Homeowners' Risk Premia:

Evidence from Zip Code Housing Returns

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Abstract

While homeownership provides consumption benefits to owner–occupiers, residential real estate is also risky. This paper documents evidence that homeowners are compensated for bearing housing risk. Our sample includes monthly zip code–level housing returns in more than 9,000 zip codes across 135 metropolitan statistical areas (MSAs), representing almost 80% of U.S. population. We find that in more than 70% of the MSAs, at least one source of risk carries a significant positive price of risk. The types of risk that are priced are mostly local; MSA–specific housing risk and idiosyncratic housing risk are the two most important risk factors. Our results indicate that housing returns display investment–good properties, even for individual owner–occupiers.

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1 Introduction

In Q2 2019, 64.1% of U.S. households own a house.[1] Homeownership offers housing consumption benefits to owner–occupiers. At the same time, homeownership is risky. House prices have experienced large swings, especially around the Great Recession. Is this housing risk rewarded? In other words, do households who are homeowners receive a compensation for bearing housing risk? And if so, what are the sources of risk that are priced? These are the key questions this paper aims to address.

Previous literature provides evidence of a risk–return trade–off in commercial real estate (e.g. Plazzi, Torous and Valkanov, 2008). Market participants typically are institutional investors for whom real estate clearly is an investment good. So far, studies that examine risk and return in residential real estate focus on housing returns at the metropolitan (or national) level (e.g., Case, Cotter and Gabriel, 2011; Han, 2013; Cotter, Gabriel and Roll, 2015). These housing returns are essentially based on a broadly diversified housing portfolio within a Metropolitan Statistical Area (MSA), which can be as large as the combined area of New York, Newark and Jersey City. Hence, for participants who hold such a broadly diversified housing portfolio, residential real estate is arguably an investment good.

However, individual homeowners do not experience these broad–based MSA housing returns as they typically own only one property. To examine the risks these owner–occupiers face and to test whether they earn a housing risk premium, we need to analyze housing returns at a more disaggregate level. Because of infrequent trading, time series of housing returns are not available at the property level. Hence, we use zip code–level housing returns as a proxy for owner–occupiers' housing returns. Our sample includes monthly zip code–level housing returns using 9,093 zip codes across 135 MSAs from Zillow.[2] This disaggregate perspective is important; we document substantial variation in average housing returns and risk exposures within an MSA. Also, idiosyncratic volatility accounts for 63% of the total zip code–level volatility on average. Hence, the housing risk and returns that owner–occupiers face are vastly different from broadly diversified MSA–level housing returns and risk.

[1] U.S. Census Bureau "Quarterly Residential Vacancies and Homeownership, Second Quarter 2019".

[2] Several papers have used zip code–level or other aggregation level data from Zillow to analyze mortgage defaults, foreclosures, and household leverage (e.g., Mian and Sufi, 2009; Mian, Sufi and Trebbi, 2015; Adelino, Schoar and Severino, 2016).

Extensive asset pricing tests document significant empirical evidence of housing risk premia at the zip code–level. Hence, even at this highly disaggregated level where many market participants are owner–occupiers, housing has a dual role of consumption and investment good. At the same time, we find substantial heterogeneity across local markets in terms of which sources of risk are priced.Our multi–factor model includes three systematic risk factors: U.S. housing market returns, U.S. equity market returns and local MSA–specific housing returns. Furthermore, we include zip code–level idiosyncratic housing risk ($IVOL$), which is measured with respect to the three systematic risk factors. By including local MSA–specific housing returns, we allow for locally segmented housing markets. This is consistent with studies showing that housing markets cluster and local aspects matter (e.g. Goetzmann, Spiegel and Wachter, 1998; Tuzel and Zhang, 2017). Consequently, we cannot estimate one asset pricing model for the entire U.S. housing market. Instead, we estimate the model separately for the cross–section of zip code–level housing returns within each of the 135 MSAs. We include idiosyncratic housing risk because of the vast underdiversification among owner–occupiers; many households own just one property which could result in a premium for idiosyncratic housing risk (Merton, 1987).[3]

Our main findings are twofold. First, in 96 (71%) out of all 135 MSAs at least once source of risk carries a significant positive risk premium.[4] This implies that for the majority of metropolitan areas, housing returns display investment good properties, even at the highly disaggregate zip code–level where many homeowners are also occupants.

Second, the two most important sources of priced risk are the local MSA–level housing risk and zip code–level idiosyncratic housing risk. MSA–level housing risk is priced in 49 MSAs and $IVOL$ is priced in 48, which is about half of all 96 MSAs where housing has investment–good properties. Heatmaps reveal that $IVOL$ is priced in a widespread range of MSAs across the country, including areas on the East Coast (e.g. New York and Washington), West Coast (e.g. San Francisco), Midwest (e.g. Columbus), Southwest (e.g. Austin), and Southeast (e.g. Charlotte). Local MSA–level housing is also priced in a broad range of MSAs across the country, albeit mostly different metropolitan areas.[5] In 21 MSAs both sources of risk are simultaneously priced.

[3]In addition, homeownership generates under–diversification of the overall wealth portfolio because housing is lumpy and hence limits the ability of a household to invest in other asset classes (e.g., Flavin and Yamashita, 2002; and Cocco, 2005).

[4]In line with theory, we focus primarily on single–sided tests for positive prices of risk.

[5]MSA–level housing risk is priced in areas on the East Coast (e.g. Boston), West Coast (e.g. Seattle), Midwest

Aggregate national U.S. housing risk and U.S. equity market risk play a much smaller role in the cross–section of residential housing returns. U.S. housing market risk is priced in only 25 MSAs, which is less than 19% of all MSAs in our sample. While the estimated price of risk for the U.S. equity market factor is significant in 30 MSAs, the stock market betas are close to zero and mostly statistically insignificant. This results in an economically negligible risk premium. The low covariance between housing and equity returns is also shown at the national level by Jordà et al. (2019).

Our main findings pass various robustness tests: 1) while our main analysis is based on the 1996–2016 period, we also restrict the sample period to 1996–2007 to control for the effects of the subprime crisis; 2) we estimate our multi–factor model for MSAs with a minimum of 15 zip codes instead of 20 to increase the number of MSAs included in our sample; 3) we control for housing value and zip code size as housing characteristics in the estimation of our multi–factor model; 4) we estimate our multi–factor model without the stock market risk factor; and 5) we unsmooth housing returns using an AR(3) model.

In the last part of the paper, we aim to link the heterogeneity in the pricing of risk across MSAs to their fundamentals, such as loan–to–value ratios, liquidity measures, and rent–to–price ratios. Preliminary results suggest, among others, that MSAs where housing has investment–good properties (i.e., where at least one source of risk carries a significant premium) have higher average household income, more regulation (making housing supply more constrained) and the average loan–to–value ratio is lower.

Understanding the risk–return trade off in housing returns is important. Besides an average homeownership rate of 64.1%, housing typically is a major part of household wealth. At the end of 2015, housing represented 49.5% of the median–wealth household portfolio, largely ahead of stocks (directly and indirectly held), which only represented 3.5% of the portfolio (Panel Study of Income Dynamics Survey PSID, 2015). Even for households at the top 1% of the wealth distribution, housing was larger than stocks (29.1% versus 25.2%).However, while numerous studies have investigated the cross–section of expected stock returns (e.g., Fama and French, 1992, 1993 and 2015; Carhart, 1997; Pastor and Stambaugh, 2003), the cross–section of expected housing returns is still largely uncharted territory.

(e.g. Chicago), Southwest (e.g. Dallas), and Southeast (e.g. Charlotte).

Our paper relates to a growing literature on housing–market risk. Most papers focus on MSA–level housing returns. For instance, Cotter, Gabriel and Roll (2015) find that, during the boom of the 2000s, a large proportion of MSA–level housing returns is explained by a common set of variables (e.g., loan–to–value ratio, industrial production, and Federal Funds rate), which suggests that MSA–level housing markets are highly integrated and offer limited opportunities for diversification.[6] Case, Cotter and Gabriel (2011) analyze the risk–return relation in MSA–level housing returns. Among other things, these authors find that, on average across MSAs, risk exposure to the U.S. housing market and equity market are positively significant. Han (2011; 2013) focuses on the puzzling negative relation between total risk and return in MSA–level housing returns. Using a panel regression framework, this author finds that this relation can be explained by the hedging that homeownership provides to households that intend to buy a larger house in the same MSA or a similar size house in a different, but highly correlated MSA (as predicted by the theory in Sinai and Souleles, 2005). Tuzel and Zhang (2017) find that local equity risk plays an important role for house prices. Landvoigt et al. (2015) analyze the cross–section of house prices within the San Diego MSA, and find that cheaper credit for poor households was a major driver of prices.

Several recent papers focus on the effect of climate risk in house prices. For example, Bernstein et al. (2019) show that homes exposed to sea level rise trade at a discount of approximately 7% relative to unexposed properties. Giglio et al. (2019) estimate the term–structure of discount rates for real estate, and show that real estate prices are exposed to climate change risk in the form of a sea level rise. They show that a general–equilibrium framework with consumption risk and climate change risk can match this term–structure.[7]

Our paper also relates to a stream of research linking housing returns to stock returns. Lustig and Nieuwerburgh (2005) show that the ratio of housing wealth to human wealth predicts future stock returns. Piazzesi, Schneider and Tuzel (2007) find that the housing share of total consumption predicts future excess returns. Using a time series of returns from 1870 to 2015 for several asset classes, Jordà et al. (2019) find that housing outperforms equity prior to World War II, but the

[6] In a recent paper, Cotter, Gabriel and Roll (2018) document that integration within and among equity, fixed income, and real estate (i.e., Real Estate Investment Trust) has increased significantly after 2000 both within and among countries, pointing to diminished opportunities for diversification across asset classes and regions.

[7] Climate risk can also be a form of disaster risk that affects all properties. In untabulated results, we estimate zip code–level exposure to the downside beta of Ang et al. (2006a) or Lettau et al. (2014) and find that neither of these downside risk factors seem to play a role for zip code–level housing returns in the majority of MSAs.

opposite occurs afterwards. In line with their findings, we report very low exposures of housing returns to U.S. stock market returns.[8]

The rest of the paper is organized as follows. Section 2 discusses the multi–factor model used to estimate systematic and idiosyncratic risk in the housing market. Section 3 introduces the data and presents descriptive statistics. In Section 4, we discuss the types of risk priced and the magnitude of the estimated risk premia across MSAs. We also discuss a battery of robustness checks. Section 5 relates the cross–MSA variation in prices of risk estimates to MSA–level characteristics. Section 6 concludes. The Appendix gives more details on the data sources and variables construction. An Internet Appendix reports the results of various robustness tests.

2 Empirical Framework

Homeowners who are also occupants obviously obtain consumption benefits from their homeownership. However, it is still an open question to what extent highly disaggregate housing returns also display investment–good characteristics. In other words, are owner–occupants compensated for the housing risks they are exposed to? If disaggregate (zip code–level) housing would merely be a consumption good, we would not expect an asset pricing model to capture cross–sectional differences in expected housing returns. Hence, the extent to which that an asset pricing model helps explain cross–sectional differences in housing returns is indicative of the investment–good properties of housing returns.[9]

2.1 Multi–factor Model for the Cross–Section of Zip Code Housing Returns

To analyze the cross-section of expected U.S. zip code–level residential housing returns, we start with the following multi–factor model

$$E[r_{i,j}] = \lambda_j^m \beta_{i,j}^m + \lambda_j^{hi} \beta_{i,j}^{hi} + \lambda_j^{msa} \beta_{i,j}^{msa} + \lambda_j^{ivol} \mathrm{IVOL}_{i,j}, \tag{1}$$

[8] Christoffersen and Sarkissian (2009) link city size to mutual fund returns. In our paper, the MSA–level housing risk factor can be related to city characteristics such as its size, local GDP, etc., which we link to housing returns.

[9] Case, Cotter and Gabriel (2011) use a similar approach to examine the cross-section of MSA–level housing returns.

where $r_{i,j}$ is the excess housing return in zip–code i within MSA j. The model includes national risk factors (aggregate housing (hi) and equity market (m)), a local MSA–level risk factor (msa) and zip code–level idiosyncratic housing risk ($IVOL$).

Three aspects are worth highlighting. First, to capture the risk and returns that under–diversified homeowners face, we need to consider housing returns at the most disaggregate level. We therefore use zip code–level housing returns. Ideally, one would like to estimate housing returns and risk at the individual house level. However, for this purpose we would need a sufficiently large time-series of prices for each house. Even transaction–level data from multiple listing services (MLSs) would not be suitable since transactions data at the house level would only give us only a few observations during our roughly 20-year sample period, and this would not allow us to run any type of time-series regression. This means that monthly frequency zip code–level data is, at this point in time, the best and most suitable dataset to run our type of analysis of idiosyncratic risk across the entire U.S. housing market. Existing papers generally focus on MSA–level housing returns (e.g., Case, Cotter and Gabriel, 2011; Han, 2013; Cotter, Gabriel and Roll, 2015).[10] These housing returns are essentially based on a broadly diversified housing portfolio within a larger metropolitan area, which can be quite different from the housing returns experienced by individual homeowners.

Second, our model includes idiosyncratic housing risk. The potential role of idiosyncratic risk for the cross–section of residential housing returns is quite different than for the cross–section of stock returns. While achieving a well–diversified stock portfolio is relatively straightforward, this is not the case for residential real estate. Homeowners often own only one property which means they hold an under–diversified real estate portfolio (Flavin and Yamashita, 2002; Cocco, 2005). Consequently, not only is systematic risk important for asset prices, but idiosyncratic risk may also play a role (Merton, 1987). In the end, the pricing of idiosyncratic housing risk is an empirical question, because even though many homeowners are under–diversified, better–diversified landlords are also active in the residential real estate market.

Third, we allow for locally segmented housing markets, following existing evidence that hous-

[10] One exception is Cannon, Miller and Pandher (2006), who study zip code–level returns. However, they only have a time-series of eight annual observations, which complicates asset pricing tests. Peng and Zhang (Forthcoming) analyze stock market betas of a sample of property–level housing returns, which are estimated from repeat–sales data. They focus on holding period returns and do not test the pricing of equity market risk in housing returns.

ing markets cluster and that local aspects matter (e.g. Goetzmann, Spiegel and Wachter, 1998; Tuzel and Zhang, 2017). Our approach follows the international finance literature where partially segmented models include both global and local (regional or country–level) risk factors (see e.g., Bekaert, Hodrick and Zhang, 2009). Therefore, rather than estimating a single model for the entire cross-section of U.S. housing returns, we allow for local segmentation by separately estimating an asset pricing model for the cross–section of zip codes within each of the 135 different MSAs. In contrast, most existing studies of housing returns (e.g. Case, Cotter and Gabriel, 2011; Cotter, Gabriel and Roll, 2015) only consider U.S.–wide housing and U.S. equity market systematic risk factors.

In sum, we include idiosyncratic housing risk in our model, in addition to the U.S.–wide and local MSA–level systematic housing risk factors. We control for potential equity market exposure of housing returns by including the equity market risk factor. By estimating the model for the cross–section of zip code–level housing returns within each MSA separately, we allow for different prices of risk across MSAs. In the second stage of our empirical analysis, we then relate the cross-MSA heterogeneity in the pricing of systematic and idiosyncratic risk to various MSA–level fundamentals, such as liquidity and the loan–to–value ratio.

2.2 Estimation

To estimate the multi–factor model for each MSA, we apply the standard two-step Fama and MacBeth (1973) approach. In the first step, we estimate time-series regressions for each zip code to obtain idiosyncratic risk and the exposures to the systematic risk factors. Given that our full sample contains just 20 years of monthly returns, we estimate exposures and idiosyncratic volatility using the full sample period.

Zip Code–level Risk Exposure Estimation The time-series regression that we use to estimate the factor exposures and idiosyncratic risk for each zip code i is given by

$$r_{i,t} = \alpha_{i,t} + \beta_i^{m} r_t^{mkt} + \beta_i^{hi} r_t^{hi} + \beta_i^{msa} r_{j,t}^{orthmsa} + \varepsilon_{i,t}, \tag{2}$$

where $r_{i,t}$ denotes the full sample time-series of zip code–level housing return in excess of the risk-free rate. The risk-free rate is measured as the one-month Treasury bill rate. r_t^{mkt} and r_t^{hi} are U.S. stock market and U.S. housing index excess returns, respectively. $r_{j,t}^{orthmsa}$ is the orthogonalized excess return for MSA j, which is the MSA to which zip code i belongs. We follow the approach in existing (international finance) studies (e.g. Bekaert, Hodrick and Zhang, 2009; Conrad, Dittmar and Ghysels, 2013) and orthogonalize the (local) MSA excess return with respect to the U.S. housing index excess return using an ordinary least squares regression given by

$$r_{j,t}^{msa} = \mu_j + \beta_j r_t^{hi} + \eta_{j,t}, \tag{3}$$

where the error term $\eta_{j,t}$ is the orthogonalized version of $r_{j,t}^{msa}$ that we use in (2).

Following the literature on stock market idiosyncratic volatility (see Ang et al. 2006b), we estimate zip code–specific idiosyncratic risk as the standard deviation of the residuals from the time–series regression of our multi–factor model specified in (2), that is $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,t})}$ for zip code i.

Next, we run cross–sectional regressions for all zip codes within each of the 135 MSAs to estimate prices of risk for each factor in a particular MSA.

MSA–level Price of Risk Estimation To estimate the MSA–specific prices of risk for each factor, we estimate for the cross–section of zip code level housing returns within each MSA j the following cross–sectional regression

$$E[r_{i,j}] = \lambda_j^0 + \lambda_j^m \beta_{i,j}^m + \lambda_j^{hi} \beta_{i,j}^{hi} + \lambda_j^{msa} \beta_{i,j}^{msa} + \lambda_j^{ivol} \text{IVOL}_{i,j} + \xi_{i,j}, \tag{4}$$

where we only include zip codes i that belong to MSA j and use the risk exposures and idiosyncratic volatilities as estimated through (2) based on the full sample.

2.3 Linking Prices of Risk Estimates to Local Housing Market Fundamentals

Our approach of estimating a multifactor model separately for each MSA will yield different estimates of the prices of risk for each local housing area (MSA). We may also have differences across MSAs on whether a price of risk is significant. For instance, we may find that in some MSAs, idiosyncratic risk is priced, while in others, only systematic risk matters. To better understand the why risk factors are priced in some MSAs but not in others, in the second step of our empirical analysis, we investigate which MSA characteristics help explain cross–MSA differences in the pricing of different sources of risk. For this purpose, we estimate a probit regression in which the dependent variable δ is an indicator equal to one if the price of risk estimate is positive and significant, and zero otherwise. The probit regression is given by

$$Pr(\delta) = \alpha + Z^{\intercal}\beta + \varepsilon.$$

We estimate this model separately for each of the estimated prices of risk of the U.S. housing index, the local MSA return and $IVOL$. Since we estimate unconditional (full sample) factor models, we can only explore cross-MSA differences in estimated prices of risk. Therefore, as independent variables Z in the probit regressions, we include time-series averages of the fundamental economic variables discussed in the next section.

3 Data and Descriptive Statistics

In this section we introduce the data and present descriptive statistics of quantities used in the empirical analysis.

3.1 Housing Returns Data

The data for residential house values are obtained from Zillow. They provide the Zillow Home Value Index (ZHVI) at a monthly frequency for different aggregation levels ranging from zip code–level to state–level. We use the ZHVI for all homes which includes single family residences, condominiums and co-ops. The ZHVI is based on estimates on the market value of individual homes that Zillow calls Zestimates, which are based on a hedonic model that includes both appraisal and transaction data on house prices.[11] Since our framework allows for idiosyncratic risk to be priced, we focus on the lowest aggregation level available, namely zip code–level data. We merge the zip code–level data with the MSA–level ZHVI data. After merging these datasets, we are left with 12,243 unique

[11]Zillow estimates Zestimates using a proprietary model and they do not reveal all the inputs into this model.

zip codes and 571 unique MSAs for the sample period April 1996-December 2016.[12] Zillow also provides the ZHVI for the entire U.S. residential housing market, which we use in our empirical analysis as a proxy for aggregate U.S. housing market prices.[13] To compute housing excess returns we subtract the one–month Treasury bill rate. These data as well as data on monthly U.S. stock market excess returns are obtained from the online data library of Kenneth R. French.[14]

The zip code–level data from Zillow does not cover all zip codes in each MSA. To obtain a measure of how well the observed zip codes cover each MSA, we obtain population data per zip code from the 2010 U.S. Census. We merge this data with the Zillow zip code–level data and compute the population per MSA. We then compare this population in relation to the reported MSA total population from the 2010 U.S. Census. We find that, on average, the Zillow zip code–level data covers 86.5% of total MSA population, with the median coverage being 91.6%. The Zillow zip code data thus provides good coverage for each MSA.

Since our multifactor model specified in (4) includes three systematic risk factors and idiosyncratic volatility, we need a sufficiently large cross-section of zip codes to be able to estimate the prices of risk. Thus, we keep only MSAs that have at least 20 zip codes. This reduces our sample size to 9,093 zip codes across 135 MSAs. However, these 135 MSAs represent 86.9% of the total population of the initial sample of 571 MSAs.[15]

3.2 Descriptive Statistics

In Table 1, we present a set of summary statistics for yearly excess housing returns at the zip code, MSA and U.S. level, as well as U.S. stock market excess returns. We present these statistics for the 9,093 zip codes across 135 MSAs sample.

[Insert Table 1 here]

The zip code–level statistics, except the cross–sectional dispersion, are computed in three steps. First, we take the time–series statistic for each zip code. Second, within each MSA we take the

[12] The 2008 financial crisis falls in the middle of our sample period and this was a turbulent period for house prices. Therefore, as a robustness check, we end the sample in 2007 for our empirical analysis (see Section 4.4).

[13] Appendix A.2 provides a detailed description on how we merge the different ZHVI geographies.

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[15] In our robustness Section 4.4, we also estimate our multifactor model with a minimum of 15 zip codes which increases the sample to 178 MSAs, and obtain similar results.

cross–sectional mean of these statistics. Finally, we take the average across MSAs. The cross–sectional dispersion measure is computed by first taking the time–series mean for each zip code, next we compute the average within each respective MSA, and finally we take the cross–sectional standard deviation across MSAs.

The MSA–level statistics, except the dispersion, are computed in two steps. First, we take the time–series statistic for each MSA. Then, we take the cross–sectional mean of these time–series statistics. The dispersion measure is computed by first taking the time–series mean of each MSA, and then taking the standard deviation of these time–series means.

As expected, we find that zip code–level excess housing returns are more volatile than both MSA– and U.S.–level excess housing returns. The standard deviations are 6.44%, 5.18% and 5.19% per annum, respectively. The zip code–level average excess return (1.67%) is higher than both the average MSA (1.22%) and U.S. housing index (1.15%) excess housing returns. This tentatively suggests that in our sample we observe a positive risk-return relationship in the aggregation level.[16] Finally, the U.S. stock market has both a higher average yearly excess return (7.95%) and a higher standard deviation (18.76%) than housing returns for any aggregation level. The average yearly excess housing returns may at first glance seem low, and this is because we have the financial crisis in our sample during which housing experienced some extremely low returns (e.g. the Zillow U.S. Housing Index had cumulative yearly excess returns of -27.4% from 2007 to 2011). In the Internet Appendix Table A2, we present the same statistics for the period of April 1996 to December 2007 and find that average yearly excess housing returns across aggregation levels is almost twice as large versus the full sample.

4 Main Results

The first step of our empirical analysis is to estimate the multi–factor asset pricing model for each of the 135 MSAs in our sample. This means that we perform cross–sectional asset pricing tests for zip code housing returns within 135 different cross–sections. As discussed in Section 2, our model includes U.S.–wide housing market and equity market returns, MSA–level housing returns and zip code–level idiosyncratic volatility. Hence, our framework allows for the pricing of systematic

[16] Note that the averages are equally weighted across zip codes and across MSAs. Therefore, we cannot directly compare these averages based on disaggregate data to U.S.-wide housing returns.

national or local risk, and idiosyncratic housing risk.

4.1 Risk Exposure Estimation

We first examine the estimated zip code–level factor exposures and idiosyncratic volatilities ($IVOL$), which are based on full sample time–series regressions based on specification (2) at the zip-code level. Table 2 presents descriptive statistics of the risk exposures (betas) and the $IVOL$ estimates of the first-stage time–series regressions. The table reports cross–sectional averages across all 9,093 zip codes.

[Insert Table 2 here]

Consistent with the existing literature (see e.g., Case and Shiller, 1989; Jordà et al., 2019) we find that the average U.S. stock market exposure β^m is essentially zero with a mean (median) of -1.3e–3 (-8.9e–4). This suggests that owning a house does not generate exposure to U.S. stock market risk. Consequently, combining residential real estate with stocks can potentially lead to substantial diversification benefits.[17] On the other hand, Cotter, Gabriel and Roll (2018) find declining diversification benefits in recent years across a range of assets including equity, debt and real estate within and across countries.

A single–factor model for housing returns including only the U.S. housing index is akin a CAPM for stock returns. In the CAPM, the (weighted) average stock market beta equals one. We find that the average U.S. housing index beta β^{hi} is close to one with a mean (median) of 1.05 (0.95). The beta does vary substantially across MSAs, as indicated by the cross–sectional standard deviation of 0.69. At first glance, these results suggests that a CAPM–like model for housing returns at the zip code–level may be appropriate. Further, we find that zip code–level housing returns carry an exposure to local MSA–level housing returns (orthogonalized with respect to U.S.–wide housing returns). The mean (median) β^{msa} is 0.77 (0.81). These beta estimates are relatively less dispersed with a cross–sectional standard deviation of 0.40. These results suggest that allowing for locally segmented housing markets and local factors may be important.

[Insert Figure 1 here]

[17] In Section 4.4, we exclude the equity market factor and find very similar results for the pricing of the different types of housing risk.

In Figure 1, we plot a histogram of Newey and West (1994) adjusted t-statistics for the estimated risk exposures. We see that the U.S. stock market beta is, in general, insignificant across zip codes. Only 420 (220) zip codes have positive and significant U.S. stock market betas at a 10% (5%) significance level. On the other hand, we find that the U.S. housing market and MSA–level housing betas are positive and significant for the vast majority of zip codes. Specifically, at the 10% (5%) significant level we find that 8,321 (8,106) and 7,877 (7,629) zip codes have positive and significant U.S. housing market and MSA–level housing betas, respectively. Further, in line with asset pricing theory, the betas are almost always positive since only 20 (16) and 24 (18) of the U.S. housing market and MSA–level housing betas, respectively, are negative and significant at a 10% (5%) significance level. Taken together, these results suggests that the U.S. stock market plays a negligible role in the cross–section of zip code–level housing returns, while the U.S. housing market and MSA–level housing risk play a significant role. However, to fully address the question of whether homeowners are actually compensated for any these risk exposures, we need to estimate prices of risk on these risk exposures, which we do in the next section.

The monthly $IVOL$ has a mean (median) of 0.66 (0.58). The cross–sectional standard deviation is 0.31. To understand these values in relation to total risk, we also compute the full sample standard deviation of zip code excess returns as a proxy for total risk (volatility). In comparison, the monthly total volatility has a mean (median) of 0.93 (0.86). We compute the ratio of $IVOL$ to total volatility to get an estimate of the share of total risk that $IVOL$ represents. We find that on average (median) across zip codes $IVOL$ represents 62.79% (62.18%) of total volatility. This means that $IVOL$ represents roughly 63% of total risk in the housing market at the zip code–level. This resonates in part with the stock market idiosyncratic volatility literature, which finds that stock volatility consists mostly of idiosyncratic volatility (e.g., Ang et al., 2009). On the other hand, systematic risk still represents roughly 37% of total risk. These results emphasize the importance of decomposing total risk into systematic and idiosyncratic risk, and analyzing each type of risk separately in order to get a full picture of housing risk at the zip code–level. However, this variance decomposition does not necessarily imply that idiosyncratic risk is priced. To draw conclusions about the sources of risk that drive expected housing returns at the zip code–level, we need to perform second–stage Fama–MacBeth cross–sectional regressions. We discuss these results in the following section.

4.2 Estimation of Prices of Risk

We estimate MSA–specific prices of risk for each risk factor by running the cross–sectional regression specified in (4) within each of the 135 MSAs in our estimation sample, using the risk exposures as estimated in Section 4.1.

Asset pricing theory predicts that the price of market risk is positive. In line with this, we choose to focus mainly on positive prices of risk for all our types of risk and perform single-sided tests. Furthermore, in Section 5 we aim to link these positive risk premia estimates to economic fundamentals. In Table **??**, we present descriptive statistics for the estimated prices of risk.

[Insert Table **??** here]

We report the number of MSAs that have significant positive prices of each risk at a 5% or 10% significance level using Newey–West standard errors with four lags.[18] We also report the average price of risk and the cross–sectional dispersion in the price of risk estimates among MSAs where the respective price of risk is statistically significant.

Housing as an investment good First, we find that in 96 (84) of our 135 MSAs, at least one price of risk is positive and significant at the 10% (5%) significance level. These 96 (84) MSAs represent 73% (65%) of the total sample population and 76% (68%) of total number of zip codes. Thus, in the majority of MSAs, residential housing (at the zip code–level) displays investment good properties where homeowners receive compensation for bearing housing risk. This is our first key finding. Next, we consider which sources of risk are priced.

U.S. Housing Market Risk For the U.S. housing market risk factor, we find that out of 135 estimated MSAs, 25 (20) have positive and significant U.S. housing market price of risk estimates at the 10% (5%) one-sided significance level, with an average price of risk of 0.15% (0.17%) per year, and a cross–sectional dispersion of 0.13% (0.13%). Thus, in only 19% (15%) of all MSAs the

[18] The four lags are obtained following Newey and West (1994) formula for lag selection $4(T/100)^{2/9}$ where T is the length of the time–series (number of monthly observations). In our case, the average number of observations per zip code is 230, which yields four lags. In untabulated results, we increase or decrease the number of lags and this does not affect our results.

U.S. housing market risk factor is positively priced. This shows that in the vast majority of MSAs, U.S.–level housing risk is not priced.

Local MSA–level Housing Risk For the local MSA–level housing risk factor, we find that out of all 135 MSAs, 49 (42) have positive and significant U.S. stock market price of risk estimates at the 10% (5%) one-sided significance level, with an average price of risk of 0.13% (0.13%) per year, and a cross–sectional dispersion of 0.09% (0.09%). Thus, at the 10% significance level more than a third of MSAs have local risk significantly priced. Further, among these 49 (42) MSAs, we find that the average yearly risk premium (i.e., the average exposure multiplied by the price of risk estimate) is 1.27% (1.03%), which is significant compared to the average yearly excess returns across all 135 MSAs of 1.22% reported in Table 1. Taken together, these results suggest that local MSA–level risk plays an important role in the pricing of the cross–section of residential zip code–level housing returns. This finding is in line with earlier papers showing that housing markets cluster and that local aspects matter for housing returns (Goetzmann, Spiegel and Wachter, 1998; Tuzel and Zhang, 2017).

Idiosyncratic Volatility For zip code–level idiosyncratic housing risk ($IVOL$) we find that in 48 (32) out of 135 estimated MSAs, $IVOL$ carries a positive and significant risk premium at the 10% (5%) one-sided significance levels respectively. The average price of risk is 0.10 (0.12) per year, and the cross–MSA dispersion is 0.05 (0.06). Further, among these 48 (32) MSAs, we find that the average yearly risk premium is 0.77% (0.58%). While, this risk premium is smaller than on the local MSA–level risk, it is still economically significant. Thus, these results suggest that idiosyncratic risk plays an important role in the pricing of the cross–section of residential zip code–level housing returns. This is in line with many homeowners being underdiversified and being less able (or unable) to obtain a well–diversified housing portfolio.

U.S. Stock Market Risk For the U.S. stock market risk factor, we find that out of 135 estimated MSAs, 30 (26) have positive and significant U.S. stock market price of risk estimates at the 10% (5%) one–sided significance level, with an average price of risk of 0.39% (0.33%) per year, and a cross–sectional dispersion of 0.64% (0.66%). While the magnitude of the price of risk estimate is higher than for the other risk factors, in Table 2, we find that the average U.S. stock market beta is close to zero, and in Figure 1 we find that most estimated U.S. stock market betas are insignificant. This means that even though the price of risk is significant in many MSAs, the risk premium is close to zero.[19] Taken together these results suggest that the U.S. stock market risk plays a negligible role in the pricing of the cross–section of residential zip code–level housing returns.

Factor Pricing Patterns In the middle and bottom panels of Table **??**, we count how many MSAs have one or more sources of risk priced, e.g., simultaneously local MSA–level and idiosyncratic risk, or U.S.–wide housing and idiosyncratic risk, etc. Further, we report the share of total population (of the 135 MSAs) and share of total zip codes (9,093) that these MSAs represent. We find that only 8 (6) MSAs have both local and national risk priced at the 10% (5%) significance level, which represents just 3.1% (2.4%) of the total sample population and just 5.4% (4.6%) of total zip codes. Further, we find that just 21 (12) or 8 (5) MSAs have both systematic (λ^{msa} or λ^{hi}) and idiosyncratic (λ^{ivol}) risk priced at the 10% (5%) significance level. Finally, just 4 (2) MSA has all three types of risk priced. Hence, there is a lot of heterogeneity across MSAs in terms of which sources of risk are priced.

Finally, in the bottom panels, we count the number of MSAs that have at least one, two, three or more significant prices of risk. Besides the 96 (84) MSAs where at least one source of risk is priced at the 10% (5%) significance level, we see that 49 (31) MSAs have at least two significant prices of risk, which represents 39.2% (28.3%) of the total sample population and 42.7% (31.8%) of total number of zip codes. Only 7 (5) MSAs have three or more significant prices of risk, and no MSAs have all four prices of risk significant. Since we find that the U.S. stock market risk is priced in many MSAs but has a negligible risk premium, we repeat this analysis by focusing only on the three types of housing risk. The results do not change much; we now find 89 (73) MSAs that have at least one of these risks significant priced.

In summary, we find that in the majority of the U.S. housing market, housing, even at the zip code–level, displays investment–good characteristics. At the same time, there is substantial heterogeneity across local markets in terms of which sources of risk are priced. Local MSA–level

[19] The average risk premium among the MSAs where the U.S. stock market risk is significantly priced at the 10% (5%) significant level is just -0.06% (-0.03%) per year.

risk and idiosyncratic housing risk are the most important sources of priced risk. Finally, U.S. national housing market risk and equity market risk do not play an important role for the cross–section of zip code housing returns.

Next, to further investigate patterns in the pricing of risk across the U.S., in Figure 2 we plot geographical heat maps of the U.S. and highlight in purple MSAs where the price of risk is positive and significant at the 10% significance level, and in yellow MSAs where the price of risk is not significant.

[Insert Figure 2 here]

In Figure 2b we see that the U.S. aggregate housing market risk carries a significant positive price of risk mainly in a few MSAs on the East Coast and on the West Coast. In contrast, Figure 2c shows that the local MSA–level housing risk is priced in a broader set of MSAs across the U.S., including areas on the East Coast (e.g. Baltimore, Boston and Washington), West Coast (e.g. San Diego, San Francisco and Seattle), Midwest (e.g. Chicago, Cleveland and St. Louis), Southwest (e.g. Albuquerque, Dallas and San Antonio), and Southeast (e.g. Charlotte, Memphis and Nashville). We also see that it is priced in smaller MSAs across the country such as Cedar Rapids, IA, Kingston, NY, Lakeland, FL and Toledo, OH.

In Figure 2d we find that idiosyncratic zip code–level housing risk ($IVOL$) is priced in a widespread range of MSAs across the country, including areas on the East Coast (e.g. Boston, New York and Washington), West Coast (e.g. San Diego, San Jose and San Francisco), Midwest (e.g. Cleveland, Columbus and Minneapolis–St. Paul), Southwest (e.g. Austin, Denver and Houston), and Southeast (e.g. Atlanta and Charlotte). Further, $IVOL$ is also priced in small MSAs across the U.S. such as Akron, OH, Stamford, CT, Springfield, IL, and Utica, NY.

Finally, in Figure 2a we see that the U.S. stock market is significantly priced in many MSAs across the U.S. However, as we see in Table 2, the average beta is essentially zero, which means the risk premium is negligible. For example, the U.S. stock market risk is significantly priced in Miami, but it carries a negligible yearly risk premium of 1.1e-4%.

Magnitudes of Prices of Risk and Risk Premia Estimates In addition to statistical significance, we also examine the economic significance of the price of risk estimates. To examine the magnitudes of the estimated prices of risk and risk premia, we plot the average yearly risk premium across MSAs for each type of risk, as well as the total risk premium composition. We also include the number of MSAs where each type of risk is significantly priced.

[Insert Figure 3 here]

Figure 3 shows that the U.S. housing market has the largest risk premium, on average between 0.89% and 1.76%. However, it is significant in few MSAs. The local MSA–level housing risk commands the second highest with an average risk premium between 0.80% and 1.27%. The idiosyncratic zip code–level housing ($IVOL$) risk premium is on average between 0.41% and 0.77%. The local and idiosyncratic risk premia are relatively large compared to the MSA average yearly excess return of 1.22% as seen in Table 1. In particular, the average yearly local MSA–level housing risk premium is larger than the MSA average yearly excess return.[20] Further, we see that the yearly local MSA–level risk premium is largest among the 21 MSAs where both local and idiosyncratic risks are priced. Finally, among the few (4) MSAs where all three risks are priced, we find that the U.S. housing market risk premium is the largest.

4.3 Negative Prices of Risk

In line with asset pricing theory, throughout our main analysis we focus on positive prices of risk. In Table 4, we relax this assumption and perform two–sided tests.

[Insert Table 4 here]

We find that the majority of idiosyncratic risk, and local MSA–level housing risk have significant prices of risk that are positive. $IVOL$ is significantly priced in 45 MSAs, with 27 (60%) carrying positive prices, and an average price of risk of 0.27. Ang et al. (2006b) find that idiosyncratic risk is negatively priced in the cross–section of equity returns. This result is generally referred to as the idiosyncratic risk puzzle. Our results suggests that this puzzle generally does not fully extend to the cross–section of housing returns, and the pricing of idiosyncratic risk in the housing market is mostly consistent with asset pricing theory (Merton, 1987).[21] Local MSA–level housing risk is

[20]This is not a perfect comparison since the average yearly excess returns in Table 1 is across all 135 MSAs, while the average local MSA–level housing risk premium is only among the MSAs in which this price of risk is significant.

[21]The empirical evidence for the pricing of idiosyncratic risk of stocks is mixed. Ang et al. (2006b) find a strong negative cross–sectional relationship between idiosyncratic volatility and expected stock returns. In contrast, Fu

significantly priced in 51 MSAs, with 34 (67%) carrying positive prices, and an average price of risk of 0.15%.

On the other hand, we find that the majority of U.S. housing market risk significant prices of risk are negative, while for the U.S. stock market risk the significant ones half are negative and half positive. The average price of risk for both of them is negative which is inconsistent with asset pricing theories. However, the average yearly risk premium of the U.S. stock market is positive but equals a mere 0.04%. In summary, these results are consistent with our main results in Table **??** focusing on positive prices of risk. We still find that it idiosyncratic zip code–level housing risk and local MSA–level housing risk play the dominant roles for the cross–section of zip code–level residential housing returns.

4.4 Robustness Tests

We perform a number of additional checks to verify the robustness of our main findings. All of these results can be found in the Internet Appendix.

Subsample Analysis Our sample includes the 2008 financial crisis when residential real estate experienced a very large drop in value. This period can be considered a large outlier for the housing market. For this reason, we exclude the financial crisis from our sample and focus on the 1996 – 2007 subsample. These results can be found in Table A1 and A2 of the Internet Appendix. In this sample, we find that average excess returns are much higher at all housing aggregation levels compared to our full sample. Further, we find that the share of MSAs with priced U.S. housing market risk, MSA–level housing risk and zip code–level idiosyncratic housing risk are similar to the full sample. In general, our main results and conclusions hold in this subsample.

Zip Code Requirement In our main analysis we require a minimum of 20 zip codes to estimate price of risk within each MSA. We estimate our model using a minimum of 15 zip codes per MSA, which leads to a larger estimation sample of 178 MSAs versus 135 MSAs previously. The results

(2009), and Huang et al. (2010) find a positive cross–sectional relationship. Bali and Cakici (2008) find no significant cross–sectional relationship when estimating idiosyncratic volatility using monthly returns. Conrad, Dittmar and Ghysels (2013) find no significant cross–sectional risk-return relationship when estimating ex-ante idiosyncratic volatility from options. Finally, Stambaugh, Yu and Yuan (2015) find a negative cross–sectional relationship for overpriced stocks, and a positive relation for underpriced stocks.

of these estimations can be found in Table A3 of the Internet Appendix. Our results are robust; we find that the percentage of MSAs that have a significant positive price of risk for the U.S. stock market risk, U.S. housing market risk, local MSA–level housing risk, and $IVOL$ are very similar to our main results.

Other Zip Code Characteristics Our main three-factor model includes $IVOL$ as the only zip code–level characteristic. To check the robustness of our main results, we include other zip code–level characteristics that have been shown to matter in the literature on the cross–section of stock returns. In particular, we include a measure of value in the housing market, and two different measures of size. Following Asness, Moskowitz and Pedersen (2013), our proxy for value in the housing market is estimated as the negative value of the last 60 months' cumulative zip code returns. The first measure of size is the log of the median zip code–level home's square footage. The second is the log of the median zip code house price. We add each of these zip code characteristics separately to the second stage cross–sectional regression specified in (4) to estimate prices of risk on all the factors and characteristics. These results can be found in Tables A4 to A6 of the Internet Appendix. We find that our main results and conclusions hold when including these characteristics.

Model without U.S. Stock Market Risk Factor Our results show that the U.S. equity market risk is not important for the cross–section of zip code–level housing returns, since the average U.S. stock market beta is essentially zero and is almost always statistically insignificant. The latter result is in line with the findings of Jordà et al. (2019) for the aggregate housing market. These two results suggest that including the U.S. stock market return as a factor in our main model may just be adding noise to our estimations. In order to see how our main results hold without the U.S. stock market return, we estimate the model specified in (2) and (4) without this risk factor. These results can be found in Table A7 of the Internet Appendix. We find that when excluding the U.S. stock market risk, our main results and conclusions still hold.

Unsmoothing Housing Returns Housing returns are relatively persistent. In Table A8 of the Internet Appendix, we report the median persistence of zip code– and MSA–level returns, and the persistence of U.S. housing market returns. We can see that there is high persistence in housing returns for any aggregation level. Zip code (MSA) housing returns have a median persistence of 0.81 (0.79), while U.S. housing market returns have a persistence of 0.96. By comparison, monthly returns on the U.S. stock market have a persistence of 0.07 during our sample period. As a robustness test, we use unsmoothed housing returns as a basis for our asset pricing tests. We unsmooth housing returns using different AR–specifications, including AR(1), AR(2), AR(3), AR(4) and AR(3 and 12). Following **?** we estimate the AR–models separately for zip code–level, MSA–level and U.S.–level housing returns. We find that an AR(3) specification that accounts for a monthly and quarterly lag is enough to remove the persistence of housing returns at the zip code–, MSA– and U.S.– levels. We then compute excess returns by subtracting the one-month Treasury bill rate from these unsmoothed returns. Estimating the two–pass cross–sectional regressions for the unsmoothed returns yields even stronger results than in our main analysis with raw returns. These results are reported in Table A9 of the Internet Appendix. Nevertheless, our main conclusions hold as we find again that MSA–level and housing idiosyncratic risk dominate.

5 Pricing of Risk and MSA–level Fundamentals

In the previous section, we showed a large heterogeneity in the pricing of different risks across MSAs. We now turn to the second step in our empirical analysis, in which we investigate which MSA fundamentals may explain the pricing of these different types of risk.

We consider the following MSA–level housing market characteristics and other economic fundamental variables: within-MSA hedging indicator, income–to–price ratio, rent–to–price ratio, loan–to–value ratio, log population, housing elasticity, WRLURI, homeownership, unemployment, and log days-on-market (illiquidity).[22] As we estimate unconditional factor models, we have unconditional price of risk estimates. We therefore use time–series averages of the fundamental variables as independent variables in our probit.

We start by looking the set of MSA characteristics and economics fundamentals listed above and how they differ across MSAs with at least one significant price of risk versus MSAs with no significant prices of risk. In Table 5, we report the average MSA fundamentals among the MSAs

[22]Since both of the hedging incentive variables measure household hedging in the housing market, they should not be included together in a regression. In untabulated results, we also estimate this probit model including the across–MSA hedging indicator instead of the within–MSA hedging indicator and find similar results.

that have at least one significant price of risk at the 10% significance level and among the MSAs that have no significant price of risk. We also report the difference in these means and if these differences are statistically different from zero.

[Insert Table 5 here]

We find that in the MSAs that have least one significant price of risk households have higher income and lower loan-to-value ratio. This suggests that wealthier households are more likely to view real estate as both a consumption and investment good. We also find that MSAs with at least one significant price of risk have larger populations. Finally, households in these MSAs are more likely to use their current housing consumption to hedge future housing consumption in another MSA, while they are less likely to hedge when moving within an MSA.

Next, to further investigate whether MSA characteristics can explain the pricing of these different types of risk, we estimate the probit model outlined in Section 2.3. The dependent variable takes a value of one when the price of risk estimate is significant and positive, and a value of zero otherwise. In Table 6 we report the marginal effects of this model for prices of risk of the U.S. stock market risk (λ^{m}) U.S. housing market risk (λ^{hi}), MSA–level housing risk (λ^{msa}), and idiosyncratic zip code–level housing risk (λ^{ivol}).[23]

[Insert Table 6 here]

We find that U.S. housing market risk (λ^{hi}) is more likely to be priced in MSAs where local land use regulation is high. Moving on, we find that this set of MSA fundamentals cannot explain the pricing of MSA–level housing risk.

We next find that idiosyncratic zip code–level housing risk (λ^{ivol}) has a lower probability of being priced in MSAs where unemployment or loan-to-value ratio is high. In these MSAs, purchasing a house will be difficult for most households, since houses will be expensive and the job market will be poor. Further, we find that in MSAs where the rent-to-price ratio is high, idiosyncratic risk is less likely to be priced. If rents are very high, households will have an incentive for homeownership. Take together, these results suggest that in MSAs where homeownership is more accessible, households who own a home will demand a risk premium for carrying idiosyncratic housing risk.

[23]Data on MSA fundamentals (complete set of variables) is available for 98 of the 135 MSAs in our sample.

Finally, we find that the U.S. stock market risk (λ^m) is more likely to be priced in highly illiquid MSAs.

While the probit regressions suggest that some fundamental variables can be linked to cross–MSA variation in the pricing of different types of housing risk, these results are still preliminary. One challenge here is that the data on fundamental variables is only available for a subset of the MSAs (98 out of 135). Also, since we estimate unconditional prices of risk, we can only link (time series averages) of fundamental variables to cross–MSA variation in prices of risk rather than analyzing time series variation.

6 Conclusion

Homeownership is risky. House prices can fluctuate substantially, as has been made clear in the Great Recession. Yet we do not know if homeowners receive a compensation for carrying this risk, nor what types of risk are compensated. In this paper, we shed light to these questions by looking at zip code–level housing returns in a sample of 9,093 zip codes across 135 metropolitan statistical areas (MSAs) that represent almost 80% of total U.S. population.

We provide extensive evidence of a risk–return trade–off in housing returns at the zip code–level. Hence, even at this highly disaggregated level where many market participants are owner–occupiers, housing has a dual role of consumption and investment good. At the same time, we find substantial heterogeneity across local markets in terms of which sources of risk are priced. Overall, we find that idiosyncratic zip code–level housing risk and local MSA–level housing risk are the two most important risks for the cross-section of zip code–level housing returns.

Our main findings are twofold. First, in 96 (71.1%) out of 135 MSAs at least once source of risk carries a significant positive risk premium. This implies that for the majority of metropolitan areas, housing returns at the zip code–level display investment good properties. Second, the two most important sources of priced risk are the local MSA–level housing risk and zip code–level idiosyncratic housing risk. MSA–level housing risk is priced in 49 MSAs and IVOL is priced in 48.

On the other hand, national U.S. housing risk and U.S. equity market risk do not play an important role in the cross–section of residential housing returns. U.S. housing market risk is priced in only 25 MSAs. While the U.S. equity market risk is in 30 MSAs, the average risk exposures are close to zero resulting in an economically negligible risk premium. There is substantial heterogeneity across MSAs in terms of which sources of risk are priced. Preliminary tests aim to link this heterogeneity to local housing market fundamentals.

Understanding which types of risk homeowners are exposed to is important. This knowledge allows them to assess how these housing risks relate to other types of risks households face (e.g., labor income risk, entrepreneurial risks, other financial risks) that may have a local and/ or national component. Further, if housing risk is not priced, it serves as a source of background risk in the households' overall wealth portfolio. On the other hand, if housing risk does carry a risk premium, it affects not only the overall risk but also the expected return of the overall wealth portfolio. Analyzing the implications of our findings on the housing risk premium for household portfolio choice is an important area for future research.

A Dataset and Variables Construction

In this appendix, we describe the different datasets from which we obtain data on MSA fundamentals. We also discuss how we merge the different geographies and construct the hedging incentive variables.

A.1 MSA–level Fundamental Housing Market and Other Economic Data

In our empirical analysis we not only estimate prices of risk and risk premia, but we also investigate MSA characteristics that can help explain cross-MSA heterogeneity in the pricing of risk. To this end, we combine multiple datasets to construct various MSA–level housing market and other economic variables. Below, we discuss the variables by data source.

Zillow Data We obtain days-on-market at the MSA–level from Zillow, which we use as an illiquidity measure in our empirical analysis. The data is available for the full sample period.

MIRS Data We obtain data on zip code–level loan–to–value ratio (LTV) from the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS) for the full sample period. The MIRS covers a large sample of zip codes for our entire sample period. We first merge this data with Zillow zip code data to obtain MSA identifiers, since our goal is to aggregate it to the MSA level. Notably, for some months, the MIRS data contains several LTV values for the same zip code. We choose take the mean LTV for each zip code. Using the zip code–level LTV, we then aggregate it MSA–level by taking the median LTV across zip codes within each MSA. This way, we avoid any data errors or outliers when calculating the MSA–level monthly LTV ratio.[24]

IRS Migration Data Among our MSA characteristics are measures of across–MSA and within–MSA hedging incentives first introduced by Han (2013). These measures capture both the likelihood that households within their local MSAs will trade up to a bigger house in the future, and the correlation between the local housing market and the market where they plan to move.[25] Both of

[24] In our empirical tests, we also use the mean LTV across zip codes as a measure of MSA–level LTV. We find similar results using this measure and these are available upon request.

[25] A detailed description on the construction of both the expected correlation and hedging incentive variables from Han (2013) and Sinai and Souleles (2013) can be found in Appendix A.3.

these measures require data on MSA-to-MSA household migration. Following Sinai and Souleles (2013), we use county-to-county migration data obtained from the Internal Revenue Service (IRS), which is aggregated to MSA–to–MSA migration. The IRS provides yearly data on county–to–county migration and we obtain this data for the period 1996–2016. Unfortunately, the IRS does not provide the MSA identifier for each county. To obtain MSA identifiers for each county, we merge the IRS county-to-county migration data with the county–level Zillow data as this data includes an MSA identifier for each county. Since we are interested in MSA–to–MSA migration, in the next step, we retain only MSA–to–MSA pairwise migration. This data then allows us to calculate the number of people that stayed in each MSA every year, which is a key component in the within–MSA hedging incentive indicator. This pairwise migration data is also needed to compute weights for the estimation of expected correlations, which are key components of the across–MSA hedging incentive variable.

IPUMS Data We use individual data from the U.S. Census and American Community Survey (ACS) obtained through the Integrated Public Use Microdata Series (IPUMS) database (see Ruggles et al. 2017). The IPUMS consists of more than 50 high–precision samples of the American population drawn from 15 federal censuses and from the American Community Surveys of 2000–2012. Geographically, we follow the 2013 definitions of MSAs from the U.S. Office of Management and Budget (OMB). Our IPUMS dataset consists of 255 MSAs and has annual data for the period 2000–2016. The IPUMS data we use covers household total income, population, homeownership, fraction of population aged 20–45, and rental costs. To obtain MSA–level data, we compute means, medians, and standard deviations across households within each MSA–year combination, applying household weights to properly incorporate the stratified sampling scheme. The fraction of population aged 20–45 is used to construct the hedging incentive variables.

BLS Data Monthly values of the consumer price index (CPI) are from the Bureau of Labor Statistics (BLS). These data are obtained for our full sample, which runs from April 1996 to December 2016. We use this data to deflate rental costs and construct a measure of real rent volatility following Sinai and Souleles (2005).

Housing Supply Constraint Data We also obtain data on local housing supply constraint measures. In particular, we use the housing elasticity of Saiz (2010), and the Wharton Residential Land Use Regulation Index (WRLURI) of Gyourko, Saiz and Summers (2008). We obtain these measures directly from the authors. The data lacks a time series dimension as these measures are available for the cross–section of MSAs in one particular year. Saiz (2010)'s measure of housing elasticity is not expected to change much over time as it is partly estimated by satellite–generated data on terrain elevation and presence of water bodies. Geographical terrain does not significantly change in such a short period. The WRLURI is comprised of 11 subindices based on the local regulatory environment of each MSA in 2008.

A.2 Merging Zillow Zip Code Data to MSA Data

Zillow provides data for their ZHVI at different aggregation levels. The lowest aggregation level is the zip code-level. For the purpose of our empirical analysis where we run cross-sectional regressions of zip code data within an MSA, we need to assign an MSA identifier to each zip code. While Zillow provides a unique numerical MSA identifier in their MSA-level data, this numerical identifier is not part of their zip code-level data. Nonetheless, it provides the name of the MSA, which can be linked directly to the name of the MSA in the MSA data. The MSA names include the state, e.g. New York, NY. Unfortunately, there are several MSAs that are across states, e.g. New York. The zip code data includes the state where the zip code is located, which means that a zip code that is part of the New York MSA, but located in New Jersey would have New York, NJ as an MSA identifier. This means that the matching will fail if looking to match with the MSA data identifier New York, NY.

A total of 40 MSAs are across states in the Zillow dataset with some notable examples, including Boston, Philadelphia, and Washington DC. It is therefore important to create a merging algorithm that takes this into account so as not to fail to merge a large number of zip codes with the MSA data. We create an algorithm that accounts for this issue and matches all zip codes correctly.

A.3 Hedging Incentive Indicators

Following Han (2013) we construct two hedging incentive indicators. The first is called the within-MSA hedging indicator. Specifically, an MSA in a given year is categorized as a market with strong hedging incentives if the fraction of population aged 20-45 exceeds the 25th percentile of the distribution of this variable across MSAs, and the fraction of the population staying within the same MSA exceeds the 25th percentile of the distribution of this variable across MSAs. The fraction of the population aged 20-45 is obtained from IPUMS at the household-level and is then aggregated to the MSA-level using the IPUMS MSA identifiers. The fraction of the population staying in the same MSA is obtained from the IRS migration data discussed above. In contrast to Han, using the IRS data we are able to compute the fraction of the population staying in the same MSA every year, while Han uses the IPUMS data that only reports the fraction in the last five years. Furthermore, the IPUMS data is a rough estimate in comparison to the more detailed data obtained from the IRS.

The second hedging indicator is called the across-MSA hedging indicator. We follow Sinai and Souleles (2013) to construct a crucial part of this variable. The first step is to construct expected correlations, which are weighted correlations. The weights for MSA i are defined as

$$w_{i,j} = \frac{Total\ Outflow\ MSA_i\ to\ MSA_j}{Total\ Outflow\ MSA_i}.$$

Using this definition we clearly see that $\sum_{j=1}^{N} w_{i,j} = 1$, where N is the number of MSAs to which households from MSA i migrated. The total outflow from each MSA-to-MSA is obtained from the IRS county-to-county migration data after aggregating it to the MSA-level as described in A.1. Using these weights follow Sinai and Souleles (2013) and define the expected correlation of MSA i with the rest of the MSAs as

$$\mathbb{E}\left[Corr\left(MSA_i\right)\right] = \sum_{j=1}^{N} w_{i,j} Corr(MSA_{i,j}).$$

This definition puts more weight on the correlations between MSA i and MSAs to which households from MSA i migrate. Following Sinai and Souleles (2013) the unweighted correlations between MSAs are computed on the real growth rate of MSA house prices. In our case, we deflate the

Zillow ZHVI MSA-level price data using the monthly CPI obtained from the Bureau of Labor Statistics. Then we calculate the growth in these deflated prices.

After estimating expected correlations for each MSA, we follow Han (2013) and rank all MSAs by the median expected price correlation across MSAs. This ranking will be used to construct the across-MSA hedging indicator. Specifically, an MSA in a given year is categorized as a market with strong hedging incentives if the fraction of population aged 20-45 exceeds the 25th percentile of the distribution of this variable across MSAs, and the expected price correlation ranks in the top 45th percentile of all MSAs.[26]

[26] Han (2013) uses the 44 MSAs from Sinai and Souleles (2013), and assumes that the top 20 out of 44 MSAs have strong hedging incentives, which means roughly the 45th percentile of MSAs in her sample.

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Table 1: Descriptive Statistics Excess Returns

This table reports descriptive statistics including mean, median, minimum, maximum, and standard deviation (SD), for zip code, Metropolitan Statistical Area (MSA), U.S. housing index and U.S. stock market yearly excess returns. We also report the cross-sectional dispersion (Dispersion) for zip code and MSA yearly excess returns. All zip code statistics, except the cross-sectional dispersion, are computed in three steps. First, we take the time-series statistic for each zip code. Second, within each MSA we take the cross-sectional mean of these statistics. Finally, we take the average across MSAs. The cross-sectional dispersion is computed by first taking the time-series mean for each zip code, then taking the average within each respective MSA, and finally the cross-sectional standard deviation across MSAs. The MSA statistics, expect the dispersion, are computed in two steps. First, we take the time-series statistic for each MSA. Second, we take the cross-sectional mean of these time-series statistics. The dispersion is computed by first taking the time-series mean of each MSA, and then taking the standard deviation of these means. The mean, median, minimum, maximum, and SD of all excess returns are annualized and are presented in percentage units. The sample period is April 1996 – December 2016.

	Excess Returns (% pa)						
	N	Mean	Median	Minimum	Maximum	SD	Dispersion
Zip Code	9093	1.67	1.21	-30.17	39.71	6.44	1.85
MSA	135	1.22	0.61	-12.43	18.76	5.18	1.39
U.S. Housing Market		1.15	1.62	-8.66	9.35	5.19	
U.S. Stock Market		7.95	11.70	-38.34	35.20	18.75	

Table 2: Factor Exposures and Idiosyncratic Volatility

This table reports descriptive statistics of risk exposures and idiosyncratic volatility for 9,093 zip codes across 135 MSAs. We report the mean, median, minimum, maximum, and standard deviation (SD), for the exposures to the U.S. stock market (β^m), the U.S. housing market (β^{hi}) and the local housing market (β^{msa}), as well as for the idiosyncratic volatility ($IVOL$). These are all estimated for each zip code using the three-factor model specified in Equation (2). We also report these statistics for the total volatility (Total Vol.), which is measured by the full sample standard deviation, and for the ratio of $IVOL$ to the standard deviation ($\overline{IVOL}$/Total Vol.). The mean, median, minimum, maximum, and SD of $IVOL$, total volatility, and $\overline{IVOL}$/Total Vol. are in percentage units. $IVOL$ and Total Volatility are monthly. The sample period is April 1996 – December 2016.

	Mean	Median	Minimum	Maximum	SD
$\beta^{\overline{m}}$	-1.3e-3	-8.9e-4	-0.15	0.12	0.01
$\beta^{\overline{hi}}$	1.05	0.95	-7.46	5.43	0.69
$\beta^{\overline{msa}}$	0.77	0.81	-2.87	5.70	0.40
$\overline{IVOL}$	0.66	0.58	0.17	2.41	0.31
Total Vol.	0.93	0.86	0.26	2.53	0.33
$\overline{IVOL}$/Total Vol.	62.79	62.18	10.67	99.99	19.70

Table 3: Positive Prices of Risk

This table reports descriptive statistics for estimated positive prices of risk. In Panel A, we report the number of MSAs for which we estimate the prices of risk (N) and the number of MSAs where each of the prices of risk are positive and significant ($\lambda > 0$). We also report the average λ as well as the cross-sectional dispersion in λ (Dispersion) within the MSAs where each respective price of risk is positive and significant. In Panel B and C, we report the number of MSAs where different sets of prices of risk are significant: e.g., we report in which MSAs the local MSA return and $IVOL$ price of risk are positive and significant. We also report the share of the full sample population (Share of Population) and number of zip codes (Share of Zip Codes) these MSAs represent. Finally, we look at how many MSAs have one or more significant prices of risk. Significance is at the 5% or 10% level one-sided using Newey and West (1994) standard errors with 4 lags. The sample period is April 1996 – December 2016.

Panel A

		5% Significance Level			10% Significance Level		
	N	$\lambda > 0$	Average λ	Dispersion λ	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	135	26	0.39%	0.66	30	0.33%	0.64
Housing Index	135	20	0.17%	0.13	25	0.15%	0.13
MSA Return	135	42	0.13%	0.09	49	0.13%	0.09
$IVOL$	135	32	0.12	0.06	48	0.10	0.05

Panel B: 5% Significance Level

	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	All three
Number of MSAs	6	12	5	2
Share of Population	2.39%	11.22%	9.80%	0.24%
Share of Zip Codes	4.64%	12.61%	9.23%	0.66%

	All Risks				Without Stock Market Risk		
	>= 1	>= 2	>= 3	= 4	>= 1	>= 2	= 3
Number of MSAs	84	31	5	0	73	19	2
Share of Population	64.95%	28.25%	3.00%	0	59.08%	22.94%	0.24%
Share of Zip Codes	68.28%	31.78%	4.17%	0	61.48%	25.16%	0.66%

Panel C: 10% Significance Level

	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	All three
Number of MSAs	8	21	8	4
Share of Population	3.11%	16.25%	12.27%	1.50%
Share of Zip Codes	5.38%	18.11%	12.76%	3.06%

	All Risks				Without Stock Market Risk		
	>= 1	>= 2	>= 3	= 4	>= 1	>= 2	= 3
Number of MSAs	96	49	7	0	89	29	4
Share of Population	72.88%	39.15%	4.27%	0	68.81%	28.63%	1.50%
Share of Zip Codes	75.67%	42.67%	6.57%	0	71.16%	30.13%	3.06%

Table 4: Positive and Negative Prices of Risk 10% Significance Level

This table reports descriptive statistics for estimated positive and negative prices of risk. Following regression (4) we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and idiosyncratic volatility ($IVOL$) for each MSA with at least 20 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk (N) and the number of MSAs where each of the prices of risk are positive ($\lambda > 0$) or negative ($\lambda < 0$) and significant. For each risk factor and $IVOL$, we also report the average λ as well as the cross-sectional dispersion in λ (Dispersion) within the MSAs where each respective price of risk is significant. In the bottom panels, we report the number of MSAs where different sets of prices of risk are significant: e.g., we report in which MSAs the local MSA return and $IVOL$ price of risk are significant. We also report the share of the full sample population (Share of Population), and the share of full sample number of zip codes (Share of Zip Codes) these MSAs represent. Finally, we look at how many MSAs have one or more significant prices of risk. The prices of risk for the U.S. stock market, U.S. housing index and local MSA return are in percentage units. Share of population and zip codes are also in percentage units. Significance is at the 10% level two-sided using Newey-West standard errors with 4 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	$\lambda < 0$	Average λ	Disp. λ
Stock Market	135	26	29	-0.06%	1.13
Housing Index	135	20	41	-0.03%	0.16
MSA Return	135	42	26	0.04%	0.14
$IVOL$	135	32	24	0.01	0.14

	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	All three
Number of MSAs	29	27	29	14
Share of Population	20.91%	22.04%	30.93%	12.22%
Share of Zip Codes	25.60%	24.15%	31.49%	14.36%

	All Risks			
	>= 1	>= 2	>= 3	= 4
Number of MSAs	121	85	27	7
Share of Population	86.64%	70.52%	18.30%	7.36%
Share of Zip Codes	89.07%	71.38%	21.82%	8.12%

	Without Stock Market Risk		
	>= 1	>= 2	= 3
Number of MSAs	110	43	12
Share of Population	81.50%	40.84%	9.69%
Share of Zip Codes	83.97%	42.77%	11.89%

Table 5: MSAs with Significant vs. MSAs without Significant Prices of Risk

In this table we report the mean for a set of MSA characteristics for the 96 MSAs that have at least 1 significant positive price of risk, and for the 39 MSAs that have no significant price of risk at a 10% significance level, respectively. We also report the difference in their means and show if they are statistically significant from zero. We report the means for the following MSA fundamentals: within- and across-MSA hedging indicators, household total income, loan-to-value ratio, population, number of time-series observations, housing elasticity, WRLURI, homeownership, fraction of population aged 20-45, expected correlation, real rent volatility, average number of zip codes, days-on-market and unemployment. For characteristics that have time-series observations, the means are computed in two steps. First, we take the cross-sectional mean each year. Second, we take the time-series mean of these time-series. The averages of the loan-to-value ratio, housing elasticity, homeownership, fraction of population aged 20-45 and real rent volatility are in percentage units. Household total income is in USD and in 10^4 units. Population is in 10^5 units. All data is yearly. Differences in means that are significant at a 10%, 5%, and 1% significance level are marked with *,**,***, respectively. The sample period is 1996 – 2016.

	Mean Sig. MSAs	Mean Not Sig. MSAs	Difference in Means
Within-MSA Hedging Indicator	0.55	0.73	-0.17***
Across-MSA Hedging Indicator	0.62	0.46	0.16***
Household Total Income	7.92	7.39	0.53**
Loan-to-value Ratio	79.36	80.42	-1.06***
Log population	18.10	14.02	4.08***
Number of Observations	197.93	195.67	2.26
Housing Elasticity	185.24	222.38	-37.15**
WRLURI	0.16	-0.27	0.42***
Homeownership	68.46	69.68	-1.22
Fraction of population aged 20-45	35.45	34.99	0.45
Expected Correlation	0.50	0.40	0.10***
Real Rent Volatility	3.95	3.81	0.14
Number of Zip Codes	71.68	56.72	14.96
Unemployment	7.66	7.78	-1.2e-3
Days on the Market	114.58	114.78	-0.20

Table 6: Probit Model for Positive Prices of Risk

This table reports the results of the marginal effects of a probit model of prices of the U.S. stock market, U.S. housing level risk, MSA local return risk, and on idiosyncratic risk ($IVOL$) on a set of MSA characteristics that include: within-MSA hedging indicator, income to price ratio, rent to price ratio, loan-to-value ratio, log of population, housing elasticity (Saiz, 2010), WRLURI (Gyourko et al., 2008), homeownership, unemployment and log of days-on-market. The left hand side variable of the probit model is a dummy that equals 1 if the price of risk is positive and significantly priced, and 0 otherwise. Robust t-statistics are reported in parentheses. Coefficients that are significant at a 10%, 5%, and 1% significance level are marked with *,** ,***, respectively. The sample period is 1996 – 2016.

	Dependent Variable				
	λ^{m}	λ^{hi}	λ^{msa}	λ^{ivol}	>= 1 sig.
Within-MSA Hedging	-0.06	-0.04	-0.08	-0.16	-0.23*
	(-0.48)	(-0.39)	(-0.62)	(-1.22)	(-1.83)
Income/Price ratio	-1.45	-0.04	-0.08	3.56	0.09
	(-1.36)	(-0.04)	(-0.06)	(2.79)	(0.08)
Rent/Price ratio	91.73	-1.06	26.78	-219.83*	-13.39
	(0.87)	(-0.01)	(0.22)	(-1.79)	(-0.11)
Loan-to-value ratio	4.74	2.27	-0.30	-11.80***	1.29
	(1.30)	(0.88)	(-0.07)	(-2.82)	(0.35)
Log Population	-0.08	-0.03	0.05	0.09	0.04
	(-1.33)	(-0.55)	(0.75)	(1.21)	(0.61)
Housing Elasticity	0.03	-0.05	0.05	0.09	0.03
	(0.44)	(-0.71)	(0.56)	(0.97)	(0.37)
WRLURI	0.11	0.13**	0.12	0.17**	0.23**
	(1.41)	(2.07)	(1.27)	(2.04)	(2.18)
Homeownership	-0.95	-1.03	-0.38	-2.25	-1.20
	(-0.74)	(-1.04)	(-0.27)	(-1.57)	(-0.83)
Unemployment	-3.57	-4.04	-3.07	-11.52***	-6.34*
	(-1.04)	(-1.32)	(-0.80)	(-2.71)	(-1.86)
Log Days on the Market	0.57*	0.26	-0.19	-0.04	0.05
	(1.89)	(1.06)	(-0.57)	(-0.13)	(0.17)
Nobs	98	98	98	98	98
Pseudo R^2	10.2%	10.5%	4.8%	22.7%	12.6%

Figure 1: Histogram of Risk Exposure t-statistics

In this figure, we plot the distribution of Newey and West (1994) adjusted t-statistics for the estimated risk exposures of zip code–level housing excess returns on the U.S. stock market, U.S. housing market and MSA–level housing excess returns. The sample period is April 1996 – December 2016.

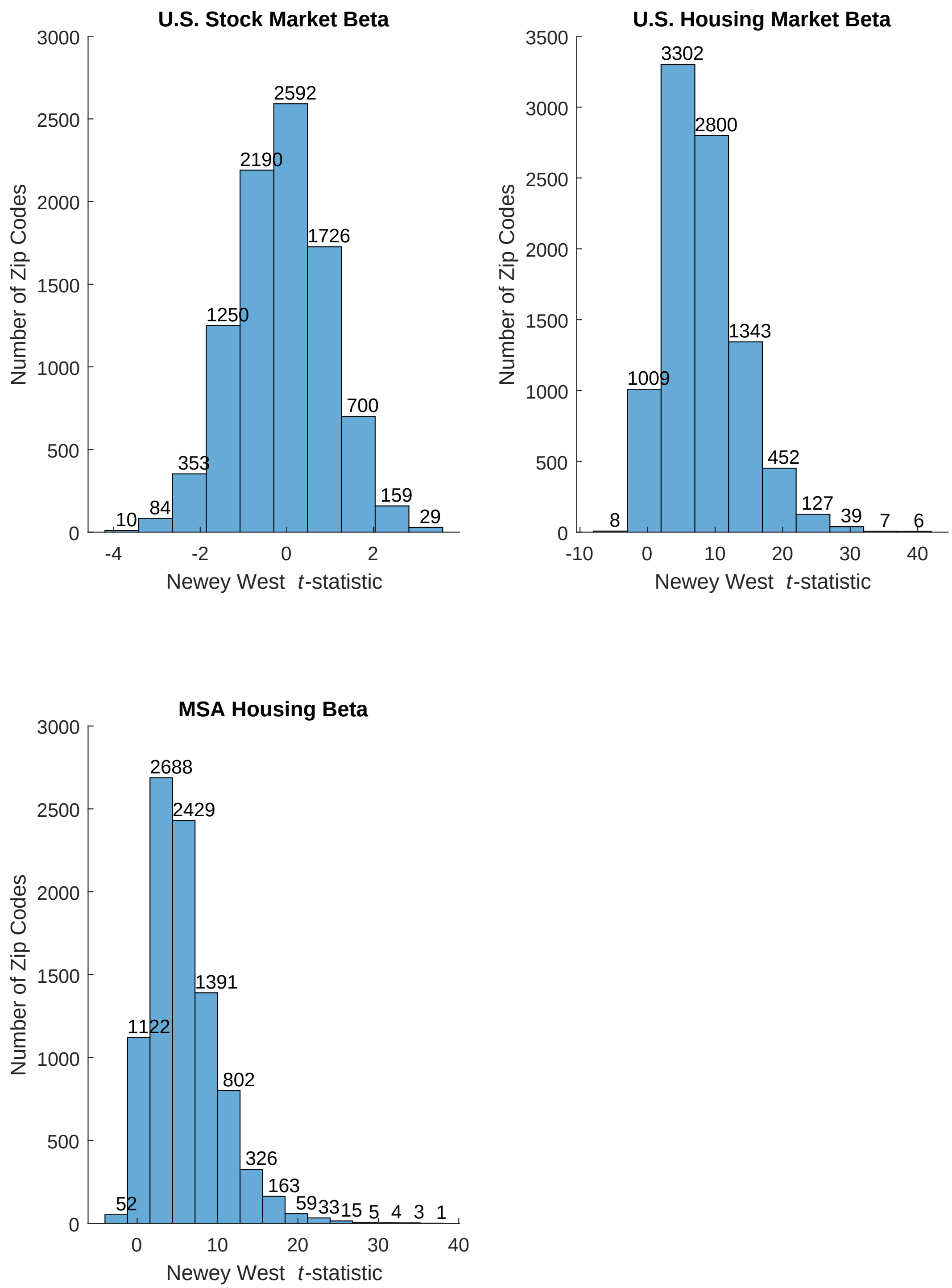
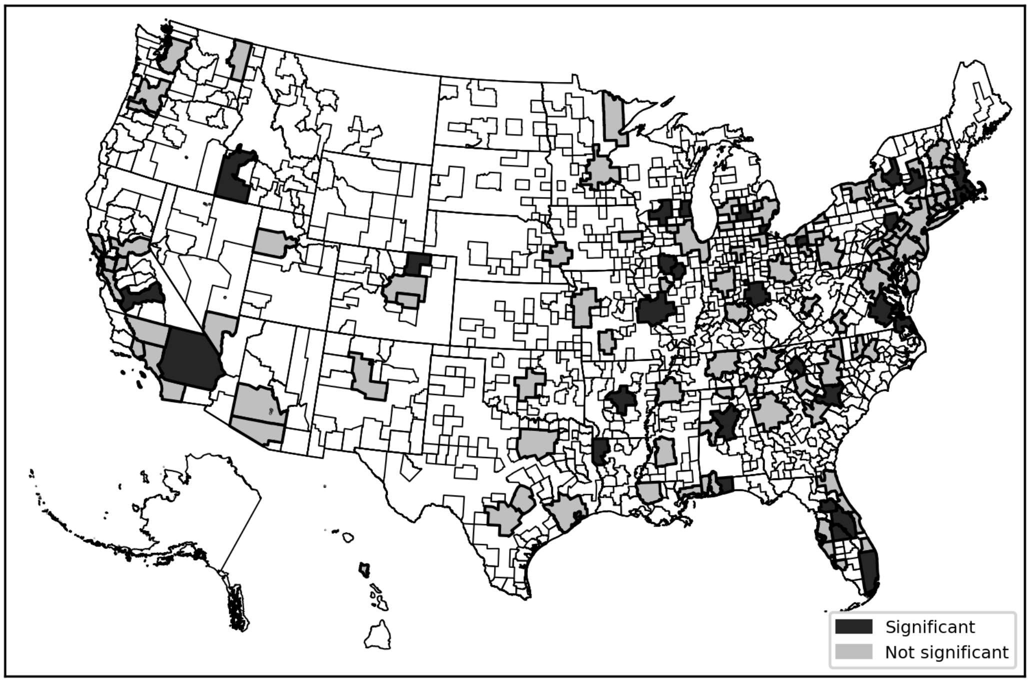


Figure 2: Prices of Risk across the U.S.

In this figure, we plot geographical heat maps of the U.S. containing the 135 MSAs for which we estimate prices of risk. In each panel, all dark purple MSAs have a statistically positive significant price of risk, while in yellow MSAs it is statistically insignificant. In Panel (a), we show a heatmap for the price of risk of the U.S. stock market, while in Panel (b) we show a heatmap for the U.S. housing market. The sample period is April 1996 – December 2016.

(a) U.S. Stock Market Risk



(b) U.S. Housing Market Risk

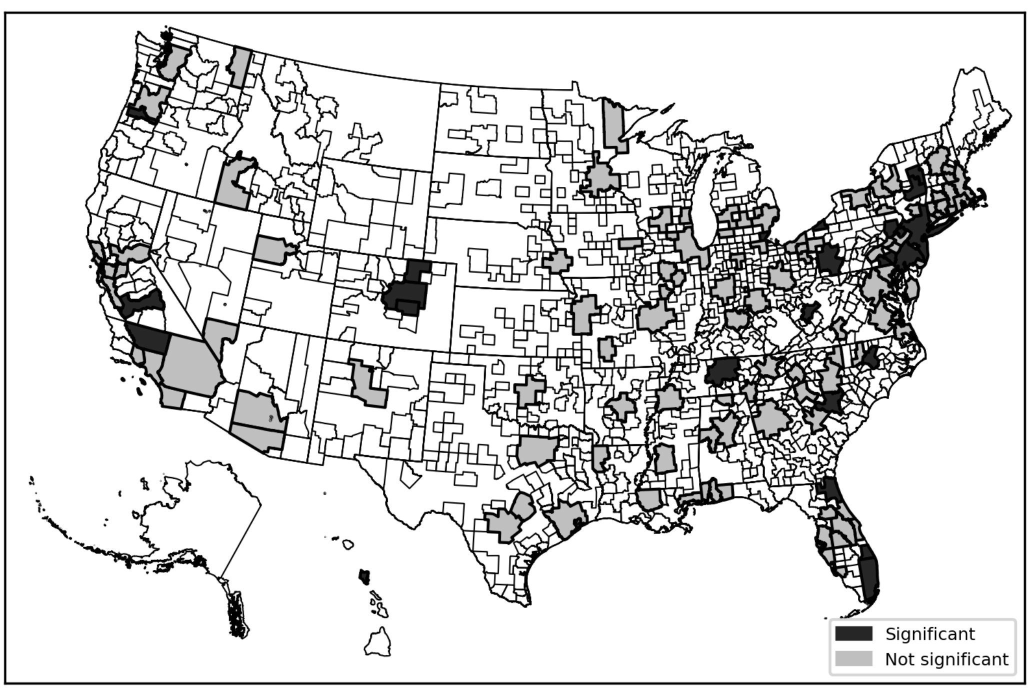
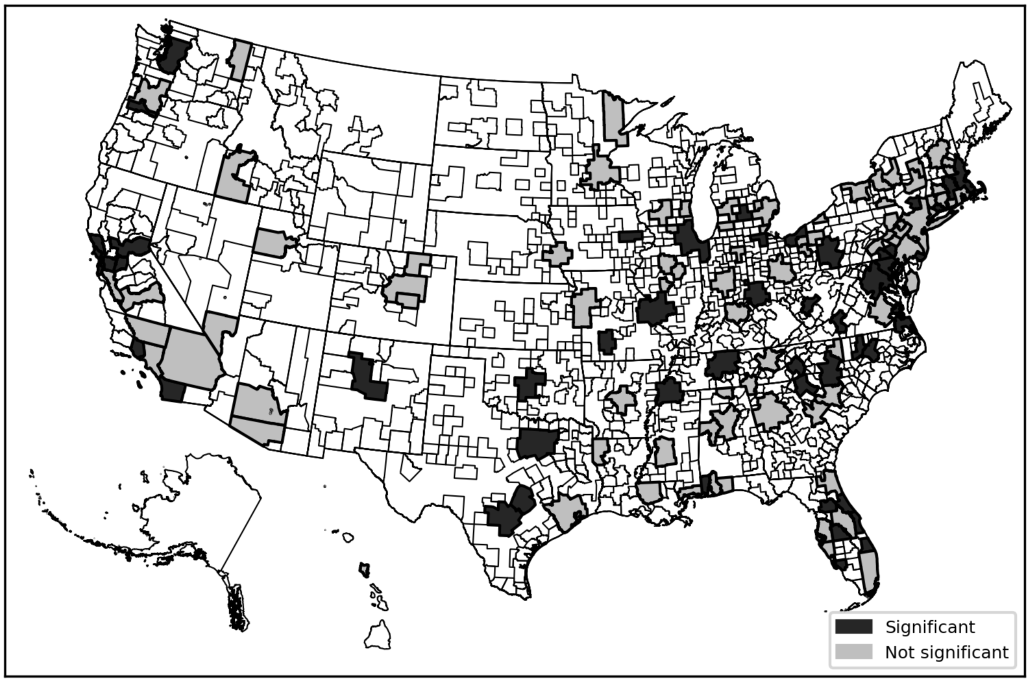


Figure 2: Prices of Risk across the U.S. (cont.)

In this figure, we plot geographical heat maps of the U.S. containing the 135 MSAs for which we estimate prices of risk. In each panel, all dark purple MSAs have a statistically positive significant price of risk, while in yellow MSAs it is statistically insignificant. In Panel (c), we show a heatmap for the price of risk of the local MSA-level housing risk factor, while in Panel (d) we show a heatmap for idiosyncratic volatility. The sample period is April 1996 – December 2016.

(c) Local MSA-level Housing Risk



(d) Idiosyncratic Volatility

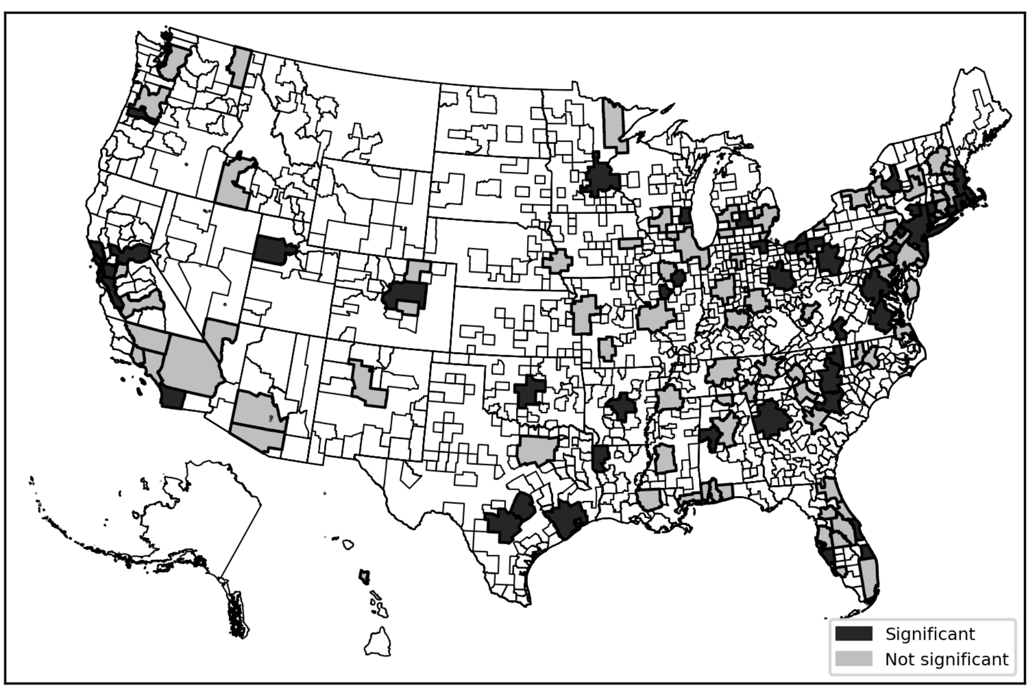


Figure 3: Average Annualized Risk Premium across MSAs

In this figure, we plot a bar chart that includes the average annualized risk premium across MSAs for each type of risk, as well as the total risk premium composition in MSAs with more than one priced risk. We also report the number of MSAs where each risk is priced. Each average annualized risk premium is computed in two steps. First, we multiply the average zip code-level beta times the significant price of risk for the respective MSA. Second, we take the average across zip codes within each MSA. The sample period is April 1996 – December 2016.