Correlated Labor Market Risk and Housing Investment

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Abstract

This paper shows that households have lower levels of housing investment when they live in areas with labor markets that are more correlated with their industry of employment. In other words, if a household lives in an area where many other households work in the same or similar industries, then housing may be a riskier asset as it is more correlated with labor market income. Thus households decrease their investment in housing. Using US microdata from 2007-2017 a one-standard deviation increase in a household's correlated labor market risk is associated with a decline in housing investment by around \$6,750. This decline is driven by concentrations and riskiness of other correlated industries, suggesting agglomeration in one industry can have negative spillovers to workers of other related industries.

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1 Introduction

For households in the United States, housing investment plays an important role in wealth accumulation. According to the Federal Reserve's *Survey of Consumer Finances*, over half of the net wealth of the median household is in single-family residential housing. Additionally, property taxes play an out-sized role in funding local governments. The Urban Institute estimates in 2016 that local governments raised \$487 billion using property taxes, which comprised nearly 30% of their general revenue.[1] In light of these realities it is important to understand the determinants of housing investment decisions that individuals make.

Within the economics literature, housing occupies a unique role as both as a consumption good as well as an asset for investment. Several papers have examined this property and shown how it can lead to housing assets comprising a large fraction of homeowner's net worth.[2] Given this large fraction, a household's decision to rent or own a home (and how much to spend when buying a home) will significantly affect the risk profile of their investment portfolio. As labor wages are the primary source of income for the vast majority of individuals, households should adjust their investment decisions in response to both labor market risk[3] and income variability.[4] As a result, rational households will incorporate labor market risk in their housing investment decisions.

House prices will fall in a particular market when many households are looking to sell their homes at the same time. Simultaneous job loss may lead to such an outcome, and when such an event is likely, housing investment is less useful for mitigating labor market risk. That is, households may invest less in housing when they perceive that their own chance of job loss is correlated with that of many other households living in their same area, making housing investment is an ineffective hedge to their labor market risk. Households want to optimize their portfolios and housing capital is a less valuable investment when its return is

[1] These taxes were split between residential and commercial properties, but Gravelle and Wallace 2007 suggest that more than 60% of property tax revenue is from residential properties.

[2] See Henderson and Ioannides 1983, Brueckner 1997 and Cocco 2005.

[3] See Betermier et al. 2011, Heaton and Lucas 2000.

[4] See Haurin 1991, Gathergood 2011, Robst et al. 1999, Diaz-Serrano 2005a, Diaz-Serrano 2005b.

correlated with the return on a household's human capital (wages).

Ortalo-Magne and Rady (2006) build a theoretical life-cycle model of housing investment that in a special case predicts when house prices and incomes are positively correlated, households will be more likely to rent. Davidoff (2006) expands on Ortalo-Mange and Rady's model, and uses 1990 US Census data to show that households living in a city with positive correlation between house prices and incomes in their industry of employment invest less in housing.

This paper attempts to provide a mechanism through which the relationship uncovered by Davidoff could operate, by building a measure of correlated labor market risk to identify whether households reduce their housing investment when their job risk is correlated with that of others living in their same area. This correlated risk could arise due to the concentration of an individual's own industry, the concentration of other closely related industries, or some combination of the two. The measure created in this paper can separate the effect on housing investment of risk arising from a household's own industry and the risk coming from other closely related industries.

Several other papers have looked at the effects of intra-household correlated labor market risk on housing investment. Shore and Sinai (2010) find that in two-income households where individuals work in the same industry, there is greater investment in housing. Jansson (2017) replicates this finding using Swedish microdata, and proposes that the pattern is likely due to a lower overall risk of any decline in income.[5] Jansson also finds that despite these same-industry households investing more in housing, they have a lower probability of ownership.

This paper looks at the linkage between inter-household correlated labor market risk and housing investment decisions by combining microdata from multiple US sources to create a measure of correlated labor market risk. This risk measure is calculated at the

[5]Households with individuals that work in the same industry are more likely to lose their jobs at the same time, but households with individuals working in different industries have a higher risk of seeing any decline in income.

industry-year-market level. The calculation of the correlated labor market risk measure is described in more detail in the next section of the paper, and the third section describes the data used. The fourth section details the empirical approach used to estimate the relationship between the correlated labor market risk measure and household housing investment decisions. The estimation uses individual-level American Community Survey data to asses the effect of the measure on both the intensive and extensive margins of housing investment. By creating a risk measure for each industry, market and year combination, estimates can be identified even in the presence of industry, market, and state-year fixed effects. The fifth section details the results, which suggest that a one standard deviation increase in the risk measure leads to a reduction in the value of housing owned of approximately $6,750. This effect is primarily driven by the risk coming from households in the same market who work in different, but related industries from the homeowner. The results also imply that a one standard deviation increase in the risk measure leads to a 2% decline in the probability of becoming a homeowner. Additional specifications suggest the impact of risk on housing investment is lower for households with other sources of savings and in states with higher unemployment benefits. The sixth section concludes.

2 Correlated Labor Market Risk Measure

A simple labor market risk measure would incorporate the concentration of various industries in a market interacted with each industry's level of riskiness. This computation would lead to a weighted risk measure of the form:

$$UncorrelatedRiskMeasure_{m,t} = \sum_j [Risk_{j,t} * Concen_{j,m,t}] \tag{1}$$

In (1), $Risk_{j,t}$ is the chance that a worker in industry j loses his job in year t and $Concen_{j,m,t})$ is the concentration of the specific industries d in market (m) and year t.[6] Note

[6]In this paper, the defined market is at the Public Use Microdata Area (PUMA) level. PUMAs are

that this weighted risk measure is specific to a market and time period, not varying across industries. Figure 1 displays what this uncorrelated risk measure looks like across PUMAs for the contiguous United States.[7]

By contrast, a correlated labor market risk measure aims to identify the risk that, when an individual loses his job, other people in the same market lose their jobs as well. The risk of many people in the same market losing their jobs will capture the risk of a decline in the local housing market relevant to a particular industry. Thus, the risk measure should include the risk an individual faces from his own job, as well as the correlated risk posed by individuals working in the same market. The likelihood that individual i loses her job when a individual j loses his own job is a function of both how correlated the individuals' industries are and how risky individual j's job is. Finally, these industry risks need to be weighted by the size of each industry in each particular market. These considerations lead to the following correlated risk measure:

$$RiskMeasure_{d,m,t} = \sum_j [Risk_{j,t} * Concen_{j,m,t} * Corr_{d,j}] \tag{2}$$

$$RiskMeasure_{d,m,t} = Risk_{d,t} * Concen_{d,m,t} + \sum_{j \neq d} [Risk_{j,t} * Concen_{j,m,t} * Corr_{d,j}] \tag{3}$$

In (2), the correlated risk measure now includes a term ($Corr_{d,j}$) that gives the correlation[8] between industry j and the given worker's own industry, d. Thus if industry j and d are closely correlated, then a worker in industry j is more likely to lose his job at the same time as a worker in industry d.[9] The risk measure equation in (2) and (3) are equivalent as $Corr_{d,d}$ is equal to one.

created from census geography and follow county or census-designated place boundaries. They generally contain between 100,000 and 200,000 residents. PUMAs created using 2000 Census boundaries are used for all analyses that follow. Industry is defined at the 3-digit NAICS code.

[7] The risk measure is expressed in percentages as it is a weighted measure of $Risk_{j,t}$ which is calculated as a percentage chance of an individual losing a job in industry j.

[8] The correlation between two industries is calculated as the correlation between the 1-year employment changes in industry j and d from 2000-2018. This is described in more detail in a following section.

[9] Implicitly $Risk_{d,t}$ is weighted by the correlation between industry d and itself, but that correlation is equal to one and is thus not shown in the equation.

This risk measure encompasses both the direct effect of labor market risk on a household's housing investment through the risk of job loss ($Risk_{d,t}$), and the indirect effect of the correlated labor market risk that impacts a household's housing investment decision through potential housing price declines. The risk measure calculated in (3) shows how the effect of a worker's own industry ($Risk_{d,t} * Concen_{d,m,t}$ referred to as "Own Industry Risk" in the rest of the paper) can be separated from the effect of other industries in a worker's market ($\sum_{j \neq d}[Risk_{j,t} * Concen_{j,m,t} * Corr_{d,j}]$ referred to as "Other Industry Risk" in the remainder of the paper). "Own Industry Risk" can be further broken down by including $Risk_{d,t}$ and $Concen_{d,m,t}$ as separate variables in the regressions. The correlated risk measure is equal to the sum of the Own Industry Risk and Other Industry Risk terms as seen in (3).

The risk of job loss is calculated nationally for each industry and each year.[10] This risk is weighted by the concentration ($Concen_{j,m,t}$) of the specific industries in each market (m) as in equation (1). It should be noted that industry concentration in equations (1), (2) and (3) is computed not for the entire labor market, but instead by residential area (at the PUMA level). The reason is that PUMA-level employment concentrations and correlations are what matter in determining the co-movement of a worker's income and his own home value, which reflects prices in the local(PUMA-level) housing market.

As an example, for construction workers in a specific Public Use Microdata Area (PUMA) in Boston, the measure in (3) takes labor market riskiness for construction workers nationally,[11] weights it by the concentration of construction workers in that PUMA in Boston,[12] and then adds the riskiness of each other industry adjusted by that industry's correlation with the construction industry and weighted by that industry's concentration in that particular PUMA in Boston. As the correlated risk measure is calculated for each industry, market, and year combination it will be different for retail workers in the same PUMA in Boston[13]

[10] The job loss risk of other industries changes each year, but the correlation between industries is assumed constant for the sample period.

[11] Labor market riskiness is calculated as the chance that a worker in that industry loses his job in a given year.

[12] The concentration is calculated as the share of employed individuals in that PUMA working in construction.

[13] Although they live in the same PUMA, retail workers have a different industry risk level and have different

and also different for construction workers in a PUMA in Hartford.[14]

Figure 2 displays the average risk measure from 2007-2017 across PUMAs weighted by the number of observed households in each industry for each PUMA.[15] Though there are some similarities with the geographic distribution of uncorrelated risk (Figure 1) there is different spatial variation to the average risk measure. Figure 3 shows the average correlated risk measure across the US for a specific industry code (NAICS code 336) corresponding to Transportation Equipment Manufacturing. The geographic patters here show higher risk in areas with higher levels of car manufacturing employment (the Midwest and Tennessee/Alabama) but also show higher levels of risk in areas not traditionally associated with transportation manufacturing (Central Florida and Las Vegas).

Figure 4 shows the geographic distribution of the Other Industry Risk term for the Transportation Equipment Manufacturing industry code. This map shows there are higher risks in areas with closely related industries (northern Indiana/Ohio and Tennessee) as well as areas with high concentrations of other cyclical industries (Nevada and Florida). Figure 5 displays the distribution of Own Industry Risk across the US for the Transportation Equipment Manufacturing industry. This map displays the average own industry risk value across years so it primarily serves as a map of industry concentration.[16] The concentration of manufacturing in the Midwest and south of the country is readily apparent.[17]

The riskiest industries in a given market tend to be Construction or a closely related field.[18] Examples of other risky industries include Furniture and Related Product Manufacturing, Food Services and Drinking Places,and Rental and Leasing Services. The safest industries in a given PUMA are often Nursing and Residential Care Facilities and National Security and

correlations with other industries than construction workers do.

[14]Each of those PUMAs will have different shares of both construction workers as well as different shares of other industries.

[15]The risk measure is expressed in percentages as it is a weighted measure of $Risk_{j,t}$ which is calculated as a percentage chance of an individual losing a job in industry j. The correlated risk measure is lower than the uncorrelated risk measure as the maximum value $Corr_{d,j}$ can take is one.

[16]$Risk_{d,t}$ is calculated nationally and thus does not vary at the PUMA level.

[17]The concentrations in the Seattle area are mostly due to airplane manufacturing for Boeing, and concentrations in Connecticut and South-Eastern Virginia are due to shipbuilding industries.

[18]Nonmetallic Mineral Product Manufacturing has a correlation of .966 with the construction industry.

International Affairs.[19] Examples of other safe industries include Administration of Human Resource Programs, Administration of Economic Programs, and Utilities.

3 Data

The correlated risk measure from above (equation 2 and 3) requires measures of industry risk, local industry concentration and cross-industry correlations. These measures are combined into a risk measure calculated at the industry-year-PUMA level and then appended to individual-level data on housing investment. All industries are defined using three-digit NAICS codes. Small industry categories are combined to insure each that classification has a large number of observations,[20] leading to 77 different industry codes being used in the main analysis.

3.1 Industry Risks

The Current Population Survey (CPS) is used to identify an individuals' industry risk. The CPS is a monthly survey of approximately 60,000 US households that follows individuals for four months, after which they are removed from the survey for eight months, and then returned to the survey for four more months. Data from 2000 to 2017 provided by the University of Minnesota's Integrated Public Use Microdata (IPUMS) is used to create a file covering each of the eight months an individual was interviewed. The industry risk is calculated for each industry, where the risk is defined as the probability of having an unemployment spell after working in a given industry.[21] In calculating the unemployment risks associated with working in a given industry the sample is limited to respondents between

[19]National Security and International Affairs are primarily civilian and military employees of the Department of Defense.

[20]Industry subcodes that average fewer than 200,000 employees a month in the Quarterly Census of Employment and Wages (QCEW) from 2000-2018 are merged into related larger subcodes. Examples of small industry codes eliminated include '521-Monetary authorities - central bank', '712-Museums, historical sites, zoos, and parks' and '927-Space research and technology'.

[21]An individual is categorized as unemployed if he is unemployed, unable to work, or unpaid and working less than 15 hours a week.

the ages of 26 and 60.[22] Industry risk measures are calculated for each year from 2000 to 2017 at the national level.

3.2 Industry Concentrations

Industry concentrations are calculated using American Community Survey (ACS) estimates provided by IPUMS at the Public Use Microdata Area (PUMA) level. The American Community Survey is an annual survey that replaced the long form census to provide more timely updates than the decennial census. The industry concentrations are calculated primarily using three-year ACS files, which are available from 2007 to 2013. Since the three-year files were discontinued after 2013, five-year estimates are used from 2014 to 2017.[23] Industry shares are calculated for each PUMA in each year from 2007 to 2017.

3.3 Industry Correlations

Correlations between industries are calculated using the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics. The QCEW is created through the tabulation of employment and wages of establishments that report to the unemployment insurance programs, and it represents around 97% of all wage and salary civilian employment. Using national data from 2000-2018, correlation coefficients for one-year employment growth rates are calculated for each pair of the 77 different industries.[24] The industry correlations are unique for each industry pair, but do not vary by year or across PUMAs.

[22] This limits the risk of identifying unemployment spells that are due to retirement or schooling instead of labor market risk.

[23] The ACS is given to roughly 1% of the US population each year. However, the Census Bureau recommends using three- or five-year ACS files for aggregation at geographic units when precision is more important than the currency of the data. The Census Bureau weights data collected in the previous three (or five) years to estimate current populations. Since all individuals are making housing investment decisions before they appear in the sample, there is no benefit to using less precise one-year samples. In an alternate specification, 2000 Census data are used as a baseline, and current year industry concentrations are calculated by assuming each industry in each PUMA grew at its respective national industry growth rate (this approach is often referred to as a Bartik shift share).

[24] The percent change in employment accurately captures correlations between job risk across industries. Additionally the one-year growth rate smooths out seasonal variation in industries such as education by comparing employment in a given month to employment in the same month one year prior.

3.4 Housing Investment Decisions

The primary data source for the level of housing investment comes from the one-year ACS files from IPUMS. The ACS includes measures of an individual's industry, occupation, self-reported income and home value along with individual controls such as marital status, age, education levels, race, ethnicity and PUMA of residence. The data are from the 2007 to 2017 period and are restricted to households that report an individual who is employed, has positive income and is between the ages of 26-60.

3.5 Sample Restrictions

PUMAs are defined by population, and thus can comprise large geographic areas that may not accurately represent local housing or labor markets. PUMAs in the sample are restricted to those within a metropolitan area that contains at least 5 PUMAs.[25] To get a better sense of how individuals make housing decisions in response to labor market decisions,[26] the sample is limited to households that have moved into their current home in the last 9 years.[27] As home values are self reported, more recent homebuyers are likely those with more accurate views of their home value. Since many homeowners do not update housing decisions frequently, limiting to this sample likely focuses on individuals whose current labor market status influenced the housing investment decision.

To protect an individual's privacy, the Census Bureau recodes households that report home values in the top 1% in each state and year. These high-home-value households list a home value equal to the average of those topcoded. Thus the top 1% of home values in each state-year are the same and do not accurately represent housing investment. Additionally,

[25]This restriction limits the sample to the 44 largest metropolitan areas, which contain 48.3% of all homeowners and 55.6% of all renters. These large metropolitan areas contain 62.6% of all homeowners and 66.8% of all renters who live in metropolitan areas.

[26]Additionally, this restriction reduces the odds that individuals may have changed jobs or industries after purchasing a home.

[27]39.1% of all homeowners have moved in the last 9 years and, of those households in larger metropolitan areas, 40.1% have moved in the last 9 years. Only 69.6% of all homeowners report when they moved into their current home.

there is likely some geographic correlation within a given state as to where these topcoded households may live. As a result, top-coded households are dropped from the analyses that focus on the value of housing investment but are included in estimations of tenure choice. Finally, each household is assigned the demographic and industry information of the highest wage earner in the household.[28]

The final sample includes 907,695 homeowners and 790,166 renters. Table 1 presents summary statistics for these households. The summary statistics show that homeowners tend to be older, whiter, wealthier and more educated than renters, with higher rates of marriage and larger household sizes. Homeowners appear to work in slightly less risky and less concentrated industries, but there does not appear to be a meaningful gap between the two.

4 Empirical Strategy

Correlated labor market risk can influence an individual's home investment decisions either by reducing the likelihood of purchasing a home (extensive margin), or by reducing the amount invested in a home once one is purchased (intensive margin). Focusing on the intensive margin leads to the following main specification:

$$HouseValue_{i,d,m,s,t} = \alpha + \theta RiskMeasure_{d,m,t} + \beta X_i + \gamma D_d + \psi T_{t,s} + \omega M_m + \nu_i \quad (4)$$

where $HouseValue$ is the reported value of house owned by household i. All regressions account for industry (D_d) and PUMA fixed effects (M_m). Additionally, to control for state specific housing or labor market shocks, state-year fixed effects are added ($T_{t,s}$). X is a vector of individual level characteristics.[29] Included in the individual specific demographic controls

[28]The household is likely to care most about the highest wage earner's correlated labor market risk.

[29]As stated in the previous section, the characteristics of the individual come from the highest wage earner in the household.

are indicators for race, ethnicity, educational attainment, veteran status,[30] self-employment,[31] marital status, presence of a mortgage as well as age, age squared, number of employed workers in the household, and number of individuals in the household. Additionally, the regression includes controls for indicators of how long a household has lived in their current house. Consistent with prior literature, the analysis should show that when correlated labor market risks are higher, households invest less in housing as the asset is less of a good hedge against labor market risk.

The correlated risk measure can be included in the regressions as one measure or broken up into own industry risk and other industry risk as detailed in equation 3. The coefficient on other industry risk is expected to be negative as higher concentrations of more risky, related industries should reduce a household's incentive to invest in housing. The predicted effect of the own industry risk measure is theoretically ambiguous. Although one would expect higher levels of own industry risk to reduce housing investment through a similar channel to other industry risk, the constituent components of own industry risk could lead to higher housing investment. Higher levels of industry concentration may result in higher levels of housing investment through agglomeration effects or more chances for career advancement which raises expectations of future earnings.

For notational convenience several additional controls are included in the regression but not shown in equation (4). To control for within and across-industry variation in housing investment decisions that could be due to the particular job held, dummies for two-digit occupation categories are included.[32] Controls for household income cannot be included since the variable of interest, correlated labor market risk, influences both an individual's housing investment choice and his wage. Income likely changes a household's housing investment decision, however the regression includes controls for both the median income by industry and occupation for each metropolitan area.

[30] Veterans can qualify for reduced cost loans which may influence housing decisions.

[31] It is likely that these individuals may face additional labor market risks not directly tied to their industry.

[32] These variables control for the fact that, although doctors and nurses work in the same industry, they likely have different levels of housing investment.

In addition to looking at the impact of local labor market risk on housing investment conditional on purchasing a house, a separate regression explores how this risk can influence the decision to become a homeowner. For this extensive margin the regression equation is:

$$Homeowner_{i,d,m,s,t} = \alpha + \theta RiskMeasure_{d,m,t} + \beta X_i + \gamma D_d + \psi T_{t,s} + \omega M_m + \nu_i \tag{5}$$

For this regression the sample includes all homeowners and renters. This regression does not require accurate estimates of an individual's home value, so households with top-coded home values are included in the sample. This regression includes the same controls as those in the home value regression, with the exception of a control for presence of a mortgage.[33] Equation (5) is estimated both as a linear probability model and a probit, with similar results. The linear probability model estimates are shown for ease of convenience. Prior literature would predict that higher correlated labor market risk should decrease the probability of being a homeowner as the benefit of housing as an investment asset is decreased.

5 Results

Of primary interest is the effect of the correlated labor market risk measure on households' housing investments. Table 2 presents a series of three regressions that include the various components of the correlated labor market risk measure. Each coefficient on the risk or concentration measure gives the effect of a one-standard deviation change in that measure. The first column reports the coefficient on the correlated labor market risk measure and shows that for a one-standard deviation increase in a household's correlated labor market risk, households reduce investment in housing by \$6,750. This result is of similar direction and magnitude to Davidoff's (2006) estimate, which showed that a one standard-deviation in income-price covariance led to a decline in housing investment of approximately \$7,500.

To identify whether households are changing housing investment in response to the risk

[33] The presence of a mortgage is limited to only those households who own a home.

faced from their own industry as opposed to the risk coming from individuals working in other industries, column 2 breaks the risk measure into the other and own industry risk. The coefficient on other industry risk is relatively large, negative and statistically significant, indicating that households reduce their housing investment in response to higher correlations and riskiness of other industries in the same PUMA. The coefficient on own industry risk is positive, suggesting that households increase their housing investment in response to higher levels of concentration and risk from their own industry.

The third column breaks apart the own industry risk term into its constituent components ($Risk_{d,t}$ and $Concen_{d,m,t}$) and shows there is a positive relationship between the concentration of a given industry in a PUMA and the household's housing investment. The positive result could come from agglomeration effects, where more concentrated industries in a particular PUMA may be more productive due to spillovers. Additionally, households may perceive less risk when there is a large concentration of same-industry jobs as they may feel they have more employment opportunities available if there is a firm specific shock as opposed to an industry specific one. Finally, a large industry concentration may lead to more opportunities for upward advancement on the career ladder, and thus households may have expectations of higher future wages, raising their investment in housing.

All of the regressions in Table 2 include state-year fixed effects and fixed-effects for PUMAs, industry codes and occupation codes as well as indicator variables for number of individuals and number of employed individuals in the household.

The coefficients on the control variables in the Table 2 models match economic intuition. Households where a female is the highest wage earner are likely to have lower wages (and thus lower investment) due to the gender wage gap in the US. Married individuals invest more in housing as do white households. Increasing levels of education lead to more housing investment, and self-employed individuals also invest more in housing. Mortgages allow households to invest more in housing as they are less credit constrained. Households that have moved more recently invest more in housing than those who have remained in place.[34] Additionally, households with higher wages in their industry or occupation also invest more in housing.

Table 3 shows the results of the linear probability model described in Equation (4). The outcome variable is tenure choice. The homeowners in this sample now include the top-coded individuals who were excluded from the previous regressions on housing investment as the outcome is now tenure choice. Similarly to Table 2, the models in Table 3 start with the effect of correlated labor market risk and suggest that a one-standard deviation increase in the correlated labor market risk measure is associated with a two percentage point decline in the probability that a household is a homeowner. In column 2 results show that both other industry and own industry risk reduce the probability of being a homeowner, and column 3 show the negative effect of own industry risk is primarily drive by changes in $Concen_{d,m,t}$. With the tenure choice model we see there is a negative effect on home ownership probabilities for both own and other industry risk, matching theoretical predictions. Using a probit or logit model for this estimation gives similar results.[35]

The coefficients on the control variables in Table 3 also match economic intuition, with a lower probability of home ownership for households with the highest wage earner being a female. Married households are more likely to own a home as are white households. Increasing levels of education lead to higher home ownership and individuals who who have recently moved are less likely to own a home.

5.1 Sources of Bias

Homeowners are a selected sample, as households that purchase a home may be a biased sub-sample of all households. This potential selection needs to be controlled for using a two-step procedure. First, a probit on likelihood of owning a home is run. The results from

[34]It is possible households that have moved less recently are reporting the value of their house when they bought it, as opposed to its current market value which could also explain this decline in home value.

[35]Probit and logit coefficients are available from the author upon request.

the probit are used to calculate an Inverse Mills ratio which is included in the OLS housing investment equation. Table 4 displays the coefficients of interest from a Heckman Two-Step Selection model for housing investment. The results in Table 4 show that controlling for this sample selection issue does not appear to have a large impact on the coefficients of interest. The coefficients in Table 4 are nearly identical to those reported in Table 2, and the coefficient on the Inverse Mills Ratio is not statistically significant. As selection does not appear to be biasing the effects of risk measures on housing investment levels, the remaining results do not incorporate the selection procedure.

The regression coefficients shown thus far are reflective of a particular sample of individuals. The sample used is limited to households living in large metropolitan areas,[36] who moved into their homes in the last 9 years.[37] Figure 6 shows the coefficient on the risk measure for a variety of choices of restrictions on how recently households moved in, and how many PUMAs a metropolitan area must have to be included. Moving from left to right across the figure restricts the sample to larger and larger metropolitan areas and leads to a slight increase in the magnitude of the coefficient.[38]. Restricting to more recent movers[39] appears to increase the magnitude of the coefficient as well. The shapes of the coefficient points correspond to their level of statistical significance. The largest triangle corresponds to the regression presented in column 1 of Table 2. The figure suggests that although there is variation in estimated coefficients for different samples, the impact of the correlated labor market risk measure is consistently negative and mostly statistically significant.

Another source of potential bias given the data used in these models is that the time period where the American Community Survey is available (2007 to 2017), overlaps with

[36]Large metropolitan areas here mean metropolitan areas with at least 5 PUMAS. PUMAs are defined by population, not geography, and thus can comprise large geographic areas that may not accurately represent local housing or labor markets. Limiting to PUMAs in larger cities restricts to PUMAs that encompass smaller areas.

[37]These households are less likely to have changed industry since purchasing their home, and likely have more accurate information about their own home's value.

[38]The coefficients are all negative so a decline in the chart is an increase in the size of the coefficient.

[39]The different color lines each refer to a different restriction on when the household must have moved into their current home.

both the great recession and the recovery afterwards. It is plausible that areas with higher levels of labor market risk were more effected by the housing crash and thus those areas would have lower house prices and lower levels of housing investment. This would lead to a larger negative estimate of teh effect of the risk measure on housing investment. Although PUMA and state-year fixed effects should absorb most of this potential, the influence of labor market risk on housing investment could have changed in response to the great recession. To identify the effect of the risk measure across time, the first column of Table 5 reports the coefficients of the risk measure interacted with the years in the sample. The coefficients suggest that the effect of risk measure on housing investment actually decreased in magnitude in the immediate aftermath of the great recession. The second column interacts own industry and other industry risk with year as well. The results suggest that the effects are relatively stable across time.

There is some concern that estimating the effect of the correlated risk measure on housing investment could be endogenous as households might choose where to work or what industry to work in based on their housing investment options. Tables 6 and 7 present ways to address two different potential sources of endogeneity. One source of bias is that individuals in certain areas may change jobs in response to this labor market risk, or the effect of risk could change the composition of people moving to the area. Both effects could result in places where people want to invest more in housing to adjust industry concentrations and increase the proportion of safer industries. This would potentially bias the estimates of the effect of the risk measure to be more negative as places with higher housing investment would have lower levels of risk. Table 6 addresses this concern by calculating the risk measure using industry concentrations from the 2000 Census and national industry growth rates. This method assumes that various industries grow at the same level in each locality as they do nationally. As with the other models, the households span from 2007-2017 and have all moved into their current homes in the last 9 years. Thus the vast majority of this sample purchased their home after the 2000 Census. Table 6 suggests that the effect of the risk measure on housing investment is similar or perhaps slightly larger in magnitude than the baseline specification.

Another potential source of endogeneity is more closely related to the individual homeowner. Individuals with unobserved preferences for greater housing consumption could self-select into industries (or PUMAs) with lower levels of correlated labor market risk. This self-selection would increase the estimated coefficient of the labor market risk variable as the unobserved housing demand would be negatively correlated with the risk measure. To address this concern, Table 7 presents results limited to households where the highest wage earner is 35 or younger and has a college degree. Chen and Rosenthal (2008) provide evidence that these young, educated individuals primarily move to locations with more favorable business environments to access more and better jobs over areas with greater amenities or lower house prices. This suggests that these individuals are more likely to choose a job first and then optimize housing investment which reduces the endogeneity referenced above. The results in Table 7 show that these individuals are, if anything, more responsive to labor market risks and reduce their housing investment by over $9,400 with a one standard-deviation increase the risk measure.

Investments in housing serve both as a hedge against labor market risk, but also as an investment generally. To the extent that locations with higher average risk lead to lower levels of housing investment the correlated labor market risk measure could be capturing the effect of households investing less in housing due to its lower return. Although the inclusion of PUMA fixed effects should capture most of the across-industry risk of housing investment in an area, Table 8 includes a measure of uncorrelated labor market risk (defined in Equation 1). The smaller coefficient on the risk measure indicates it may have been capturing some of this effect. The coefficient is still negative and of a similar magnitude to previous specifications. The coefficient on the uncorrelated risk measure is large and negative suggesting that households do invest less in housing in riskier markets. The results from column 2 suggest that most of the decline in the coefficient on the risk measure is coming from the other industry risk coefficient which declines relative to the baseline model (Table

2) while the own industry risk coefficient stays stable.

Similarly, a household that has lived in a house for a while should be less concerned about the impact of the risk measure on their housing investment.[40] These households should still worry about the effect of the uncorrelated risk measure as housing is still an investment for them. Table 9 Panel A shows the coefficients on the risk measure for households that have lived in their homes for different periods of time. Households that have lived in a house for longer have a smaller effect of the risk measure. Panel B of Table 9 includes the uncorrelated risk measure into the same regressions from Panel A. Including the uncorrelated risk measure reduces the magnitude of the coefficient on the risk measure, but it stays negative and statistically significant for more recent movers (column 1). While the effect of the risk measure decreases over the length of time living in a home, the coefficient on the uncorrelated risk measure stays more consistent across households.

5.2 Alternate Specifications

The specifications presented thus far allow for risk measures calculated to vary at the PUMA level. This is the smallest geographic level of aggregation publicly available and assumes households care about the labor market risk to housing caused by the people living in close vicinity to themselves.[41] As PUMAs are relatively arbitrary geographic designations it may be better to think about this relationship occurring at the metropolitan level. Table 10 reports the effects of risk measures calculated at the MSA level on housing investment. The results are noisier, but consistent with prior results presented suggesting a one-standard deviation increase in the MSA-calculated risk measure leads to a decline in housing investment of

[40] These households have built up higher levels of home equity, giving them larger a cushion to support a job loss. Additionally with time households could change jobs or adjust housing investment levels (through remodeling or an addition) to reduce the impact of the risk measure. Finally these households may reflect housing investment decisions that predate the more currently calculated correlated risk measure and thus would not be sensitive to them.

[41] That is, households care more about the risk to local housing markets posed by the chance that people who live in their more immediate area lose their jobs and/or sell their houses. The regressions implicitly assume labor markets are at the city level by including metropolitan area average industry and occupation wages. The assumption is the value of your house depends more on the value of other houses in a more local area , but wages are competitive across the entire city.

$7,770.

Instead of using individual level data, Table 11 reports coefficients on the effect of the risk measure for collapsed PUMA-Industry-Year cells. The previous regressions implicitly give weight to areas with larger populations[42] and industries with higher levels of employment. The results from Table 11 suggest that these factors serve to reduce the magnitudes of the estimated coefficients as a one-standard deviation increase in the risk measure is now associated with a decrease in housing investment of $11,586. Table 12 combines the approaches of Tables 10 and 11 by calculating the effect of the risk measure for collapsed MSA-Industry-Year cells. The sample size is greatly reduced and the results are not statistically significant, but the magnitudes of the estimated coefficients are consistent with the previous estimates (-7,558 vs. -6,749 in the baseline specification). Finally Table 13 reports results from a regression on collapsed PUMA-Industry-Year cells but for all metropolitan areas.[43] As in the baseline specifications including smaller metropolitan areas reduces the magnitude of the coefficient on the risk measure,[44] but the results tell a similar story.

5.3 Heterogeneous Effects

The results above suggest that households adjust their housing investment in response to correlated labor market risks. However not all households should react in the same way to higher levels of risk. Households that derive a large fraction of their earnings from the labor market will be more responsive to correlated labor market risk. Conversely, households will be less concerned with correlated labor market risk when they have other forms of savings to rely on if they lose their job. Columns 1 and 2 of Table 14 restrict the sample to households that only report wage income. This restriction reduces the sample size,[45] and the coefficient on the overall correlated labor market risk measure increases slightly in comparison to the baseline

[42]Given that PUMAs are created using population this weights results more for PUMAs that have seen greater levels of population growth.

[43]Table 11 was limited to the same set of large metropolitan areas as all other regressions.

[44]See Figure 6.

[45]The number of observations fall from 879,398 households to 461,980.

sample. Similarly, when restricting to households with no investment income (columns 3 and 4) the coefficient on the overall correlated labor market risk measure is still similar to the baseline model. However, when limiting to households that have positive investment income[46] the coefficient on the risk measure declines greatly and is no longer statistically significant. Crucially, this decline seems primarily driven by the decline in the coefficient on other industry risk, as the effect of own industry risk does not appear to drastically change across samples.

The results from Table 14 suggest that households that have alternate sources of income are less likely to adjust their housing investment in response to correlated labor market risk. When these households lose a job, they are less concerned about the effects on local house prices as they do not need to capitalize their housing investment to provide for living expenses. Thus households with savings or investments are insured to a degree against the threat of job loss. Unemployment insurance provides a similar guarantee. In the United States, unemployment insurance is provided by the states, with each state choosing its own level of income provided in the event of a job loss and the duration for which benefits can be received. Thus each state has a different maximum benefit amount that can be obtained through unemployment insurance.[47] Table 15 shows the effect of the risk measures on housing investment in states with higher and lower levels of maximum unemployment insurance benefits. States with higher levels of benefits (columns 1, 3, 5, and 7) have smaller effects of correlated labor market risk on housing investment, while states with lower levels of benefits see higher effects. The differences in coefficients match with the theory that households change their housing investment less when they have alternative sources of living expenses in the event of job loss.

[46]Positive investment income indicates the household likely has positive savings or investments that generate this income.

[47]The maximum unemployment benefit is calculated as the maximum weekly benefit multiplied by the maximum number of weeks covered. The maximum weekly benefit is calculated as a fraction of income up to an income cap. As the sample here is limited to homeowners in large metropolitan areas, the vast majority of households are above the income cap (average wage income in the sample of owners is over $88,000).

6 Conclusion

For most households, housing comprises their single largest asset and wages provide the vast majority of their income. Previous literature showed that when incomes and house prices are correlated, households invest less in housing. This paper builds off that result to suggest that households incorporate correlated labor market risk into their housing investment decisions. The results presented suggest that for a one-standard deviation increase in correlated labor market risk, households reduce housing investment by around \$6,750. Additionally the model suggests that households adjust on the extensive margin and that a one-standard deviation increase in correlated labor market risk is associated with a 2% decline in the probability of becoming a homeowner. Crucially, the decline in housing investment due to correlated labor market risk is driven almost entirely by risk to the household from individuals in industries other than their own.

Municipalities are increasingly using targeted incentives to attract businesses to their area. Though the results presented here do not contradict benefits from agglomeration, they do suggest an unintended side effect. As concentration in one industry grows, the correlated labor market risk for households in other closely related industries increases. Municipalities derive large fractions of their revenue from property taxes, and the increase in tax revenue from bringing in outside companies may be offset to a degree by decreases in housing investment by households in other closely related industries. The results of this paper suggest there may be benefits to localities diversifying their industry concentrations to increase home values (and thus tax revenue).

Finally, these results also suggest there may be underprovision of unemployment insurance for individuals. Households are using housing investment as a hedge against loss in labor market income, but this does not work well when labor markets are highly correlated. In states with higher levels of unemployment insurance, there is suggestive evidence that households are less concerned about correlated labor market risk and invest in housing more optimally.

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Table 1
Summary Statistics

	Owners		Renters	
	mean	s.d.	mean	s.d.
Economic Data				
Average Home Value/Monthly Rent	\$345,506	\$278,564	\$1,166.53	\$636.44
Household Income	\$123,564	\$103,792	\$67,639	\$66,319
Wage Income	\$88,174	\$81,840	\$50,915	\$54,040
Labor Market Conditions in Percents				
Risk Measure	2.79	2.00	2.89	2.10
Other Industry Risk	2.50	1.95	2.55	2.03
Own Industry Risk	0.29	0.31	0.34	0.34
$Risk_{d,t}$	7.75	3.25	8.50	3.40
$Concen_{d,m,t}$	3.68	3.22	3.92	3.42
Demographic Controls				
Age	42.47	9.07	40.26	9.85
White	0.76	0.37	0.61	0.47
Black	0.09	0.28	0.19	0.40
College	0.56	0.49	0.35	0.45
Male	0.64	0.48	0.55	0.50
Self Employed	0.09	0.28	0.07	0.26
Veteran	0.07	0.25	0.05	0.21
Household Composition				
Fraction Married	0.61	0.49	0.39	0.49
Household Size	2.92	1.54	2.62	1.57
Employed Workers	1.64	0.70	1.51	0.72
Fraction with Children	0.57	0.50	0.48	0.50

Notes: Household-weighted summary statistics calculated for the highest wage earner in the household from 2007-2017. All dollars are adjusted to 2017 dollars. Data comes from 2007-2017 one-year ACS samples from the US Census Bureau.

Table 2
OLS Regression of Risk on Housing Investment

	(1)	(2)	(3)
Risk Measure	-6,749**		
	(3,064)		
Other Industry Risk		-12,434***	-13,307***
		(2,790)	(2,839)
Own Industry Risk		4,582***	
		(1,258)	
$Risk_{d,t}$			2,627**
			(1,301)
$Concen_{d,m,t}$			5,212***
			(1,175)
Female	-23,422***	-23,420***	-23,393***
	(887)	(887)	(886)
Age	12,538***	12,534***	12,547***
	(382)	(382)	(383)
Age Squared	-102***	-102***	-102***
	(4)	(4)	(4)
Married	39,407***	39,373***	39,381***
	(1,189)	(1,189)	(1,189)
Veteran	-18,823***	-18,802***	-18,785***
	(1,324)	(1,320)	(1,317)
Black	-41,561***	-41,583***	-41,575***
	(2,980)	(2,977)	(2,972)
Native American	-35,031***	-34,833***	-34,796***
	(4,772)	(4,769)	(4,762)
Asian	-14,269***	-14,407***	-14,393***
	(3,284)	(3,278)	(3,273)
Other Race	-13,329***	-13,323***	-13,337***
	(2,863)	(2,869)	(2,865)
Two or More Races	-22,753***	-22,683***	-22,630***
	(2,395)	(2,395)	(2,391)
Not Hispanic	47,978***	48,073***	47,984***
	(3,308)	(3,312)	(3,314)
GED	28,644***	28,775***	28,683***
	(3,063)	(3,061)	(3,032)
HS Grad	23,160***	23,554***	23,333***
	(1,878)	(1,863)	(1,881)
Some College	37,515***	37,918***	37,728***
	(1,907)	(1,895)	(1,904)
Associate's Degree	43,682***	44,074***	43,913***
	(2,274)	(2,262)	(2,271)
Bachelor's Degree	82,619***	83,017***	82,904***
	(2,897)	(2,892)	(2,894)
Advanced Degree	119,345***	119,614***	119,456***
	(3,915)	(3,915)	(3,914)
Mortgage	24,613***	24,593***	24,592***
	(1,985)	(1,983)	(1,982)
Moved in last 2 years	-1,685	-1,683	-1,660
	(1,046)	(1,044)	(1,043)
Moved in last 4 years	-10,392***	-10,423***	-10,407***
	(1,000)	(998)	(998)
Moved in last 9 years	-25,897***	-25,938***	-25,914***
	(1,036)	(1,035)	(1,035)
Median Metro Ind Wage (000s)	1,042***	991***	958***
	(100)	(99)	(99)
Median Metro Occ Wage (000s)	984***	982***	979***
	(37)	(37)	(36)
Self Employed	88,916***	89,050***	89,021***
	(4,156)	(4,153)	(4,154)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	879,398	879,398	879,398
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 3
Linear Probability Model of Risk on Tenure Choice

	(1)	(2)	(3)
Risk Measure	-0.02007***		
	(0.00351)		
Other Industry Risk		-0.01468***	-0.01439***
		(0.00333)	(0.00336)
Own Industry Risk		-0.00769***	
		(0.00157)	
$Risk_{d,t}$			0.00115
			(0.00220)
$Concen_{d,m,t}$			-0.00897***
			(0.00140)
Female	-0.00733***	-0.00734***	-0.00736***
	(0.00128)	(0.00128)	(0.00128)
Age	0.01658***	0.01656***	0.01653***
	(0.00071)	(0.00071)	(0.00071)
Age Squared	-0.00014***	-0.00014***	-0.00014***
	(0.00001)	(0.00001)	(0.00001)
Married	0.12468***	0.12471***	0.12472***
	(0.00202)	(0.00201)	(0.00201)
Veteran	-0.01012***	-0.01013***	-0.01018***
	(0.00233)	(0.00233)	(0.00234)
Black	-0.15040***	-0.15040***	-0.15040***
	(0.00366)	(0.00366)	(0.00366)
Native American	-0.05149***	-0.05165***	-0.05166***
	(0.00721)	(0.00721)	(0.00721)
Asian	-0.03744***	-0.03750***	
	(0.00582)	(0.00582)	(0.00581)
Other Race	-0.03612***	-0.03612***	-0.03608***
	(0.00329)	(0.00329)	(0.00329)
Two or More Races	-0.04706***	-0.04714***	-0.04738***
	(0.00372)	(0.00372)	(0.00371)
Not Hispanic	0.06066***	0.06061***	0.06072***
	(0.00326)	(0.00328)	(0.00326)
GED	0.04198***	0.04183***	0.04218***
	(0.00417)	(0.00418)	(0.00417)
HS Grad	0.04144***	0.04114***	0.04134***
	(0.00260)	(0.00260)	(0.00260)
Some College	0.07659***	0.07628***	0.07647***
	(0.00285)	(0.00285)	(0.00284)
Associate's Degree	0.11061***	0.11029***	0.11040***
	(0.00323)	(0.00323)	(0.00322)
Bachelor's Degree	0.16752***	0.16721***	0.16725***
	(0.00340)	(0.00340)	(0.00339)
Advanced Degree	0.19404***	0.19385***	0.19398***
	(0.00388)	(0.00388)	(0.00387)
Moved in last 2 years	0.03476***	0.03475***	0.03474***
	(0.00257)	(0.00257)	(0.00257)
Moved in last 4 years	0.12618***	0.12617***	0.12615***
	(0.00277)	(0.00277)	(0.00276)
Moved in last 9 years	0.29445***	0.29445***	0.29438***
	(0.00511)	(0.00511)	(0.00511)
Median Metro Ind Wage (000s)	0.00102***	0.00106***	0.00112***
	(0.00009)	(0.00009)	(0.00009)
Median Metro Occ Wage (000s)	0.00127***	0.00127***	0.00128***
	(0.00003)	(0.00003)	(0.00003)
Self Employed	0.08717***	0.08703***	0.08706***
	(0.00222)	(0.00221)	(0.00222)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	1,651,282	1,651,282	1,651,282
R-squared	.33	.33	.33

Robust standard errors in parentheses clustered at the PUMA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$.

Table 4
OLS Regression of Risk on Housing Investment: Heckman Sample-Selection Results

	(1)	(2)	(3)
Risk Measure	-6,381**		
	(3,235)		
Other Industry Risk		-12,189***	-13,082***
		(2,867)	(2,917)
Own Industry Risk		4,764***	
		(1,357)	
$Risk_{d,t}$			2,640**
			(1,296)
$Concen_{d,m,t}$			5,390***
			(1,275)
Inverse Mills Ratio	-9,077	-9,367	-9,258
	(10,596)	(10,591)	(10,569)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	879,395	879,395	879,395
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Regressions also include controls for presence of a mortgage, years since moved into home, metropolitan median wage by industry and occupation. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$.

Table 5
Housing Investment with Risk Interacted with Year

	(1)		(2)	
Risk Measure				
2007	-11,786***	(3,991)		
2008	-7,105*	(4,310)		
2009	-6,208	(4,047)		
2010	-8,077**	(3,796)		
2011	-9,251**	(3,660)		
2012	-7,474**	(3,538)		
2013	-8,158**	(3,595)		
2014	-7,803**	(3,914)		
2015	-9,829**	(4,138)		
2016	-10,254**	(4,647)		
2017	-10,723**	(4,864)		
Other Industry Risk				
2007			-18,541***	(3,694)
2008			-14,929***	(3,940)
2009			-13,550***	(3,689)
2010			-15,080***	(3,453)
2011			-15,797***	(3,336)
2012			-13,616***	(3,292)
2013			-14,422***	(3,247)
2014			-14,527***	(3,565)
2015			-16,715***	(3,745)
2016			-17,380***	(4,151)
2017			-18,149***	(4,400)
Own Industry Risk				
2007			1,836	(1,412)
2008			5,509***	(1,652)
2009			5,236***	(1,528)
2010			5,149***	(1,472)
2011			4,223***	(1,338)
2012			3,413***	(1,230)
2013			4,338***	(1,536)
2014			5,568***	(1,741)
2015			4,105**	(1,726)
2016			4,177**	(2,116)
2017			4,550*	(2,351)
State-Year F.E.	Yes		Yes	
PUMA F.E.	Yes		Yes	
Industry F.E.	Yes		Yes	
Occupation F.E.	Yes		Yes	
Observations	879,398		879,398	
R-squared	.54		.54	

Robust standard errors in parentheses clustered at the PUMA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$.

Table 6
OLS Regression of Risk on Housing Investment: Industry Concentration from 2000 Census

	(1)	(2)	(3)
Risk Measure	-8,772***		
	(2,837)		
Other Industry Risk		-12,983***	-13,667***
		(2,745)	(2,767)
Own Industry Risk		2,887***	
		(1,106)	
$Risk_{d,t}$			2,276*
			(1,235)
$Concen_{d,m,t}$			3,616***
			(1,063)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	879,398	879,398	879,398
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area, moved into their current home in the last 9 years are 35 or younger and have a college degree. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 7

OLS Regression of Risk on Housing Investment: Restricted to Age<= 35 and College Degrees

	(1)	(2)	(3)
Risk Measure	-9,402**		
	(3,965)		
Other Industry Risk		-13,402***	-13,086***
		(3,938)	(3,970)
Own Industry Risk		3,145**	
		(1,586)	
$Risk_{d,t}$			-1,978
			(2,671)
$Concen_{d,m,t}$			2,477**
			(1,206)
State-Year F.E.	Yes	Yes	Yes
MSA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	No	No	No
Observations	146,012	146,012	146,012
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 8

OLS Regression of Risk on Housing Investment: Including Uncorrelated Risk

	(1)	(2)	(3)
Risk Measure	-5,916*		
	(3,124)		
Other Industry Risk		-11,606***	-12,588***
		(2,799)	(2,841)
Own Industry Risk		4,661***	
		(1,267)	
$Risk_{d,t}$			2,804**
			(1,294)
$Concen_{d,m,t}$			5,197***
			(1,171)
Uncorrelated Risk	-11,702**	-11,159*	-10,535*
	(5,732)	(5,697)	(5,636)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	879,398	879,398	879,398
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$.

Table 9

OLS Regression of Risk on Housing Investment: When Households Moved into Current Home

	(1)	(2)	(3)	(4)
Panel A:				
Risk Measure	-7,857**	-6,749**	-3,209	-3,141
	(3,242)	(3,064)	(2,606)	(2,125)
Panel B:				
Risk Measure	-6,762**	-5,916*	-2,475	-2,189
	(3,293)	(3,124)	(2,665)	(2,187)
Uncorrelated Risk	-15,447**	-11,702**	-10,326*	-13,712**
	(6,268)	(5,732)	(5,883)	(5,658)
Moved In	0-4 Years Ago	0-9 Years Ago	10-19 Years Ago	10+ Years Ago
State-Year F.E.	Yes	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes
Observations	487,483	879,398	475,187	715,865
R-squared	.54	.54	.55	.55

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 10

OLS Regression of Risk on Housing Investment: Industry Concentration at MSA Level

	(1)	(2)	(3)
Risk Measure	-7,770**		
	(3,893)		
Other Industry Risk		-10,953***	-11,919***
		(3,462)	(3,648)
Own Industry Risk		2,599	
		(1,645)	
$Risk_{d,t}$			2,354*
			(1,361)
$Concen_{d,m,t}$			4,310***
			(1,574)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes
Observations	879,398	879,398	879,398
R-squared	.54	.54	.54

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 11
OLS Regression of Risk on Housing Investment: Collapsed to PUMA-Industry-Year Level

	(1)	(2)	(3)
Risk Measure	-11,586***		
	(2,748)		
Other Industry Risk		-16,370***	-16,963***
		(2,809)	(2,836)
Own Industry Risk		6,648***	
		(1,390)	
$Risk_{d,t}$			72
			(1,716)
$Concen_{d,m,t}$			8,018***
			(1,283)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	No	No	No
Observations	226,467	226,467	226,467
R-squared	.62	.62	.62

Robust standard errors in parentheses clustered at the PUMA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. Household data is collapsed to Industry-PUMA-Year cells. Regressions include controls for average age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the Industry-PUMA-Year cell. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 12
OLS Regression of Risk on Housing Investment: Collapsed to MSA-Industry-Year Level

	(1)	(2)	(3)
Risk Measure	-7,558		
	(5,429)		
Other Industry Risk		-10,145*	-10,590*
		(5,672)	(5,871)
Own Industry Risk		6,510*	
		(3,461)	
$Risk_{d,t}$			674
			(2,513)
$Concen_{d,m,t}$			5,843*
			(3,133)
State-Year F.E.	Yes	Yes	Yes
MSA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	No	No	No
Observations	44,942	44,942	44,942
R-squared	.71	.71	.71

Robust standard errors in parentheses clustered at the MSA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a metropolitan area and moved into their current home in the last 9 years. Household data is collapsed to Industry-MSA-Year cells. Risk measures calculated at MSA level. Regressions include controls for average age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the Industry-MSA-Year cell. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$.

Table 13

OLS Regression of Risk on Housing Investment: Collapsed to PUMA-Industry-Year Level for all Metros

	(1)	(2)	(3)
Risk Measure	-7,681***		
	(2,014)		
Other Industry Risk		-11,276***	-11,916***
		(2,104)	(2,132)
Own Industry Risk		4,646***	
		(995)	
$Risk_{d,t}$			1,235
			(1,197)
$Concen_{d,m,t}$			6,330***
			(940)
State-Year F.E.	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Occupation F.E.	No	No	No
Observations	354,202	354,202	354,202
R-squared	.62	.62	.62

Robust standard errors in parentheses clustered at the PUMA level. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a metropolitan area and moved into their current home in the last 9 years. Household data is collapsed to Industry-PUMA-Year cells. Regressions include controls for average age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the Industry-PUMA-Year cell. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 14

OLS Regression of Risk on Housing Investment: Income Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Measure	-7,476**		-6,604**		-2,769	
	(3,161)		(2,644)		(5,911)	
Other Industry Risk		-12,793***		-11,848***		-7,396
		(2,850)		(2,467)		(5,687)
Own Industry Risk		4,105***		4,194***		4,060**
		(1,359)		(1,217)		(1,866)
Income Restriction	100% Wage	100% Wage	No Investment Inc	No Investment Inc	Investment Inc	Investment Inc
State-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
PUMA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	461,980	461,980	671,036	671,036	201,422	201,422
R-squared	.53	.53	.52	.52	.53	.53

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$.

Table 15

Housing Investment in High and Low Maximum Unemployment Insurance Benefit States

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk Measure	1,824	-15,608***			-5,689	-8,412**		
	(4,846)	(3,383)			(4,288)	(4,008)		
Other Industry Risk			-5,552	-19,141***			-8,015**	-15,063***
			(4,331)	(3,464)			(3,801)	(3,788)
Own Industry Risk			6,556***	1,877			1,389	5,564***
			(1,873)	(1,236)			(1,764)	(1,578)
UI	Above	Below	Above	Below	Above	Below	Above	Below
Benefits	Median	Median	Median	Median	Mean	Mean	Mean	Mean
State-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
PUMA F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,856	372,542	506,856	372,542	384,079	495,319	384,079	495,319
R-squared	.54	.52	.54	.52	.48	.55	.48	.55

Robust standard errors in parentheses clustered at the PUMA level. Regressions include controls for age, age squared, marital status, race, education, ethnicity, self employment status and veteran status of the household's highest wage earner. Data is limited to employed homeowners that are the highest wage earner in their household, who are located in a major metropolitan area and moved into their current home in the last 9 years. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Figure 1
Average Uncorrelated Risk by PUMA

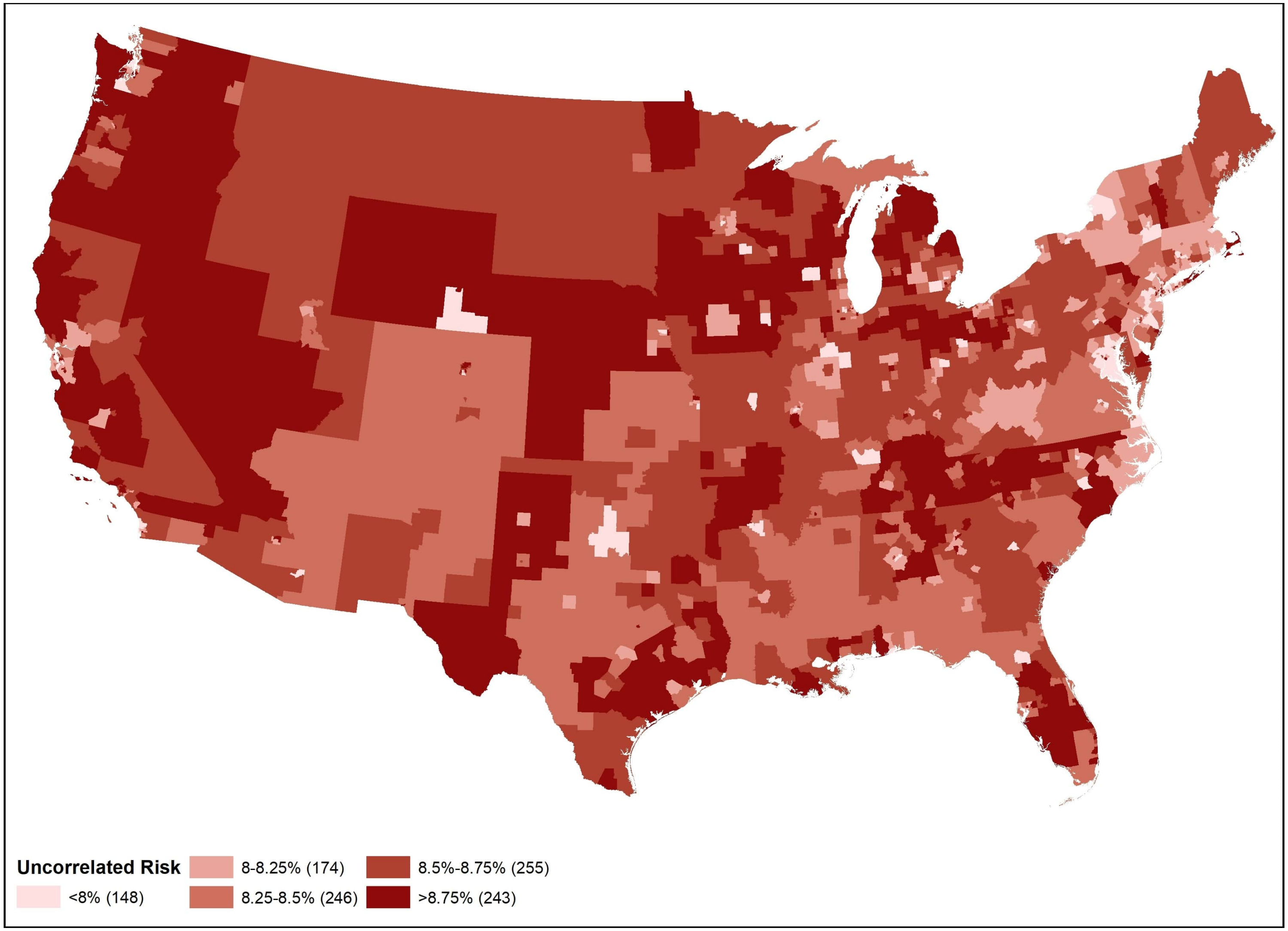


Figure 2
Average Risk Measure by PUMA

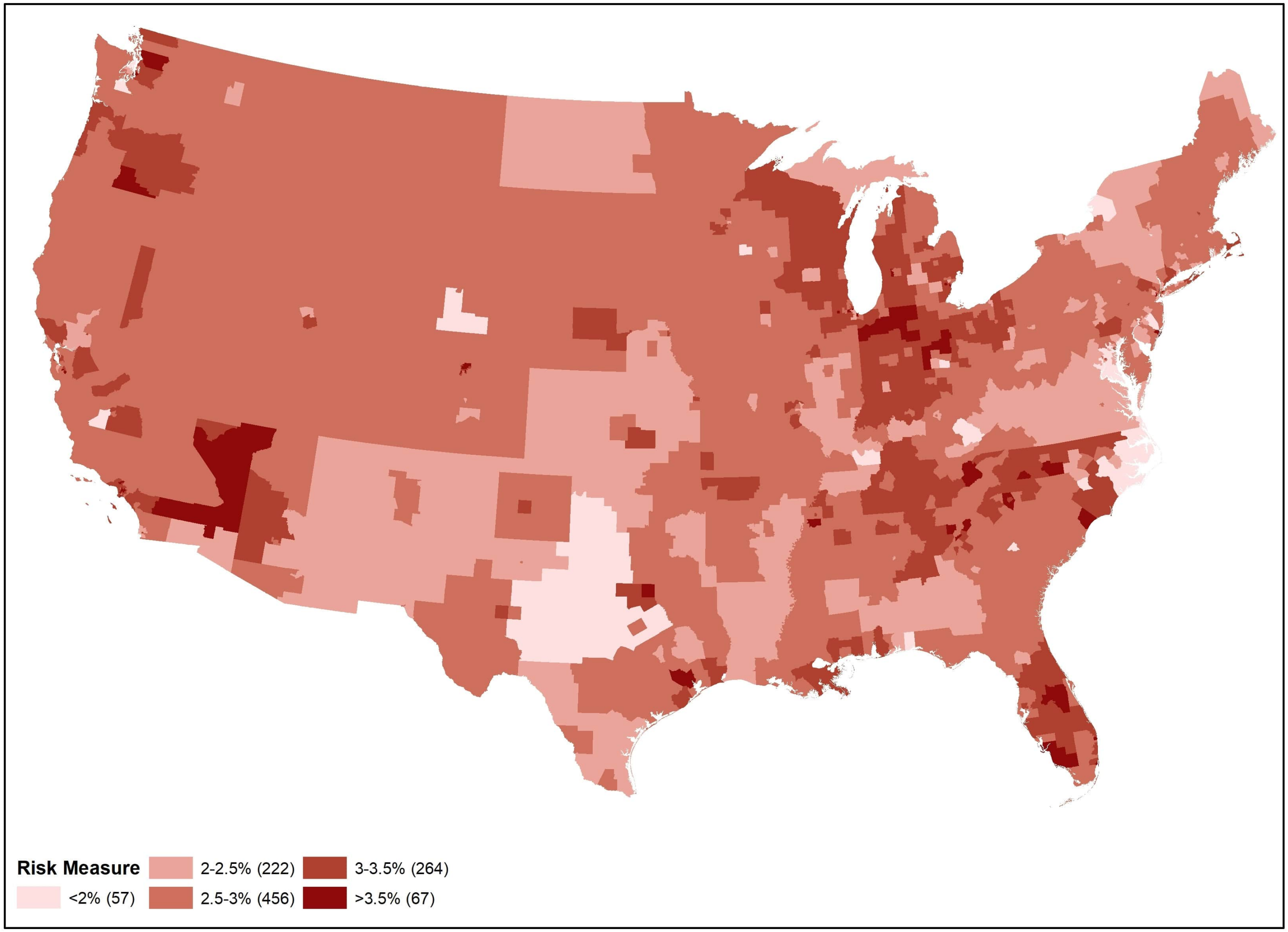


Figure 3
Average Risk Measure by PUMA for Industry Code 336 (Transportation Equipment Manufacturing)

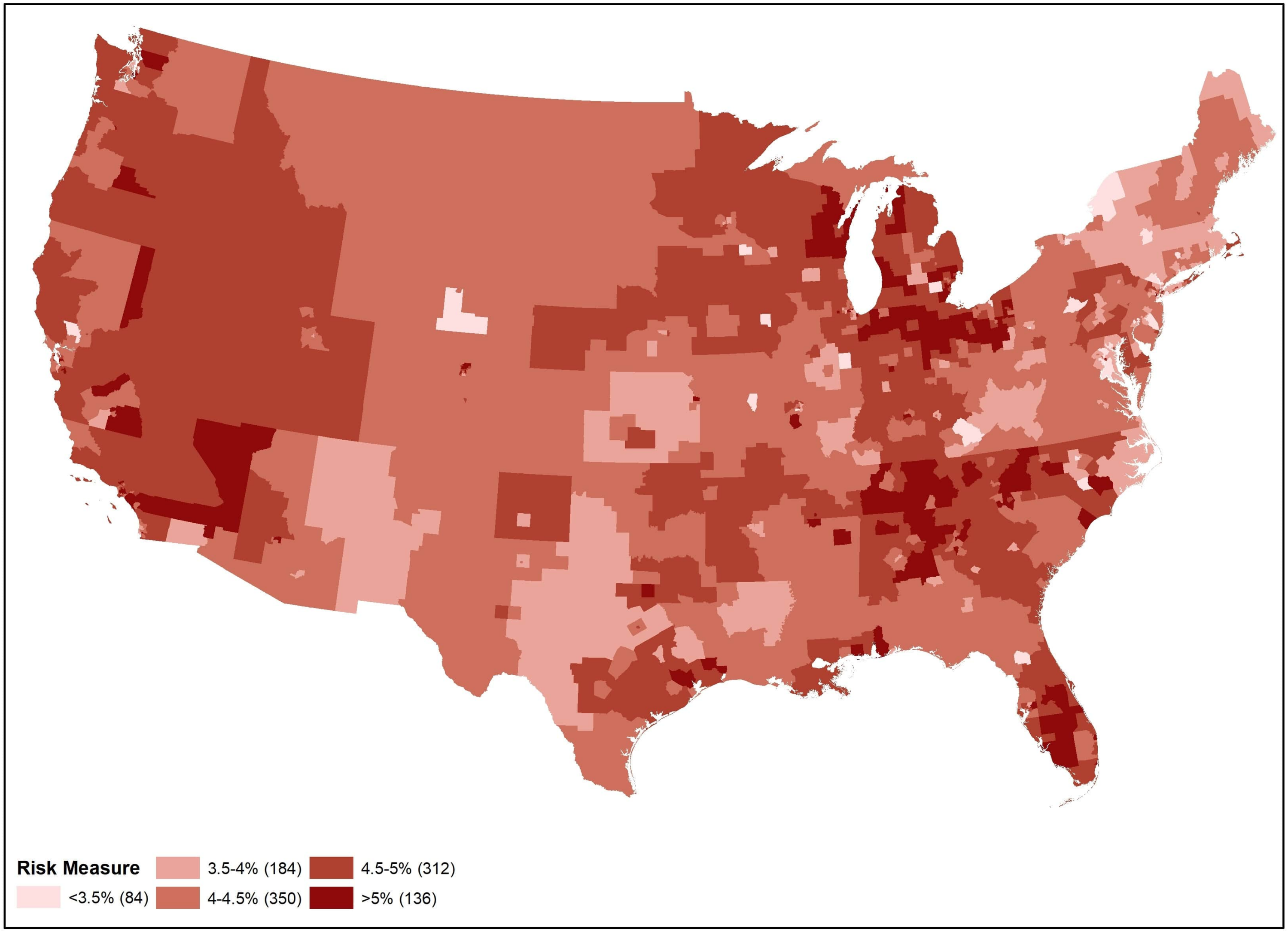


Figure 4
Average Other Industry Risk by PUMA for Industry Code 336 (Transportation Equipment Manufacturing)

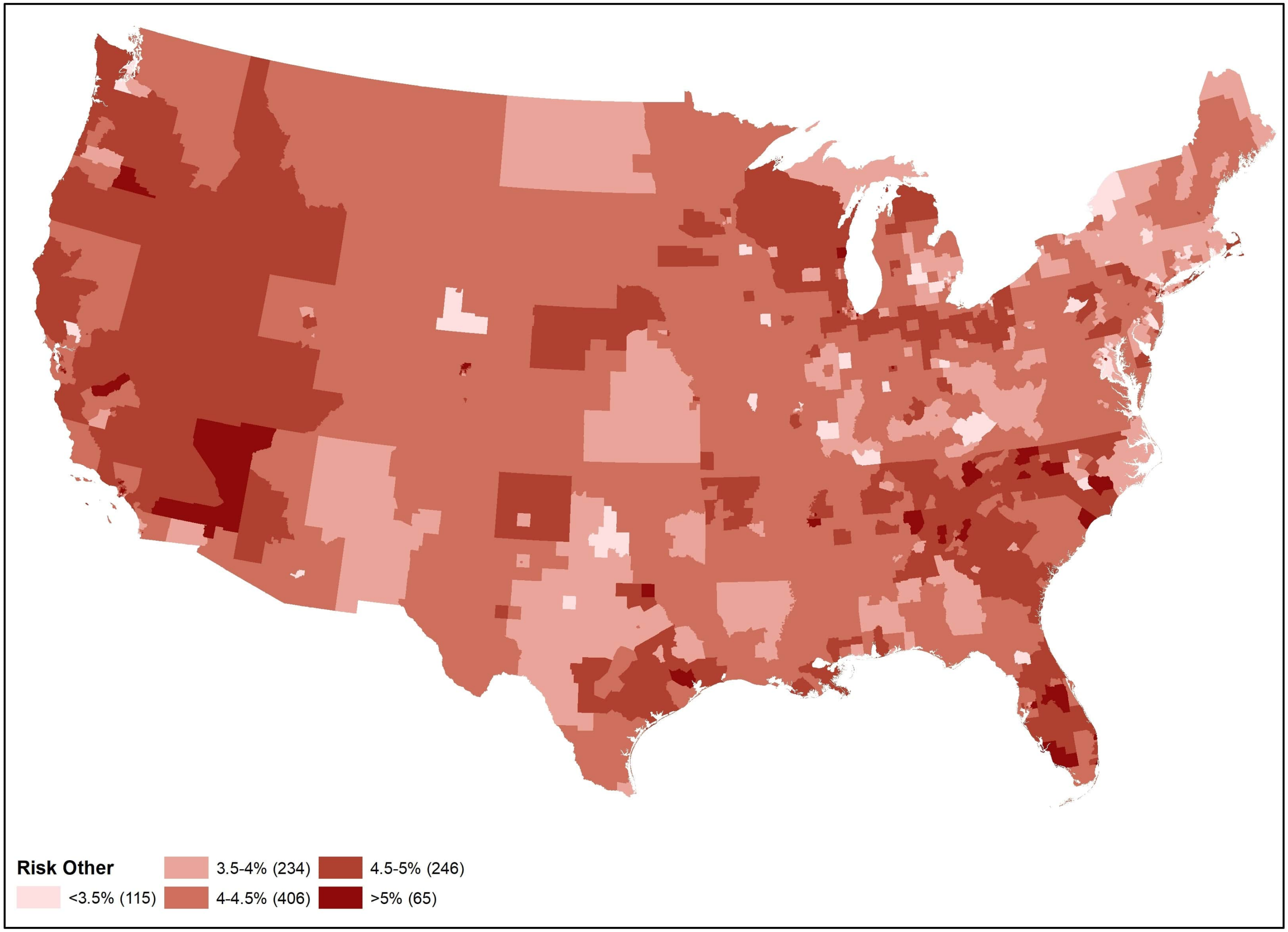


Figure 5
Average Own Industry Risk by PUMA for Industry Code 336 (Transportation Equipment Manufacturing)

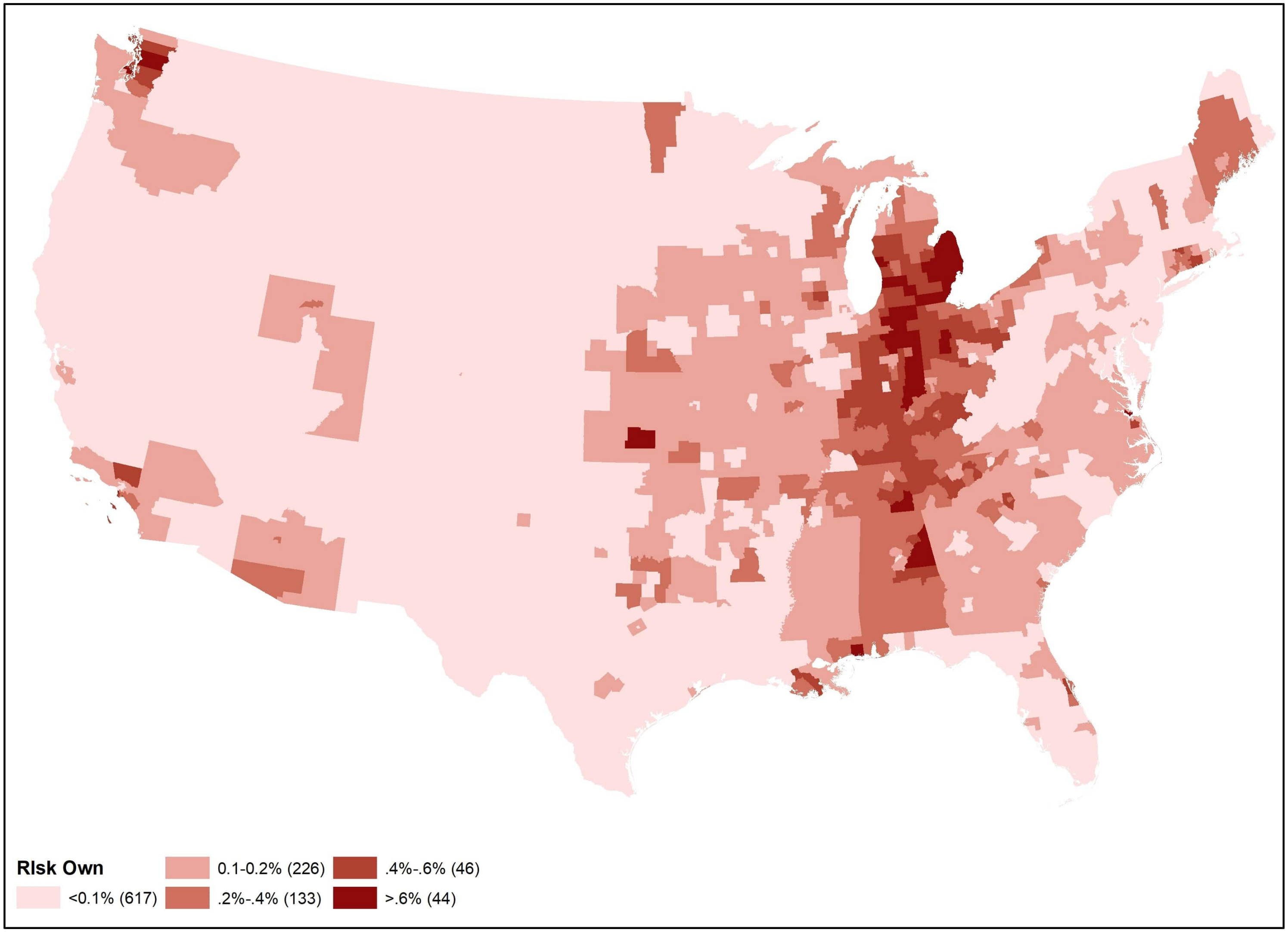
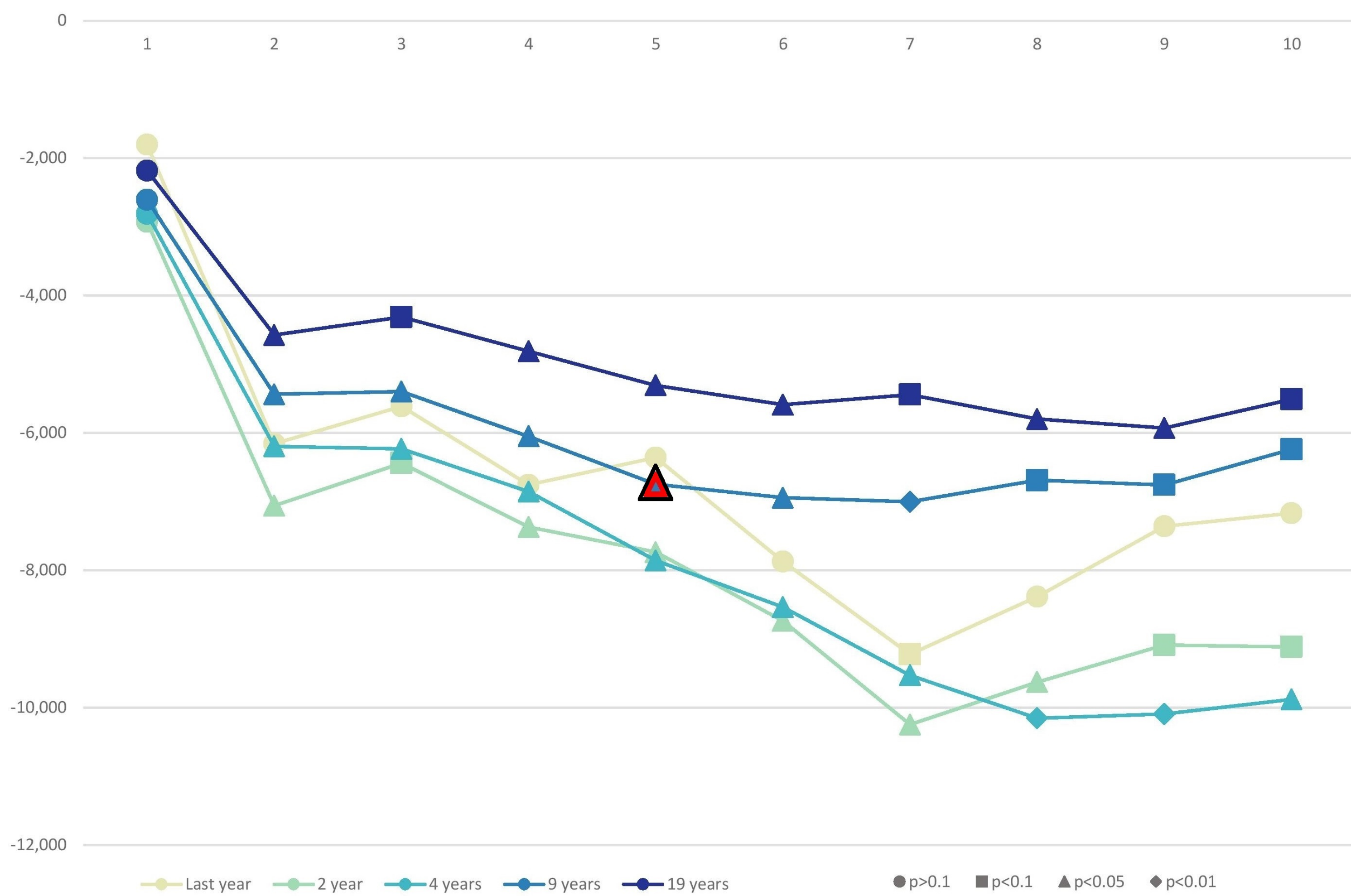


Figure 6
Coefficient on Correlated Labor Market Risk by Metro Size and Years Since Moved into Current House



Notes: Coefficients on Correlated Labor Market Risk for regressions with varying restrictions on sample. Regressions limit to metropolitan areas with at least X PUMAs (1 to 10) and households who moved into their current homes in the last 1 to 19 years. Regressions include all controls listed in Table 2. The highlighted coefficient corresponds to the coefficient in column 1 of Table 2.