000324***
	(0.00290)	(0.000238)	(0.0000752)
Los Angeles, CA	0.000814	-0.0000147	-0.000209***
	(0.00238)	(0.000110)	(0.0000517)
Miami, FL	0.00712***	-0.000455	-0.000604***
	(0.000945)	(0.000433)	(0.0000865)
New Haven, CT	0.000904	0.000328	-0.000414***
	(0.00226)	(0.000200)	(0.000110)
Orlando, FL	0.00111	-0.000595*	-0.000333***
	(0.00169)	(0.000361)	(0.000118)
Phoenix, AZ	0.00435***	-0.000214**	-0.000350***
	(0.00108)	(0.0000878)	(0.0000522)
Riverside, CA	0.00513***	-0.000220	-0.000408***
	(0.00172)	(0.000247)	(0.0000832)
San Diego, CA	0.0230***	-0.0000463	-0.000389***
	(0.00747)	(0.000120)	(0.0000802)
San Francisco, CA	-0.00209	0.000545***	-0.000279**
	(0.00257)	(0.000156)	(0.000124)
Tampa, FL	0.0162**	-0.000313*	-0.000257***
	(0.00640)	(0.000180)	(0.0000704)
Tucson, AZ	0.00297	-0.0000947	-0.000272***
	(0.00260)	(0.000282)	(0.0000635)
Virginia Beach, VA	0.0896***	-0.000305***	-0.000251***
	(0.0124)	(0.000115)	(0.0000324)

Table 11: Regressions of Zip Code Measures of Risk on Zip Code Average Equifax Risk Score. *Note:* Values are coefficients from regressions of each risk measure on the average zip code-level Equifax Risk Score as of 2010. The Sharpe ratio for land is calculated as the average total return to land in each zip code over the standard deviation of that return between 2010 and 2020. Land rent volatility is the standard deviation of of the annual log difference in land rent. Cap gains volatility is the standard deviation of capital gains to land. Regressions are weighted by the number households residing in one-unit housing units in 2011. *Source:* Authors' calculations using the Corelogic MLS data and the New York Consumer Credit Panel.

	$R_m - R_f$	Credit Score	$R_m - R_f \times$ Credit Score	CBSA Net Return	CBSA Net Return $\times$ Credit Score	Constant
Atlanta, GA	0.0752***	-1.106***	-0.00829	0.995***	-0.129***	10.51***
	(0.0159)	(0.379)	(0.0192)	(0.0389)	(0.0486)	(0.315)
Boston, MA	0.00968	-1.587**	-0.00351	0.797***	0.113	10.34***
	(0.0420)	(0.800)	(0.0403)	(0.244)	(0.232)	(0.830)
Bridgeport, CT	0.0351	-1.473**	0.0330	1.866***	-0.589**	5.189***
	(0.0363)	(0.607)	(0.0290)	(0.296)	(0.236)	(0.752)
Charlotte, NC	0.0520***	-1.073***	-0.0130	1.040***	-0.119	11.04***
	(0.0146)	(0.318)	(0.0161)	(0.0845)	(0.0933)	(0.289)
Chicago, IL	0.107***	-0.921***	0.00568	1.125***	-0.152**	4.643***
	(0.0166)	(0.341)	(0.0174)	(0.0621)	(0.0650)	(0.325)
Dallas, TX	0.0428***	-0.645***	0.000985	1.032***	-0.0419	12.39***
	(0.00766)	(0.154)	(0.00787)	(0.0350)	(0.0350)	(0.151)
Detroit, MI	0.130***	-0.462	-0.00217	1.201***	-0.117**	6.866***
	(0.0191)	(0.353)	(0.0188)	(0.0586)	(0.0560)	(0.364)
Hartford, CT	0.0486**	-1.164***	0.0105	1.431***	-0.416***	6.835***
	(0.0228)	(0.421)	(0.0215)	(0.131)	(0.124)	(0.443)
Houston, TX	0.0305***	-0.864***	0.00416	1.025***	0.0527	10.50***
	(0.00927)	(0.154)	(0.00772)	(0.0635)	(0.0524)	(0.185)
Jacksonville, FL	0.160***	-0.319	0.0110	1.145***	-0.403**	6.583***
	(0.0318)	(0.787)	(0.0407)	(0.121)	(0.159)	(0.608)
Los Angeles, CA	0.0988***	-0.309	-0.0473***	1.163***	-0.198***	6.642***
	(0.0134)	(0.308)	(0.0156)	(0.0511)	(0.0594)	(0.264)
Miami, FL	0.151***	-0.232	0.0139	0.882***	-0.202***	7.317***
	(0.0280)	(0.549)	(0.0279)	(0.0553)	(0.0544)	(0.553)
Orlando, FL	0.0975**	0.130	-0.0513	1.011***	-0.158*	7.468***
	(0.0381)	(0.830)	(0.0418)	(0.0851)	(0.0916)	(0.757)
Phoenix, AZ	0.155***	-0.425	-0.00333	1.115***	-0.460***	7.586***
	(0.0180)	(0.350)	(0.0174)	(0.0830)	(0.0800)	(0.360)
Riverside, CA	0.109***	-0.930	0.00456	0.959***	-0.386***	6.664***
	(0.0278)	(0.643)	(0.0330)	(0.0821)	(0.0968)	(0.548)
St. Louis, MO	0.141***	0.857	-0.0765***	1.779***	-0.457	6.173***
	(0.0306)	(0.527)	(0.0266)	(0.343)	(0.296)	(0.603)
San Diego, CA	0.0877***	-0.300	-0.0441*	1.357***	-0.444***	8.248***
	(0.0235)	(0.487)	(0.0245)	(0.128)	(0.132)	(0.466)
San Francisco, CA	0.0829**	-1.202***	-0.0340	0.898***	-0.0109	6.760***
	(0.0333)	(0.467)	(0.0247)	(0.0915)	(0.0679)	(0.627)
Tampa, FL	0.144***	-0.121	-0.0240	1.232***	-0.263**	8.903***
	(0.0196)	(0.536)	(0.0273)	(0.0853)	(0.122)	(0.383)
Tucson, AZ	0.154***	-0.0524	-0.0449	1.496***	-0.378**	5.449***
	(0.0296)	(0.602)	(0.0321)	(0.160)	(0.174)	(0.562)
Virginia Beach, VA	0.0483***	-0.395	-0.00469	0.943***	-0.452***	6.967***
	(0.0128)	(0.277)	(0.0136)	(0.102)	(0.110)	(0.260)

Table 12: DETERMINANTS OF β AND α. *Note:* The average credit score is normalized to have mean zero and standard deviation equal to 1. *Source:* Authors' calculations using Corelogic MLS data, FHFA house price indices, the New York Consumer Credit Panel, and Fama-French factors.

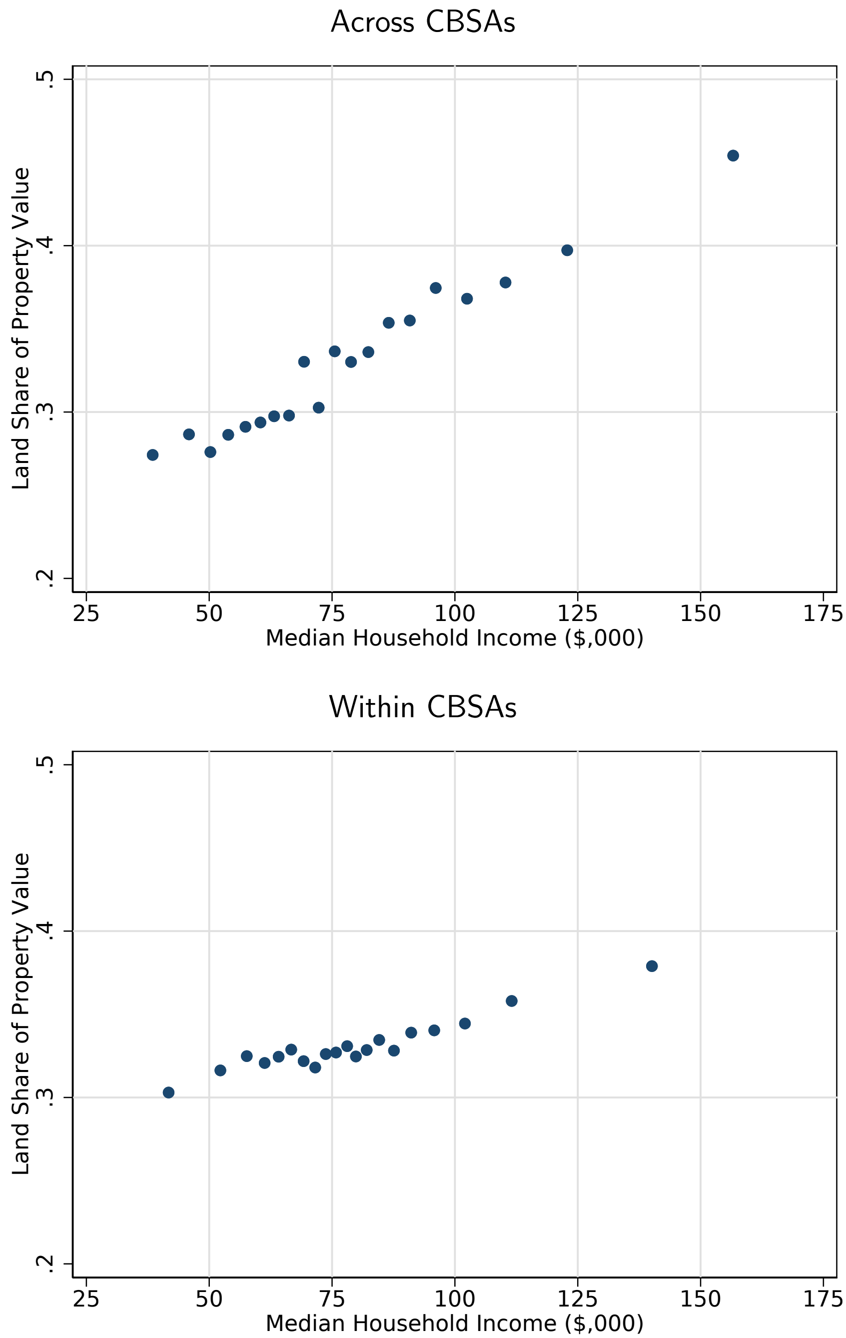

Figure 1: The Land Share of Property Values by Median Household Income. *Note:* Values are by census-tract. The land share of property values is measured as of 2012. Median household income is measured as of 2010. *Source:* Davis et al. (2021) and the Decennial Census.

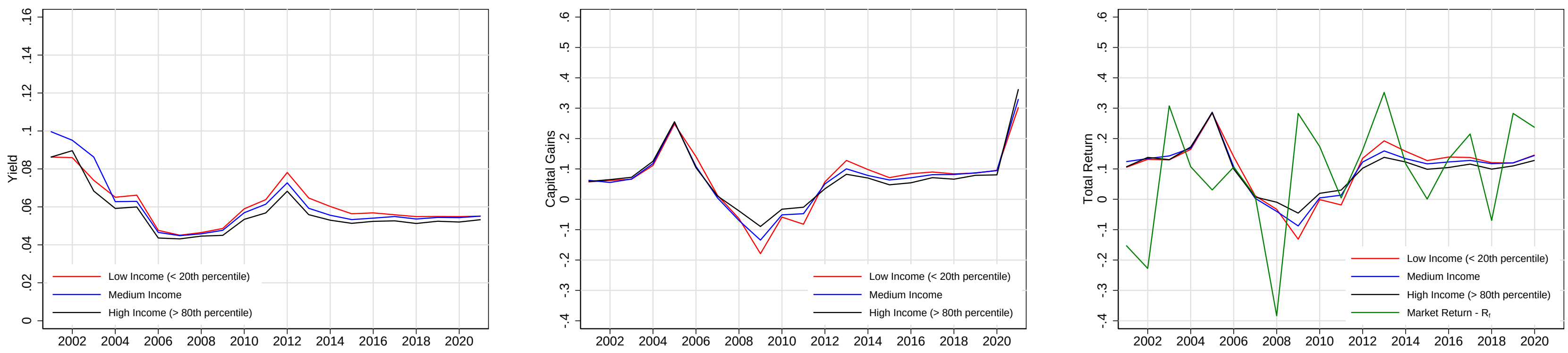

Figure 2: Yields, capital gains, and total returns on land in Phoenix, AR. *Note: Source:* Authors' calculations using Corelogic MLS and FHFA data.

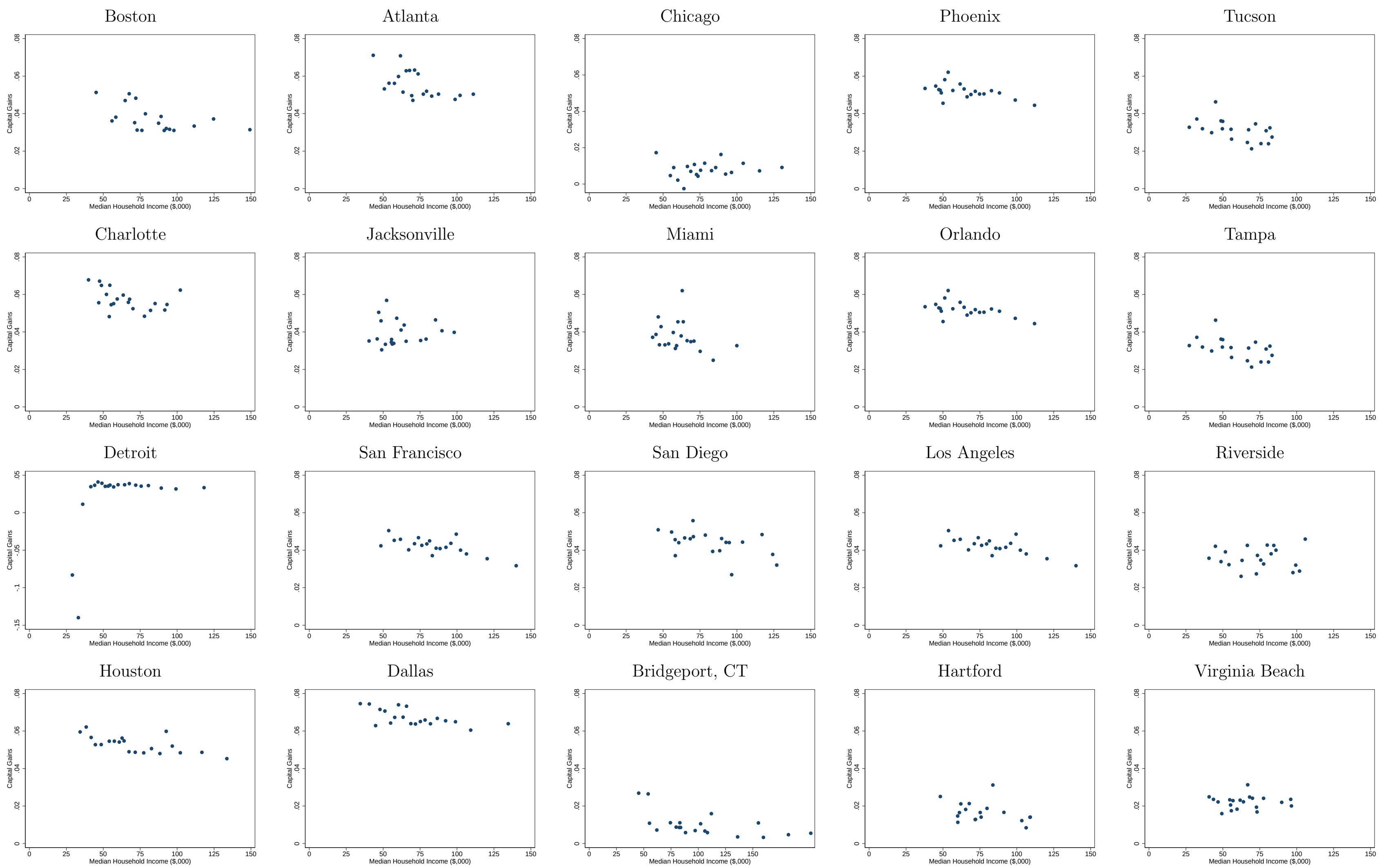

Figure 3: Capital Gains on Land by Median Household Income. *Note:* Zip codes are weighted by the number of households in single-unit structures in 2011. *Source:* Corelogic MLS data and the American Community Survey.

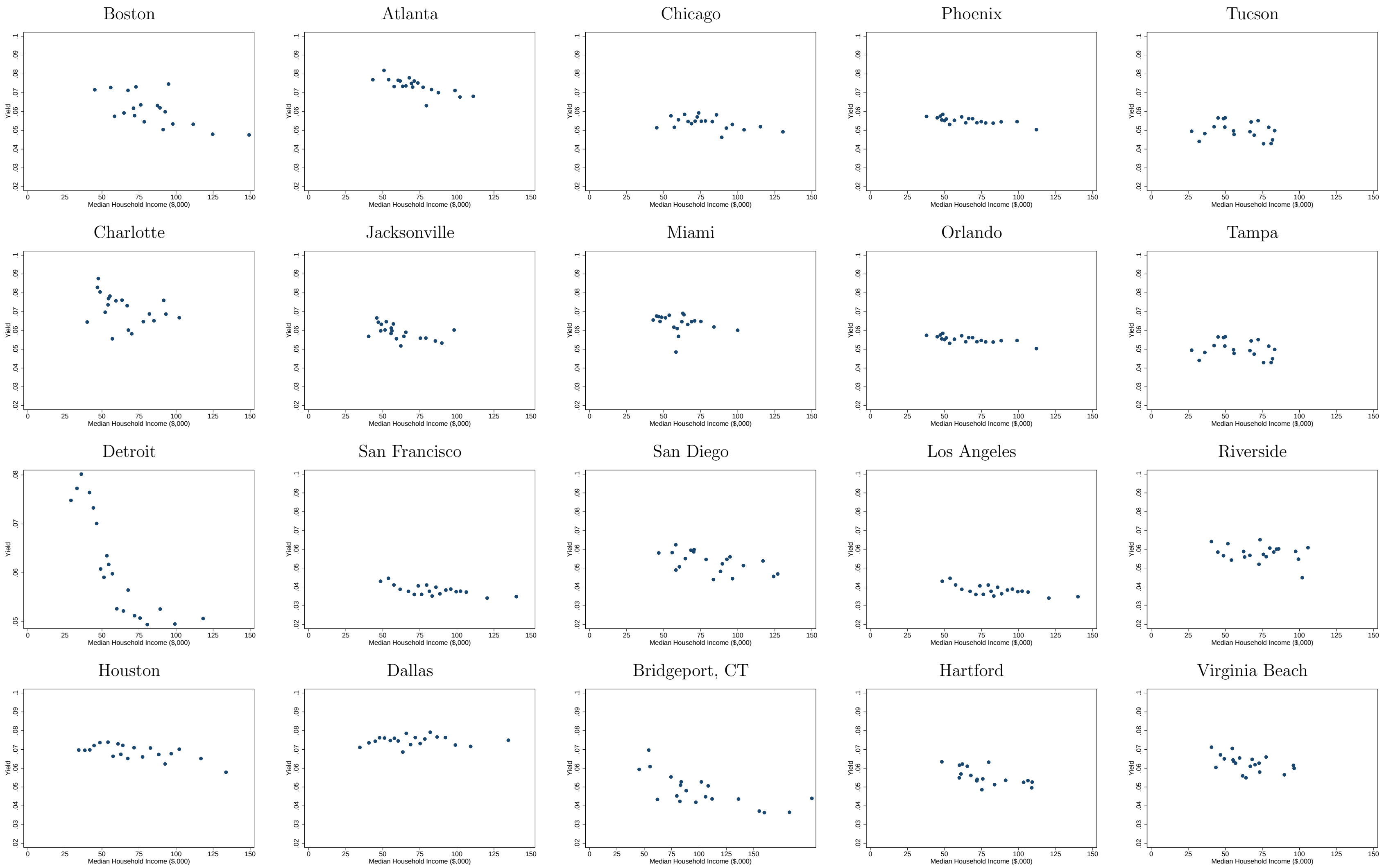

Figure 4: Yields on Land by Median Household Income. *Note:* Zip codes are weighted by the number of households in single-unit structures in 2011. *Source:* Corelogic MLS data and the American Community Survey.

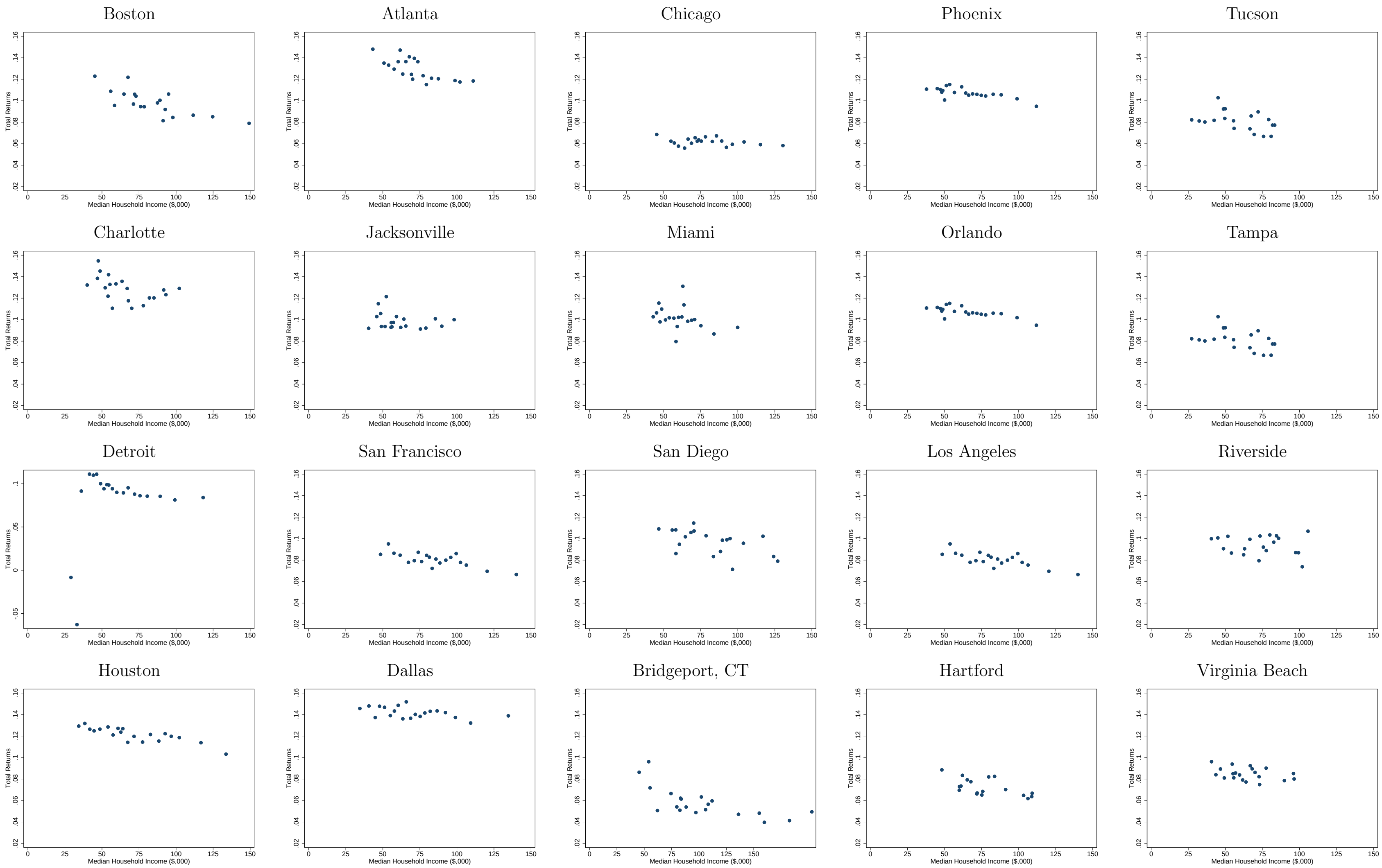

Figure 5: Total Returns on Land by Median Household Income. *Note:* Zip codes are weighted by the number of households in single-unit structures in 2011. *Source:* Corelogic MLS data and the American Community Survey.

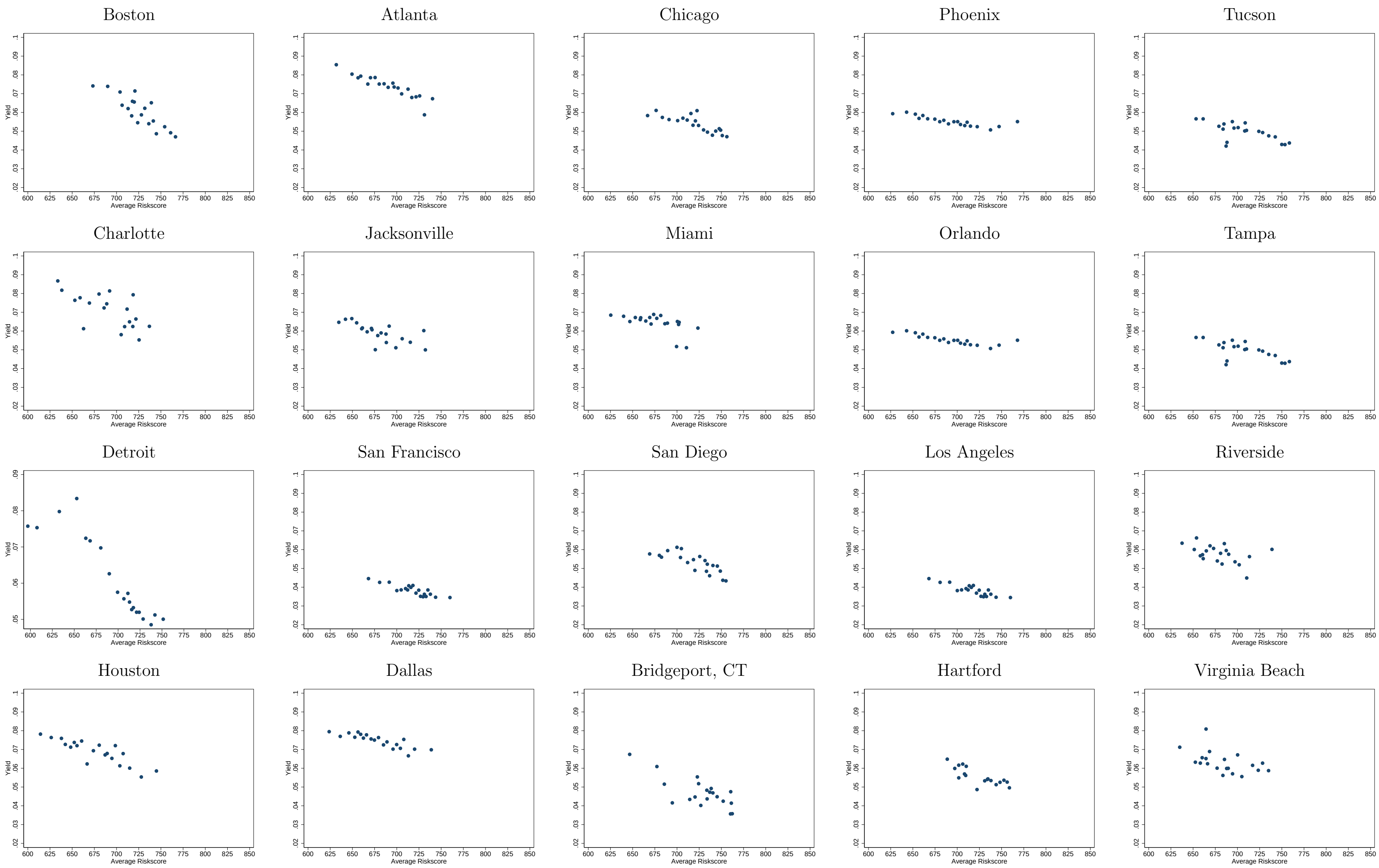

Figure 6: YIELDS ON LAND BY AVERAGE EQUIFAX RISKSCORE OF POPULATION. *Note:* Zip codes are weighted by the number of households in single-unit structures in 2011. *Source:* Corelogic MLS data, the American Community Survey, and and the New York Consumer Credit Panel.

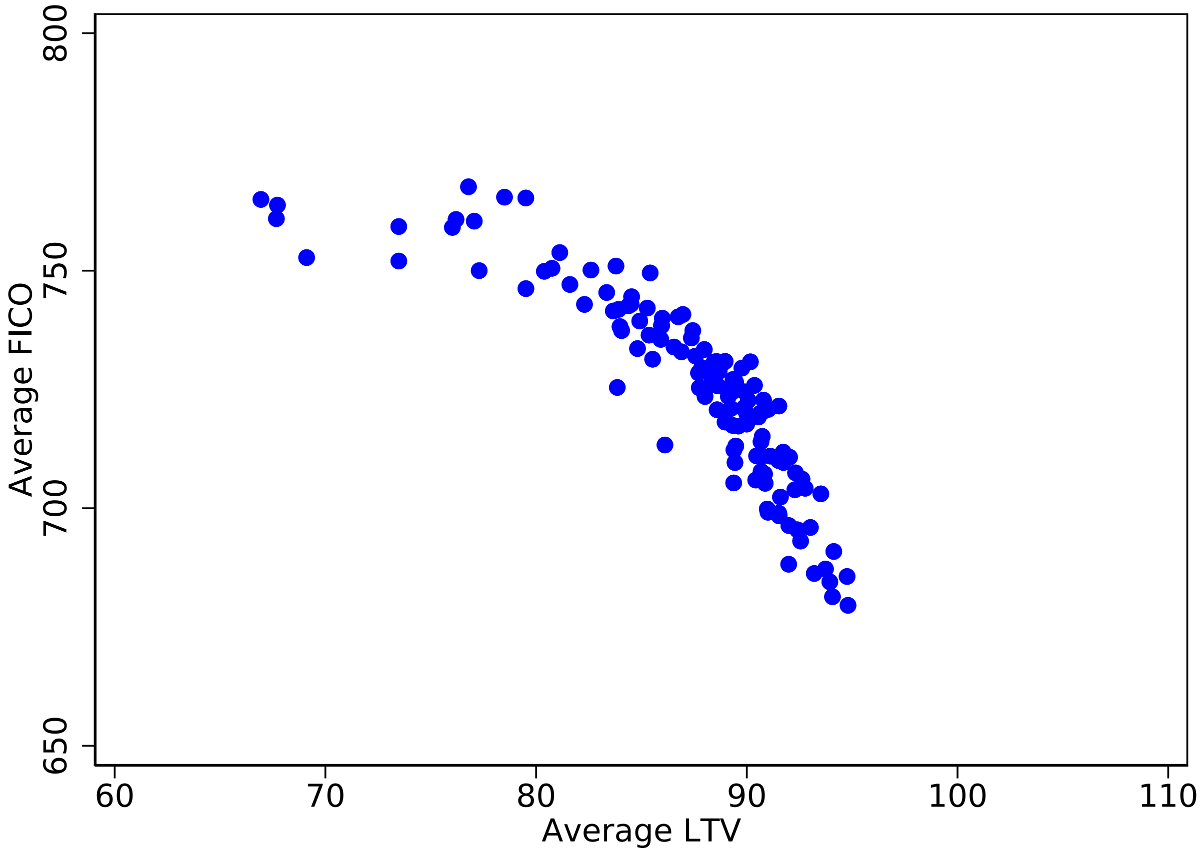

Figure 7: LTVs and FICO Scores. *Note:* Average values by zip code for first-lien purchase mortgage originations in 2010. *Source:* Black Knight Analytics.

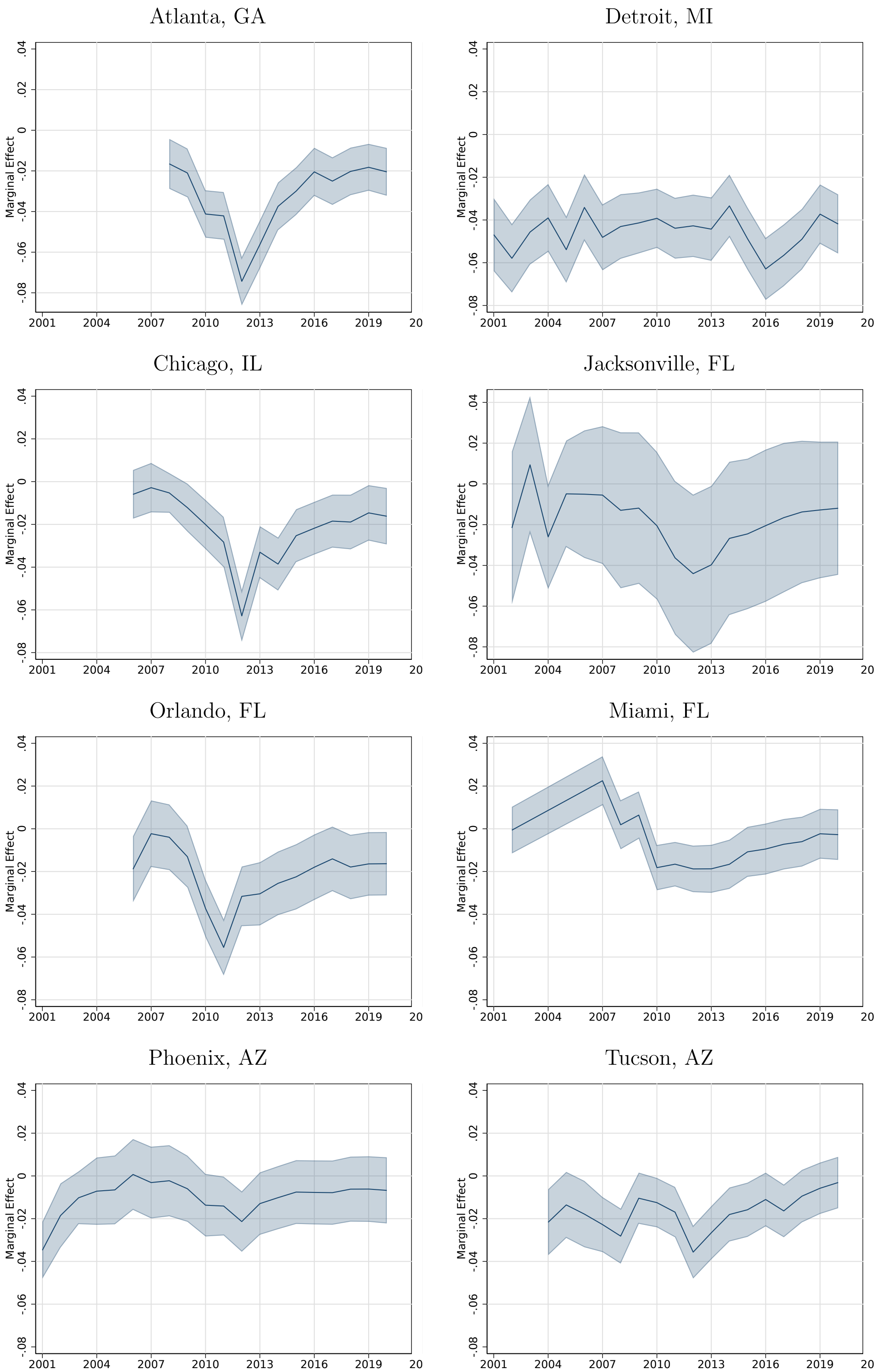

Figure 8: Relationship Between Land Yields and Credit Scores Over Time. Values are slope coefficients from CBSA-level regressions of zip code-level land yields on the zip code average Equifax Risk Score. *Source:* Authors' calculations using Corelogic MLS and the New York Consumer Credit Panel.

A Appendices

A.1 MLS Rental Listings

A potential issue with using information on rents from MLS is that properties listed for rent on MLS are higher quality the average rental unit in the US. This can be seen in Table A.1, in which we compare rents on properties listed in MLS between 1999 and 2019 to rents on housing units in the 1999-2019 waves of the American Housing Survey (AHS). We limit the AHS sample to market-rate units[12] in which the household moved since the previous survey and convert all prices to 2010 dollars. Rental listings in MLS are higher priced, on newer buildings, and for larger units than the average rental unit in the AHS. By comparison, sale transactions in MLS are representative, matching closely statistics for newly occupied owner-occupied units in the AHS. In the third column, we weight the MLS data to match the AHS size distribution, which results in moving our MLS sample somewhat closer to the AHS.

[12] We remove all rent-controlled and subsidized housing units.

	Renter Occupied			Owner-Occupied	
	AHS	MLS Unweighted	MLS Weighted	AHS	MLS Unweighted
Characteristics					
Rent or Price (2010 $)	919	1,875	1,795	225,648	261,043
Year Built	1967	1979	1974	1976	1976
Bedrooms (#)	2	3	2	3	3
Bathrooms (#)	2	2	2	3	2
Size					
Share < 500 Sq. Ft.	7	1	7	1	8
Share 500–750 Sq. Ft.	19	4	19	2	2
Share 750–1,000 Sq. Ft.	27	9	27	7	7
Share 1,000–1,500 Sq. Ft.	29	30	30	23	28
Share 1500+ Sq. Ft.	17	54	17	61	56

Table A.1: Comparison of AHS and MLS. *Note:* Values for the AHS are weighted averages from the 1999–2019 surveys and are limited to households that moved since the previous survey. Rental units from the AHS exclude all rent controlled and subsidized housing units. Values from MLS are from listings closed in 1999–2019. *Source:* AHS and MLS.

A.2 Supplemental Exhibits

This section contains additional figures and tables referenced in the main text.

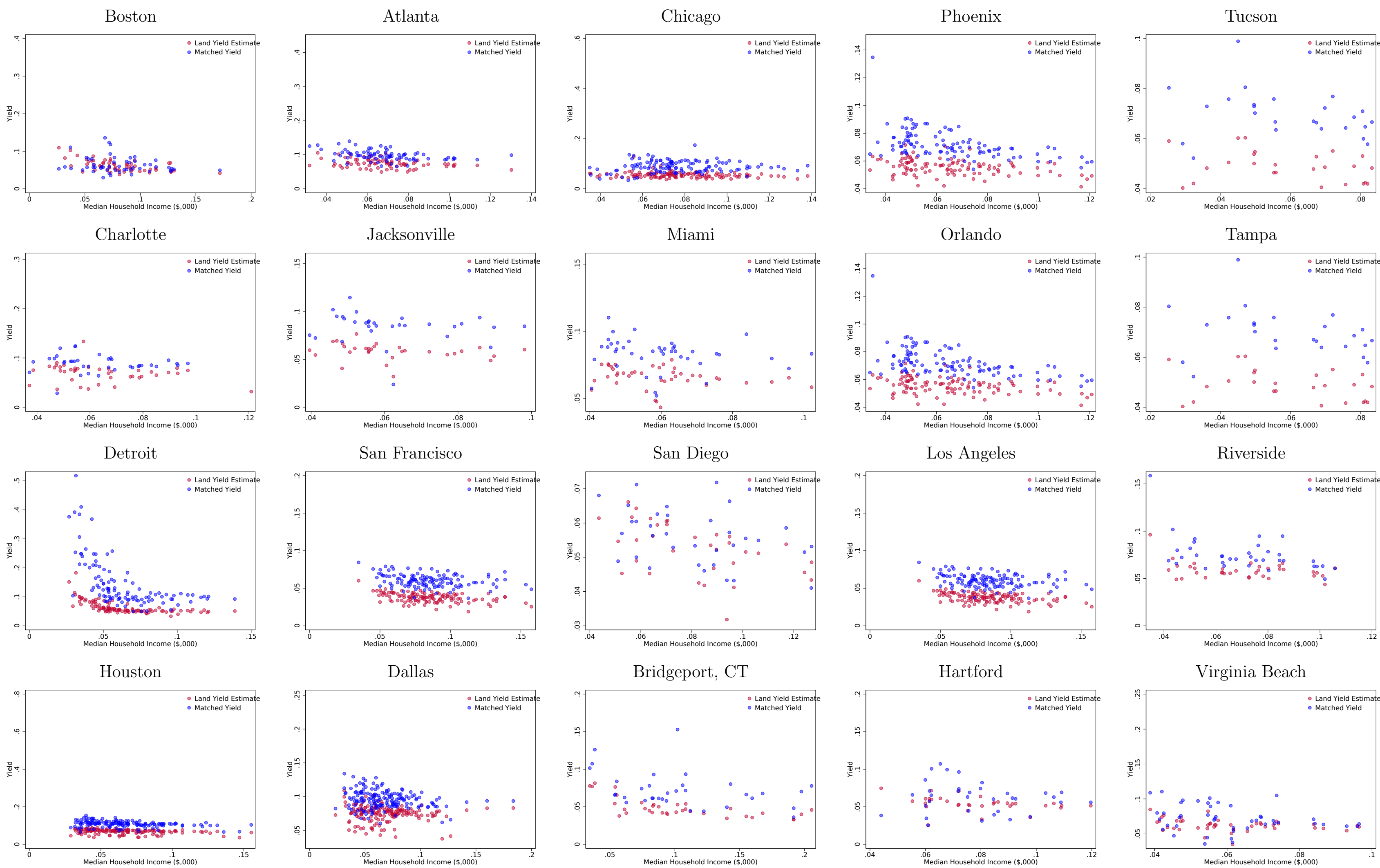

Figure A.1: Average matched yields and estimated land yields by zip code. *Note:* Average matched yields are averages of predicted values based on a single regression of property-level price-rent ratios on hedonics. The estimated land yields are estimated as described in Section 4. The x-axis is 2010 median household income from the decennial census. *Source:* Corelogic MLS data and the Decennial Census.

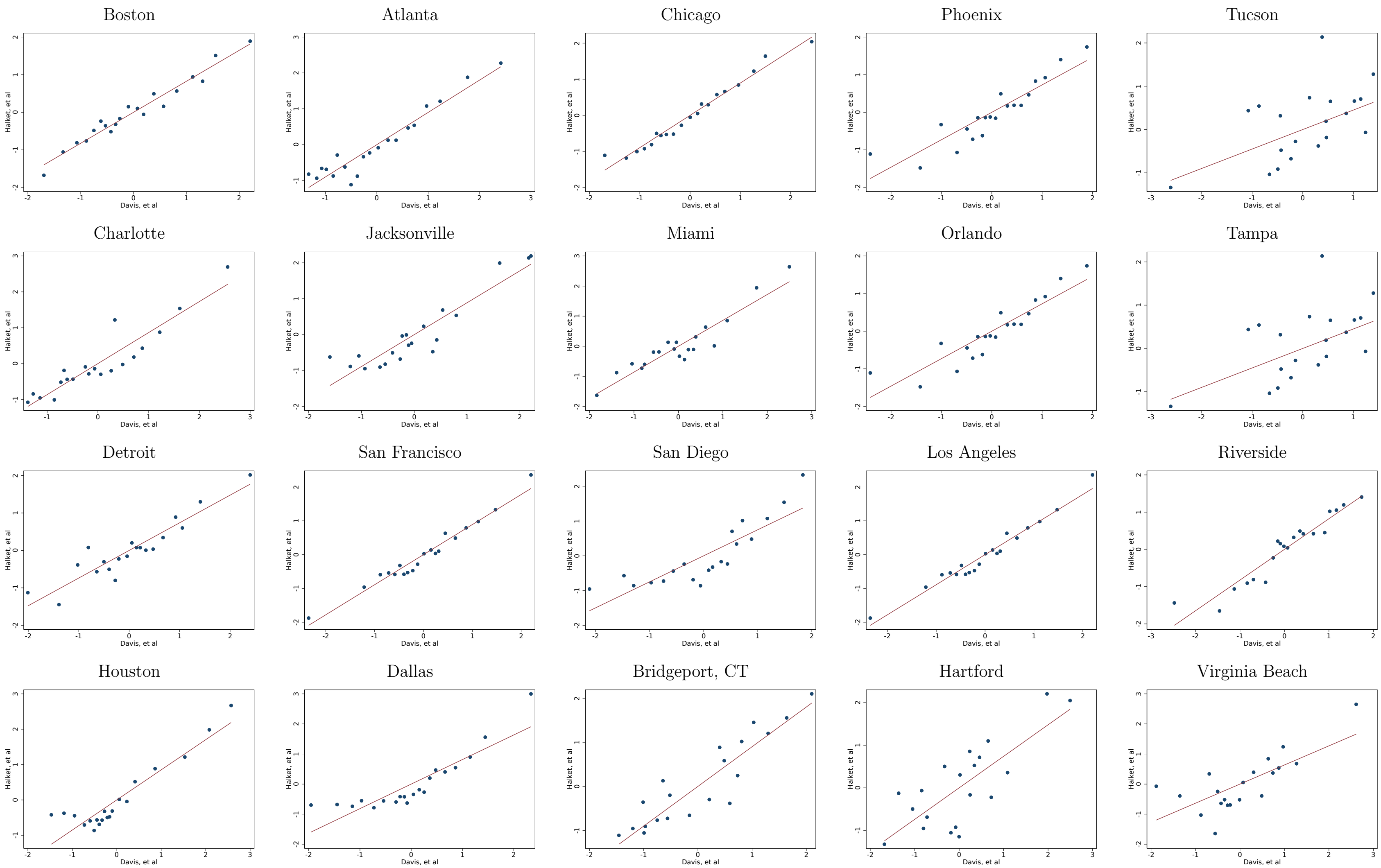

Figure A.2: Price of Land Per Sq. Ft., Comparison with Davis et al. (2021) *Note:* Our rices per square foot of land are estimated as described in Section 4. Both our estimates, and the estimates from Davis et al. (2021) are normalized to be mean zero and have a standard deviation of one. *Source:* Corelogic MLS data and Davis et al. (2021)

	Average					Std. Dev.				
	Yield Base House Val	Yield House	Yield Base Land Val	Yield Land	Jensen	Yield Base House Val	Yield House	Yield Base Land Val	Yield Land	Jensen
Atlanta, GA	–0.37	–0.43	–2.15	–2.25	0.03	0.00	0.09	0.00	0.18	0.04
Boston, MA-NH	0.44	0.39	–3.18	–3.27	0.02	0.00	0.13	0.00	0.13	0.00
Bridgeport, CT	0.11	0.11	–3.50	–3.19	0.04	0.00	0.07	0.00	0.12	0.02
Charlotte, NC-SC	–0.54	–0.61	–2.12	–2.19	0.05	0.00	0.12	0.00	0.18	0.04
Chicago, IL-IN-WI	–0.22	–0.17	–2.84	–2.74	0.05	0.00	0.07	0.00	0.16	0.01
Dallas, TX	–0.23	–0.34	–2.28	–2.38	0.01	0.00	0.07	0.00	0.13	0.01
Detroit, MI	–0.50	–0.34	–2.05	–2.31	0.04	0.00	0.11	0.00	0.15	0.01
Hartford, CT	–0.08	–0.16	–2.89	–2.92	0.11	0.00	0.18	0.00	0.15	0.01
Houston, TX	–0.40	–0.39	–2.21	–2.31	0.02	0.00	0.04	0.00	0.10	0.01
Jacksonville, FL	–0.71	–0.66	–2.02	–2.21	0.08	0.00	0.15	0.00	0.13	0.04
Los Angeles, CA	–0.07	–0.02	–3.09	–3.23	0.01	0.00	0.06	0.00	0.11	0.00
Miami, FL	–0.58	–0.61	–2.14	–2.21	0.06	0.00	0.08	0.00	0.21	0.03
Orlando, FL	–0.55	–0.66	–2.28	–2.21	0.03	0.00	0.16	0.00	0.15	0.04
Phoenix, AZ	–0.52	–0.54	–2.43	–2.37	–0.00	0.00	0.07	0.00	0.09	0.03
Riverside, CA	–0.22	–0.27	–2.68	–2.69	0.04	0.00	0.19	0.00	0.15	0.02
San Diego, CA	0.00	–0.09	–2.85	–2.95	0.01	0.00	0.10	0.00	0.10	0.00
San Francisco, CA	–0.28	–0.18	–2.72	–3.16	0.02	0.00	0.08	0.00	0.14	0.01
St. Louis, MO-IL	–0.45	–0.35	–2.29	–2.40	0.06	0.00	0.19	0.00	0.16	0.02
Tampa, FL	–0.37	–0.60	–2.21	–2.21	0.05	0.00	0.25	0.00	0.21	0.04
Tucson, AZ	–0.35	–0.22	–2.61	–2.72	0.03	0.00	0.28	0.00	0.20	0.02
Virginia Beach, VA-NC	–0.54	–0.52	–2.24	–2.26	0.01	0.00	0.05	0.00	0.07	0.01

Table A.2: Summary Statistics for Log Yield Components by CBSA. *Note:* Values are weighted averages and standard deviations of mean zip code-level returns from 2009–2019. Weights are the number of housing units in the zip code in 2010. *Source:* Corelogic MLS.

	Average		Std. Dev.	
	Cap Gain House	Cap Gain Land	Cap Gain House	Cap Gain Land
Atlanta, GA	–0.02	0.05	0.02	0.08
Boston, MA-NH	–0.01	0.04	0.00	0.05
Bridgeport, CT	–0.01	0.01	0.01	0.05
Charlotte, NC-SC	–0.02	0.06	0.01	0.05
Chicago, IL-IN-WI	–0.01	0.01	0.01	0.05
Dallas, TX	–0.02	0.06	0.01	0.04
Detroit, MI	–0.01	0.03	0.01	0.08
Hartford, CT	–0.01	0.01	0.01	0.04
Houston, TX	–0.02	0.05	0.01	0.03
Jacksonville, FL	–0.02	0.04	0.02	0.07
Los Angeles, CA	–0.01	0.04	0.01	0.05
Miami, FL	–0.01	0.04	0.02	0.10
Orlando, FL	–0.01	0.03	0.02	0.09
Phoenix, AZ	–0.02	0.05	0.01	0.08
Riverside, CA	–0.01	0.04	0.01	0.07
San Diego, CA	–0.01	0.04	0.01	0.05
San Francisco, CA	–0.01	0.03	0.01	0.06
St. Louis, MO-IL	–0.01	0.03	0.01	0.03
Tampa, FL	–0.01	0.04	0.01	0.07
Tucson, AZ	–0.02	0.03	0.01	0.06
Virginia Beach, VA-NC	–0.01	0.02	0.01	0.03

Table A.3: Summary Statistics for Log Cap Gains Components by CBSA. *Note:* Values are weighted averages and standard deviations of mean zip code-level returns from 2009–2019. Weights are the number of housing units in the zip code in 2010. *Source:* Corelogic MLS.