The Cross-Section of Expected Housing Returns

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Abstract

This paper performs a large-scale empirical asset pricing analysis of the cross-section of residential real-estate returns. Using monthly housing returns for 9,831 different zip codes across 178 Metropolitan Statistical Areas (MSAs), we estimate, for each MSA, a multifactor model with systematic housing-market risk (U.S. and local MSA) and idiosyncratic zip code-specific housing risk. We find that U.S. and MSA housing risks are positively priced in 26% and 22% of the MSAs, respectively. The evidence that MSA-level housing-market risk is priced in roughly a fifth of all MSAs runs counter to the common belief that the U.S. housing market is locally segmented. We also find that idiosyncratic risk is positively priced only in 22% of the MSAs, suggesting that the under-diversification of households' real estate portfolios is not widely priced. In the last part of the paper, we link MSA variation in the pricing of risk to MSA fundamentals. We find that illiquidity is important for the pricing of the U.S. housing-market risk, while homeownership increases the probability that MSA-level risk is positively priced. Idiosyncratic risk is more likely to be positively priced in MSAs with less undevelopable land and lower liquidity, indicating that under-diversification is more binding when households face fewer housing supply constraints and more illiquidity.

Keywords: Expected Housing Returns, Idiosyncratic Risk, Systematic Risk, Market Segmentation.

JEL Classification: G12, R30.

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1 Introduction

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%).[1] 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. In addition, homeownership generates under-diversification 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). Further, households are typically limited in the extent to which they can diversify the real estate component of their wealth portfolios. The under-diversification associated with homeownership suggests that idiosyncratic risk should matter in the housing market. But again, while idiosyncratic volatility has been extensively studied for stocks (e.g., Goyal and Santa-Clara, 2003; Ang et al., 2006; Herskovic et al., 2016), idiosyncratic housing risk has hardly been investigated.

This paper fills these voids by performing an extensive zip code-level asset pricing analysis for a large cross-section of 9,831 zip code-level U.S. housing returns from Zillow.[2] As for commercial real estate, there is a significant presence of diversified landlords (e.g., local-residential companies, large apartment and single-family housing REITs, and individuals owning more than one property) in the residential market.[3] When diversified landlords and undiversified owner-occupants participate in the same housing market, the degree of under-diversification is a function of this participation and the relative pricing of systematic and idiosyncratic risk becomes an empirical question.[4] A few earlier studies have analyzed the risk-return trade-off in the housing market, but their focus has

[1] It is at the very top of the households' wealth distribution that stocks dominate housing (e.g., at the top 0.1% of the wealth distribution, stocks represented 21.1% of the average portfolio compared to 18.0% for housing). These figures are in line with those reported by earlier studies (e.g., Campbell, 2006; Guiso and Sodini, 2013; Barras and Betermier, 2016).

[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, 2011; Mian, Sufi and Trebbi, 2015; and Adelino, Schoar and Severino, 2016).

[3] Ioannides and Rosenthal (1994) document that about 23% of homeowners have more than one property.

[4] Plazzi, Torous and Valkanov (2008) find a positive relation between idiosyncratic risk and expected returns on commercial real estate, suggesting that owners of commercial real estate are not always well diversified.

been exclusively on housing returns at the metropolitan statistical area (MSA) level.[5] Our zip code-level data allows us to estimate idiosyncratic risk at the zip code-level, which leads to important new insights on the pricing of systematic and idiosyncratic risks and on the determinants of these housing risk premia.

We estimate risk exposures and prices of risk with respect to U.S. housing market returns (national factor), MSA-level housing market returns (local factor), and equity market returns using the Fama and MacBeth (1973) methodology. To estimate zip code-level idiosyncratic housing risk (IVOL), we follow Ang et al. (2006) and take the standard deviation of the residuals from this model. Because we have access to zip code-level housing returns, we can estimate our multifactor model separately for each MSA. This allows us to provide new insights on an additional question, one that is highly debated in the housing literature: the extent to which the U.S. housing market is locally segmented.[6]

Our sample consists of monthly housing returns for 9,831 zip codes across 178 Metropolitan Statistical Areas (MSAs) from April 1996 to December 2016.[7] To the best of our knowledge, we are the first to consider monthly housing returns at this highly disaggregate level, covering a large part of the U.S. housing market. We find striking differences across MSAs on whether a certain type of risk is priced. Even though we focus on a minimum of only 15 zip codes per MSA, we find that, for 103 MSAs, at least one source of risk carries a significantly positive premium.[8] This suggests that the risk-return relationship in housing is important in the majority of MSAs. Specifically, U.S. and MSA-level housing-market risks are positively priced in 47 and 39 MSAs, respectively. Notably, the evidence that MSA-level housing-market risk is priced in roughly a fifth of the MSAs runs counter to the common belief that the U.S. housing market is locally segmented. Both types of systematic

[5] See, e.g., Case, Cotter and Gabriel (2011), Han (2013) and Cotter, Gabriel and Roll (2015). One exception is Cannon, Miller and Pandher (2006), who also consider zip code-level housing returns. However, they only have eight annual time series observations, which complicates asset pricing tests.

[6] One possible reason for locally segmented housing markets is that if the local economy is in a downturn, housing supply might increase (this may result, for instance, from households trying to relocate to markets with better employment opportunities), while demand may decrease. In turn, this put a downward pressure on local-house prices.

[7] Our initial sample includes monthly-housing returns from Zillow for 12,243 zip codes across 571 Metropolitan Statistical Areas (MSAs) from April 1996 to December 2016. However, to ensure that we have a sufficiently large cross-section of housing returns, in our estimations of the multifactor model, we require each MSA to have at least 15 zip codes. Because of infrequent trading, time series of housing returns are not available at the property level. Hence, we rely on the next best thing: zip code-level housing returns from Zillow.

[8] When we allow for positive and negative risk premia estimates and we use a minimum of 20 zip codes per MSA, we have a significant price of risk for 76% of all MSAs.

housing risk are positively priced in only eight of the MSAs. The equity market risk is positively priced in just five MSAs, which suggests that it plays a marginal role in housing.

Contrary to the expectation that idiosyncratic risk should be widely priced in the housing market because homeowners typically own only one property (and hence hold undiversified real estate portfolios), we find that it is positively priced in only 39 MSAs. Both idiosyncratic and systematic (national and/or local) risks are priced in 19 MSAs.

We make use of heat maps to help visualize whether there are systemic patterns in the pricing of the different types of risks across regions. We find that the U.S. housing index is positively priced in many large MSAs on the East Coast (e.g., New York and Philadelphia), the South (e.g., Austin and Houston), and the West Coast (e.g., Seattle and Fresno), but also in several small MSAs across the country. We further find that the average annualized risk premium across MSAs for the U.S. housing index is 1.07%, which is sizable compared to the average MSA excess return of 0.86%. We document similar patterns in the pricing of risk for the MSA housing index and idiosyncratic risk, while, as discussed earlier, the equity market index is hardly ever priced. Overall, our analysis suggests that U.S. housing index risk, MSA housing index risk, and idiosyncratic risk are priced in a wide range of different-sized MSAs across the entire U.S., although smaller MSAs command higher risk premiums.

In the last part of the paper, we link MSA variation in the estimated prices of risk to MSA fundamentals using probit regressions. MSA characteristics are obtained from multiple sources, including Zillow, the U.S. Census and American Community Survey (ACS)-Integrated Public Use Microdata Series (IPUMS), the Internal Revenue Service (IRS), and the Federal Housing Finance Agencys Monthly Interest Rate Survey (MIRS). Housing-supply elasticity data are obtained from Saiz (2010) and Gyourko, Saiz and Summers (2008). We find that U.S.-wide housing-market risk is more likely to be priced in MSAs with relatively more illiquid housing markets, where liquidity is measured as average (log) days on the market. MSA-level housing risk is more likely priced in MSAs where homeownership rates are higher. In these areas, there are fewer renters and hence fewer well-diversified landlords. Consequently, the marginal investor is more likely to be someone exposed to local MSA-level housing risk, which then carries a risk premium.

We also find that the probability of idiosyncratic risk being positively priced is lower in MSAs where market liquidity (measured as days-on-market) is higher. Further, we find that idiosyncratic housing risk is less likely to be positively priced in MSAs with more undevelopable land. To the extent that more undevelopable land makes it is easier for homeowners to sell existing properties, these two findings suggest that under-diversification is less binding when liquidity is higher. Finally, idiosyncratic risk is less likely to be priced for homeowners with strong-hedging incentives within MSAs. In line with the insights in Sinai and Souleles (2005; 2013) and Han (2013), this result suggests that homeowners are less concerned with under-diversification if homeownership is an instrument to benefit from potential house price increases that can be used in the future for the purchase of a larger house within the same MSA.

In line with economic theory, we primarily focus on positive price of risk estimates. At the same time, several studies have found negative premiums for idiosyncratic risk in the cross-section of equity returns (e.g., Ang et al. 2006).[9] Nevertheless, we find that for housing most of the significant idiosyncratic risk premia are positive which suggests that the idiosyncratic risk puzzle for equity returns does not extend to the cross-section of housing returns. Hence, our overall results remain very similar when we allow for negative prices of risk.

Our main findings pass a significant number of robustness tests. We find that our results hold in the following conditions: 1) when we restrict the sample period to 1996-2007 to control for the effects of the subprime crisis; 2) when we estimate our multifactor model for MSAs with a minimum of 20 instead of 15 zip codes; 3) when we control for housing value and zip code size in the estimation of our multifactor model; 4) when we estimate our multifactor model without the stock market risk factor.

Our paper relates to a growing literature on housing-market risk. Using MSA-level data, Cotter, Gabriel and Roll (2015) find that, during the boom of the 2000s, a large proportion of MSA 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 housing markets are highly integrated and offer limited opportunities for diversification.[10] Case, Cotter and Gabriel (2011) analyze the risk-

[9]The empirical evidence for the pricing of idiosyncratic risk of stocks is mixed. Ang et al. (2006) find a strong negative cross-sectional relationship between idiosyncratic volatility and expected stock returns. In contrast, Fu (2009), and Huang et al. (2010) find a positive cross-sectional relationship. 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.

[10]In a recent study, Cotter, Gabriel and Roll (2018) document that integration within and among equity, fixed

return relation at the MSA level. 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. Cannon, Miller and Pandher (2006) estimate a single-factor model of housing exposure to the equity market and find that equity risk and idiosyncratic risk are important in explaining the risk-return relationship for the overall U.S. housing market. Han (2011; 2013) focuses on the puzzling negative relation between total risk and return in the U.S. housing market. 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).[11]

In our paper, we estimate a multifactor model with monthly zip code-level data. This allows us to make four important contributions to the literature: 1) we measure idiosyncratic housing risk at the zip code-level, which is the most disaggregated-level possible based on data availability; 2) we pinpoint the risk factors (systematic and/or idiosyncratic) that are priced in each MSA; 3) we identify the MSA characteristics that can help explain whether a certain risk exposure is priced; and 4) we shed light on the degree of local segmentation of the U.S. housing market.

The rest of the paper is organized as follows. Section 2 discusses the multifactor models used to estimate systematic and idiosyncratic risks in the housing market. Section 3 introduces the data and presents descriptive statistics of all the variables. In section 4, we discuss the types of risk priced and the magnitude of the estimated risk premia across MSAs. Section 5 relates the cross-MSA variation in risk premia to MSA-level characteristics. Section 6 concludes. The Appendix gives more details on the data sources and variables construction. An Online Appendix provides details on data sources and variable constructions and reports the results of various robustness tests.

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.

[11] 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 predict 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. (2018) find that housing outperforms equity prior to World War II, but the opposite occurs afterwards.

2 Empirical Framework

Our empirical analysis consists of two steps. First, we perform cross-sectional asset pricing tests to analyze the pricing of systematic and idiosyncratic risk in the housing market. As we discuss in detail below, we perform these tests for each local housing market (i.e., for each MSA) separately, in order to allow for local risk factors and to be able to test whether housing markets are locally segmented or not. In the second step, we analyze differences in the estimated prices of risk across MSAs by linking them to MSA-level housing market and other economic fundamentals.

2.1 Multifactor Model for the Cross-Section of Expected Housing Returns

To analyze the cross-section of expected U.S. residential housing returns, we estimate multifactor models using the Fama and MacBeth (1973) approach. While this is similar to the typical analysis of the cross-section of expected U.S. stock returns, there are two important differences between the stock market and the housing market that need to be taken into account.

First, there is evidence that housing markets cluster and local aspects matter (e.g. Goetzmann, Spiegel and Wachter 1998, Cotter, Gabriel and Roll 2015). 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 each MSA. The model includes U.S.-wide housing returns (and equity market returns) as well as local housing returns as risk factors. In contrast, existing studies of housing returns (e.g. Case, Cotter and Gabriel 2011 and Cotter, Gabriel and Roll 2015) only consider U.S.-wide housing and equity-market systematic risk factors.[12] Thus, we estimate a multifactor model separately for each of the 178 MSAs (with a total of 9,831 unique zip codes) in our estimation sample.[13]

A second difference between the cross-section of stock returns and the cross-section of housing returns is the potential role of idiosyncratic risk. While achieving a well-diversified stock portfolio is 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 and Cocco 2005). Consequently, not only is systematic risk important for asset prices, but

[12]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).

[13]This specification is also in line with Goetzmann, Spiegel and Wachter (1998), who find that zip code-level housing returns tend to cluster with the return of the central city in their metropolitan area.

idiosyncratic risk may also play a role (Merton 1987).

We deviate from existing papers that analyze housing returns (e.g., Case et al. 2011, Han 2013 and Cotter, Gabriel and Roll 2015) in two ways. First, we recognize that even though many homeowners are under-diversified, better-diversified landlords are also active in the residential real estate market. As we do not know who the marginal investor is, we allow for the possibility that idiosyncratic risk is priced. We therefore include idiosyncratic volatility in our model, in addition to the U.S.-wide and local systematic risk factors. In the second stage of our empirical analysis, we relate the cross-MSA heterogeneity in the pricing of systematic and idiosyncratic risk to various MSA-level fundamentals, such as the homeownership rate.

Second, to capture the idiosyncratic risk that under-diversified homeowners face, we need to consider housing returns at the most disaggregated-level. We therefore use zip codelevel housing returns. Ideally, one would like to estimate idiosyncratic 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 codelevel 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 et al. 2011, Han 2013 and Cotter, Gabriel and Roll 2015), which does not allow for an analysis of idiosyncratic housing risk. One exception is Cannon, Miller and Pandher (2006), who study zip codelevel returns. However, they only have a time-series of eight annual observations, which complicates asset pricing tests. Further, their main focus is analyzing the pricing of equity risk across the entire U.S. housing market, rather than within each MSA, which means they do not allow and cannot test for local market segmentation.

We apply the standard two-step Fama and MacBeth (1973) approach to estimate each multifactor model. 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 20 years of monthly returns, we use rolling-window regressions based on the previous 48 months.[14]

[14]Following Fama and MacBeth (1973) and Bali and Cakici (2008) among others we also estimate our model using

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

$$r_{i,s} = \alpha_{i,t} + \beta_{i,t}^{m} r_s^{mkt} + \beta_{i,t}^{hi} r_s^{hi} + \beta_{i,t}^{msa} r_{j,s}^{orthmsa} + \varepsilon_{i,s},\ for\ s = t-47, ..., t, \tag{1}$$

where $r_{i,s}$ denotes the time-$s = t-47, ..., t$ 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_s^{mkt} and r_s^{hi} are U.S. stock market and U.S. housing index excess returns, respectively. $r_{j,s}^{orthmsa}$ is the orthogonalized excess return for MSA j, which is the MSA to which zip code i belongs. We follow Bekaert, Hodrick and Zhang (2009) and orthogonalize the MSA excess return with respect to the U.S. housing index excess return using an ordinary least squares regression given by

$$r_{j,t}^{msa} = \mu_j + \beta_j r_t^{hi} + \eta_{j,t}, \tag{2}$$

where the error term $\eta_{j,t}$ is the orthogonalized version of $r_{j,t}^{msa}$ that we use in (1).

Following the literature on stock market idiosyncratic volatility (see Ang et al. 2006), 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 (1), that is $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,s})}$ for zip code i.

Next, for each month, we run cross-sectional regressions for all zip-codes within each of the 178 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, for each MSA j we run the contemporaneous cross-sectional regression given by

$$r_{i,t} = \lambda_{j,t}^{0} + \lambda_{j,t}^{m} \beta_{i,t}^{m} + \lambda_{j,t}^{hi} \beta_{i,t}^{hi} + \lambda_{j,t}^{msa} \beta_{i,t}^{msa} + \lambda_{j,t}^{ivol} \mathrm{IVOL}_{i,t} + \xi_{i,t}, \tag{3}$$

where we only include zip codes i that belong to MSA j and use the risk exposures and idiosyncratic volatilities as estimated through (1) based on the previous 48 months. We run this cross-sectional regression for each month t in the sample which yields a time-series of $\lambda_{j,t}^{k}$ for each type of risk k.

60 monthly returns. This limits our sample for the second-stage estimation of prices of risk. Nevertheless, our main results and conclusions hold using this longer rolling window sample. These results are available upon request.

The estimate of price of risk λ_j^k for each risk factor is found by taking the time-series average of the corresponding $\lambda_{j,t}^k$. Finally, we test whether each average price of risk is different from zero.

2.2 Heterogeneity in the Pricing of Risk and 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. 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 risk. For this purpose, we estimate a probit regression in which the dependent variable δ_t is an indicator equal to one if the price of risk is positive and significant, and zero otherwise. The probit regression is given by

$$Pr(\delta_t) = \alpha + Z_t^{\intercal}\beta + \varepsilon_t$$

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 factor models, we can only explore cross-MSA differences in estimated prices of risk. Therefore, as independent variables Z_t 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 all quantities used in the empirical analysis.

3.1 Asset Pricing Analysis Data

The data for residential housing prices 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. The ZHVI is based on estimates on the market value of individual homes that Zillow calls Zestimates. 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 zip codes and 571 unique MSAs for the sample period April 1996-December 2016.[15] Zillow also provides the ZHVI for the entire U.S. residential housing market, which we use in our empirical analysis as a proxy for U.S. housing market prices.[16] 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.[17]

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.

3.2 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.

[15]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)

[16]Appendix A.1 provides a detailed description on how we merge the different ZHVI geographies.

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

Zillow Data We obtain days-on-market at the MSA-level from Zillow, which we use as a liquidity 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.[18]

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.[19] Both of 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.

[18] 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.

[19] 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.2.

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 20002012. 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 20002016. 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 share of undevelopable land from Saiz (2010), and the Wharton Residential Land Use Regulation Index (WRLURI) from 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 the share of undevelopable land is not expected to change much over time as it is 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.

3.3 Descriptive Statistics

In Table 1, we present a set of summary statistics for excess housing returns at the zip code, MSA and U.S. level, as well as U.S. stock market excess returns. These include the number of observations, mean, median, minimum, maximum, and standard deviation. All statistics are based on annualized excess returns. For the zip code-level and MSA-level excess returns we also report the dispersion across MSAs. Excess returns are computed by subtracting the one-month Treasury bill rate. For this part of the analysis, we consider the full sample of 12,243 zip codes across 571 MSAs.

[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 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 12.73%, 9.63% and 5.39% per annum, respectively. The zip code-level average excess return (0.84%) is lower than both the average MSA (0.86%) and U.S. housing index (1.07%) excess housing returns.[20] 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.

[Insert Figure 1 here]

In Figure 1 we plot a geographical heat map of the U.S. and highlight the range of average yearly excess returns for all 571 MSAs present in our sample. In line with our expectations, we see that the highest excess returns (shown in purple) are mostly found in Californian MSAs. California has had a large increase in house prices in recent years. On the East Coast we see large excess returns

[20]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.

in the largest MSAs, including New York. Some smaller MSAs such as Syracuse, NY had excess returns close to zero. We also see very few MSAs with negative average excess returns, and in general these MSAs are small (e.g. Albany, GA, Bennington, VT, and Chambersburg, PA).

[Insert Figure 2 here]

In Figure 2 we plot a geographical heat map of the U.S. and highlight the range of average yearly excess returns for all 12,243 zip codes in our sample. As expected, based on the MSA excess returns, we find that many of the highest excess returns can be found in zip codes in Los Angeles and San Francisco, CA on the West Coast, and New York, NY on the East Coast.[21]

[Insert Table 2 here]

In Table 2, we present a set of summary statistics for MSA-level characteristics listed in Section 3.2. In the second part of our empirical analysis, we will use these variables to help explain cross-MSA variation in estimated risk premia. Here, we briefly discuss their summary statistics in order to gain more insight into the characteristics of the local housing markets under consideration.

Note that the most of MSA-level characteristics are available for a smaller set of MSAs than in the Zillow MSA-level housing price data. For the full sample of 571 MSAs, we can match characteristics for 214 up to 534 MSAs. At the same time, for our empirical analysis we require a cross-section of at least 15 zip codes per MSA to be able to estimate prices of risk for that MSA. Table 2 shows that the average number of zip codes per MSA varies widely. While the average number of zip codes across MSAs is 21.44, the median is nine, with a minimum of one and a maximum of 736 zip codes. The constraint of at least 15 zip codes implies that we are can perform the asset pricing tests for 178 MSAs. We can match all characteristics for 118 of them.

The population across MSAs varies widely as we have very large MSAs (e.g., New York) to much smaller MSAs (e.g., Syracuse). The share of undevelopable land is, on average, 25.86% with a median of 18.60%. Both these values are in line with Saiz (2010). Our sample of MSAs has a notably broad range of shares of undevelopable land with a minimum of 1.04%, a maximum of 86.01%, and standard devation of 21.05%. This means that in some MSAs, almost all available land

[21] For 2017, 77 of the 100 most expensive zip codes for housing in the U.S. were found in California, see e.g. http://www.latimes.com/business/realestate/hot-property/la-fi-hotprop-propertyshark-zip-codes-20180117-story.html.

is developable, while in others, less than 20% of the available land can be used for housing. Our measure of local housing regulations WRLURI has a negative mean of -0.08 and a median of -0.15. These are in line with Gyourko, Saiz and Summers (2008). The original WRLURI is constructed to have a mean of zero and a standard deviation of one. The negative average and median in our sample indicate that the median MSA is less regulated than the average MSA. Further, we see a broad range of values for the WRLURI in our sample of MSAs, with a minimum of -1.76 and a maximum of 3.12, with a standard devation of 0.78. Our sample thus contains both highly locally regulated and relatively unregulated MSAs. The average homeownership rate across our MSAs is 67.83% with a broad range of values and a high dispersion across MSAs of 6.22%. Volatility of real rents is on average 4.64%, with a slightly lower median of 4.09%. The average number of days-on-market for listed houses in our sample of MSAs is roughly 114 days, but liquidity varies widely across our MSAs with a minimum of 51 days and a maximum of roughly 219 days. Our sample thus includes both liquid and illiquid local housing markets. The fraction of the population aged 20-45 is on average 35.42%, with a similar median and a low dispersion across MSAs of 3.53%. Thus, most MSAs in our sample have a similar number of relatively young households.

The mean within (across) -MSA hedging indicator is 0.50 (0.47), which implies that about 50% (47%) of local housing markets have strong hedging incentives. The average across-MSA hedging indicator is in line with Han (2013) but the within-MSA hedging indicator is slightly lower. This could be explained in part by the fact that we have a different sample of MSAs, and a different sample period. Most importantly, we use detailed migration data from the IRS to create this variable. In contrast, Han (2013) uses IPUMS migration data which is only available once every ten years (i.e., 1990, 2000 and 2010), and assumes that it stays constant in between. As the IRS migration data is yearly we do not need to assume constant mobility rates within a decade.

Expected correlation is a measure of the correlation between the housing market where households currently reside and the housing market where they plan to move. Our mean expected correlation is 0.35, which is lower than the mean of 0.57 found in Sinai and Souleles (2013). However, if we restrict our MSA sample to match Sinai and Souleles's 44 MSAs (of which we can match 39 to the Zillow data) we find a similar mean, 0.53 versus 0.57, respectively.

4 Empirical Asset Pricing Results

The first step of our empirical analysis is to estimate the multifactor asset pricing model for each of the 178 MSAs in our estimation sample. This means that we perform cross-sectional asset pricing tests for 178 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 and/or idiosyncratic risk. Further, our framework also allows us to test whether markets are locally segmented or not.

4.1 Risk Exposure Estimation

We first examine the estimated zip code-level factor exposures and idiosyncratic volatilities ($IVOL$), which are based on rolling window regressions based on Equation (1) at the zip-code level using 48 monthly returns. Table 3 presents descriptive statistics of the risk exposures (betas) and the $IVOL$ estimates of the first-stage time-series regressions. All statistics are computed in two steps. First, we take the time-series average of the monthly factor exposures and $IVOL$ for each zip code. Second, we take cross-sectional statistics of these time-series means.

[Insert Table 3 here]

We have sufficient time series observations to run the regressions for all of the 12,243 unique zip codes except two. In Panel A, we report descriptive statistics for the entire sample. Panel B reports the same statistics for our estimation sample used in the cross-sectional regressions. As explained in the previous section, the estimation sample consists of the 178 MSAs with at least 15 zip codes, resulting in a total of 9,831 zip codes.[22]

Consistent with existing literature (see e.g., Case and Shiller 1989, and Jordà et al. 2018) in both panels we find that the average U.S. stock market exposure β^m is essentially zero with a mean (median) of -1.2e-3 (-9.0e-4) and -1.3e-3 (-1.0e-3), respectively. This implies that owning a house does not generate exposure to stock market risk. Consequently, combining residential real estate with stocks can potentially lead to substantial diversification benefits.[23] Nevertheless,

[22]In Section 4.4, we perform our asset pricing tests including only MSAs with at least 20 zip codes and find similar results.

[23]In the robustness tests discussed in the following section, we exclude the equity market factor and find very similar results.

Cotter, Gabriel and Roll (2018) find declining diversification benefits after 2000 across a range of assets including equity, debt and real estate within and across countries.

A one-factor model for housing returns including only the U.S. housing index would be similar to a CAPM for stock returns, and the CAPM predicts an (weighted) average stock market beta equal to one. In both the full and the estimation sample, we find that indeed the average U.S. housing index beta is close to one at 0.92 and 0.97, respectively. The beta does vary substantially across MSAs, as indicated by the cross-MSA dispersion of 0.75. Further, we find that zip code-level housing returns carry a substantial exposure to local MSA-level housing returns (orthogonalized with respect to U.S.-wide housing returns). The mean (median) β^{msa} is 0.72 (0.74) and 0.71 (0.75) in the two panels. These beta estimates are relatively less dispersed with a cross-MSA standard deviation of 0.41 and 0.43, respectively. These results suggest that allowing for locally segmented housing markets may be important. However, to fully address the issue of market segmentation, we need to estimate prices of risk, which we do in the next section.

The monthly $IVOL$ has a mean (median) of 0.60% (0.53%) and 0.58% (0.51%) in the full and estimation samples, respectively. The dispersion across MSAs is 0.29% and 0.30%, respectively. To understand these values in relation to total risk, we also compute the rolling window standard deviation of zip code excess returns as a proxy for total risk (volatility). To be consistent with our estimation of $IVOL$, we use 48 months rolling windows. In comparison, the monthly total volatility has a mean (median) of 0.82% (0.76%) and 0.78% (0.73%) respectively for our full and estimation samples. We compute the ratio of $IVOL$ to total volatility to see the share of total risk that $IVOL$ represents. We find that on average (median) across zip codes $IVOL$ represents 75.36% (77.41%) and 76.04% (78.16%), respectively, of total volatility. This means that $IVOL$ represents roughly 75% of total risk in the housing market. This resonates with the stock market idiosyncratic volatility literature, which finds that stock volatility consists mostly of idiosyncratic volatility (e.g., Ang et al. 2009). Nevertheless, systematic risk still represents roughly 25% of total risk. These results point to the fact that it is crucial to decompose total risk into systematic and idiosyncratic risk, and analyze each risk separately in order to get a full picture of housing-market risk. Notably, 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, we need to perform second-stage Fama-Mac Beth cross-sectional regressions. We discuss those 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 (3) within each of the 178 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 on positive prices of risk for all our types of risk and perform single-sided statistics tests. Furthermore, in Section 5 we link these positive risk premia estimates to economic fundamentals.[24] First, Table 4 presents descriptive statistics for the estimated prices of risk.

[Insert Table 4 here]

We report the number of MSAs that have significant positive prices of each risk at a 10% significance one-sided level using Newey-West standard errors with two lags. We also report the average price of risk and the dispersion across MSAs. We then look at how many MSAs have two, three or all significant prices of risk.

U.S. Stock Market For the stock market return, we find that out of 178 estimated MSAs only five (2.81%) have positive and significant U.S. stock market price of risk estimates, with an average price of risk of 0.21 per annum, and a dispersion of 0.93. These findings, coupled with our previous results showing that the U.S. stock market beta is close to zero for zip code-level housing returns, suggests that the U.S. stock market risk plays a negligible role in the pricing of the cross-section of residential housing returns.

U.S. Housing Index For the housing index return, we find that out of 178 estimated MSAs, 47 (26.40%) have significantly positive U.S. housing index prices of risk. The average price of risk across MSAs is 0.01 per annum with a dispersion of 0.04. Previously, we found that the average U.S. housing index beta in our estimation sample was, at 0.97, remarkably close to 1. These two

[24] In Section 4.4 we relax this assumption, allow prices of risk to be both positive and negative, and find similar results.

results imply that U.S. housing risk is relevant for the cross-section of residential housing returns. Note that based on pure chance, we could expect to find significant price of risk estimates in 10% of the MSAs, and 26.40% surpasses this threshold level.

Local MSA Return For the local MSA housing risk factor (orthogonalized with respect to the U.S. housing return), we find that out of 178 estimated MSAs, 39 (21.91%) have significantly positive local MSA return prices of risk, with an average of 0.01 per annum and dispersion of 0.06. This result shows that housing markets are not always locally segmented, as in roughly 78% of MSAs local risk is not priced.

Idiosyncratic Volatility For $IVOL$ we find that out of 178 estimated MSAs, 39 (21.91%) have significantly positive $IVOL$ prices of risk. The average $IVOL$ price of risk is 2.05 per annum with a dispersion of 9.93. This means that in roughly 78% of our estimated MSAs, idiosyncratic risk is not priced. This finding stands in contrast to the argument that $IVOL$ should be widely priced in the housing market because homeowners typically own only one property (and hence hold under-diversified real estate portfolios).

Factor Pricing Patterns In the bottom panel of Table 4, we report the number of MSAs that have one or more significant prices of risk. We find that 78 MSAs have either λ^{msa} or λ^{hi} significant, which means that in 43.82% of our MSAs systematic risk (local or national) matters. Furthermore, in 69 and 76 MSAs, respectively, we find that either λ^{msa} or λ^{ivol}, or λ^{hi} or λ^{ivol} are significant, which means that in 38.76% or 42.70% either systematic or idiosyncratic risk matters. We also note in 101 MSAs either λ^{msa} or λ^{ivol} or λ^{hi} is significant, which means that 56.74% of MSAs have systematic or idiosyncratic risk priced.[25] While we find that at least one of the type of risks is priced in a majority of our MSAs, it is interesting to see how many MSAs have both type of risks priced. We find that only eight MSAs have both local and national risk priced, which represents 4.49% of all estimated MSAs. Further, we find that just nine or 10 MSAs have both systematic (λ^{msa} or

[25] When we impose a minimum of 20 zip codes per MSA and we allow for both positive and negative price of risk estimates, we find that for 77% of MSAs there is at least one source of risk that carries a significant risk premium. This suggests that the lack of statistical significance may in some MSAs be related to the relatively small cross-section of zip codes. At the same time, when we set the minimum at 20 zip codes, we lose a number of smaller MSAs. The results of this robustness check are discussed in Section 4.4. Furthermore, when we link the risk premia estimates to economic fundamentals, we control for the number of zip codes within each MSA.

λ^{hi}) and idiosyncratic (λ^{ivol}) risk priced, which represents 5.06% and 5.62% of all estimated MSAs, respectively. Finally, only three MSAs have all three types of risk priced, which represents just 1.69% of all estimated MSAs.[26] In the bottom of Table 4 we show that while we observe 178 MSAs with at least one month of estimated price of risk, we find that 103 (57.87%) have one or more significant prices of risk, 48 (26.97%) have two or more, 11 (6.18%) have three or more and none have all four significant prices of risk.[27]

To investigate patterns in the pricing of risk across the U.S., in Figures 3a, 4a, 5a and 6a we plot geographical heat maps of the U.S. and highlight in purple MSAs where the each respective price of risk is positive and significant, and in yellow MSAs where each respective price of risk is not significant.

[Insert Figures 3a and 4a here]

In Figure 3a we see that the U.S. stock market is not significantly priced in the majority of our MSAs. On the other hand, in Figure 4a we see that the U.S. housing index is positively priced in many East Coast MSAs, including New York and Philadelphia. It is also priced in some large southern U.S. MSAs such as Austin and Houston. In the West Coast, we see that the U.S. housing-market risk is priced in Seattle and Fresno. While the U.S. housing-market risk is priced in many large MSAs, it is also priced in several small MSAs across the country such as e.g. Cedar Rapids, IA, Salem, OR, and Savannah, GA, among others. These results show that the U.S. housing index is priced in a wide range of different sized MSAs across the U.S.

[Insert Figure 5a here]

In Figure 5a we see that the local MSA return is priced in a broader set of MSAs that are located all throughout the country, including Charlotte, Chicago, Dallas and Philadelphia. However, we also see that the local MSA return is priced in many smaller MSAs (e.g.,San Luis Obispo, CA, Yakima, WA, and Watertown, NY). Thus, we also find that the local MSA return is priced in wide range of different sized MSAs across the U.S. This finding is in line with earlier papers showing that housing markets cluster and that local aspects matter for housing returns (Goetzmann, Spiegel and

[26] These three MSAs are Cedar Rapids, IA, Oklahoma City, OK and Philadelphia, PA.

[27] In untabulated results, we find that, on average across MSAs, this three-factor model including idiosyncratic volatility explains 27.99% of the cross-sectional variation in zip code excess returns.

Wachter 1998). Nevertheless, in many of our estimated MSAs we do not find evidence of locally segmented markets.

[Insert Figure 6a here]

Finally, in Figure 6a we find that $IVOL$ is priced in many large East Coast MSAs, including Boston, New York and Philadelphia. $IVOL$ is also priced in a few large MSAs in the southern part of the U.S. including San Antonio. While we see that $IVOL$ is positively priced in many East Coast MSAs, it is also priced in several large MSAs throughout the U.S. including Charlotte, Pittsburgh, Minneapolis-St. Paul, and Columbus. Further, $IVOL$ is also priced in small MSAs across the U.S. (e.g. Appleton, WI, Ocala, FL, Peoria, IL, and Utica, NY). These results also suggest that $IVOL$ is priced in a wide range of MSAs across the entire U.S.

Prices of Risk and Risk Premiums While in Table 4 we present descriptive statistics of prices of risk, in Figures 3a, 4b, 5b and 6b we focus instead on the risk premia associated with each type of risk. For this purpose, we plot geographical heat maps of the U.S. and highlight the range of annualized risk premia for each type of risk in MSAs where the respective price of risk is significant.[28]

[Insert Figures 3b, 4b, 5b and 6b here]

In Figure 3b we see that in the very few MSAs where the U.S. stock market has a positive significant price of risk, the risk premium is relatively low ranging from 0.15% to 1%. In Figure 4b we see that in the majority of MSAs the U.S. housing index risk premium is economically large, ranging from 2.40% to 4.00%, while the highest risk premium is found in Naples, FL at 7.13%. For the local MSA return risk premium, Figure 5b shows that the values are somewhat lower, with the majority of MSAs having an annualized risk premium ranging between 1.60% to 3.20%, while the highest risk premium is found in Yakima, WA at 6.93%. Finally, Figure 6b shows $IVOL$ has an annualized risk premium in the majority of MSAs ranging from 3.20% to 4.80%, with the highest risk premium found in Fort Smith, AR at 6.98%.

[28]The risk premium for each risk is calculated in several steps. First, we calculate the time-series average beta for each zip code. Second, we multiply each zip codes average beta with the estimated price of risk for the respective MSA. Finally, we take the average across zip codes within each respective MSA. Risk premia are annualized by multiplying by 12.

[Insert Figure 7 here]

In Figure 7 we plot the average annualized 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 risk is significantly priced. We see that the $IVOL$ risk premium is the largest, on average between 1.55% and 2.05%. The local MSA return risk premium commands the second highest with an average between 0.88 and 1.15%, while the U.S. housing index has an average risk premium between 0.48% and 1.06%. All three risk premia are large compared to the average annual MSA-level excess return of 0.86% as seen in Table 1. In particular, the average yearly $IVOL$ risk premium is almost twice the size of the average MSA-level excess return.[29] Finally, we see that the $IVOL$ yearly risk premium is largest in MSAs where all there risks are priced and constitutes more than half of the total risk premium in these MSAs. On the other hand, we see that in MSAs where more than one risk is priced, the U.S. housing index commands a low risk premium and constitutes a small part of the total risk premium.

We saw in Table 3 that $IVOL$ commands roughly 75% of the total risk at the zip code-level. Since idiosyncratic risk represents on average the largest part of total risk, it is not surprising that we find that it also commands the highest risk premium in MSAs where it is significantly priced. Further, given the relative importance of idiosyncratic versus systematic risk, as well as local versus national risk, our results also suggest that when analyzing the risk-return relationship in the cross-section of residential housing returns, it is crucial to not only decompose total risk into systematic and idiosyncratic risk but also to allow for local and national systematic risk.

[Insert Table 5 here]

4.3 Negative Prices of Risk

In line with asset pricing theory, throughout our main analysis we analyze only positive prices of risk. In Table 5 we relax this assumption and allow prices of risk to be either positive or negative. We find that the majority of U.S. housing index, local MSA return, and $IVOL$ prices of risk are positive. U.S. housing risk is significantly priced in 41 MSAs, with 34 (83%) carrying positive

[29] Note, that this is not a perfect comparison since the average excess return from Table 1 is across all 571 MSAs in the full sample, while the average $IVOL$ risk premium is only for MSAs in which this price of risk is significant.

prices. Only seven MSAs carry a significant negative price of U.S. housing risk, which represents just 3.93% of the 178 estimated MSAs. However, since we are looking at a 10% significance level, these may fall within the false significant margin. Notably, we find that out of a total of 44 MSAs that have significant $IVOL$ prices of risk, 30 (68%) have positive prices. Ang et al. (2006) 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 extend to the cross-section of housing returns, and the pricing of idiosyncratic risk in the housing market is consistent with asset pricing theory (see, e.g., Merton 1987). Further, by relaxing the positive price of risk assumption, we find that the number of MSAs with at least one significant price of risk increases to 115 versus 103 previously, which means that in 64.6% of all MSAs at least one price of risk is significant. Overall, we find that our main results and conclusions hold when we relax the assumption of positive prices of risk.

4.4 Additional Checks

We perform a number of additional checks to verify the stability of our main findings. Most of these results can be found in the Online 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. In this subsample we have fewer zip codes and MSAs. Unsurprisingly, we find that housing average excess returns at all geographies are much higher than in the full sample. We also find that the average population in the 2007 subsample is lower, while homeownership is higher consistent with the fact that homeownership reached a record high in the years preceding the financial crisis. Further, we find that the fraction of population aged 20-45 is lower in our full sample, which is consistent with the demographic trend that the population as a whole is growing older.

Most importantly, we find that the share of MSAs with priced idiosyncratic risk is similar to the full sample. On the other hand, in the pre-crisis period we see that with regards to systematic risk, it is the local MSA risk rather than U.S. housing risk that seems to matter relatively more contrary to what we found in the full sample. This indicates that housing markets were more locally segmented prior to the financial crisis. Finally, in the pre-crisis sample we observe fewer MSAs with significantly positive prices of U.S. housing risk compared to the full sample.

MSA Estimation Sample Representativeness Since our estimation sample is smaller than the full sample due to the requirement of a minimum of 15 zip codes per MSA, one may wonder whether our sample of estimated MSAs is representative of the full sample. The estimation sample contains 9,832 zip codes, which represents 80.3% of the full sample number of zip codes (12,243). Further, the total average yearly population of the 178 MSAs represents 91.1% of the total average yearly population of our full sample of 571 MSAs. Thus, our estimation sample provides good coverage of the full sample both in terms of population and number of zip codes.

[Insert Table 6 here]

In Table 6 we present averages for a set of MSA characteristics previously in the literature to analyze risk in the housing market (see, e.g., Han 2013). We present these means for both our full sample and our estimation sample, as well as the difference in means, and we test whether they are statistically significant different from zero or not. Our goal is to identify any major differences between the two sets of MSAs.

We find that MSAs with at least 15 zip codes are quite representative of our full sample since we find no significant differences in MSA fundamentals. There are a few exceptions. First, we find that the average household in our estimated sample of MSAs has stronger hedging incentives. Unsurprisingly, given that our estimated sample has MSAs with many more zip codes on average, we also find these MSAs are much larger on average in terms of population. Finally, we find some evidence that our estimated MSAs have lower rental volatility on average. In conclusion, we do not find any major differences in MSA characteristics between our estimated sample and our full sample.

Zip Code Requirement In our main analysis we require a minimum of 15 zip codes to estimate price of risk within each MSA. To check the robustness of our findings, we increase the requirement to 20 zip codes. As expected, the increase of minimum required zip codes leads to a smaller estimation sample of MSAs, 135 versus 178 previously. Nevertheless, we find that the percentage of MSAs that have a significant positive price of risk for the U.S. stock market, local MSA return, and $IVOL$ are very similar to our main results. For the U.S. housing-market risk, we now find significantly more MSAs with significant positive prices of risk. In summary, we see that while increasing the minimum required zip codes to 20 decreases the sample size, our previous results and conclusions still hold.

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 price. We add each of these zip code characteristics separately to the second stage cross-sectional regression specified in (3) to estimate prices of risk on all the factors and characteristics. We find that our main results and conclusions hold when including these characteristics. Interestingly, we find that value is priced in 36 MSAs, which represents 20.2% of all estimated MSAs. Asness, Moskowitz and Pedersen (2013) find that a value is priced across a range of assets including stocks, bonds, currencies and commodities. Our findings suggest that value is also an important characteristic for housing returns and may warrant further analysis in the future.

Model without Stock Market Risk Factor We provide strong evidence that the U.S. stock market is not priced in the cross-section of housing returns, and that the average U.S. stock market beta is essentially zero. The latter result is in line with the findings of Jordà et al. (2018). 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 (1) and (3) without this risk factor. We find that when excluding the U.S. stock market return, our main results and conclusions still hold.

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.

As discussed in the data section, we consider the following MSA-level housing market and other economic fundamental variables: the within-MSA hedging indicator, log income, LTV ratio, log population, share of undevelopable land, WRLURI, homeownership, real rent volatility, and a measure of liquidity in the housing market (log days-on-market).[30] As we estimate unconditional factor models, we have unconditional risk premia estimates. We therefore use time series averages of the fundamental variables as independent variables in our probit. Further, since our prices of risk are estimated using the two-stage Fama-MacBeth procedure, we also wish to control for the length of the time series of the MSAs since this will affect both the estimation of the risk exposure to MSA local risk and the number of price of risk estimates. For this purpose, we also include the number of excess return observations of each MSA in the probit regression.

We first start by looking at a broad set of MSA characteristics that have been previously used to analyze the risk-return relationship in the housing market (see, e.g., Han 2013) and how they differ across MSAs with at least one significant price of risk versus MSAs with no significant prices of risk.

[Insert Table 7 here]

In Table 7 we compare a set of MSA characteristics across the 75 MSAs where none of the four risks are positively priced versus MSAs that have at least one significant positive price of risk. We find that MSAs with no significant positive price of risk have on average a larger population, lower loan-to-value ratio (LTV), and households have stronger hedging incentives. However, the differences are economically relatively small for most variables: 79.77% versus 79.26% for the average LTV and 0.53 versus 0.59 for the hedging indicator.

[30] Since both of the hedging incentive variables measure household hedging in the housing market, they should not be included together in a regression. Nevertheless, we also estimate this probit model including the across-MSA hedging indicator instead of the within-MSA hedging indicator and find similar results. These results can be found in the Online Appendix.

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 2.2. The dependent variable takes a value of one when the price of risk estimate is significant and positive and a value of zero otherwise.

[Insert Table 8 here]

In Table 8 we report the marginal effects of this model for prices of risk of the U.S. housing index, MSA local return, and idiosyncratic volatility ($IVOL$). We find that U.S.-wide housing-market risk is more likely to be priced in MSAs with relatively more illiquid housing markets. MSA-level housing risk is more likely priced in MSAs where homeownership rates are higher. In these areas, there are fewer renters and hence fewer well-diversified landlords. Consequently, the marginal investor is more likely to be someone exposed to local MSA-level housing risk, which then carries a risk premium.

We also find that the likelihood of idiosyncratic risk being positively priced is higher in MSAs where market liquidity is lower. We further find that idiosyncratic housing risk is less likely to be positively priced in MSAs with more undevelopable land. To the extent that more undevelopable land makes it is easier for homeowners to sell existing properties, these two findings suggest that under-diversification is less binding when liquidity is higher. Finally, idiosyncratic risk is less likely to be priced for homeowners with strong-hedging incentives within MSAs. In line with the insights in Sinai and Souleles (2005; 2013) and Han (2013), this result suggests that homeowners are less concerned with under-diversification if homeownership is an instrument to benefit from potential house price increases that can be used in the future for the purchase of a larger house within the same MSA.

6 Conclusion

This paper performs a large-scale empirical asset pricing analysis of the cross-section of residential real estate returns for 9,831 different zip codes across 178 Metropolitan Statistical Areas (MSAs) from April 1996 to December 2016. Our sample covers a large part of the U.S. residential real estate market.

For each MSA, we estimate a three-factor model that includes systematic (U.S. and local MSA) housing-market risk as well as idiosyncratic zip code-specific housing risk. Next, we estimate prices of risk by running 178cross-sectional regressions (one for each MSA) of zip code excess returns on the factor exposures and $IVOL$. Our approach not only allows us to include local risk factors, but also to test to what extent the U.S. housing market is locally segmented.

We find striking differences in the types of risks priced across MSAs. For instance, we find that idiosyncratic risk is positively priced in 39 of the MSAs. This finding stands in contrast to the argument that idiosyncratic risk should be widely priced in the housing market because homeowners typically own only one property (and hence hold under-diversified real estate portfolios). One possible explanation is that the presence of better diversified landlords mitigates the pricing of idiosyncratic risk. Our analysis also shows that local MSA housing risk is positively priced in 39 MSAs. Notably, this finding suggests that, in contrast to common belief, the U.S. housing market is not locally segmented in most areas. We also find that U.S. housing-market risk is positively priced in 47 MSAs, while both systematic and idiosyncratic risk are positively priced in only eight MSAs. Using heat maps we show that the U.S. housing-market risk and idiosyncratic risk are priced in a broad range of MSAs across the U.S.

Finally, we link the heterogeneity in the pricing of risk across MSAs to various local housing market fundamentals. Among other things, we find that in MSAs with less undevelopable land and where market liquidity is lower, idiosyncratic risk is more likely to be positively priced. This suggests that under-diversification is less binding when liquidity is higher. Liquidity is also important for the pricing of the U.S. housing-market risk, while higher homeownership rates increase the probability that MSA-level risk is positively priced.

A Dataset and Variables Construction

In this appendix, we describe how we merge the different geographies and how we construct the hedging incentive variables.

A.1 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.2 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 3.2. 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.[31]

[31] 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

This table reports excess-return descriptive statistics including mean, median, minimum, maximum, and standard deviation (SD), for zip code-level (Panel A), MSA-level (Panel B), U.S. housing index (Panel C) and U.S. stock market (Panel D) excess returns. We also report the cross-sectional dispersion (Dispersion) for zip code-level and MSA-level excess returns. All the 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-level 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 time-series 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.

Panel A: Zip Code-Level Data							
	N	Mean	Median	Minimum	Maximum	SD	Dispersion
Excess Returns (% pa)	12243	0.84	1.03	-41.72	38.59	12.73	1.26
Panel B: MSA-Level Data							
	N	Mean	Median	Minimum	Maximum	SD	Dispersion
Excess Returns (% pa)	571	0.86	0.64	-45.80	45.08	9.63	1.30
Panel C: U.S. housing index							
		Mean	Median	Minimum	Maximum	SD	
Excess Returns (% pa)		1.07	1.83	-12.19	10.16	5.39	
Panel D: U.S. stock market							
		Mean	Median	Minimum	Maximum	SD	
Excess Returns (% pa)		7.95	11.70	-38.34	35.20	18.76	

Table 2: Descriptive Statistics of MSA-Level Variables

This table reports descriptive statistics for all the MSAs in the sample. We report the mean, median, minimum, maximum, and standard deviation (SD) of within- and across-MSA hedging indicators, household total income, loan-to-value ratio, population, share of undevelopable land, WRLURI, homeownership, real rent volatility, days-on-market, fraction of the population aged 20-45, expected correlation, and average number of zip codes per MSA. For characteristics that have time-series observations, the statistics are computed in two steps. First, we take the cross-sectional statistics each year. Second, we take the time-series means of these statistics. The mean, median, minimum, maximum, and SD of the loan-to-value ratio, share of undevelopable land, unemployment, homeownership, fraction of population aged 20-45 and real rent volatility are in percentage units. Household total income is in 10^4 units and in USD. Population is in 10^5 units. All data is yearly. The sample period is 1996 – 2016.

MSA-Level Data						
	N	Mean	Median	Min	Max	SD
Within-MSA Hedging Indicator	250	0.50	0.49	0	1	0.50
Across-MSA Hedging Indicator	254	0.47	0.46	0	1	0.50
Household Total Income	254	7.33	7.10	4.70	14.59	1.38
Loan-to-value Ratio	518	79.34	80.17	28.02	98.73	10.24
Population	254	10.06	3.89	1	196.20	19.66
Undevelopable Land	214	25.86	18.60	1.04	86.01	21.05
WRLURI	214	-0.08	-0.15	-1.76	3.12	0.78
Homeownership	254	67.83	68.79	49.48	83.01	6.22
Real Rent Volatility	254	4.64	4.09	0.80	14.98	2.34
Days-on-market	221	113.81	113.15	51.13	218.45	25.10
Fraction of population aged 20-45	254	35.42	35.36	22.09	48.39	3.53
Expected Correlation	534	0.35	0.37	-0.35	0.77	0.20
Number of Zip Codes	571	21.44	9	1	736	48.69

Table 3: Descriptive Statistics of Factor Exposures and $IVOL$

This table reports descriptive statistics of risk exposures and idiosyncratic volatility. In Panel A we report the mean, median, minimum, maximum, and standard deviation (SD), for the three risk exposures β^{m}, β^{hi} and β^{msa}, and for $IVOL$ estimated for each zip code using the three-factor model (1). We also report these statistics for the total volatility (Total Vol.), as measured by the rolling window standard deviation using 48 months to be consistent with the $IVOL$ estimation, and for the ratio of the $IVOL$ to the standard deviation ($\overline{IVOL}$/Total Vol.). In Panel B we report the same statistics for our limited estimation sample that consists of 9,831 zip codes. The statistics for the β and $IVOL$ are computed in two steps. First, we take the time-series mean of each variable. Second, we take cross-sectional statistics of these time-series means. For the total volatility, the statistics are computed only using the second step. The mean, median, minimum, maximum, and SD of $IVOL$, Total Vol., and $\overline{IVOL}$/Total Vol. are in percentage units. $IVOL$ and Total Volatility are monthly. The sample period is April 1996 – December 2016.

	Number of Zip Codes	Mean	Median	Minimum	Maximum	SD
Panel A: Full Sample						
$\beta^{\overline{m}}$	12241	-1.2e-3	-9.0e-4	-0.18	0.12	0.01
$\beta^{\overline{hi}}$	12241	0.92	0.81	-7.60	6.85	0.75
$\beta^{\overline{msa}}$	12241	0.72	0.74	-3.17	4.74	0.41
$\overline{IVOL}$	12241	0.60	0.53	0.04	2.64	0.29
Total Vol.	12241	0.82	0.76	0.12	2.78	0.32
$\overline{IVOL}$/Total Vol.	12241	75.36	77.41	13.60	99.33	13.49
Panel B: Estimation Sample						
	Number of Zip Codes	Mean	Median	Minimum	Maximum	SD
$\beta^{\overline{m}}$	9831	-1.3e-3	-1.0e-3	-0.13	0.12	0.01
$\beta^{\overline{hi}}$	9831	0.97	0.87	-7.60	6.85	0.75
$\beta^{\overline{msa}}$	9831	0.71	0.75	-3.17	4.74	0.43
$\overline{IVOL}$	9831	0.58	0.51	0.13	2.43	0.28
Total Vol.	9831	0.78	0.73	0.14	2.48	0.30
$\overline{IVOL}$/Total Vol.	9831	76.04	78.16	25.71	99.33	12.98

Table 4: Prices of Risk

This table reports descriptive statistics for estimated positive prices of risk. Following regression (3) we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	178	5	0.21	0.93
Housing Index	178	47	0.01	0.04
MSA Return	178	39	0.01	0.06
$IVOL$	178	39	2.05	9.93
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	78	69	76	101
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	8	9	10	3
Sig. prices of risk	$>= 1$	$>= 2$	$>= 3$	$= 4$
Number of MSAs	103	48	11	0

Table 5: Positive and Negative Prices of Risk

This table reports descriptive statistics for estimated positive and negative prices of risk. Following regression (3) we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level two-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	$\lambda < 0$	Average λ	Disp. λ
Stock Market	178	2	40	-0.10	1.03
Housing Index	178	34	7	1.8e-3	0.04
MSA Return	178	18	11	2.8e-4	0.08
$IVOL$	178	30	14	0.29	9.93
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}	
Number of MSAs	61	69	76	94	
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}	
Number of MSAs	9	4	9	2	
Sig. prices of risk	$>= 1$	$>= 2$	$>= 3$	$= 4$	
Number of MSAs	115	50	18	2	

Table 6: MSA Characteristics: Estimated vs. Full Sample

This table reports the mean for a set of MSA characteristics for MSAs that have more than 15 zip codes and are included in the price of risk estimation, the mean for MSAs in the full sample, as well as the difference in their means. We report these statistics for the within- and across-MSA hedging indicators, household total income, loan-to-value ratio, population, share of undevelopable land, WRLURI, homeownership, real rent volatility, days-on-market, fraction of the population aged 20-45, expected correlation, and average number of zip codes per MSA. 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 statistics. The averages of the loan-to-value ratio, share of undevelopable land, homeownership, fraction of population aged 20-45 and real rent volatility are in percentage units. Household total income is in 10^4 units and in USD. 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 Estimated MSAs	Mean Full Sample MSAs	Difference in Means
Within-MSA Hedging Indicator	0.56	0.50	0.06***
Across-MSA Hedging Indicator	0.57	0.47	0.10***
Household Total Income	7.68	7.33	0.35
Loan-to-value Ratio	79.55	79.34	0.21
Population	14.46	10.06	4.41***
Undevelopable Land	27.31	25.86	1.45
WRLURI	-0.00	-0.08	0.08
Homeownership	68.34	67.83	0.50
Real Rent Volatility	4.07	4.64	-0.57*
Days-on-market	114.35	113.81	0.54
Fraction of population aged 20-45	35.36	35.42	-0.06
Expected Correlation	0.46	0.35	0.11***
Number of Zip Codes	55.24	21.44	33.79***

Table 7: MSA Characteristics: MSAs with (without) Significant Prices of Risk

This table reports the mean for a set of MSA characteristics for MSAs that have at least 1 significant positive price of risk, for MSAs that have no significant price of risk, as well as the difference in their means. We report these statistics for the within- and across-MSA hedging indicators, household total income, loan-to-value ratio, population, share of undevelopable land, WRLURI, homeownership, real rent volatility, days-on-market, fraction of the population aged 20-45, expected correlation, and average number of zip codes per MSA. 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 statistics. The averages of the loan-to-value ratio, share of undevelopable land, homeownership, fraction of population aged 20-45 and real rent volatility are in percentage units. Household total income is in 10^4 units and in USD. 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	0.53	0.59	-0.06***
Across-MSA Hedging Indicator	0.57	0.57	0.01
Household Total Income	7.62	7.77	-0.14
Loan-to-value Ratio	79.77	79.26	0.51***
Population	14.03	15.09	-1.06***
Undevelopable Land	25.45	30.09	-4.64
WRLURI	-0.01	0.01	-0.02
Homeownership	68.72	67.79	0.93
Real Rent Volatility	3.99	4.18	-0.19
Days-on-market	114.46	114.22	0.24
Fraction of population aged 20-45	35.20	35.59	-0.38
Expected Correlation	0.47	0.45	0.01
Number of Zip Codes	55.38	55.04	0.34

Table 8: 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. housing level risk, MSA local return risk, and on idiosyncratic risk ($IVOL$) on a set of MSA characteristics that include: within-MSA hedging indicator, log of household total income, loan-to-value ratio, log of population, share of undevelopable land, WRLURI, homeownership, real rent volatility, log of days-on-market, and to control for time-series size the number of excess return observations per MSA. 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^{hi}	λ^{msa}	λ^{ivol}
Within-MSA Hedging Indicator	-0.12	0.11	-0.23**
	(-1.01)	(1.04)	(-2.36)
Log Income	0.38	-0.36	0.03
	(0.89)	(-1.03)	(0.09)
Loan-to-value ratio	-2.25	-1.46	2.44
	(-0.78)	(-0.54)	(1.01)
Log Population	3.7e-4	-0.01	0.08
	(0.01)	(-0.14)	(1.43)
Undevelopable Land	0.04	0.12	-0.57**
	(0.12)	(0.43)	(-1.95)
WRLURI	-0.08	0.03	0.06
	(-1.14)	(0.52)	(1.13)
Homeownership	-0.17	1.73**	0.37
	(-0.18)	(2.14)	(0.48)
Real Rent Volatility	-2.16	-0.25	-2.25
	(-0.60)	(-0.07)	(-0.75)
Log Days-on-market	0.59**	-0.13	0.47*
	(2.21)	(-0.50)	(1.93)
Number of Excess Return Obs.	-0.65***	-0.10	0.06
	(-3.12)	(-0.53)	(0.33)
Nobs	118	118	118
Pseudo R^2	11.6%	3.6%	15.3%

Figure 1: Metropolitan Statistical Area (MSA) Excess Returns

This figure plots a geographical heat map of the U.S. with the average excess return for all 571 MSAs in our sample. The sample period is April 1996 – December 2016.

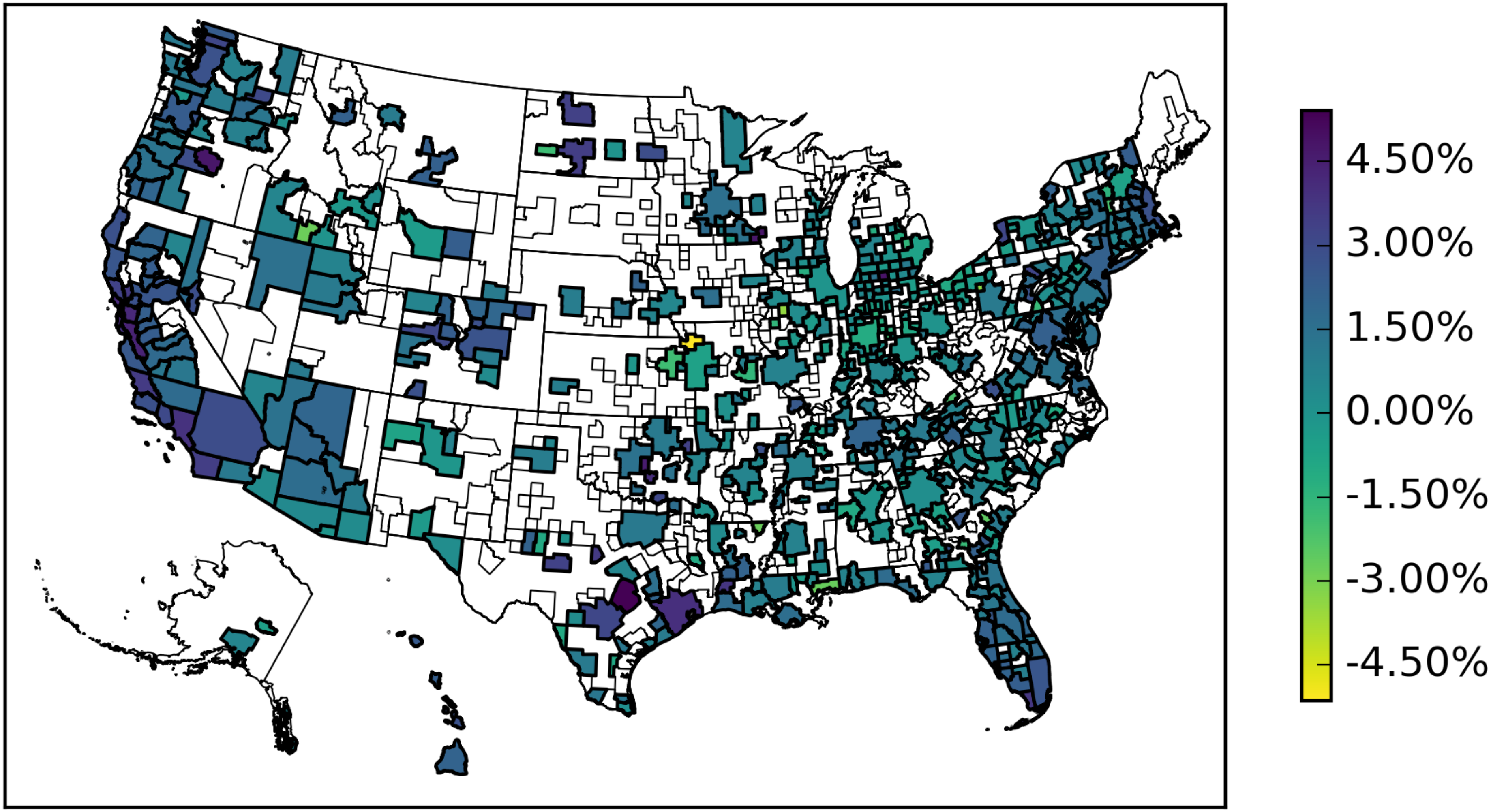


Figure 2: Zip code Excess Returns

This figure plots a geographical heat map of the U.S. with the average excess return for all 12,243 zip codes in our sample. The sample period is April 1996 – December 2016.

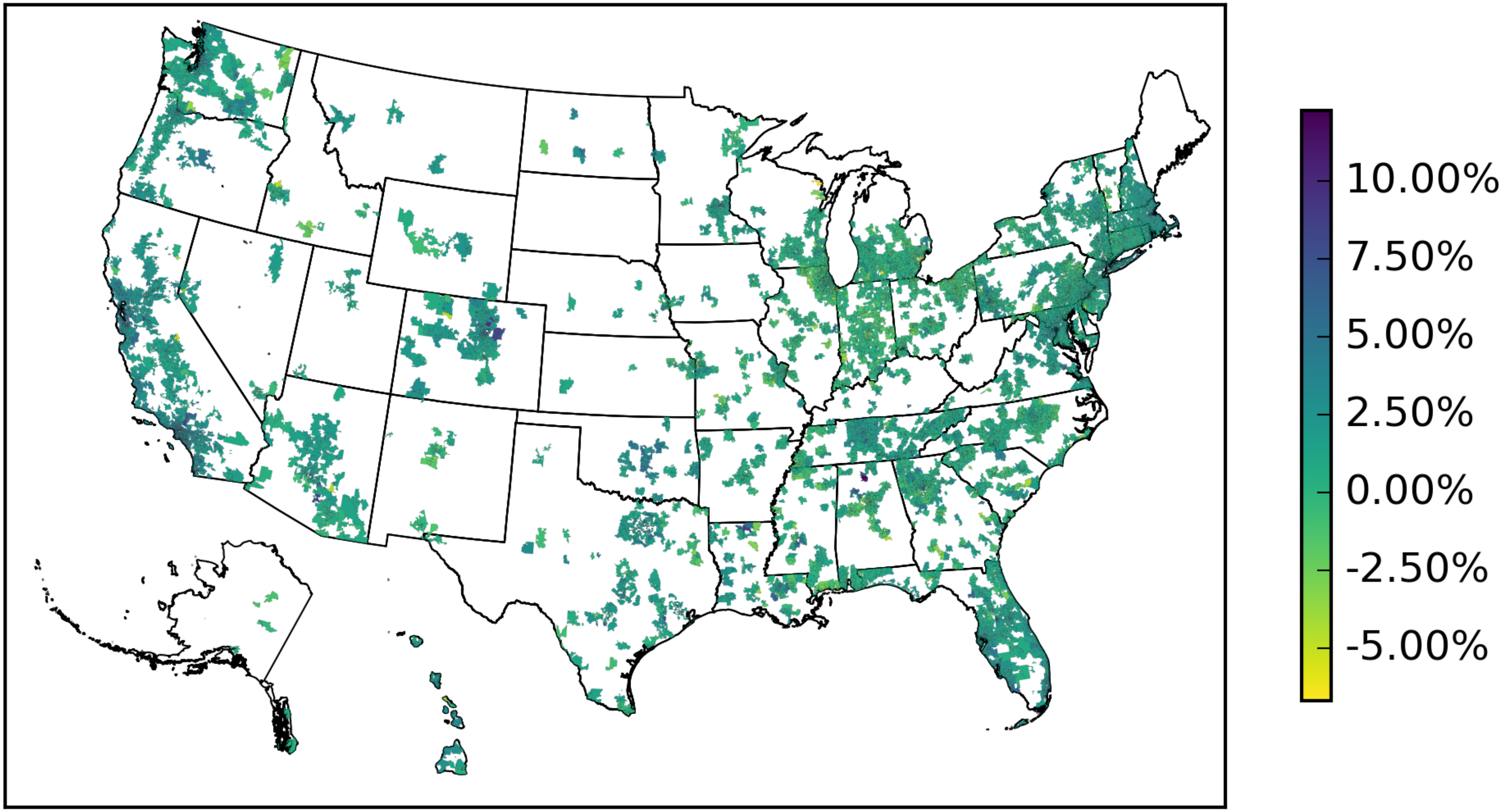
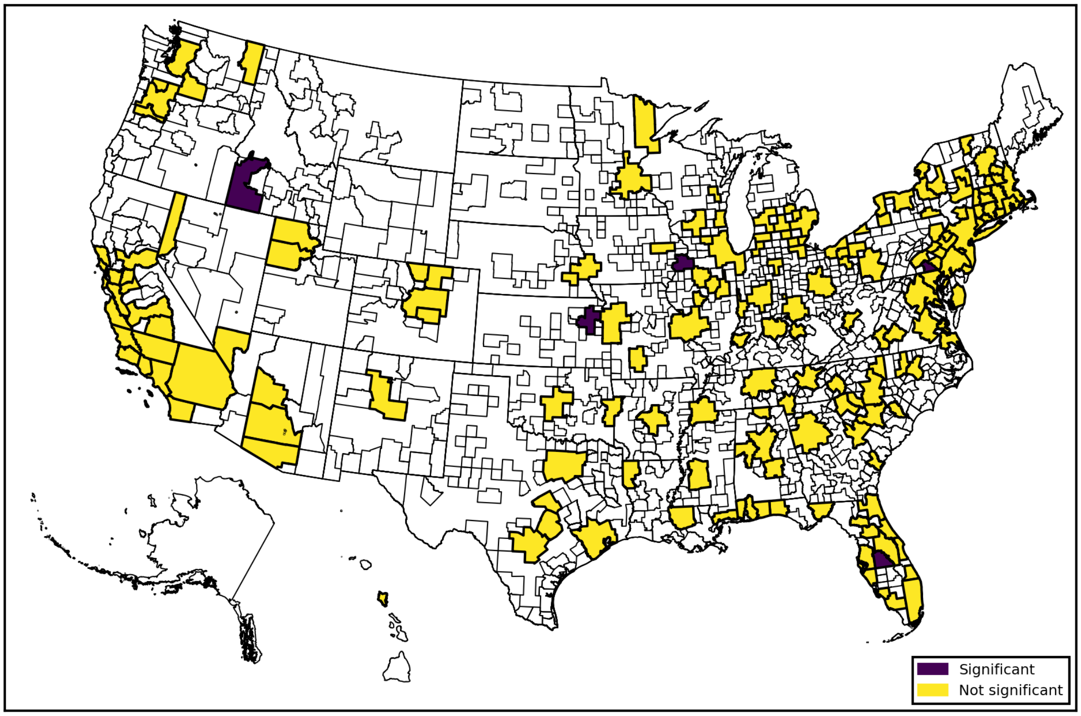


Figure 3: U.S. Stock Market Risk Premium across MSAs

This figure plots geographical heat maps of the U.S. containing the 178 MSAs for which we estimate prices of risk. In Panel (a), all dark red MSAs have a statistically positive significant U.S. stock market price of risk, while in blue MSAs it is statistically insignificant. In Panel (b), we show a heat map of the U.S. stock market annualized risk premium in the MSAs where the price of risk is significant. The sample period is April 1996 – December 2016.

(a) Prices of Risk



(b) Annualized Risk Premium

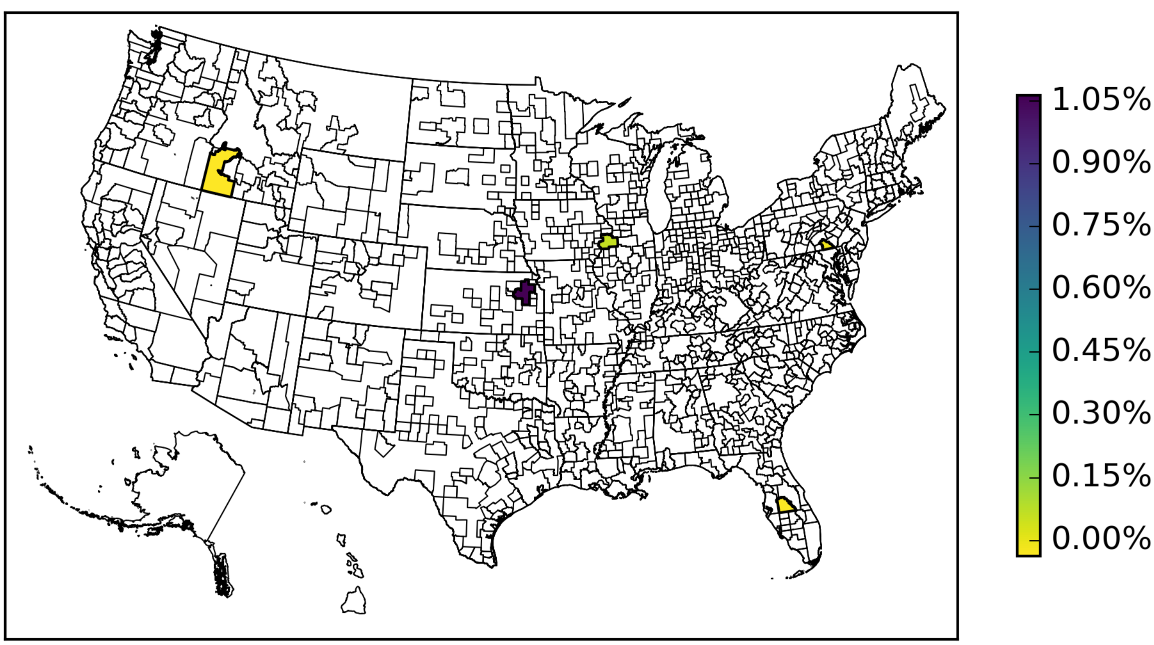
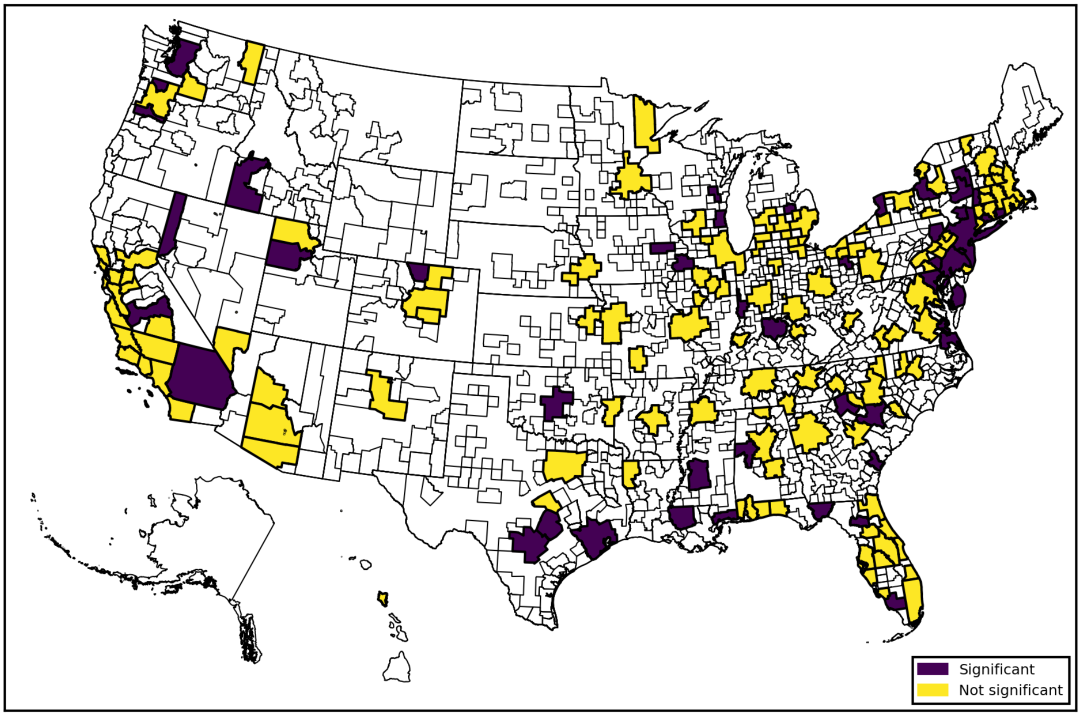


Figure 4: U.S. Housing Index Risk Premium across MSAs

This figure plots geographical heat maps of the U.S. with the 178 MSAs for which we estimate prices of risk. In Panel (a), all dark red MSAs have a statistically positive significant U.S. housing index price of risk, while in blue MSAs it is statistically insignificant. In Panel (b), we show a heat map of the U.S. housing index annualized risk premium in the MSAs where this price of risk is significant. The sample period is April 1996 – December 2016.

(a) Prices of Risk



(b) Annualized Risk Premium

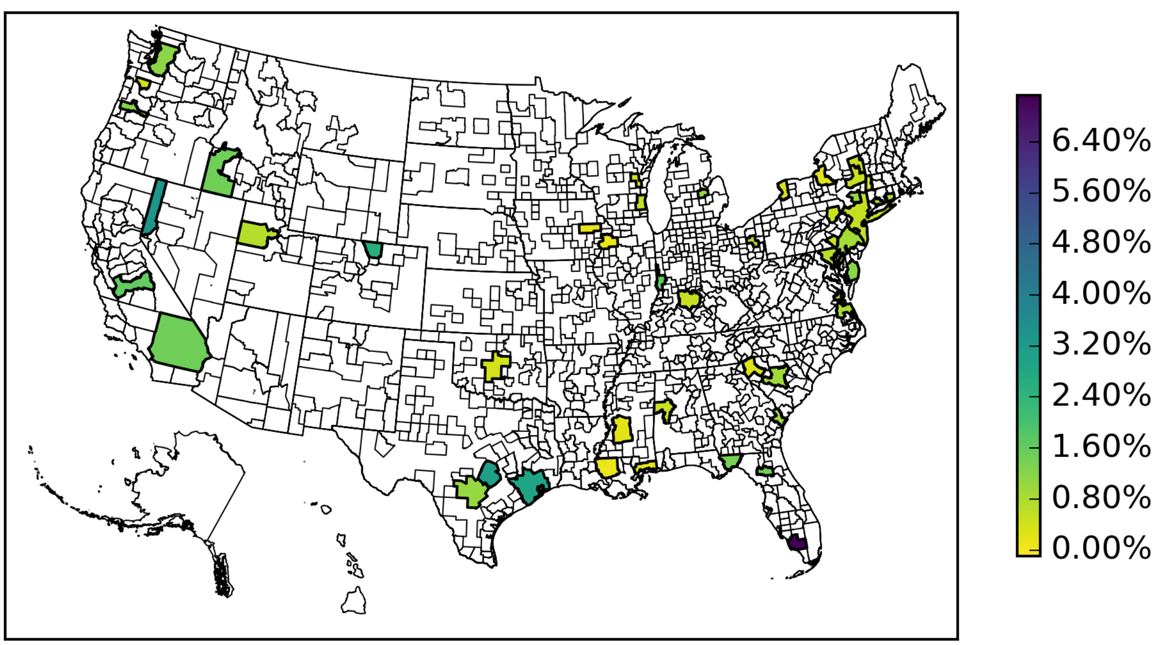
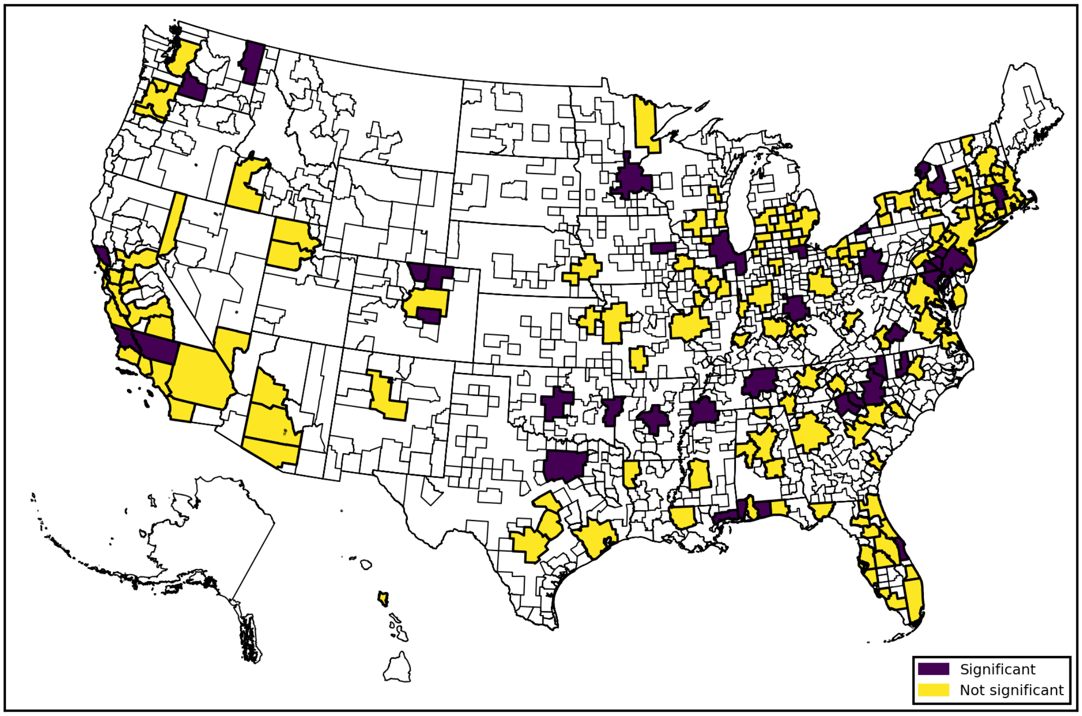


Figure 5: MSA Return Risk Premium across MSAs

This figure plots geographical heat maps of the U.S. with the 178 MSAs for which we estimate prices of risk. In Panel (a), all dark red MSAs have a statistically positive significant local MSA return price of risk, while in blue MSAs it is statistically insignificant. In Panel (b), we show a heat map of the local MSA return annualized risk premium in the MSAs where this price of risk is significant. The sample period is April 1996 – December 2016.

(a) Prices of Risk



(b) Annualized Risk Premium

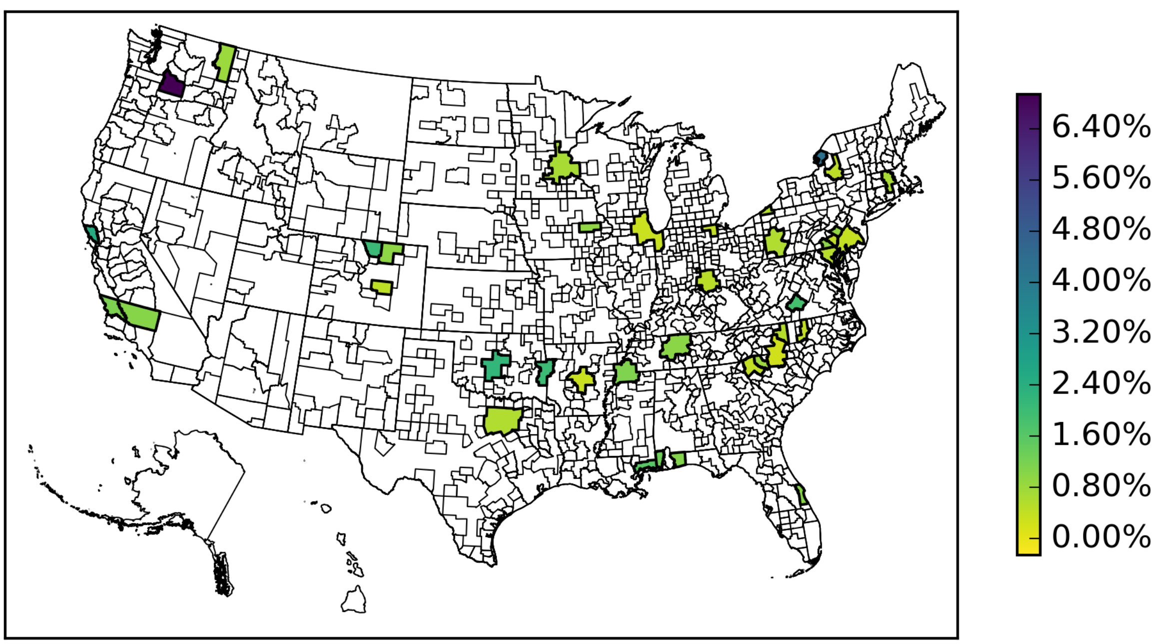
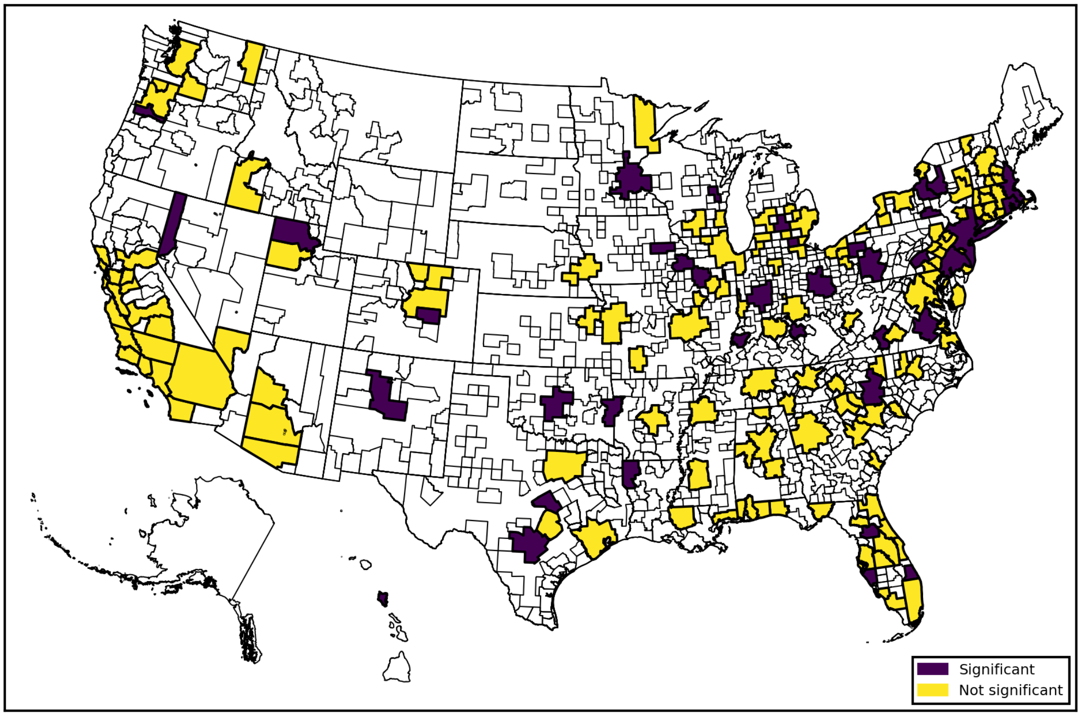


Figure 6: Idiosyncratic Volatility Risk Premium across MSAs

This figure plots geographical heat maps of the U.S. with the 178 MSAs for which we estimate prices of risk. In Panel (a), all dark red MSAs have a statistically positive significant idiosyncratic volatility ($IVOL$) price of risk, while in blue MSAs it is statistically insignificant. In Panel (b), we show a heat map of $IVOL$ annualized risk premium in the MSAs where this price of risk is significant. The sample period is April 1996 – December 2016.

(a) Prices of Risk



(b) Annualized Risk Premium

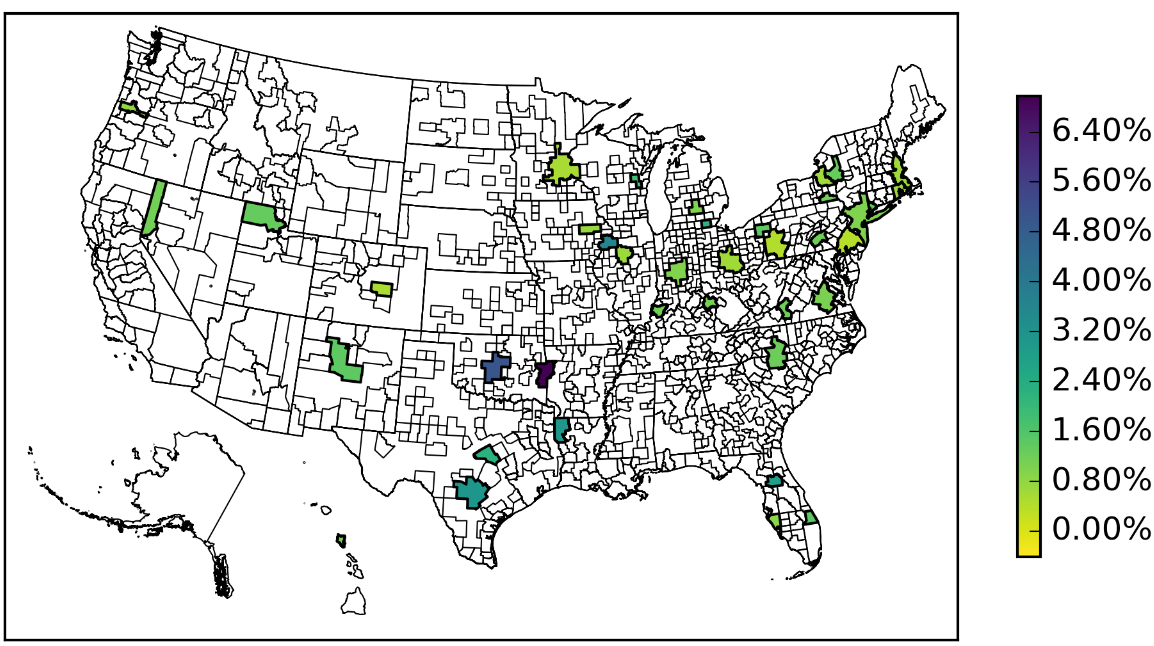
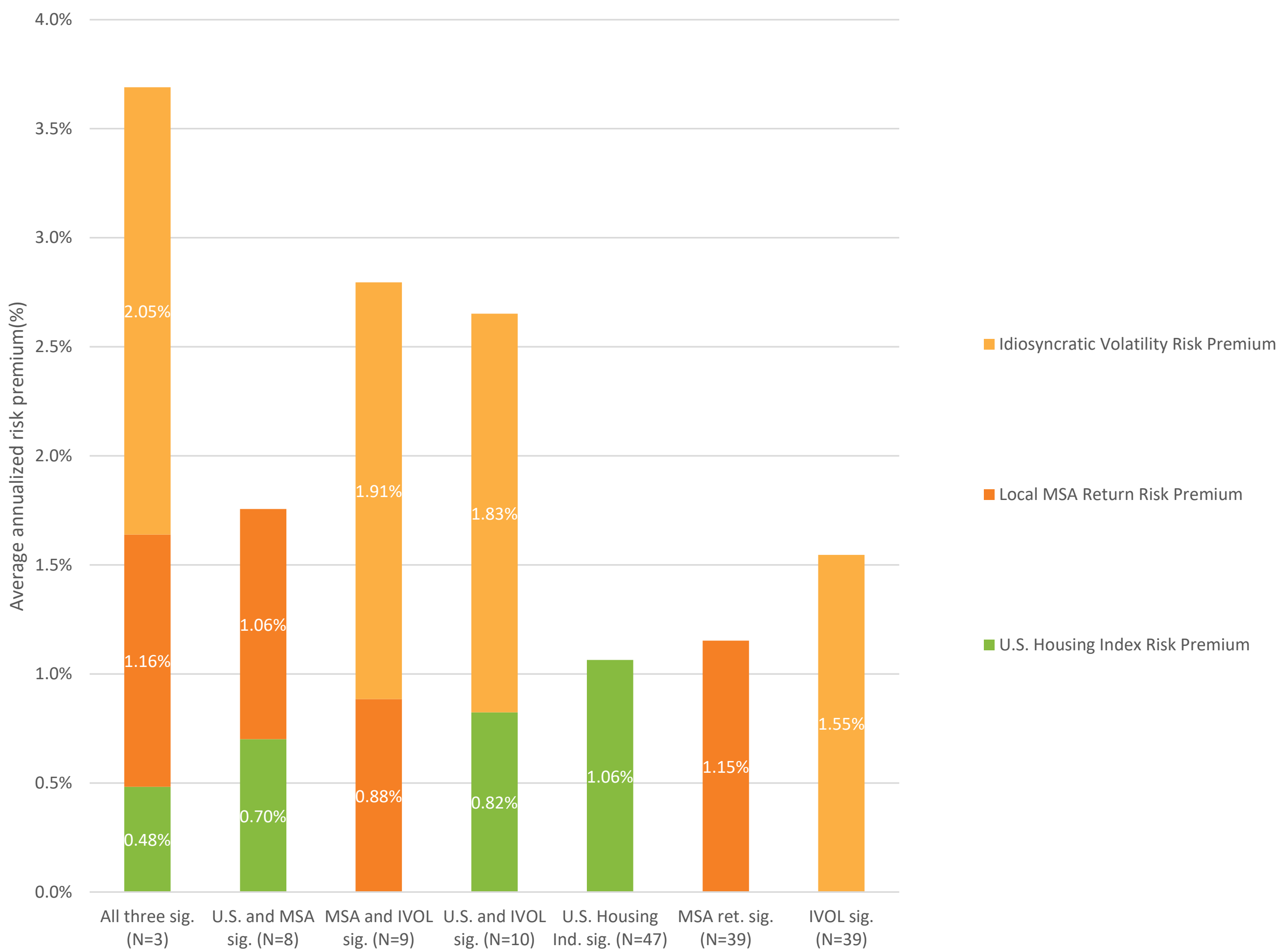


Figure 7: Average Annualized Risk Premium across MSAs

This figure plots 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 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.



The Cross-Section of Expected Housing Returns

Online Appendix

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Abstract

This paper performs a large-scale empirical asset pricing analysis of the cross-section of residential real-estate returns. Using monthly housing returns for 9,831 different zip codes across 178 Metropolitan Statistical Areas (MSAs), we estimate, for each MSA, a multifactor model with systematic housing-market risk (U.S. and local MSA) and idiosyncratic zip code-specific housing risk. We find that U.S. and MSA housing risks are positively priced in 26% and 22% of the MSAs, respectively. The evidence that MSA-level housing-market risk is priced in roughly a fifth of all MSAs runs counter to the common belief that the U.S. housing market is locally segmented. We also find that idiosyncratic risk is positively priced only in 22% of the MSAs, suggesting that the under-diversification of households' real estate portfolios is not widely priced. In the last part of the paper, we link MSA variation in the pricing of risk to MSA fundamentals. We find that illiquidity is important for the pricing of the U.S. housing-market risk, while homeownership increases the probability that MSA-level risk is positively priced. Idiosyncratic risk is more likely to be positively priced in MSAs with less undevelopable land and lower liquidity, indicating that under-diversification is more binding when households face fewer housing supply constraints and more illiquidity.

Keywords: Expected Housing Returns, Idiosyncratic Risk, Systematic Risk, Market Segmentation.

JEL Classification: G12, R30.

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Table 1: Descriptive Statistics 2007 Subsample

This table reports excess-return descriptive statistics including the mean, median, minimum, maximum, and standard deviation (SD), for zip code-level (Panel A), MSA-level (Panel B), U.S. housing index (Panel C) and U.S. stock market (Panel D) excess returns. We also report the cross-sectional dispersion (Dispersion) for zip code-level and MSA-level excess returns. All the 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-level 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 time-series 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 2007.

Panel A: Zip-Code Level Data							
	N	Mean	Median	Minimum	Maximum	SD	Dispersion
Excess Returns (% pa)	11010	1.25	1.18	-32.04	34.11	12.39	3.02
Panel B: MSA-Level Data							
	N	Mean	Median	Minimum	Maximum	SD	Dispersion
Excess Returns (% pa)	505	1.35	1.18	-24.56	27.07	9.76	2.79
Panel C: U.S. housing index							
		Mean	Median	Minimum	Maximum	SD	
Excess Returns (% pa)		1.91	1.73	-10.09	10.16	4.73	
Panel D: U.S. stock market							
		Mean	Median	Minimum	Maximum	SD	
Excess Returns (% pa)		6.88	10.66	-22.76	30.75	17.59	

Table 2: MSA Characteristics: 2007 vs. 2016 Sample

This table reports the mean for a set of MSA characteristics for MSAs in our main 1996-2016 sample and for a limited subsample from 1996-2007. We also report the difference in their means. We report these statistics for the within- and across-MSA hedging indicators, household total income, loan-to-value ratio, population, homeownership, average number of zip codes per MSA, and fraction of the population aged 20-45. 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 statistics. The averages of the loan-to-value ratio, share of undevelopable land, homeownership, fraction of population aged 20-45 and real rent volatility are in percentage units. Household total income is in 10^4 units and in USD. 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.

	Mean 2016 Sample MSAs	Mean 2007 Sample MSAs	Difference in Means
Within-MSA Hedging Indicator	0.50	0.49	3.8e-3
Across-MSA Hedging Indicator	0.47	0.46	8.6e-3
Household Total Income	7.33	6.64	0.69*
Loan-to-value Ratio	80.27	79.10	1.17**
Population	10.06	9.47	0.59**
Homeownership	67.83	70.13	-2.30**
Number of Zip Codes	21.44	20.89	0.55
Fraction of population aged 20-45	35.42	36.96	-1.54**

Table 3: Prices of Risk 2007 Subsample

This table reports descriptive statistics for estimated positive prices of risk. Following regression (3) in the main paper we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2007.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	149	8	0.23	0.82
Housing Index	149	9	0.01	0.03
Local MSA Return	149	32	0.02	0.07
$IVOL$	149	40	2.92	8.73
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	40	60	47	67
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	1	12	2	1
Sig. prices of risk	$>= 1$	$>= 2$	$>= 3$	$= 4$
Number of MSAs	71	50	9	1

Table 4: Prices of Risk 20 Zip Codes

This table reports descriptive statistics for estimated positive prices of risk. Following regression (3) in the main paper we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ 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 and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	135	3	0.17	0.80
Housing Index	135	72	9.4e-3	0.02
Local MSA Return	135	20	8.7e-3	0.04
$IVOL$	135	39	2.02	8.22
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	81	50	88	93
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	11	9	23	5
Sig. prices of risk	>= 1	>= 2	>= 3	= 4
Number of MSAs	93	45	13	3

Table 5: Prices of Risk with Value Characteristic

This table reports descriptive statistics for estimated positive prices of risk. We include our measure of zip code-level value in regression (3) in the main paper and estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return, $IVOL$ and value for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	178	10	0.22	0.90
Housing Index	178	50	0.01	0.04
MSA Return	178	27	0.01	0.06
$IVOL$	178	40	2.14	10.59
Value	178	36	0.03	0.16
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	69	62	79	94
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	8	5	11	1
Sig. prices of risk	>= 1	>= 2	>= 3	= 4
Number of MSAs	111	40	11	1

Table 6: Prices of Risk with Size I Characteristic

This table reports descriptive statistics for estimated positive prices of risk. We include our first measure of zip code-level size (log square feet) in regression (3) in the main paper and estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return, $IVOL$ and size (log square feet) for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	155	3	0.20	0.73
Housing Index	155	48	0.01	0.04
MSA Return	155	33	0.01	0.06
$IVOL$	155	34	2.24	10.20
Size	155	20	0.02	0.10
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	69	59	70	86
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	12	8	12	3
Sig. prices of risk	>= 1	>= 2	>= 3	= 4
Number of MSAs	92	38	8	0

Table 7: Prices of Risk with Size II Characteristic

This table reports descriptive statistics for estimated positive prices of risk. We include our second measure of zip code-level size (log price) in regression (3) in the main paper and estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return, $IVOL$ and size (log price) for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	178	8	0.19	1.13
Housing Index	178	53	0.01	0.04
MSA Return	178	38	0.01	0.06
$IVOL$	178	36	2.24	10.29
Size	178	30	0.01	0.05
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	84	65	78	101
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	7	9	11	1
Sig. prices of risk	>= 1	>= 2	>= 3	= 4
Number of MSAs	117	41	7	0

Table 8: Prices of Risk without U.S. Stock Market Risk Factor

This table reports descriptive statistics for estimated positive prices of risk. We estimate our model in equations (1) and (3) in the main paper excluding the stock market return (r_t^{mkt}) to obtain prices of risk on the U.S. housing index, local MSA return and $IVOL$ for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Housing Index	178	50	0.01	0.04
MSA Return	178	33	0.01	0.06
$IVOL$	178	39	1.99	9.94
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	75	63	79	99
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	8	9	10	4
Sig. prices of risk	>= 1	>= 2	>= 3	
Number of MSAs	99	19	4	

Table 9: Positive and Negative Prices of Risk 20 Zip Codes

This table reports descriptive statistics for estimated positive and negative prices of risk. Following regression (3) we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ 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 and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 10% level two-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	$\lambda < 0$	Average λ	Disp. λ
Stock Market	135	1	29	-0.18	0.64
Housing Index	135	53	0	6.7e-3	0.02
MSA Return	135	11	5	4.7e-4	0.06
$IVOL$	135	34	13	0.83	8.64
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}	
Number of MSAs	64	60	80	88	
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}	
Number of MSAs	5	3	20	0	
Sig. prices of risk	>= 1	>= 2	>= 3	= 4	
Number of MSAs	102	36	8	0	

Table 10: Prices of Risk and 5% Significance Level

This table reports descriptive statistics for estimated positive prices of risk. Following regression (3) in the main paper we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ for each MSA with at least 15 zip codes. We report the number of MSAs for which we are able to estimate the prices of risk and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 5% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	178	2	0.19	0.17
Housing Index	178	35	0.01	0.04
MSA Return	178	20	0.01	0.06
$IVOL$	178	32	2.14	9.66
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	53	51	63	80
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	2	1	4	0
Sig. prices of risk	$>= 1$	$>= 2$	$>= 3$	$= 4$
Number of MSAs	81	8	0	0

Table 11: Prices of Risk and 5% Significance Level 20 Zip Codes

This table reports descriptive statistics for estimated positive prices of risk. Following regression (3) in the main paper we estimate prices of risk on the U.S. stock market, U.S. housing index, local MSA return and $IVOL$ 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 and the number of MSAs where each of the risks are significant (positive and negative). We also report the average λ as well as the cross-sectional dispersion (Dispersion) of the prices of risk. In the bottom panels, we also report the number of MSAs different combinations of prices of risk that are significant. We look at MSAs were either one of the other price of risk is significant, and also at MSAs were both prices of risk are significant. Finally, we look at how many MSAs have at least one, two, three or all significant prices of risk. Average prices of risk are annualized by multiplying them by 12. Significance is at the 5% level one-sided using Newey-West standard errors with 2 lags. The sample period is April 1996 – December 2016.

	N	$\lambda > 0$	Average λ	Dispersion λ
Stock Market	135	1	0.16	0
Housing Index	135	53	6.7e-3	0.02
MSA Return	135	11	7.0e-3	0.04
$IVOL$	135	35	1.81	8.18
Price of Risk	λ^{msa} or λ^{hi}	λ^{msa} or λ^{ivol}	λ^{hi} or λ^{ivol}	λ^{msa} or λ^{hi} or λ^{ivol}
Number of MSAs	61	44	72	78
Price of Risk	λ^{msa} and λ^{hi}	λ^{msa} and λ^{ivol}	λ^{hi} and λ^{ivol}	λ^{msa} and λ^{hi} and λ^{ivol}
Number of MSAs	3	2	16	0
Sig. prices of risk	$>= 1$	$>= 2$	$>= 3$	$= 4$
Number of MSAs	78	21	1	0

Table 12: 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. housing level risk, MSA local return risk, and on idiosyncratic risk ($IVOL$) on a set of MSA characteristics that include: across-MSA hedging indicator, log of household total income, loan-to-value ratio, log of population, share of undevelopable land, WRLURI, homeownership, real rent volatility, log of days-on-market, and to control for time-series size the number of excess return observations per MSA. 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^{hi}	λ^{msa}	λ^{ivol}
Across-MSA Hedging Indicator	0.20	0.14	-0.07
	(1.52)	(1.15)	(-0.75)
Log Income	0.10	-0.54	0.08
	(0.22)	(-1.44)	(0.20)
Loan-to-value ratio	-2.88	-1.52	2.36
	(-0.97)	(-0.54)	(0.98)
Log Population	-0.03	4.1e-3	0.04
	(-0.47)	(0.07)	(0.62)
Undevelopable Land	0.17	0.07	-0.38
	(0.59)	(0.27)	(-1.31)
WRLURI	-0.08	0.03	0.08
	(-1.16)	(0.42)	(1.34)
Homeownership	0.46	2.04**	0.28
	(0.39)	(2.08)	(0.33)
Real Rent Volatility	-1.20	0.19	-2.54
	(-0.33)	(0.06)	(-0.85)
Log Days-on-market	0.62**	-0.10	0.44*
	(2.35)	(-0.40)	(1.75)
Number of Excess Return Obs.	-0.61***	-0.09	0.06
	(-2.79)	(-0.45)	(0.33)
Nobs	118	118	118
Pseudo R^2	12.7%	4.0%	11.8%