Collateral constraints, wealth effects, and volatility: evidence from real estate markets *

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Abstract

We document new findings on within-region volatility of returns to residential housing in the United States. Lower-income zip codes have more volatile returns to housing than do higher income zip codes, without any corresponding higher returns. We rationalize these findings with a simple model that features a collateral constraint on borrowing and non-homothetic preferences over housing and other consumption. In our model, shocks to the representative household's marginal rate of substitution lead to volatility in the return to housing via the collateral constraint. We argue that poorer households have a more volatile marginal rate of substitution than wealthier households. As a result, areas populated by lower-income households should also have more volatile returns to housing, consistent with our empirical findings. We provide further evidence for our mechanism using variation in lagged housing returns, using data on the housing expenditure share, and using state-level non-recourse status as an instrument for the strictness of collateral constraints.

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Introduction

The topic of housing affordability is generally framed through either the level or the growth rate of real estate values, compared with income. For example, popular housing affordability indices compare household income with the level of real estate values, while homeownership subsidies focus on wealth accumulation via the growth in those values. We argue that the second moment – the *volatility* of housing returns – is also important to understand the homeownership decisions of low-income households.

We begin with a theoretical analysis of the causes of housing return volatility that rests on the interaction of two key features of housing as an asset class: first, the use of housing as collateral for borrowing; and second, the non-homotheticity of preferences over housing and other consumption. Both features have been documented and studied previously, but our contribution is to show that they combine to produce endogenous volatility in home prices. Importantly, this effect strengthens as wealth falls: housing return volatility is larger for poorer households.

Our model consists of a representative household endowed with a risky income stream. This household derives utility from durable housing and other consumption and has access to a market for Arrow-Debreu (AD) securities. For simplicity, we do not model the preferences of other agents in this market and rather assume they are risk-neutral and employ some exogenous risk-free rate. We assume that the representative household is impatient relative to the AD market and thus would like to borrow.

The price of housing in our model is the present value of the marginal rate of substitution (MRS) between housing and other consumption at all dates. We assume the representative household has non-homothetic preferences over housing and other consumption and as a result, the price for housing can respond to income shocks through a change in her MRS. Absent any frictions, the representative household would trade in the AD market and smooth income shocks so that her MRS, and hence the price of housing, would remain constant.

Finally, we assume the household faces a standard borrowing constraint. Specifically, the household can sell standard AD securities so long as each claim is directly collateralized by its position in housing. This constraint means that the household cannot fully smooth consumption, and thus its MRS will fluctuate over time, producing volatility in the return to housing. The extent to which volatility in the MRS between housing and consumption translates to to volatility in housing returns depends on the extent to which housing can be collateralized. If the household is more constrained – that is, if it can borrow a smaller fraction of the value of its house – volatility in its MRS has a larger effect on the volatility of housing returns.

A key prediction of our model is that housing markets will have different volatilities of housing returns depending on the volatility of the MRS of households in that market. Under a standard specification of non-homethetic preferences, households with lower incomes have a higher volatility of the MRS between housing and other consumption. Our model then predicts that lower-income households experience more-volatile housing returns.

We corroborate this novel prediction empirically by measuring home price volatility within zip codes. To our knowledge, no previous paper studies home price volatility at this fine a level of disaggregation. We demonstrate that low-income zip codes feature consistently higher return volatilities, with no compensating increase in the level of their return. This novel finding holds across two data sources (CoreLogic and Zillow), and within each of the largest metropolitan statistical areas (MSAs) in the United States. In our main result, a doubling of annual income is associated with 1.3% less annual volatility in housing returns when that volatility is measured with CoreLogic data, or 2.7% less annual volatility when mesaured with Zillow data. Importantly, returns are not any higher in the low-income, high-volatility zip codes.

To rule out other forms of cross-sectional variation, we show that *within* zip code, lagged income changes have the same association with volatility, even controlling for state, MSA, or zip-code fixed effects. Housing exenditure share, a more direct measure of wealth effects, also has a strongly positive relationship with volatility for the 28 MSAs in which it is available, as predicted by our model. We conclude that the first of the two key mechanisms of our model, a wealth effect in willingness to pay for housing, has significant explanatory power for housing return volatility in the data.

Finally, we offer evidence on the second mechanism of our model, binding collateral constraints. To proxy for the tightness of collateral constraints, we measure the state-level degree of lender recourse, following the coding of Ghent and Kudlyak (2011). Controlling for the direct effect of wealth, we find that states allowing a lesser degree of recourse also have greater volatility, and that this finding is robust to including various demographic characteristics. The prior research on lender non-recourse laws emphasizes that they constrain access to credit, but outside the argument captured by our model, it is difficult to imagine why they should increase the volatility of home price returns. That volatility seems to be affected by a significant interaction between wealth effects and collateral constraints.

Our model of the housing market builds on the literature that emphasizes the importance of collateral constraints for asset markets. Kiyotaki and Moore (1997) show how the presence of collateral constrained agents can amplify fundamental shocks in asset markets. Many studies have demonstrated the importance of this effect in real estate markets. For example Lamont and Stein (1999) and Almeida, Campello, and Liu (2006) demonstrate that house prices are more sensitive to shocks to economic fundamentals in locations in which households are more highly levered.

More recently Justiniano, Primiceri, and Tambalotti (2015) study a model similar to Kiyotaki and Moore (1997) to show that collateral constraints can quantitatively explain many features of the housing boom and bust of the 2000's. Our model is similar in spirit to Justiniano et al. (2015), but bears closer resemblance to that of Rampini and Viswanathan (2010) and Rampini and Viswanathan (2013).

To our knowledge, ours is the first model to integrate non-homethetic prefences into a dynamic model of house prices with collateral constraints. However, such preferences have been emphasized as an important driver of real estate markets. Notably, Albouy, Ehrlich, and Liu (2016) show that non-hometheticity can help explain the secular trend in housing expenditure shares.

There is also a body of evidence that shows that credit constraints can have an important impact on house prices. Ben-David (2011) shows that financially constrained borrowers inflated house prices in order to draw larger mortgages. Ortalo-Magne and Rady (2006) highlight how young households' leverage in their first home can have an important effect on the volatility of house prices.

Housing as a source of collateral has also been shown to have important implications for the broader economy. Lustig and Van Nieuwerburgh (2005) show that the use of housing as collateral affects the market price of risk and that the ratio of housing wealth to human wealth can explain the cross section of stock returns. Mian and Sufi (2011) provide evidence that increased home equity during the early 2000's allowed for an increase in borrowing and the subsequent default crisis of the late 2000's.

1 Model

In this section, we present a model in which volatility in returns to housing arises due to the combination of non-homothetic preferences and collateral constraints. Our model of collateralized borrowing is similar to that in Justiniano et al. (2015) and Rampini and Viswanathan (2010), and like them we create demand for borrowing via an impatient agent (as also in Kiyotaki and Moore (1995)). We shut down the equilibrium determination of the risk-free rate, while allowing for non-homothetic preferences over housing captured by a dynamically evolving marginal rate of substitution (MRS) with consumption.

A representative household values consumption and housing according to the utility function $u(c_t, h_t)$, and discounts future consumption at rate β. The household's endowment income can take on two values, y^1 or y^2. This is the only fundamental source of uncertainty in the model, and we index these states by $s \in \{1, 2\}$. After realizing its income y, the household repays obligations made last period $\bar{b}(s)$ that depend on the realization of the current state. The household then chooses housing consumption h_{t+1}, and borrows again by making new state-contingent repayment promises for tomorrow. The price of the consumption good is normalized to 1.

The risk-free rate $R_f < 1/\beta$ is exogenously determined by deep-pocketed lenders who are outside of the model, and the impatient household borrows as much as possible given that rate. However, a collateral constraint limits this borrowing: To borrow today, the household must make state-contingent promises of repayment tomorrow. Specifically, we follow Rampini and Viswanathan (2010) by assuming that the household can only promise to pay up to fraction θ of the value of the house in a given state. Today, it can effectively only borrow up to the discounted expected value of that future repayment capacity. This constraint can be motivated by assuming that loans are subject to limited enforcement.

The household's problem can be summarized as

$$\max_{c_t,h_t,b_t} \quad \mathbb{E}\left[\sum_t \beta^t u(c_t, h_t)\right] \tag{1}$$

$$s.t. \quad c_t + p_t h_t \leq W_t + b_t \tag{2}$$

$$W_{t+1}(s_{t+1}) \equiv y_{t+1}(s_{t+1}) - \bar{b}_t(s_{t+1}) + h_t p_{t+1}(s_{t+1}), \tag{3}$$

$$\bar{b}_t(s_{t+1}) \leq \theta h_t p_{t+1}(s_{t+1}), \tag{4}$$

$$b_t = \frac{\mathbb{E}[\bar{b}_t(s_{t+1})]}{R_f}. \tag{5}$$

Equations (2)-(3) jointly characterize the budget constraint, and equation (4) is the collateral constraint. The household makes state-contingent repayment promises $\bar{b}$ which can't be any more than the value of housing in those states. Equation (5) is a lender optimality condition: The upfront loan proceeds b are equal to the discounted value of those state-contingent promises.

We simplify the problem in two steps. First, we note that constraint (4) will always bind since this household is impatient and will always borrow the maximum possible, so we set it to equality and substitute it into the definition of W_{t+1} and into the final condition defining b_t. Second, we substitute that final condition into the RHS of the budget constraint. The first-order condition for h then yields

$$p_t = \frac{u_2(c_t, h_t)}{u_1(c_t, h_t)} + \frac{\theta}{R_f}\mathbb{E}[p_{t+1}]$$

As is intuitive, the housing price reflects the contemporaneous marginal rate of substitution with consumption (whose price is normalized to 1) plus the extra value derived from the ability to borrow up to the LTV constraint captured by θ and computed based on tomorrow's housing price. We can iterate this forward to get

$$p_t = \sum_{\tau=0}^{\infty} \left(\frac{\theta}{R_f}\right)^{\tau} \mathbb{E}_t \left[\frac{u_2(c_{t+\tau}, h_{t+\tau})}{u_1(c_{t+\tau}, h_{t+\tau})}\right].$$

The above expression illustrates how home prices in our model are determined by the interplay between borrowing capacity and a dynamic MRS with consumption.

To study log returns, as we will do the empirical section, we can use the identity

$$\ln(R_{t+1}) = \ln\left(\frac{p_{t+1}}{p_t}\right) = \ln\left(\frac{MRS_{t+1}}{MRS_t}\right) + \ln\left(\frac{p_{t+1}}{MRS_{t+1}} \Big/ \frac{p_t}{MRS_t}\right),$$

where $MRS_t \equiv \frac{u_2(c_t,h_t)}{u_1(c_t,h_t)}$. We can rewrite the price equation as

$$\frac{p_t}{MRS_t} = \sum_{\tau=0}^{\infty} \left(\frac{\theta}{R_f}\right)^{\tau} \mathbb{E}_t \left[\frac{MRS_{t+\tau}}{MRS_t}\right], \tag{6}$$

so that the equilibrium dynamics of prices are given by the equilibrium dynamics of MRS. Moreover, the dynamics of the income process y, give rise to the equilibrium dynamics for MRS. However, rather than fully solving for equilibrium, we simplify the analysis by assuming particularly tractable dynamics for MRS. To that end, we assume that MRS can only take one of two values, $MRS^L < MRS^H$, and let $\gamma \equiv \frac{MRS^H}{MRS^L} > 1$. We also assume a symmetric transition matrix between these two realizations, with probability $p > 1/2$ of staying in either of the states and probability $1-p$ of transitioning to the other. It is then easily verified that the probability at time t of being in the same state at time $t+\tau$ is $\frac{1}{2} + \frac{1}{2}(2p-1)^\tau$. Then, if $MRS_t = MRS^L$,

$$\begin{aligned} \mathbb{E}_t\left[\frac{MRS_{t+\tau}}{MRS_t}\right] &= \left(\frac{1}{2} + \frac{1}{2}(2p-1)^\tau\right)\gamma + \left(\frac{1}{2} - \frac{1}{2}(2p-1)^\tau\right) \\ &= \frac{1}{2}(\gamma+1) + \frac{1}{2}(2p-1)^\tau(\gamma-1) \end{aligned}$$

while if $MRS_t = MRS^H$,

$$\begin{aligned} \mathbb{E}_t\left[\frac{MRS_{t+\tau}}{MRS_t}\right] &= \left(\frac{1}{2} + \frac{1}{2}(2p-1)^\tau\right)\frac{1}{\gamma} + \left(\frac{1}{2} - \frac{1}{2}(2p-1)^\tau\right), \\ &= \frac{1}{2}\left(\frac{1}{\gamma}+1\right) + \frac{1}{2}(2p-1)^\tau\left(\frac{1}{\gamma}-1\right). \end{aligned}$$

Applying equation (6), and summing over τ yields: If $MRS_t = MRS^L$,

$$\frac{p^L}{MRS^L} = \frac{1}{2}\left(\frac{\gamma+1}{1-\frac{\theta}{R_f}} + \frac{\gamma-1}{1-\frac{\theta}{R_f}(2p-1)}\right),$$

while if $MRS_t = MRS^H$,

$$\frac{p^H}{MRS^H} = \frac{1}{2}\left(\frac{\frac{1}{\gamma}+1}{1-\frac{\theta}{R_f}} + \frac{\frac{1}{\gamma}-1}{1-\frac{\theta}{R_f}(2p-1)}\right).$$

Thus, whenever the state stays the same (with probability p), the price of housing is constant and the return on housing is zero. When the state changes (with probability $1-p$), the log return is $\ln(\bar{R})$ if we transition from H to L, and $-\ln(\bar{R})$ if we transition from L to

H, where

$$\bar{R} \equiv \frac{\frac{1-\frac{\theta}{R_f}(2p-1)}{1-\frac{\theta}{R_f}} + \frac{\gamma-1}{\gamma+1}}{\frac{1-\frac{\theta}{R_f}(2p-1)}{1-\frac{\theta}{R_f}} - \frac{\gamma-1}{\gamma+1}} \geq 1.$$

Finally, in the stationary distribution the probability is 1/2 of being in either state. This implies that the stationary expected (log) return on housing is always zero; but there is unconditional *volatility* in that return, given by

$$Var(\ln(R)) = (1-p)(\ln \bar{R})^2.$$

Comparative statics reveal that $\bar{R}$, and therefore $Var(\ln(R))$, are decreasing in θ and increasing in γ. Together, these two features capture the core narrative of our model: First, γ captures the volatility of MRS. If MRS is constant, as in many prior models, then $\gamma = 1$, which in turn leads to $\bar{R} = 1$ and zero return volatility. On the other hand, if the MRS is volatile, then returns are volatile as well. However, the volatility generated by $\gamma > 1$ also depends on the degree of financial constraints, captured by the maximum LTV ratio θ. Indeed, the highest value of $\bar{R}$, and thus return volatility, obtains when $\theta = 0$ (when the constraint is most binding, and there is no ability to borrow against the house at all). In this case, the price of housing is always the contemporaneous MRS, and $\bar{R} = \gamma$, reflecting the transition between low and high MRS states. On the other hand, as θ increases, moving us towards a model with no financial constraints, then volatility falls.

To connect this model to the data, imagine a comparative static on the average level of income. This falls outside our formal analysis, as we do not explicitly solve for MRS. However, it should be clear that a decrease in income, and thus lifetime wealth, generally leads to a higher volatility in marginal utility for a risk-averse household, as its average level of consumption will be lower, and thus will fall in the more-concave region of its utility function. This means low-income households will face larger disparities between high- and low-MRS states, which manifests in higher values of γ in our model. The end result is that, in the presence of borrowing constraints, the financial returns to housing are *endogenously* more volatile for low-income households, which in turn will affect their investment and consumption decisions. (Note that we have assumed no frictions in the lending market other than the limited borrowing capacity of the impatient household.) The next section turns to an empirical analysis of this prediction.

2 Data and measurement

The goal of this section is to demonstrate that the central prediction of the model – the volatility of housing returns is higher for lower-income households – is empirically present, quantitatively large, and a robust feature across many distinct housing markets. We disaggregate our analysis at a fine geographical level by measuring income and housing returns *within* Metropolitan Statistical Areas (MSAs), using variation by zip code.[1]

To measure housing returns, and the volatility of those returns, we obtain home price data from two alternative sources. The first is the CoreLogic Single Family Combined Home Price Index (HPI), which is the standard in much real estate research. The second is the Zillow Home Value Index (ZHVI), a newer and less-used dataset. Our results are qualitatively similar with either index, but are more stark using the Zillow than the CoreLogic data. The primary difference between the two, which likely explains this discrepancy, is that CoreLogic is based on a repeat-sales methodology, capturing innovations to a home's value only when that home is actually sold. In contrast, Zillow's ZHVI uses hedonic regressions to update the value of *all* homes in a region in response to each transaction price.

For either the HPI or ZHVI, we use the time series for each zip code to construct two cross-sectional variables: the average 12-month return in home prices, and the standard

[1] To be clear, zip codes are not themselves geographical concepts. Our references to zip codes throughout the paper are actually to Zip Code Tabulation Areas (ZCTAs), which are constructed by the US Census as geographic partitions of the United States that roughly correspond to actual zip codes.

deviation of that return. Specifically, for region z, we calculate

$$
\begin{aligned}
r_{z,t}^{ann} &= \ln\left(\frac{p_{z,t+12}}{p_{z,t}}\right), \\
\bar{r}_{z}^{ann} &= \frac{1}{T}\sum_{t=0}^{T} r_{z,t}^{ann}, \\
\bar{\sigma}_{z}^{ann} &= \sqrt{\frac{1}{T-1}\sum_{t=0}^{T}\left(r_{z,t}^{ann}-\bar{r}_{z}^{ann}\right)^{2}}.
\end{aligned}
$$

where t indexes months from January 1976 ($t = 0$) to October 2015 ($t = T$), and p is the zip-code-month level of the specific index employed.

Finally, to measure household income, we obtain from the IRS zip-code-level statistics on Adjusted Gross Income (AGI) as reported in tax returns. These statistics are available at irregular frequencies beginning in 1998. For each zip code, the IRS reports both the number of tax returns, and the total AGI reported summing across all returns, so we divide the two to obtain a mean AGI per household for each zip code. We use the 1998 cross-section of AGI, the earliest available observations, as the measure of household income throughout our analysis. Because our home price data begin long before 1998, it is important to note that our results are robust to using just post-1998 home prices, alleviating concerns about reverse causality from housing returns to income.

Our analysis is performed on the cross-section of 5,573 zip codes that have non-missing CoreLogic and Zillow indices for every month from 1998-2014. Figure 1 shows the distribution of average returns and return volatilies across these zip codes, comparing the numbers from the CoreLogic and the Zillow data. Figure 2 shows scatter plots of the CoreLogic and Zillow values against each other for a given zip code. While the average housing return within a zip code calculated using either index appears roughly the same, the volatility of that return can be dramatically different between the two, with the Zillow volatilities typically lower and seeming to follow a skewed distribution, where the CoreLogic volatilities are higher on average and symmetrically distributed. The discrepancy in the estimated volatilities is intriguing, especially given that the estimated returns are so similar, but for now we simply use this as motivation to examine qualitative results based on both data sources.

3 Volatility and income

We first observe that the volatility of housing returns has a very different cross-sectional distribution than the mean return. In particular, volatility is higher in lower-income areas. Figure 3 separates zip codes into six bins by AGI, and plots volatilities (in Panel (a)) and returns (in Panel (b)). Volatility in Panel (a) is noticeably higher for lower-income areas. The spread in annual volatility between the lowest- and highest-AGI bins is roughly 2% in the CoreLogic data and over 3.5% in the Zillow data. On the other hand, Panel (b) shows that this higher volatility is not compensated in the data by higher returns. If anything, returns seem to be slightly increasing in AGI, but there is no quantitatively meaningful relationship.

Figure 4 looks for the same pattern using only *within*-MSA variation. Returns and volatilities calculated with either index are adjusted by the MSA-level mean, and the six bins are recalculated separately for each MSA, so that they capture relative income position within-MSA instead of nationwide. Despite these adjustments, we see that the disparities in volatility across bins remains sizeable. Using the CoreLogic data, the highest AGI bin has 1.3% lower annual return volatility than the lowest-AGI bin, with no meaningful difference in annual return level. In the Zillow data, the disparity is larger, as before, at 2.88%. In both cases we see a steady decline in return volatility across the bins from low to high AGI.

Tables 1 and 2 display regressions confirming that these findings are statistically significant and robust, using respectively the CoreLogic and the Zillow data. Instead of bins of AGI, the logarithm of zip-code mean AGI is used as the independent variable in the regressions, and all regressions include MSA fixed effects to preserve the within-MSA interpretation of Figure 4. Finally, standard errors are clustered by state to allow for possible geographical clustering in the residuals.

Column (1) of each table performs this regression in the full sample of 5,573 zip codes. The estimated coefficients suggest that a doubling of income is associated with 1.23% lower annual housing return volatility as measured through CoreLogic data, or with 2.68% less annual volatility as measured through Zillow. Column (2) of each table shows that this result is not driven by relatively sparsely-populated MSAs; if anything, the estimated effects strengthen slightly when the analysis is restricted to MSAs with at least a million 1998 tax returns. This reduces by about half the number of zip codes in the regression, but the coefficients remain statistically significant. Meanwhile, Columns (3) and (4) of the table reiterate that the higher volatility of housing returns in low-income zip codes is not associated with higher average returns; if anything, the relationship is slightly in the opposite direction.

Aside from showing that volatility is a larger concern for lower-income households, these findings can also be viewed as documenting a surprising disconnect between risk and expected return in the housing market. Indeed, unreported regressions confirm that Sharpe ratios of housing (average annualized return divided by annualized volatility) are dramatically lower for low-income than high-income households. Our model can then be interpreted as a resolution of this apparent puzzle: The interplay between financial constraints and volatile marginal rates of substitution leads endogenously to uncompensated volatility in housing returns for low-income neighborhoods.

Figure 5 demonstrates our central finding visually with zip-code maps of the largest three MSAs in the sample, Los Angeles (Panel (a)), New York City (Panel (b)), and Chicago (Panel (c)). These figures measure housing returns with the Zillow index, which yields the most stark results. For all three panels, the left figure shades zip codes according to eight bins of the volatility of the Zillow HVI return from 1997-2014, with darker shading corresponding to more volatility. In Los Angeles, for example, the returns to housing have been most volatile in poorer areas to the south and in the San Fernando valley. The right figure in each panel shades zip codes according to eight bins of 1998 mean AGI, but with darker shading corresponding to lower income. The resemblance to the left figures in each panel is striking. Put simply, high-volatility zip codes are also low-income zip codes.

Similar figures to Figure 5 can be constructed for every major MSA in the country (available on request). To summarize the figures, Tables 3 and 4 perform the prior within-MSA regression of return volatility on log AGI, explicitly breaking out each of the 16 largest MSAs in the sample, and using (respectively) the CoreLogic index and the Zillow index to measure housing returns. In all 32 specifications, the point-estimate of the coefficient on log AGI is negative. In all but one, it is statistically significant, and in all but five it is less than -1%. The negative relationship between income and return volatility appears to be a fundamental feature of the market for housing.

4 Panel evidence

The results in the previous section were purely cross-sectional. Here we return to the full zip-code-month panel and exploit the panel dimension to firm up our interpretation. Our goal is to show that volatility responds to *changes* in wealth in the direction one would expect based on our model. This exercise helps isolate our proposed mechanism from several alternative interpretations, most importantly any omitted variables that are fixed in the cross-section or that do not fluctuate with wealth.

Our instrument for household wealth is the lagged return of either of the two home value indices. Intuitively, an individual observation of this high-frequency (monthly) return has a persistent effect on the wealth of homeowners, and our model predicts that this wealth effect should then alter the volatility of future housing returns. On the other hand, outside of our proposed mechanism, there is no obvious reason for individual monthly returns to have persistent effects on volatility. Thus, if high (low) individual monthly housing returns predict low (high) future *volatilities* of monthly returns within the same zip code, we will regard this as evidence of our proposed mechanism at work.

To implement this logic, we calculate rolling volatility measures at the zip code level for each of our two indices based on the prior 12 months of returns, starting in 1990. Using this rolling volatility as our outcome variable, we regress on lags of the monthly return series. To avoid using observations based on overlapping windows, we retain only January of every year in these regressions, so the regression is performed on a zip-code-year panel, and we lag the returns on the right-hand side by a year or more. Our results are presented in Tables 5 and 6.

Table 5 shows that housing returns negatively predict future volatility within a zip code. Panel (a) uses the CoreLogic HPI series to measure housing returns and volatilities, and Panel (b) uses the Zillow ZHVI series. In both cases, the coefficient on distributed lags of the monthly housing return is significant and negative. The interpretation is that a positive (negative) wealth shock, via a positive (negative) individual monthly housing return, predicts a lower (higher) future degree of volatility in housing returns. Again, our model explains this fact through the marginal rate of substitution between housing and non-housing consumption, which changes as the agent becomes richer or poorer.[2]

The magnitudes are sizeable: In the first column of Panel (a), a one-standard-deviation increase in the HPI return a year ago predicts a 0.10 standard deviation decrease in current volatility of the HPI return, based on sample standard deviations of 0.0156 and 0.0045 respectively. Moreover, the dynamics of the effects decay as longer lags are used, which is intuitive. Columns 2 through 4 show that the magnitudes of the coefficients are virtually unchanged when including state, MSA, and finally zip-code fixed effects. In Panel (b), the Zillow series exhibits the same qualitative effects, although the magnitudes are about half as large: A one-standard-deviation increase in ZHVI return a year ago predicts a 0.04 standard deviation decrease in current volatility, based on sample standard deviations of 0.0097 and 0.0038 respectively.

We can pin down our interpretation even further by exploiting cross-sectional variation

[2]Formally, a negative wealth shock leads to an increase in γ, the ratio of high to low MRS, and the comparative statics of the model show that this increases housing return volatility.

in household income, as in the previous section. A change in housing value should have a proportionally bigger effect among households that are poorer to begin with, and therefore should lead to a larger subsequent effect on volatility. Thus, we expect that the magnitude of the coefficients from Table 5 should be relatively higher in low-income zip codes, and relatively lower among high-income zip codes. Indeed, Table 6 documents exactly this relationship. This table repeats the analysis of Table 5, interacting all explanatory variables with 1998 log AGI (the same measure of income employed in the previous section), after demeaning that variable across the full sample. (For compactness, only three lags are employed instead of four).

For a household of average income, Table 6 continues to document the negative relationship between housing return and future volatility that was reported in Table 5. However, a significant and positive coefficient on the interaction with income indicates that the relationship is stronger (weaker) for lower (higher) income households. With the CoreLogic data, this interaction is rarely significant beyond a one-year lag, but with the Zillow data it shows up two and even three years later. Again, our interpretation is that the wealth effect of a monthly housing return is proportionally larger in areas with lower income (which proxies for lower wealth). Our model then predicts that the relationship between housing return and future volatility is stronger in lower-income areas, a prediction that is confirmed in the data.

While we cannot rule out the possibility, we find it unlikely that there is a mechanism, aside from a wealth effect, by which a low (high) monthly return observation should predict higher (lower) future return volatility, and moreover for which this effect is moderated by the cross-section of income. In sum, the dynamic patterns of within-zip-code volatility lend support to our proposed mechanism by which wealth affects the volatility of housing returns.

5 Volatility and housing expenditure share

When households have non-homothetic preferences over housing, income effects cause the housing expenditure share to fall as wealth incresases (see Albouy et al. (2016)). In this section we show that the housing share directly predicts volatility. We collapse to the cross-section of zip codes that was used in the core results, rather than the panel from the previous section, as our measures in this and the net section are primarily cross-sectional.

We use data from the Bureau of Labor Statistics' 2003-2004 Consumer Expenditure Survey, which provides characteristic spending patterns of households in 28 MSAs across the country. While coarse in its aggregation, this dataset allows us to see how household spending patterns correlate with volatility. Our key variable of interest is total expenditures on housing, divided by the household's total annual expenditures. This variable falls within a tight range, between 0.3 and 0.4 for all 28 MSAs in the sample.

The results of this analysis are in Table 7. Column 1 demonstrates that a unit increase in the housing expenditure share is associated with a 58 percentage point increase in return volatility. For a better sense of magnitudes, the cross-sectional standard deviations of these variables is about .024 and .038 respectively, so a one-standard-deviation increase in housing share is associated with about a one-quarter standard deviation in return volatility. Column 2 shows that the effects are if anything stronger when we restrict only to expenditures on owned (as opposed to rented) housing.

Like AGI in the previous sets of results, housing expenditure share is best regarded as a proxy for γ in our model, capturing the wealth effect of non-homothetic preferences over housing. In Column 3, we include both proxies at once to check that they have independent explanatory power. Columns 4 and 5 repeat the previous results with state fixed effects. Finally, Column 6 adds food expenditure share as an explanatory variable, showing that it does not have the same power as housing to explain return volatility.

However, AGI and housing expenditure share may proxy not only for γ (via the marginal rate of substitution that changes with wealth), but also for the degree of credit constraints

θ, as lower-income households may also face tighter credit constraints. In the next section, we attempt to disentangle these by seeking out variation in θ.

6 Volatility and constraints: Non-recourse states

The analysis so far shows, consistent with our model, that income and housing expenditure share both predict housing return volatility. However, our model provides two different mechanisms by which these relationships can arise. Low-wealth households likely feature both greater volatility in MRS and tighter credit constraints, reflected in γ and θ respectively. To help disentangle these mechanisms, we augment the regressions of the previous section with variation in the tightness of the housing collateral constraint, measured in the model by θ.

A commonly-explored source of such variation is the degree of lender recourse in the case of default, which varies substantially around the country due to state laws adopted in past decades, mostly in response to idiosyncratic circumstances (see Ghent (2014)). In some states, notably Florida, lenders can pursue a deficiency judgment granting it a claim on the borrower's other assets; while in others, notably California, the lender must be satisfied with foreclosure and sale of the house itself. Ex ante, this should limit the amount the household can borrow as a fraction of its home value, leading in our model to a lower θ, a tighter collateral constraint, and greater volatility in home price appreciation.

Our approach in this section is to regress return volatility on a measure of the state-level degree of lender (non-)recourse. To classify states along this dimension, we employ employ the coding of Ghent and Kudlyak (2011), who conduct a detailed reading of state-level policies banning or hindering deficiency judgments against residential properties. Under their coding, California, Washington, North Carolina, Arizona, Minnesota, Wisconsin, Oregon, and Iowa are coded as non-recourse states.[3]

[3] In 2009, in the middle of our sample period, Nevada also passed an anti-deficiency law. See Li and Oswald (2014) and Ghent (2014). We code Nevada as a recourse state, as in Ghent and Kudlyak (2011), but our results are not meaningfully affected if we instead drop Nevada.

We find that lender non-recourse is associated with much higher housing return volatility. The results are presented in Table 8. Column 1 uses the non-recourse score as an explanatory variable, controlling for the household expenditure share from the CEX data as in the previous section, in order to disentangle the wealth and constraint mechanisms. Non-recourse states have a 3.2 percentage point higher return volatility, compared to a cross-sectional standard deviation of 4.4 percentage points.

Since we cannot employ the tight fixed effects of our earlier specifications, we condition on other characteristics to control for as much unobserved heterogeneity as possible. Column 2 adds our other wealth proxy, the zip-code median AGI. Column 3 adds the zip-code number of tax returns filed with the IRS, and the fraction of residents who are black as recorded by the Census. Finally, Column 4 excludes California, which is the largest of the non-recourse states, and shows that the estimated coefficients barely change, although their standard errors increase substantially.

In all these specifications, the estimated coefficients on non-recourse status, housing share, and AGI remain consistent with the prior tables. The housing share coefficient decreases slightly in statistical significance across these specifications, suggesting that the added predictors also have some power to proxy for the wealth effect operating through γ in our model, but the non-recourse coefficient capturing the effect of θ remains roughly equally significant as in Column 1.

To explore the effect of non-recourse status further, we observe that its effect in our model should come through a reduction in realized credit, for which loan-to-value (LTV) is a good proxy. We obtain from CoreLogic the zip-code level median LTV ratio, average this value for each zip code throughout the sample period 1998-2014, and employ this average as an outcome variable in Column 5. Non-recourse states have LTVs that are about 2 percentage points lower on average, which is about one-third of the cross-sectional standard deviation. This finding does not appear to be present in the literature, and substantiates the idea that recourse status is important for credit availability, which in turn affects return volatility in our model.

Having shown that non-recourse status affects credit, which in turn affects volatility, a natural step is to combine these effects in an instrumental-variables (IV) regression, translating their magnitudes into a marginal effect of an increased LTV on return volatility. Column 6 reports this IV regression. The estimated coefficient on LTV (just the ratio of those in Columns 1 and 5) suggests that a percentage point increase in LTV would lower ZHVI return volatility by 1.4 percentage points.

7 Conclusion

In this paper, we demonstrate empirically and theoretically that two widely-studied features of housing – its collateral value for constrained households, and the non-homotheticity of preferences over it – lead in equilibrium to greater volatility of home price appreciation for low-income households, without any compensating increase expected return. Our theoretical analysis assumes no frictions in mortgage markets beyond the limited borrowing capacity of the impatient household. In fact, the model could likely be applied to a wide range of durable goods, although housing is its natural setting. Likewise, our empirical analysis did not focus on any particular time period (such as the housing boom or bust) nor on any particular region. Our results thus capture a fundamental connection between financial constraints and the return patterns of assets with collateral value in the presence of non-homothetic preferences. Because housing is such a large fraction of expenditures for the typical household, this is a quantitatively important pattern to understand for policy analysis of the housing affordability problem.

References

Albouy, D., Ehrlich, G., Liu, Y., 2016. Housing demand, cost-of-living inequality, and the affordability crisis. Working paper.

Almeida, H., Campello, M., Liu, C., 2006. The financial accelerator: evidence from international housing markets. Review of Finance 10 (3), 321–352.

Ben-David, I., 2011. Financial constraints and inflated home prices during the real estate boom. American Economic Journal: Applied Economics, 55–87.

Ghent, A., 2014. How do case law and statute differ? Lessons from the evolution of mortage law. Journal of Law and Economics 57 (4), 1085–1122.

Ghent, A., Kudlyak, M., 2011. Recourse and residential mortgage default: Evidence from us states. Review of Financial Studies 24 (9), 3139–3186.

Justiniano, A., Primiceri, G. E., Tambalotti, A., 2015. Credit supply and the housing boom. Tech. rep., National Bureau of Economic Research.

Kiyotaki, N., Moore, J., 1997. Credit Cycles. The Journal of Political Economy 105 (2), 211–248.

Lamont, O., Stein, J. C., 1999. Leverage and house-price dynamics in us cities. RAND Journal of Economics 30 (3), 498–514.

Li, W., Oswald, F., 2014. Recourse and residential mortgages: The case of nevada. Working paper.

Lustig, H. N., Van Nieuwerburgh, S. G., 2005. Housing collateral, consumption insurance, and risk premia: An empirical perspective. The Journal of Finance 60 (3), 1167–1219.

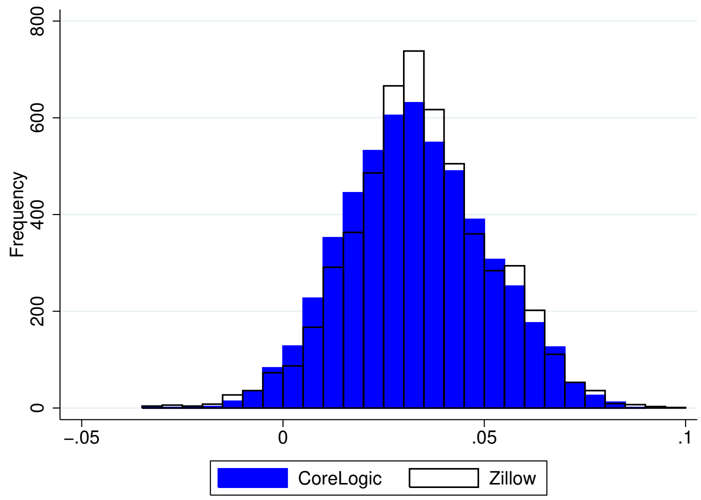
Mian, A., Sufi, A., 2011. House prices, home equity-based borrowing, and the us household leverage crisis. The American Economic Review 101 (5), 2132–56.

Ortalo-Magne, F., Rady, S., 2006. Housing market dynamics: On the contribution of income shocks and credit constraints. The Review of Economic Studies 73 (2), 459–485.

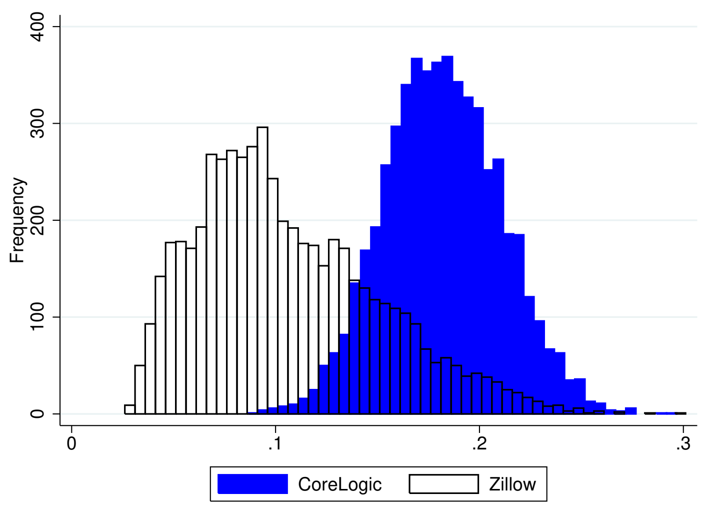
Rampini, A. A., Viswanathan, S., 2010. Collateral, risk management, and the distribution of debt capacity. The Journal of Finance 65 (6), 2293–2322.

Rampini, A. A., Viswanathan, S., 2013. Collateral and capital structure. Journal of Financial Economics 109 (2), 466–492.

A Figures and tables

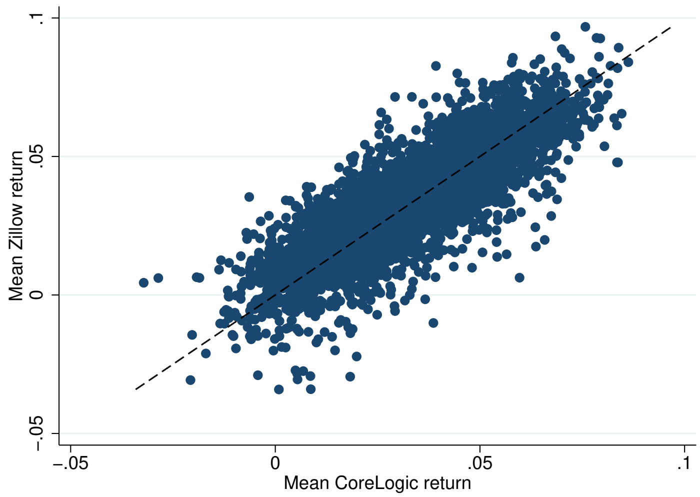


(a) Distribution of zip-code level averages of annualized log monthly returns, 1998-2015. The solid blue bars are calculated using the CoreLogic Home Price Index, Single Family Combined series. The black outlined bars are calculated using the Zillow Home Value Index.

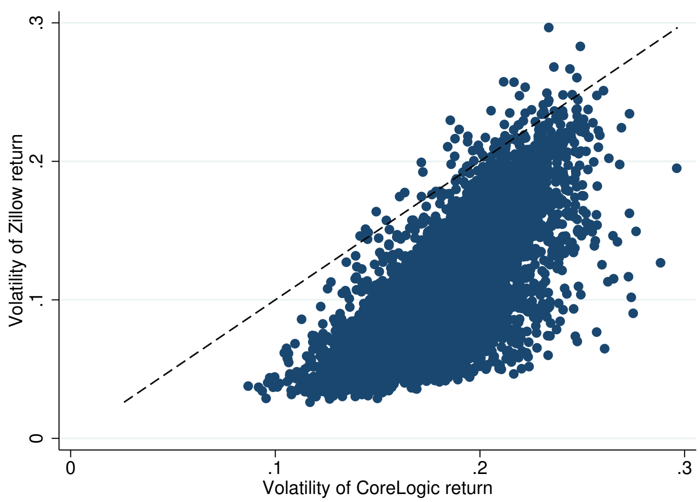


(b) Distribution of zip-code level volatilities of annualized log monthly returns, 1998-2015. The solid blue bars are calculated using the CoreLogic Home Price Index, Single Family Combined series. The black outlined bars are calculated using the Zillow Home Value Index.

Figure 1: Comparison of return and volatility distributions from CoreLogic and Zillow data.

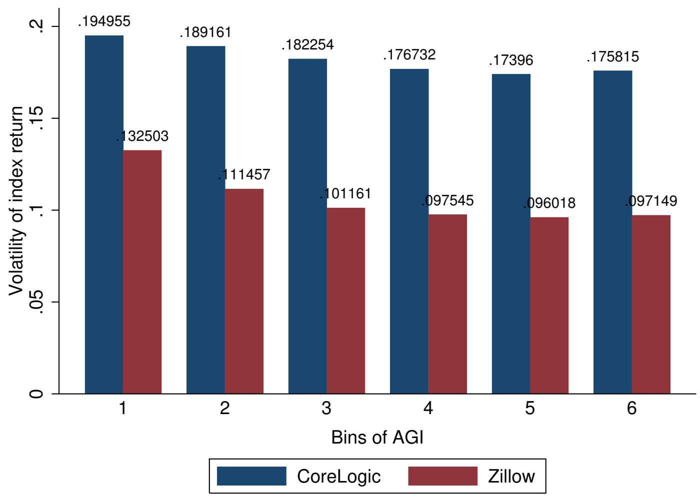


(a) Scatter plot of zip-code level average returns calculated using Zillow data against those calculated using CoreLogic data.

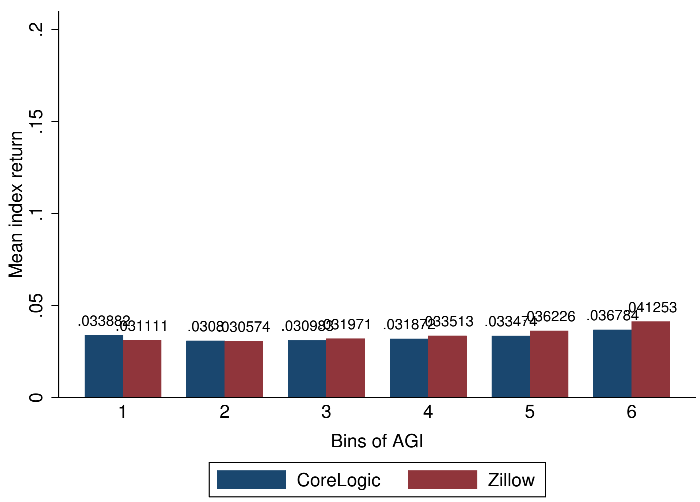


(b) Scatter plot of zip-code level return volatilities calculated using Zillow data against those calculated using CoreLogic data.

Figure 2: Comparison of return and volatility distributions from CoreLogic and Zillow data.

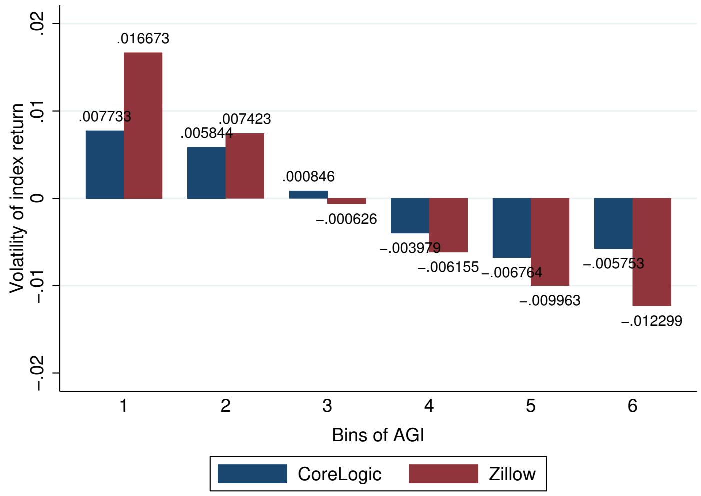


(a) Zip-code level housing return volatility, 1998-2015, by bins of 1998 mean adjusted gross income (AGI). Blue bars are calculated using CoreLogic data, and red bars using Zillow data.

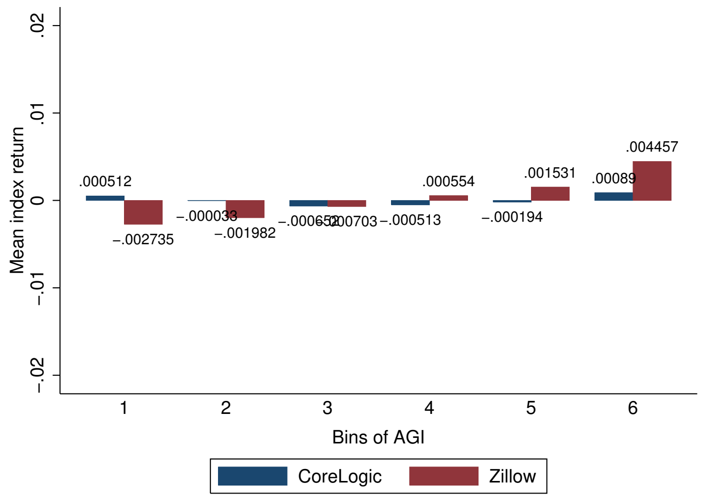


(b) Zip-code level average housing return, 1998-2015, by bins of 1998 zip code-level mean adjusted gross income (AGI). Blue bars are calculated using CoreLogic data, and red bars using Zillow data.

Figure 3: Housing returns and volatilities across zip codes.



(a) Zip-code level housing return volatility, 1998-2015, by bins of 1998 zip code-level mean adjusted gross income (AGI). Blue bars are calculated using CoreLogic data, and red bars using Zillow data. Volatilities are demeaned within-MSA, and the bins are also constructed within-MSA.



(b) Zip-code level average housing return, 1998-2015, by bins of 1998 zip code-level mean adjusted gross income (AGI). Blue bars are calculated using CoreLogic data, and red bars using Zillow data. Returns are demeaned within-MSA, and the bins are also constructed within-MSA.

Figure 4: Housing returns and volatilities across zip codes, within-MSA.

	(1) HPI return vol	(2) HPI return vol	(3) HPI return	(4) HPI return
Ln(Mean AGI)	-0.0129***	-0.0128***	-0.0000160	-0.00138
	(0.00140)	(0.00166)	(0.00102)	(0.00143)
Fixed effect	MSA	MSA	MSA	MSA
Sample	All	MSA pop 1M+	All	MSA pop 1M+
Obs.	5438	2312	5438	2312
R^2	0.0954	0.114	0.000000488	0.00393

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

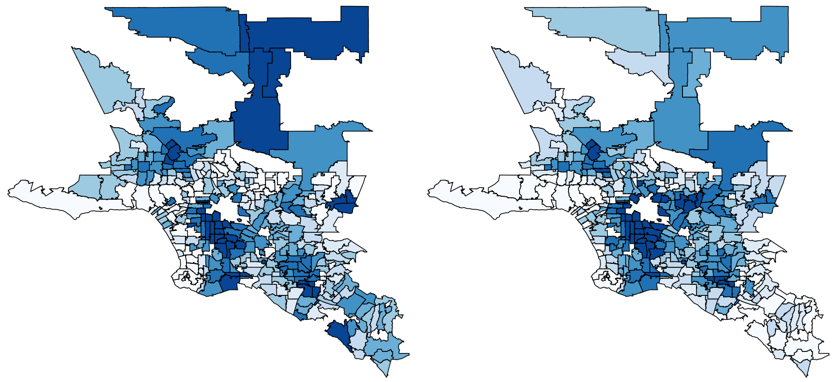
Table 1: In the first two columns, the dependent variable is $\bar{\sigma}_z^{ann}$, the volatility of the zip-code-level annualized monthly log housing return. In the last two columns, the dependent variable is $\bar{r}_z^{ann}$, the average of that return. Returns are measured using the CoreLogic Home Price Index (Single Family Combined) for a cross-section of 5,573 zip codes from 1998-2014. The explanatory variable is the natural logarithm of the zip code's mean adjusted gross income (AGI) from 1998, as reported by the IRS. Both variables are demeaned within-MSA, and MSA fixed effects are also included. Standard errors are clustered by state. Columns (2) and (4) restrict to MSAs in which one million or more tax returns were filed with the IRS in 1998.

	(1) ZHVI return vol	(2) ZHVI return vol	(3) ZHVI return	(4) ZHVI return
Ln(Mean AGI)	-0.0272***	-0.0309***	0.00637***	0.00541**
	(0.00289)	(0.00284)	(0.00149)	(0.00203)
Fixed effect	MSA	MSA	MSA	MSA
Sample	All	MSA pop 1M+	All	MSA pop 1M+
Obs.	5438	2312	5438	2312
R^2	0.280	0.342	0.0845	0.0554

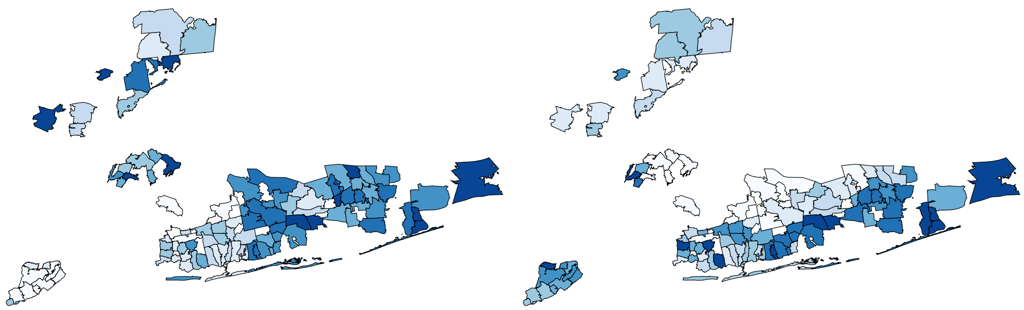
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

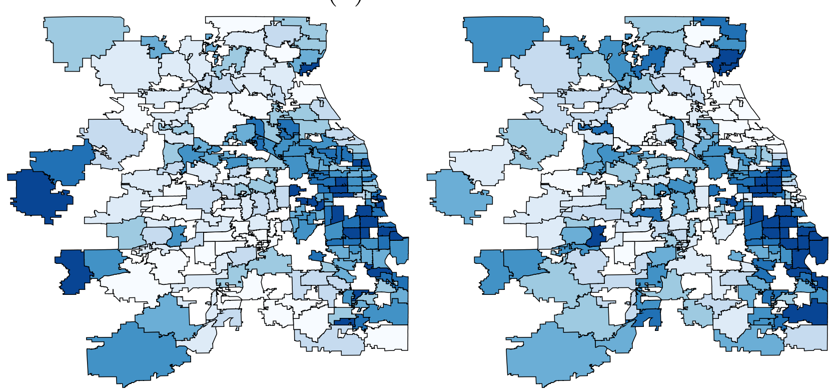
Table 2: In the first two columns, the dependent variable is $\bar{\sigma}_z^{ann}$, the volatility of the zip-code-level annualized monthly log housing return. In the last two columns, the dependent variable is $\bar{r}_z^{ann}$, the average of that return. Returns are measured using the Zillow Home Value Index for a cross-section of 5,573 zip codes from 1998-2014 (that is, restricting to zip codes that also have non-missing information in the CoreLogic HPI series). The explanatory variable is the natural logarithm of the zip code's mean adjusted gross income (AGI) from 1998, as reported by the IRS. Both variables are demeaned within-MSA, and MSA fixed effects are also included. Standard errors are clustered by state. Columns (2) and (4) restrict to MSAs in which one million or more tax returns were filed with the IRS in 1998.



(a) Los Angeles.



(b) New York.



(c) Chicago.

Figure 5: Income and housing return volatility for the largest three MSAs. The three panels on the left show the annualized zip-code level volatility of home price returns from 1998-2014, based on Zillow data. Darker shading corresponds to higher volatility, using eight bins. The three panels on the right show zip-code level 1998 adjusted gross income, again using eight bins, but here darker shading corresponds to lower AGI.

	(1)	(2)	(3)	(4)
	HPI return vol	HPI return vol	HPI return vol	HPI return vol
Ln(Mean AGI)	-0.0131***	-0.0102***	-0.00856***	-0.0139***
	(0.00271)	(0.00147)	(0.00235)	(0.00264)
Metro	New_York	Los_Angeles	Chicago	Philadelphia
Obs.	291	289	213	178
R^2	0.0755	0.143	0.0594	0.136

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	HPI return vol	HPI return vol	HPI return vol	HPI return vol
Ln(Mean AGI)	-0.00663***	-0.0269***	-0.0150***	-0.0117***
	(0.00195)	(0.00451)	(0.00290)	(0.00277)
Metro	Miami_Fort_Lauderdale	Atlanta	Boston	San_Francisco
Obs.	155	142	147	113
R^2	0.0700	0.203	0.156	0.138

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	HPI return vol	HPI return vol	HPI return vol	HPI return vol
Ln(Mean AGI)	-0.0172***	-0.00396	-0.0148***	-0.0178***
	(0.00394)	(0.00255)	(0.00331)	(0.00343)
Metro	Detroit	Seattle	Riverside	Phoenix
Obs.	132	112	95	89
R^2	0.128	0.0215	0.177	0.237

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	HPI return vol	HPI return vol	HPI return vol	HPI return vol
Ln(Mean AGI)	-0.0125***	-0.00749*	-0.0477***	-0.0155***
	(0.00352)	(0.00446)	(0.00632)	(0.00459)
Metro	Minneapolis_St_Paul	Tampa	Baltimore	Denver
Obs.	104	100	71	81
R^2	0.110	0.0279	0.452	0.126

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Regressions of return volatility, based on CoreLogic data from 1998-2014, on 1998 mean household AGI, within each of the 16 largest MSAs in the sample.

	(1)	(2)	(3)	(4)
	ZHVI return vol	ZHVI return vol	ZHVI return vol	ZHVI return vol
Ln(Mean AGI)	-0.0240***	-0.0342***	-0.0193***	-0.0196***
	(0.00208)	(0.00256)	(0.00274)	(0.00221)
Metro	New_York	Los_Angeles	Chicago	Philadelphia
Obs.	291	289	213	178
R^2	0.316	0.385	0.190	0.307

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	ZHVI return vol	ZHVI return vol	ZHVI return vol	ZHVI return vol
Ln(Mean AGI)	-0.0322***	-0.0543***	-0.0243***	-0.0393***
	(0.00285)	(0.00530)	(0.00229)	(0.00470)
Metro	Miami_Fort_Lauderdale	Atlanta	Boston	San_Francisco
Obs.	155	142	147	113
R^2	0.455	0.428	0.439	0.387

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	ZHVI return vol	ZHVI return vol	ZHVI return vol	ZHVI return vol
Ln(Mean AGI)	-0.0366***	-0.00777***	-0.0380***	-0.0376***
	(0.00442)	(0.00210)	(0.00528)	(0.00436)
Metro	Detroit	Seattle	Riverside	Phoenix
Obs.	132	112	95	89
R^2	0.346	0.111	0.357	0.461

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	ZHVI return vol	ZHVI return vol	ZHVI return vol	ZHVI return vol
Ln(Mean AGI)	-0.0314***	-0.0258***	-0.0278***	-0.0251***
	(0.00498)	(0.00410)	(0.00411)	(0.00351)
Metro	Minneapolis_St_Paul	Tampa	Baltimore	Denver
Obs.	104	100	71	81
R^2	0.280	0.288	0.398	0.392

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regressions of return volatility, based on Zillow data from 1998-2014, on 1998 mean household AGI, within each of the 16 largest MSAs in the sample.

	(1) HPI vol	(2) HPI vol	(3) HPI vol	(4) HPI vol
$\Delta \ln(HPI)_{t-12}$	-0.0374***	-0.0352***	-0.0357***	-0.0365***
	(0.00790)	(0.00742)	(0.00750)	(0.00774)
$\Delta \ln(HPI)_{t-24}$	-0.0241***	-0.0231***	-0.0234***	-0.0241***
	(0.00572)	(0.00535)	(0.00530)	(0.00553)
$\Delta \ln(HPI)_{t-36}$	-0.0122**	-0.0115**	-0.0117**	-0.0123**
	(0.00506)	(0.00484)	(0.00486)	(0.00518)
$\Delta \ln(HPI)_{t-48}$	-0.00807	-0.00669	-0.00774	-0.00945
	(0.00903)	(0.00881)	(0.00878)	(0.00926)
Fixed effect	None	State	MSA	Zip Code
Obs.	76467	76467	76467	76467
R^2	0.0617	0.0848	0.129	0.0642

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) Using CoreLogic HPI

	(1) ZHVI vol	(2) ZHVI vol	(3) ZHVI vol	(4) ZHVI vol
$\Delta \ln(ZHVI)_{t-12}$	-0.0166**	-0.0222**	-0.0221***	-0.0216***
	(0.00713)	(0.00824)	(0.00796)	(0.00795)
$\Delta \ln(ZHVI)_{t-24}$	-0.0182***	-0.0173***	-0.0174***	-0.0171***
	(0.00318)	(0.00324)	(0.00311)	(0.00315)
$\Delta \ln(ZHVI)_{t-36}$	-0.00872*	-0.00855**	-0.00827**	-0.00821**
	(0.00472)	(0.00384)	(0.00387)	(0.00383)
$\Delta \ln(ZHVI)_{t-48}$	0.0154	0.0113	0.0119	0.0117
	(0.0111)	(0.00948)	(0.00975)	(0.00975)
Fixed effect	None	State	MSA	Zip Code
Obs.	76467	76467	76467	76467
R^2	0.0131	0.143	0.216	0.0231

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Using Zillow ZHVI

Table 5: Zip-code level panel regressions of housing return volatility (calculated on a rolling basis with 12 months of data) on lags of monthly housing returns.

	(1) HPI vol	(2) HPI vol	(3) HPI vol	(4) HPI vol
$\Delta \ln(HPI)_{t-12}$	-0.0363***	-0.0342***	-0.0349***	-0.0360***
	(0.00772)	(0.00721)	(0.00724)	(0.00741)
$\Delta \ln(HPI)_{t-24}$	-0.0259***	-0.0248***	-0.0255***	-0.0266***
	(0.00630)	(0.00593)	(0.00593)	(0.00625)
$\Delta \ln(HPI)_{t-36}$	-0.0144*	-0.0131*	-0.0141*	-0.0156*
	(0.00784)	(0.00747)	(0.00738)	(0.00770)
$\ln(AGI)_{1998}$	-0.000486**	-0.000507**	-0.000386***	
	(0.000190)	(0.000190)	(0.000117)	
$\ln(AGI)_{1998} \times \Delta \ln(HPI)_{t-12}$	0.0157**	0.0163**	0.0151**	0.0125**
	(0.00703)	(0.00701)	(0.00604)	(0.00536)
$\ln(AGI)_{1998} \times \Delta \ln(HPI)_{t-24}$	0.00169	0.00207	0.00157	-0.0000620
	(0.00371)	(0.00358)	(0.00385)	(0.00396)
$\ln(AGI)_{1998} \times \Delta \ln(HPI)_{t-36}$	-0.00712	-0.00664	-0.00744	-0.00921*
	(0.00447)	(0.00428)	(0.00475)	(0.00529)
Fixed effect	None	State	Metro	Zip Code
Obs.	82070	82070	82070	82070
R^2	0.0628	0.0848	0.128	0.0648

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) Using CoreLogic HPI

	(1) ZHVI vol	(2) ZHVI vol	(3) ZHVI vol	(4) ZHVI vol
$\Delta \ln(ZHVI)_{t-12}$	-0.0113*	-0.0162**	-0.0165**	-0.0170**
	(0.00650)	(0.00742)	(0.00719)	(0.00729)
$\Delta \ln(ZHVI)_{t-24}$	-0.0126***	-0.0132***	-0.0133***	-0.0140***
	(0.00320)	(0.00296)	(0.00290)	(0.00297)
$\Delta \ln(ZHVI)_{t-36}$	-0.00147	-0.00323	-0.00303	-0.00375
	(0.00841)	(0.00679)	(0.00701)	(0.00686)
$\ln(AGI)_{1998}$	-0.000935***	-0.000860***	-0.000873***	
	(0.000113)	(0.000131)	(0.000131)	
$\ln(AGI)_{1998} \times \Delta \ln(ZHVI)_{t-12}$	0.0575***	0.0560***	0.0552***	0.0514***
	(0.00794)	(0.00718)	(0.00731)	(0.00711)
$\ln(AGI)_{1998} \times \Delta \ln(ZHVI)_{t-24}$	0.0208***	0.0196***	0.0191***	0.0177***
	(0.00604)	(0.00577)	(0.00573)	(0.00518)
$\ln(AGI)_{1998} \times \Delta \ln(ZHVI)_{t-36}$	0.0109	0.00872	0.00776	0.00363
	(0.00750)	(0.00851)	(0.00822)	(0.00867)
Fixed effect	None	State	Metro	Zip Code
Obs.	82070	82070	82070	82070
R^2	0.0320	0.154	0.226	0.0329

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Using Zillow ZHVI

Table 6: Repeats Table 5, interacting explanatory variables with 1998 log AGI.

	(1) ZHVI vol	(2) ZHVI vol	(3) ZHVI vol	(4) ZHVI vol	(5) ZHVI vol	(6) ZHVI vol
Housing / expenditures	0.578*		0.593*	0.565***	0.688***	0.582**
	(0.315)		(0.303)	(0.113)	(0.108)	(0.277)
Owned / expenditures		0.799*				
		(0.464)				
Ln(AGI)			-0.0308***		-0.0292***	-0.0307***
			(0.00328)		(0.00231)	(0.00314)
Food / expenditures						0.0812
						(0.554)
Constant	-0.0931	-0.00647	0.0208	-0.0884**	-0.0193	0.0133
	(0.110)	(0.0682)	(0.106)	(0.0400)	(0.0369)	(0.135)
Fixed Effect	None	None	None	State	State	None
Obs.	2804	2804	2804	2804	2804	2804
R^2	0.136	0.0981	0.263	0.652	0.761	0.264

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: This table reports zip-code-level regressions of return volatility on MSA-level measures of the housing expenditure share from the Consumer Expenditure Survey. Standard errors are clustered by MSA in columns 1-3 and by state in columns 4-6.

	(1) ZHVI vol	(2) ZHVI vol	(3) ZHVI vol	(4) ZHVI vol	(5) LTV	(6) ZHVI vol
Non-recourse	0.0324***	0.0319***	0.0341***	0.0322*	-0.0233*	
	(0.00865)	(0.00869)	(0.00895)	(0.0182)	(0.0119)	
LTV						-1.393*
						(0.736)
Housing expenditure share	0.741**	0.753**	0.719*	0.739	-0.672***	-0.195
	(0.296)	(0.284)	(0.394)	(0.479)	(0.210)	(0.725)
Ln(AGI)		-0.0302***	-0.0252***	-0.0221***		
		(0.00360)	(0.00418)	(0.00432)		
Ln(Population)			0.000631	-0.00179		
			(0.00958)	(0.0125)		
Fraction black residents			0.0286***	0.0292***		
			(0.00800)	(0.00902)		
Constant	-0.161	-0.0480	-0.0690	-0.0530	1.133***	1.418
	(0.103)	(0.0945)	(0.0846)	(0.0858)	(0.0720)	(0.863)
Sample	All	All	All	Excl. CA	All	All
Obs.	2804	2804	2803	2330	2804	2804
R^2	0.286	0.408	0.425	0.335	0.0701	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: This table reports zip-code-level regressions of return volatility on the state-level non-recourse indicator from Ghent and Kudlyak (2011). Standard errors clustered by state.