Can Owning a Home Hedge the Risk of Moving?

Todd Sinai
The Wharton School
University of Pennsylvania
and NBER

and

Nicholas S. Souleles
The Wharton School
University of Pennsylvania
and NBER

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ABSTRACT

For households that face a possibility of moving across MSAs, the risk of home owning depends critically on the covariance of the sale prices of their current houses with the purchase prices of their likely future houses. We find empirically that households tend to move between highly correlated MSAs, significantly increasing the distribution of *expected* correlations in real house price growth across MSAs, and so raising the "moving-hedge" value of owning. We also find that tenure decisions are sensitive to this hedging value, with households being more likely to own, ceteris paribus, when their hedging value is greater due to higher expected correlations and likelihoods of moving.

Conventional wisdom holds that one of the riskiest aspects of owning a house is the uncertainty surrounding its sale price. It is now well appreciated that house prices can be quite volatile. Between the end of 2005 and the end of 2008, real house prices fell by more than 31 percent, according to the Case-Shiller 10-city composite house price index. Over the prior five years, real house prices in the same cities rose by almost 73 percent. Similarly, after real house prices rose substantially during the 1980s, they fell by 26 percent between 1990 and 1997.

Historically, analysts have concluded that this volatility in house prices makes home owning risky. One common argument is that a gain or a loss on a house could have a considerable effect on a household's balance sheet, especially since the primary residence comprises about two-thirds of the median homeowner's assets (2004 Survey of Consumer Finances). The resulting change in household wealth could have significant effects on household consumption. [Case *et al* (2002), Calomiris *et al* (2009), Attanasio *et al* (2009), Campbell and Cocco (2007)] Another common claim is that a loss on a house could impair a household's ability to purchase their next house. Since nearly 45 percent of households move within a five-year period, and one-fifth of such households leave their metropolitan area, this risk is potentially large.

These arguments rely on an assumption that houses are like standard financial assets, where increases in value, once realized, can be spent on a greater quantity of goods and services. However, a homeowner who sells his house still has to live somewhere after the house is sold. Although the sale price of the current house is uncertain, the purchase price of the subsequent house is also uncertain. If the prices of the current and subsequent houses move independently, a homeowner actually faces two sources of risk: sale price risk (for the current house) and purchase price risk (for a subsequent house). But if current and future houses have positively covarying prices, gains or declines in value are offset by increases or decreases in price. In fact, sale price uncertainty for the current house could actually undo purchase price uncertainty for the subsequent house, reducing the volatility in the quantity of housing that could be purchased after a move.

A few recent papers have recognized that it is the sale price *net* of the subsequent purchase price, rather than the sale price alone, that matters for the risk of home owning. [Ortalo-Magne and Rady (2002), Sinai and Souleles (2005), Han (2008)] However, these papers – along with conventional wisdom – assume that the correlation in house price across housing

markets is low, which implies that the volatility of the sale price of a house is risky given how frequently households move across MSAs.

Our main contribution is to show that, for many households, the sale price of their current house positively commoves with the purchase price of their next house even when the next house is in a different city. Due to the positive covariance, the volatility of the sale price of a house at least partially undoes the volatility of the cost of obtaining the next house. In effect, owning a house provides a hedge against the uncertain purchase price of a future house in another city.[1]

The conventional wisdom – that house prices do not covary much – is correct when one considers the U.S. on average. However, the unconditional national average masks two important factors. First, there is considerable heterogeneity across city pairs within the U.S. in how much their house prices covary, ranging from negative covariances to very highly positive covariances. Second, households do not move to random locations; instead, they tend to move between highly covarying housing markets. Because of these two factors, the expected covariance in house prices – where the expectation is weighted by the household's own probabilities of moving to each other location – is quite high. For example, the simple unweighted median correlation in house price growth across U.S. metropolitan statistical areas (MSAs) is only 0.35. When we account for where households are likely to move, the baseline effective correlation faced by the median household rises substantially, to 0.60. The 75th percentile household enjoys an even higher correlation, of 0.89.

That the *expected* covariance in house prices is high for many households yields important implications for several areas of economics. For example, a household's marginal propensity to consume (MPC) out of housing wealth is determined, in part, by the degree to which a change in house value constitutes a change in wealth. If, due to a high expected covariance in house prices, a housing capital gain is undone by a rise in expected future housing

[1] The benefit of home owning as a hedge against future house price risk in other cities is generally undeveloped in prior research. Ortalo-Magne and Rady (2002) illustrate in a simple theoretical model that house prices in one period hedge prices in the next period if the prices covary across the periods, but provide no empirical evidence on the magnitude or effect of the hedge. Sinai and Souleles (2005) show theoretically how sale price risk depends on the covariance between house prices in the current and future housing markets, but their primary empirical focus is on how home owning hedges volatility in housing costs *within* a given housing market. Han (2008) distinguishes within- and out-of-state moves in a structural model of housing consumption using the Panel Study of Income Dynamics. However, she does not know where households move if they move out of state, so she does not estimate cross-state covariances. To the degree that the sell/buy risk is considered in the prior literature, it emphasizes buying and selling houses within the *same* market, where the correlation in house prices is presumed to be high. For example, Cocco (2000) considers how home owning hedges the cost of trading up to a larger house within the same housing market for liquidity constrained households.

expenses, then the true change in household wealth from a rise in house prices is small, and so the MPC out of that capital gain should be low. Second, the expected covariance in house prices potentially affects the demand for home owning. Because expected covariances are quite high for many households, owning a house can provide a valuable hedge against house price risk, especially for households who are likely to move. This benefit extends even to those households who do not know exactly where they are going to move. As long as they are likely to move between positively covarying markets, home owning helps hedge their expected purchase price risk.[2] Since all households have to obtain future housing somehow, home owning actually can reduce the expected volatility in the net cost of selling one house and buying another. Third, Ortalo-Magne and Prat (2010) show theoretically that this expected covariance is one of the key parameters in the asset pricing of a house. Higher expected covariances yield higher house prices in their model, and reduce the demand for stocks that are correlated with housing markets. Finally, the degree of covariance affects the demand for housing derivatives of the sort proposed by Case *et al.* (1993) or housing equity insurance programs of the kind described by Caplin *et al.* (2003). When owning a house already acts as a natural hedge for future housing consumption, it reduces the demand for derivatives intended to reduce housing volatility, depending on how complete the natural hedge is.

Our second contribution is an application of our estimates of expected covariance to the context of housing demand. We show that households' tenure decisions (to rent versus own) appear to be sensitive to the "moving-hedge" benefit of owning. We bring three sources of variation to bear on this issue. First, the typical household *across* different MSAs may have a bigger, smaller, or even negative hedging benefit of home owning depending on the variance of house prices in the local MSA and the covariances with prices in other MSAs. Second, *within* an MSA, households differ in their expected covariances because they differ in their likelihoods of moving to each of the other MSAs. Third, the effect of the expected house price covariance should be attenuated for households who, for demographic reasons, appear unlikely to move in the near future. Households who do not anticipate moving have little need for a hedge against

[2] In order to highlight how the risk of home owning is affected by the house's moving-hedge properties, we abstract from the important effect of housing finance on household risk. Financing any volatile asset with high leverage creates risk, a topic which has been considered at length in prior research. For example, for leveraged, liquidity-constrained households, downturns in prices can lead to lock-in and more volatile consumption and prices. [Chan (2001), Stein (1995), Genesove and Mayer (1997, 2001), Hurst and Stafford (2004), Lustig and Van Nieuwerburgh (2005), Li and Yao (2007), Ferreira *et al* (2010)]

future house prices, and thus differences in the potential moving-hedge benefit of owning should have little effect on their tenure decisions.

We use household-level data on homeownership and moving probabilities, and MSA-level estimates of house price variances and covariances, to identify the effect of expected house price covariances on homeownership decisions. We use demographic characteristics such as age, marital status, and occupation to impute an exogenous probability of moving for each household. We impute the odds of a household moving to specific MSAs, conditional on moving at all, by applying the actual geographic distribution of moves by other households in similar industry or age categories in the originating MSA. This combination of MSA and household level variation enables us to identify the effect of expected house price covariances on homeownership decisions while controlling separately for MSA and household characteristics.

Overall, we find that for a household with an average expected length-of-stay in its house, the likelihood of home owning increases by 0.6 percentage points when the expected covariance rises by one standard deviation. This effect is larger for households with a higher likelihood of moving to another MSA. A household who is imputed to have a one-in-three chance of moving would have a 1 to 2 percentage point higher likelihood of home owning if faced with a one standard deviation increase in expected covariance. The results are robust to different ways of imputing the likelihood of a household's moving to the various MSAs, such as instrumenting for the actual moving patterns of households with the patterns we would predict if households moved based on the distribution of their industry's employment or their occupations across MSAs.

In the next section, we estimate households' effective covariances between house price growth in their current markets and in their expected future markets, and explain why conventional wisdom has assumed those covariances are low when they are actually quite high on average. We turn to our application in Section 2, where we present a simple theoretical framework that illustrates the moving-hedge benefit of owning and motivates our empirical tests. Section 3 describes the various data sources we use. The empirical identification strategy and results are presented in Section 4, with some robustness tests in Section 5. Section 6 briefly concludes.

1. The correlation of house prices across MSAs

Most analysts have concluded that there is little covariance in prices across markets because the national average covariance (equally weighting MSAs) is fairly low. However, that simple average masks three important factors that together often cause the effective covariance faced by households to be quite high. First, there is considerable heterogeneity across housing markets in their covariances with other housing markets. The national average covariance obscures this heterogeneity. Second, households do not move at random. Instead, they are more likely to move between more highly covarying housing markets. Because of the systematic moving, the average household's expected covariance is higher than the average covariance across MSAs (equally- or population-weighted).

Third, the distribution of expected covariances has a long lower tail. Because of this skewness, the median household's expected covariance is even higher than that of the average household. That is, while many households have high expected covariances, a minority has very low expected covariances, which lowers the average.

The heterogeneity across and within housing markets can be seen in Figure 1, which graphs the distribution of house price correlations by MSA, for a subsample of the largest MSAs.[3] We estimate the correlations in real annual growth in the OFHEO constant-quality MSA-level house price index over the 1980 to 2005 time period. The OFHEO index is computed using repeat sales of single-family houses with conforming mortgages. While the index is widely believed to understate effective house price volatility because it does not take into account differences in liquidity between housing booms and busts, it is available for a long period for many different MSAs, making it the best price index available for our purposes.

In Figure 1, each vertical grey/black bar represents a metropolitan area. The bottom of each bar is set at the fifth percentile of the MSA's house price correlations with each of the other MSAs. In this chart, each MSA is equally weighted and the correlation of an MSA with itself (which would equal one) is excluded. Moving from bottom to top, a bar turns from grey to black at the 25th percentile, then from black to grey at the 75th percentile, and the grey portion ends at the 95th percentile. Thus the black part of a bar covers the interquartile range of correlations across MSAs, and the entire grey/black bar covers the 5th percentile to the 95th percentile.

[3] In our empirical application, the across-MSA hedging depends on the covariance of house prices across MSAs. However, since correlations are easier to interpret visually, this section discusses the correlations of prices across MSAs. The conclusions using covariances are the same.

The first thing to note in Figure 1 is that there is substantial heterogeneity across MSAs in their house price correlations with the rest of the country, since the bars for some MSAs start and end higher than the others. For example, consider the distribution of correlations $\{\rho_{ATL,j}\}$ between house prices in Atlanta (the first city in the figure) and each of the other cities *j*. The 5th percentile correlation is −0.05, and the 95th percentile correlation is 0.73. By contrast, for Austin the corresponding percentiles are lower, −0.40 and 0.54. San Antonio has the lowest 5th and 95th percentiles, ranging from −0.50 to 0.47. The highest among the 5th percentiles of correlations is in Miami (0.13), and the highest of the 95th percentiles is in New York (0.94).

While the 5th through the 95th percentile correlations always overlap across cities, some of the interquartile ranges (the black bars) do not overlap. In Atlanta, the interquartile range of the correlations runs from 0.27 to 0.50, which does not overlap at all with the interquartile range in Austin, which runs from −0.22 to 0.17.

The second interesting fact apparent in Figure 1 is that the within-MSA heterogeneity in correlations (with other MSAs) also varies considerably across MSAs. This variation can be seen in the lengths of the grey and black bars. MSAs whose bars are stretched out relative to the other MSAs have more heterogeneity in their correlations, being relatively uncorrelated with other MSAs and relatively highly correlated with others. For example, New York has a -0.22 correlation with its 5th percentile correlation city, but a 0.94 correlation with its 95th percentile city. There is relatively less heterogeneity within Minneapolis, where the corresponding correlations range from 0.12 (5th percentile) to 0.68 (95th percentile). There is also significant heterogeneity in the sizes of the interquartile ranges. The widest interquartile range is in Salt Lake City, which spans from -0.18 to 0.33. The narrowest range is in Minneapolis. However, the cities with the widest 5th to 95th percentile ranges are not necessarily the same ones with the widest interquartile ranges. For example, New York's interquartile range runs from 0.12 to 0.53, about the same as Nashville, even though Nashville's 5th to 95th range is much tighter. San Jose's interquartile range is fairly tight at 0.15 to 0.38, even though the 5th to 95th percentile range is middle-of-the-road.

In Figure 2, by contrast, we take into account where households are likely to move, by weighting the correlations by the probability of moving. We compute the weighted correlation for a household living in MSA *k* by combining the vector of house price correlations between MSA *k* and the other MSAs (denoted by *l*), with the probability that a given household living in

MSA k would move to each of the other MSAs: $E\big(corr(P_A, P_B)\big)_k = \sum_l w_{k,l} corr(P_k, P_l)$. The house price correlation vector, $corr(P_k, P_l)$, is constructed by computing the correlation of real annual house price growth over the 1980 – 2005 period based on the OFHEO index described earlier.

To impute a household's likelihood of moving from a given MSA to each other MSA, we use data from the U.S. Department of the Treasury's County-to-County Migration Patterns. The Treasury data uses the addresses listed on tax returns to determine whether a household moved. It aggregates the gross flows across counties and reports, annually for each county pair, the number of tax returns where the taxpayers moved from the origination county to the destination county. We aggregated the counties into MSAs, and for each MSA computed the fraction of its tax-filing households who move to each of the other MSAs. We use those fractions as estimates of the probabilities of any household in the MSA making the corresponding MSA-to-MSA move. These moving-shares are the weights for computing the distributions in Figure 2. Note that the figure considers only out-of-MSA moves – within-MSA moves are excluded from the weights and the graph.

When we weight by where households typically move, it becomes clear that most households face much higher effective correlations than indicated in the first figure, because households are more likely to move to more highly correlated MSAs. In Figure 2, the distributions of correlations shift upwards in nearly every MSA.[4] In many MSAs the top of the black bar shifts up near the top of the grey bar. This implies that the entire top quartile of correlations for these MSAs is close to one. (It is impossible to obtain a correlation of exactly one in our data since we exclude within-MSA moves and no MSAs are perfectly correlated with each other.)

For example, in New York, the 75th percentile correlation shifts up to 0.95 from 0.53 in Figure 1, and the 25th percentile shifts to 0.50 from 0.12. In Miami and Detroit, the correlation is expected to be at least 0.66 three-quarters of the time. In most cities, even the 5th percentile

[4] The exceptions are minor and tend to occur in cities where there are relatively few high-correlation destinations. Every reported percentile cutoff increases once we weight by the moving probabilities, except: Chicago's 75th and 95th percentiles decline from 0.70 to 0.67, and 0.81 to 0.75, respectively; Indianapolis' 95 percentile declines from 0.80 to 0.79; Phoenix's 75th percentile declines from 0.49 to 0.47; and Salt Lake City's 95th percentile declines from 0.55 to 0.51. Even in those cities, the rest of the distribution shifts upward considerably. For example, Chicago's median correlation rises from 0.55 to 0.63; Indianapolis' 75th percentile rises from 0.49 to 0.59; Phoenix's median rises from 0.37 to 0.42; and Salt Lake City's 75th percentile rises from 0.33 to 0.51.

correlation rises considerably. In New York, it increases to 0.31 from −0.22. Similarly large shifts of the entire probability distribution occur in San Francisco, Dallas, and Philadelphia, among others.

Not every metro area experiences such a sizeable shift in their correlation distributions after weighting. Atlanta and Phoenix, for example, change relatively little. Also, in many MSAs the 5th percentile correlation remains fairly low or negative. While those MSAs still exhibit an overall upwards shift in their distributions, the top three quartiles of the distributions shift by more than the bottom quartiles, with Austin and Seattle being representative examples.

To illustrate the range of the effective expected correlations in real annual house price growth, Table 1 presents the distributions of the correlations across MSA-pairs. To convert the raw correlations to expected correlations, we weight each MSA-pair observation by the imputed probability of a household moving between those two MSAs. For comparison, the first column of Table 1 assumes that households have an equal probability of moving across any MSA-pair. This column corresponds to Figure 1, but with all MSAs pooled together. In the equally-weighted case, the average pairwise correlation is just 0.34.[5] However, 25 percent of the MSA-pairs have correlations of at least 0.54. Column (2) uses population-weighted correlations, where the probability of a household moving to an MSA, conditional on moving at all, is proportional to that MSA's share of the total population in all MSAs. This assumption makes little difference relative to column (1): The median correlation rises from 0.35 to 0.39 and the 95th percentile correlation rises from 0.82 to 0.86.

The expected correlation in house price growth rises considerably across the distribution when we recognize that households tend to move between highly covarying MSAs. In column (3), we weight the MSA-pair correlations by the actual rate at which households moved between them, computed using the Treasury's county-to-county migration data described above. This column corresponds to Figure 2. Using the migration weights, the average correlation rises to 0.57 from 0.34 in column (1), and the median correlation rises to 0.60 from 0.35. An even more striking finding is that the 75th percentile correlation rises from 0.54 to 0.89 – i.e., 25 percent of household moves are between MSAs that have correlations in annual house price growth of 0.89 or above. Even the lower end of the distribution has remarkably high correlations. The 25th

[5] We use equal weights for consistency with prior research. See, for example, Glaeser and Gyourko (2006).

percentile correlation in column (3), 0.34, is about the same as the median correlation in column (1).

Overall, accounting for where households actually move shifts the entire distribution of expected correlations to the right. This conclusion is confirmed in the bottom panel of Table 1 which reports various summary statistics for the (within-MSA) distribution of correlations. When MSA-pairs are weighted by migration flows, the difference between the 95th and 75th percentile correlations within each MSA shrinks dramatically, from 0.26 in column (1) to 0.08 in column (3), because the distribution is capped at 1.0 as it shifts to the right. Thus, the 75th percentile value rises considerably, but the 95th percentile cannot rise by as much. However, neither the interquartile range nor the difference between the 25th and 5th percentiles changes much between columns (1) and (3), indicating that the other points in the distribution increase in near-lockstep.

The next three columns of Table 1 show that the propensity to move between highly-covarying MSAs is not driven by relative house price changes in those markets. In the fourth column, we adjust the cross-MSA mobility rates by regressing the moving rate between a MSA-pair in a given year on the difference between the two MSAs in annual house price growth over the prior year, that difference squared, and a constant term. We then use the residuals from that regression, plus the constant term, as the moving weights.[6] If moving patterns were determined by where households could afford to move rather than where they wished to move, controlling for relative house price growth should affect the expected correlations. Instead, the basic pattern of results is little changed from the one using the unadjusted moving rates, in the third column. The median expected covariance is 0.58 and the 95th percentile is 0.96. Although the 75th percentile covariance drops from 0.89 to 0.79, it is still considerably larger than for the unweighted or population-weighted moves in the first two columns.

In the fifth and sixth columns, we check whether the moving patterns are different in periods of house price growth or decline. They do not appear to be. The fifth column restricts the sample to MSAs in years where they had experienced positive nominal house price growth

[6] This is akin to setting the difference in price growth between the two MSAs to zero. Negative predicted moving rates are truncated at zero. While the estimated coefficients on the price difference terms are statistically significant and of an intuitive sign – households are less likely to move to an MSA whose price growth was higher than their own, and that effect accelerates as the price growth gap gets bigger – the magnitude is economically small and the R-squared is just 0.0013.

("booms"). The sixth column restricts the sample to MSAs in years where they did not ("busts"). In both cases, the basic pattern of results is little changed from column (3).

Finally, we also compute correlations in five-year house price growth rates, rather than annual growth rates, to try to more closely match the average household's holding period for its house. As in column (3), we use raw household mobility patterns as the weights in forming expected correlations. The distribution of expected correlations, reported in the last column, rises across the board since using the longer-difference growth rates reduces the effect of high-frequency fluctuations or noise in house prices. 75 percent of households have house price correlations of at least 0.44, 50 percent have correlations of at least 0.74, and 25 percent of households have correlations of 0.94 or more. Our ability to compute growth rates over even longer horizons is limited because of the length of the sample. However, the distribution using 10-year growth rates in house prices looks very similar to that reported in the last column of Table 1.

The reason that the expected correlation in house price growth rises when we account for households' moving tendencies is that the relation between household moves and house price correlation is skewed. The set of city pairs with high gross migration flows includes mostly city pairs with high price correlations, whereas the city pairs with low gross migration flows include both low and high correlation pairs. This pattern can be seen in Figure 3, which graphs the kernel density of the correlations in annual house price growth among various subsets of the 18,090 pairs of the 135 cities. The solid black line restricts the sample to the 4,812 city pairs that, according to the Treasury data, experienced no (gross) migration. A few of these pairs had correlations below −0.5, some had correlations of nearly 1, and the peak of the distribution is around 0.3. The dashed line shows the kernel density of the correlations for the remaining city pairs that experience positive gross migration. This distribution is slightly to the right of the distribution for city pairs with no migration, so on average households who move migrate between more highly correlated housing markets, but the overall difference is small. By contrast, the dotted line considers only those city pairs (A,B) where, of the households who moved out of city A, at least 1 percent moved to city B. One percent of moving households is a high moving rate, since most city pairs have few moves. The distribution of correlations shifts considerably to the right. That rightward shift is even more pronounced for the dash-dot line, which restricts the set of city pairs to those where the rate of moving out of A to B was at least

2.5 percent. These last two kernel densities indicate that the rate of moving is high mainly between high-correlation city pairs.

The patterns in Figure 3 explain the differences between Figures 1 and 2. When city pairs are equally weighted, the distribution of correlations looks like the solid and dashed lines. But when city pairs are weighted by the probability of a household moving between the two cities, the pairs represented by the solid line get no weight, while the pairs represented by the dotted and dash-dot distributions get significant weight. This reweighting shifts the mass of the correlation distribution (in most cities) to the right.

Investigating why MSAs have correlated house price growth rates – or why households tend to move between MSAs with correlated housing markets – is beyond the scope of this paper. Indeed, the value, to an individual household, of owning a house as a hedge against moving risk is separable from the reasons for the correlation or the potential move. For example, one possible reason for moving is that the shocks that induce the correlation in prices also induce labor market flows. That is, cities that are similar enough for households to want to move between are also likely to share the same economic fundamentals, leading to a correlation in their housing markets. Another possible reason is that cities with correlated house prices are demand substitutes. [McDuff (2011)] In either case, for an individual household, owning a house still helps hedge the purchase price risk in the city that is moved to. Nonetheless, in our empirical section, below, we will confirm this conclusion by using exogenous predictors of cross-MSA mobility to form expected correlations and covariances.

2. *An Application of Expected Covariances to Housing Demand – Theoretical Framework*

In the remainder of this paper, we provide an application of our estimates of the expected covariance in house price growth. Specifically, we examine whether the hedging benefit from owning a house whose value covaries positively with housing costs in likely future cities increases the demand for home owning. We start by outlining a simple theory that illustrates how owning a house can hedge against the house price risk from future moves, and why that hedging benefit might increase the demand for home owning. This illustration will also provide guidance for the empirical tests that follow.

The theory behind the hedging value of home owning has been discussed in several prior papers – such as Ortalo-Magne and Rady (2002), Sinai and Souleles (2005), and Han (2008) –

with varying degrees of generality. Our exposition generally follows Sinai and Souleles (2005), in which house prices are endogenous, but rents, incomes, housing quantity, and households' moving decisions and location choices are exogenous. The model also abstracts from some other important issues, such as leverage and down payment requirements, portfolio allocation, taxes, and moving costs. We make these simplifications to focus the model on the concept of the moving hedge – they are not intended to minimize the importance of other factors in housing demand and housing risk. Many of those other factors have been examined in prior work, such as leverage (Cocco (2000), Stein (1995), Hurst and Stafford (2004), Lustig and Van Nieuwerburgh (2005)), the potential correlation of labor income and house prices (Davidoff (2006)), endogenous quantity (Han (2008)), portfolio implications (Flavin and Yamashita (2002); Piazessi et al (2007)), and endogenous initial location choice and portfolio allocation (Ortalo-Magne and Prat (2010)), and would operate in addition to the hedging benefit that is the focus of this paper.[7]

Since our focus is on demonstrating how owning a house in one city can hedge against house price volatility in the next city, we will consider a representative household who initially lives in some city, *A,* and then moves to another city, *B*. To simplify, we assume that the household knows with certainty that it will live in *A*, and then in *B*, for *N* years each, after which it will die. (In our empirical work, we will recognize that *N* can vary across households, with some expecting to not move very often and others expecting to move more frequently, and that there are multiple destination cities to which households could move.) At birth, labeled year 0, the household chooses whether to be a homeowner in both locations or a renter in both locations.[8] The household chooses its tenure mode to maximize its expected utility of wealth net of total housing costs, or equivalently to minimize its total risk-adjusted housing costs.

[7] It is worth noting that theoretical papers that relax many of our more restrictive assumptions still yield similar qualitative implications. For example, Ortalo-Magne and Prat (2010), which in part generalizes the theoretical concepts in Ortalo-Magne and Rady (2002) and Sinai and Souleles (2005) to allow for multiple locations, a full portfolio decision, correlation between income and house prices, and endogenous leverage, still predicts that the hedging benefit of home ownership would have a positive effect on housing demand.

[8] The desired quantity of housing services is normalized to be one unit in each location. For convenience, rental units and owner-occupied units, in fixed supply and together equal to the number of households, both provide one unit of housing services. The results below can be generalized to allow the services from an owner-occupied house to exceed those from renting, perhaps due to agency problems. Additional extensions are discussed in Sinai and Souleles (2005).

The cost of obtaining a year's worth of housing services is the rent, denoted by $\tilde{r}_t^A$ in city A in year t, and $\tilde{r}_t^B$ in city B. The tildes denote that the rent in year t is not known at time zero, because rents fluctuate due to shocks to underlying housing demand and supply. To allow for correlation in rents (and, endogenously, in house prices) across cities, we assume that rents in the two locations follow correlated AR(1) processes: $r_n^A = \mu^A + \varphi r_{n-1}^A + k(\eta_n^A + \rho\eta_n^B)$ and $r_n^B = \mu^B + \varphi r_{n-1}^B + k(\rho\eta_n^A + \eta_n^B)$, where $\varphi \in [0,1]$ measures the persistence of rents, μ^A and μ^B measure the expected level or growth rate of rents (depending on φ), and the shocks η^A and η^B are independently distributed IID$(0,\sigma^2_A)$ and IID$(0,\sigma^2_B)$. ρ parameterizes the spatial correlation in rents (and in house prices) across the two locations, with ρ=0 implying independence and ρ=1 implying perfect correlation. To control the total magnitude of housing shocks incurred as ρ varies, the scaling constant κ can be set to $1/(1+\rho^2)^{1/2}$. For simplicity in this exposition, we will set the persistence term φ to 0. We find similar qualitative results with the more realistic assumption of φ>0. [Case and Shiller (1989)]

From a homeowner's perspective, the lifetime *ex post* cost of owning, discounted to year 0, is $C_O \equiv P_0^A + \delta^N\left(\tilde{P}_N^B - \tilde{P}_N^A\right) - \delta^{2N}\tilde{P}_{2N}^B$. The P_0^A term is the initial purchase price in city A, which is known at time 0. In the last term, $\tilde{P}_{2N}^B$ is the uncertain residual value of the house in B at the time of death. It is discounted since death occurs $2N$ years in the future. Our emphasis in this paper is on the middle term, $\delta^N\left(\tilde{P}_N^B - \tilde{P}_N^A\right)$, which is the difference between the sale price of the house in A at time N and the purchase price of the house in B at time N.[9]

For renters, the ex post cost of renting is the present value of the annual rents paid:

$$C_R \equiv r_0^A + \sum_{n=1}^{N-1}\delta^n\tilde{r}_n^A + \sum_{n=N}^{2N-1}\delta^n\tilde{r}_n^B .$$

[9] A capital gains tax, τ, on house price appreciation in A would create a wedge between the sale price in A and purchase price in B, reducing the effective covariance by a factor of $(1-\tau)$. In the U.S., however, τ is small. Since 1997, housing capital gains have been essentially untaxed since homeowners can exclude $500,000 of gains on their primary residence from tax if married, and $250,000 if single. Prior to 1997, homeowners faced capital gains tax at the time of the sale but could roll over the gain into their next house to the extent that the purchase price exceeded the basis of the old house and the new house was purchased it within two years of the prior sale. This enabled most households to effectively avoid the tax. Even a home owner that did not "trade up" to a more expensive house could receive a one-time $125,000 capital gains exclusion if over the age of 55. (The exclusion was lower, and the minimum age higher, before 1981.) Prior research has found that household mobility and the rate of house sales increased when the capital gains tax exclusion was expanded in 1997. [Cunningham and Engelhardt (2008); Shan (2011)] In our empirical work, we will condition on household mobility and instead identify our results based on where households are likely to move.

Sinai and Souleles (2005) derive house prices in this setting assuming they endogenously adjust to leave households indifferent between owning and renting. The resulting price in city *A*, P_0^A, can be expressed as the expected present value of future rents, $PV(r_0^A)$, plus the total risk premium the household is willing to pay to own rather than to rent:

$$P_0^A = PV(r_0^A) + \frac{(\pi_R - \pi_O)}{1-\delta^N} - \frac{\delta^N(\pi_R^B - \pi_O^B)}{1-\delta^N}. \qquad (1)$$

In the second term, the risk premium for owning, π_O, measures the risk associated with the cost C_O of owning, which in equilibrium reduces the price P_0^A in equation (1), ceteris paribus. The risk premium for renting, π_R, measures the risk associated with the cost C_R of renting. Since owning avoids this risk, π_R increases P_0^A, ceteris paribus. P_0^A also capitalizes $\Delta\pi^B \equiv (\pi_R^B - \pi_O^B)$, a net risk premium for renting versus owning in *B* that in equilibrium P_0^A inherits from house prices in *B*.

For owners, π_O measures the total house price risk from the three future housing transactions; i.e., the sale of the first house in *A*, and the purchase price and subsequent sale price of the second house in *B*:

$$\pi_O \equiv \frac{\alpha}{2}\left[\delta^{2N}\kappa^2(1-\rho)^2\left(s_A^2 + s_B^2\right) + \delta^{4N}\left(s_B^2\right)\right], \qquad (2)$$

where $s_A^2 \equiv \mathrm{var}(r_A)$ and $s_B^2 \equiv \mathrm{var}(r_B)$ are the variance of rents in cities *A* and *B*, respectively, and α is household risk aversion. Since house prices are endogenously related to rents (as in eq. (1)), house price volatility follows from rent volatility. Thus we can use s_A^2 and s_B^2 to measure the underlying housing market volatility.[10]

In the final term in eq. (2), s_B^2 reflects the risk associated with the sale of the house in *B*, discounted by $\delta^{(2N)2}$ since it takes place in year *2N*.

[10] If $\rho>0$, the variance of observed rents in a given city includes the contribution of the underlying housing market shocks η from the other city as well: $s_A^2 = \kappa^2(\sigma_A{}^2 + \rho^2\sigma_B{}^2)$ and $s_B^2 = \kappa^2(\sigma_B{}^2 + \rho^2\sigma_A{}^2)$. In the symmetric case with $\sigma_A{}^2 = \sigma_B{}^2 = \sigma^2$, then $s_A^2 = s_B{}^2 = \sigma^2$, independent of ρ. With $\varphi=0$ in eq. (2), the price risks come from the contemporaneous rent shocks: $\eta_N{}^A$ on $P_N{}^A$, $\eta_N{}^B$ on $P_N{}^B$, and $\eta_{2N}{}^B$ on $P_{2N}{}^B$. With $\varphi>0$, the prices would also include the persistent effect of the preceding rent shocks. [See Sinai and Souleles (2005).]

The first term in eq. (2) reflects the net risk from the sell-in-*A* and buy-in-*B* transactions in year *N*, i.e. the risk associated with the *difference* between the purchase price and sale proceeds, $\left(\widetilde{P}_N^B - \widetilde{P}_N^A\right)$. The net risk depends on the correlation ρ between house prices in *A* and *B*. The part of the first term inside the square brackets can be written as $\delta^{2N} f(\rho)\left(s_A^2 + s_B^2\right)$, with $f(\rho) \equiv \kappa^2(1-\rho)^2 = \frac{(1-\rho)^2}{1+\rho^2}$. If prices in the two markets are uncorrelated, with ρ=0, then $f(\rho) = 1$, so the net risk from the two transactions is simply the sum of the risks of the individual transactions $\left(s_A^2 + s_B^2\right)$, appropriately discounted. But as the two markets become increasingly correlated, the net risk declines. That is, owning the house in *A* helps to hedge against the uncertainty of the purchase in *B*. In the polar case when ρ=1, then $f(\rho)$=0, and so the sale and subsequent purchase fully net out. By contrast, if the prices in the two markets are perfectly negatively correlated, with ρ=−1, then $f(\rho)$=2, and the net risk is twice as large as the sum of the individual risks.

Since $f(\rho)$ is monotonically decreasing in ρ, in our empirical work it will be useful to use the approximation

$$\pi_O \approx \frac{\alpha}{2}\left[-\delta^{2N}\operatorname{cov}(A,B) + \delta^{4N}\left(s_B^2\right)\right], \tag{3}$$

where $\operatorname{cov}(A,B)$ is the covariance of rents (and prices) in *A* and *B*. The risk premium from owning should decline with this covariance.

For renters, uncertainty comes from not having locked-in the future price of housing services, so the risk of renting is proportional to the discounted sum of the corresponding rent shocks:

$$\pi_R \equiv \frac{\alpha}{2}\left(s_A^2 \sum_{n=1}^{N-1} \delta^{2n} + s_B^2 \sum_{n=N}^{2N-1} \delta^{2n}\right). \tag{4}$$

Turning to the remaining terms in eq. (1), the net risk premium in *B* that is capitalized into P_0^A analogously depends on the net risk of owning versus renting while living in *B*:

$$(\pi_R^B - \pi_O^B) \approx \frac{\alpha}{2} s_B^2 \left(\sum_{n=1}^{N-1}\left(\delta^n\right)^2 - \left(\delta^N\right)^2\right). \tag{5}$$

Finally, the present value of expected rents in A increases with the trend μ^A:

$$PV(r_0{}^A) \equiv \left(r_0{}^A + \mu^A \frac{\delta}{1-\delta} \right) \tag{6}$$

Generalizing this framework to a setting with heterogeneous households, $P_0{}^A$ can be thought of as reflecting a household's latent demand for owning. If the household's willingness-to-pay is above the market-clearing house price determined by the marginal homebuyer, the household would own, otherwise it would rent. In our empirical work, we observe the own/rent decision but not latent demand. We will control nonparametrically for differences across MSAs in the clearing prices for houses, by including MSA × year fixed effects, and will allow for heterogeneity across households (in particular in N and ρ). This approach allows us to map our empirical results on the determinants of the tenure decision to inferences about the latent demand for home ownership.

This framework yields several empirical predictions. First, as the covariance in house prices between cities A and B rises, a household living in A should be more likely to own its house. By equation (3), the risk of owning declines with the covariance, because the house acts as a hedge. Thus the demand for owning and the price $P_0{}^A$ should increase with the covariance, ceteris paribus.

It is important to note that this first prediction applies to exogenous moves. Endogenous moves raise the possibility that there is an option value to owning a house, which in theory could generate the opposite effect of covariance on the demand for home owning. If a household owns a house in city A and prices fall relative to house prices in city B, the household could choose not to move and continue to consume the same housing services. However, if house prices in city A rise relative to house prices in city B, the household could sell its house in A and use the proceeds to purchase more housing in B. In that example, the option to move potentially is valuable, and would be more valuable when the house prices in the origin city covaried less with possible future cities. Thus the option value of moving would imply that the demand for owning would increase as expected covariance fell. Of course, exogenous and endogenous reasons for moving are not mutually exclusive. Any given household presumably has some probability of a forced (exogenous) move and some desire to have the opportunity to expand its housing consumption (endogenous move). We focus the empirical analysis that follows on exogenous

moves by using exogenous household characteristics to predict the probability of moving and the destination conditional on a move.[11]

The second empirical prediction of the model is that the hedging value should diminish as the likelihood of moving falls. As a household's expected length-of-stay, *N*, in city *A* increases, the net price risk in eq. (3) is expected to occur further in the future and thus is discounted more heavily. That is, in making its tenure decision a household who expects to be mobile (small *N*) should be more sensitive to the moving-hedge benefit of owning, since its move will occur sooner and thus the net price risk will be larger in present value, ceteris paribus. Conversely, a household who expects it will never move has no need to worry about future housing markets. Thus the model predicts that the demand for owning should decline with the interaction of *N* and *cov(A,B)*.[12]

These cross-market implications operate in addition to the within-market implications already empirically established in Sinai and Souleles (2005). The key implication tested in that paper is that the effect of local rent volatility s_A^2 on demand generally increases with the horizon (*N*). Households with longer expected horizons are exposed to a larger number of rent shocks (in π_R), whereas the expected sale price risk (in π_O) comes further in the future and hence is discounted more heavily. Thus the demand for owning should increase with the interaction of *N* and s_A^2 – an implication that Sinai and Souleles confirm empirically. Here we focus instead on the cross-market implications described above.

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[11] Our econometric analysis represents a joint test that the benefit from hedging the risk from exogenous moves exceeds the loss from a reduced option to move on average, and that our model matches actual consumer choice. Our prior is that the hedging benefit exceeds the value of the option, and our empirical results support this view. First, the cross-MSA moves that we study seem unlikely to be motivated by changing housing consumption because it would be easier to adjust the quantity of housing consumed by moving *within* MSA. Second, as reported in Section 1, households tend to move between covarying MSAs. If their motivation was to exercise an option, they would move between uncorrelated MSAs. Third, Paciorek and Sinai (2011) report that the distribution of where households move, conditional on moving, changes little over time. Again, that pattern is consistent with a relatively stable, exogenous distribution of preferred destinations. In any case, as discussed below our empirical results imply that the average benefit from hedging the risk from exogenous moves exceeds the loss from a reduced option to move.

[12] These results generalize to the case when $\varphi>0$. First, P_0^A still increases with ρ, $\partial P_0^A/\partial\rho>0$. This is because $\partial\pi_0/\partial\rho$ remains negative, and $(\pi_R^B-\pi_O^B)$ is independent of ρ given $s^2{}_B$. When $\varphi>0$, π_R is no longer independent of ρ, but $\partial\pi_R/\partial\rho$ is positive. That is, a higher covariance also increases the amount of rent risk, which reinforces (though for realistic parameters is quantitatively smaller than) the effect of the reduced price risk due to $\partial\pi_0/\partial\rho<0$. Second, $\partial P_0^A/\partial\rho$ generally declines with *N* (i.e., the interaction term $\partial^2 P_0^A/\partial\rho\partial N<0$) for realistic parameters and *N* not too small (*N*>3).

3. Data

We use household level data from the 1980, 1990, and 2000 waves of the Integrated Public Use Microsample of the U.S. Census (IPUMS) as our base data set. The IPUMS is a representative cross-section sample of U.S. residents drawn from the decennial Census. It is well-suited for our purpose because it has many observations (in the 5 percent sample that we use, there are nearly 38 million person-level observations in total in the three waves), contains MSA identifiers, reports whether households own their homes, and provides a host of household-level income and demographic characteristics that we use as controls. We construct two subsamples from this data using the procedure outlined in Appendix Table A. Both subsamples are restricted to household heads age 25 and over, among other conditions. One sample, which we call the 'migration' subsample, excludes the households from the 1980 Census that due to the design of that year's Census were not asked about prior residences. After these restrictions, 10.3 million household-level observations remain. The other sample, which we call the 'regression' sample, excludes households who either do not live in an MSA or live in MSAs that are not covered in our other data sets (as well as other, relatively minor, sample restrictions), for a net total of 4.2 million household-level observations.

The other variables of interest – the expected covariances (cov), rent risks (s^2_r), and expected lengths-of-stay (N) – need to be imputed into the IPUMS. The expected covariance for a household living in MSA k is comprised of two parts: the vector of house price covariances between MSA k and the other MSAs l, and the probability weights that a given household (of group g) living in MSA k would apply to the likelihood of moving to each of the other MSAs: $E\left(\text{cov}(P_A, P_B)\right)_{k,g} = \sum_l w_{k,l,g} \text{cov}(P_k, P_l)$. The house price covariance vector, $\text{cov}(P_k, P_l)$, is constructed by computing the covariance of real annual house price growth over the 1980 – 2005 period based on the OFHEO index described earlier.

We use several different approaches to estimate the moving weights, $w_{k,l,g}$. The IPUMS reports each household's current MSA of residence and their MSA of residence five years earlier. Using the migration sample, we construct the average annual rate of moving from each MSA to each of the other MSAs conditional on moving out of the origin MSA, weighting the observations by the IPUMS household weights. We also repeat the weighting exercise allowing

the MSA-to-MSA moving matrix to differ by group, *g*. As groups, we use the Census's 381 detailed industries (1990 definition) as well as the Census's 243 detailed occupations (1990 definition). When we allow the weights to vary by MSA and group, $E\left(\text{cov}(P_A, P_B)\right)_{k,g}$ varies both across and within MSAs.

Because the weights condition on moving out of the MSA, the expected covariance excludes the potential hedging benefit of home ownership for within-MSA moves. In the empirical analysis, we will consider within-MSA moving separately. Our baseline specification will include a control for the probability of moving within the MSA and the robustness section of the paper will explore this issue further. To preview our rationale, in our baseline specification we are reluctant to assume that within-MSA moves should be restricted to have the same effect on housing demand as cross-MSA moves. In addition, we cannot estimate the expected covariance in house prices within an MSA since we do not know the distribution of locations within a given city that a household might move between, and not all parts of a metropolitan area necessarily appreciate at the same rate.

We construct expected horizon and rent volatility in the same manner as Sinai and Souleles (2005). We proxy for the expected horizon with the probability of not moving, imputed using exogenous demographic characteristics. The IPUMS reports whether a household has moved in the last year. To generate the expected probability of moving, we take the average rate of moving over the last year in the age (in 10-year bins) × marital status × occupation cell that matches the household in question (excluding the household from the cell). We subtract that average from one to obtain the probability of staying, P(stay). This is our proxy for the expected horizon *N*. In the regression analysis, we will control separately for age, marital status, and occupation in the vector of demographic controls, so the probability of staying will be identified from the interaction of these three variables, i.e. from households having a different mobility profile over their lifetimes depending on their marital status and occupation.

To estimate rent volatility, we use data from REIS, a commercial real estate data provider that has surveyed 'Class A' apartment buildings in 44 major markets between 1980 and the present. We use their measure of average effective rents by MSA, deflated using the CPI less shelter. To estimate the volatility, we de-trend the log annual average real rent in each MSA and compute the standard deviation of the deviations from the trend between 1980 and 2002. By

using logs, the standard deviation is calculated as a percent of the rent and so the measured rent risk is not affected by the level or average growth rate of rents.

Key summary statistics from the combined data set are reported in Appendix Table B.

4. *Application to Housing Demand -- Estimation strategy and results*

We wish to estimate the following regression, for household *i* in MSA *k* at time *t*:

$$\begin{aligned} OWN_{i,k,t} &= \beta_0 + \beta_1 f(s_r)_k + \beta_2 g(N)_i + \beta_3 f(s_r)_k \times g(N)_i + \\ &\beta_4 E\left(\text{cov}(P_A, P_B)\right)^{\frac{1}{2}}{}_{i,k} + \beta_5 E\left(\text{cov}(P_A, P_B)\right)^{\frac{1}{2}}{}_{i,k} \times g(N)_i + \\ &\theta X_i + \psi Z_{k,t} + \zeta_t + \varepsilon_{i,k,t}, \end{aligned} \tag{5}$$

where 'OWN' is an indicator variable for home ownership, s_r is the measure of the local rent volatility, *N* is the imputed probability of not moving (P(stay)), and $E\left(\text{cov}(P_A, P_B)\right)^{\frac{1}{2}}$ is the square root of the household's expected covariance in house prices. Our rationale for using the covariance in house price rather than the covariance of the underlying economic fundamental, rent, is a pragmatic one. We have both house price and migration data for 119 MSAs but rent data for just 44 MSAs. We can use the full set of 119 MSAs to construct the expected covariance if we use the price covariances.

The remaining variables in equation (5) are controls: *X* is a vector of household-level characteristics, *Z* controls for time-varying MSA-level characteristics, and ζ is a vector of year dummies. We will estimate equation (5) using OLS and linear IV.

The main predictions from the framework in Section 2 are that $\beta_3 > 0$, $\beta_4 > 0$, and $\beta_5 < 0$. The tests of $\beta_4 > 0$ and $\beta_5 < 0$ are novel to this paper, while $\beta_3 > 0$ was tested in Sinai and Souleles (2005) using a different data set. The framework in Section 1 also shows that the probability of owning should increase with the horizon *N*, which implies that $\beta_2>0$. In practice the coefficient on the uninteracted horizon term can also pick up the effects of other factors affecting the probability of owning, such as fixed costs being amortized over longer stays, and so we will not emphasize β_2. Also, we will include MSA × year dummies, which will subsume the effect of β_1, the coefficient on the uninteracted rent volatility. Sinai and Souleles (2005) estimated β_1 to be negative, which is consistent both with the theory in that paper and Section 2

of this paper.[13] In preliminary analysis, our estimates of β_1 generally replicated those in Sinai and Souleles (2005) despite the difference in data sets, so we treat β_1 as a nuisance parameter in this paper.

Most of our empirical focus will be on identifying the estimates of β_4 and β_5. One way to identify β_4, the effect of the expected covariance on the decision to own, is to make use of the fact that different types of households within each MSA can have different weights applied to the MSA × MSA house price covariance matrix, reflecting their different probabilities of moving to different MSAs. This yields variation in *expected* covariances within *and* across MSA. Since we allow the moving weights to differ by industry or occupation groups, the resulting variation is at the industry × MSA or the occupation × MSA level. Thus we can include MSA × year dummies and a complete set of industry or occupation dummies, and still identify β_4. If we assume instead that all households within an MSA have the same probabilities of moving to the other MSAs, β_4 cannot be separately identified from the MSA × year fixed effects.

To illustrate, we could compare the homeownership rates of electricians and lawyers in Philadelphia since those two industry groups, despite living in the same MSA, are likely to move to different cities and thus have different expected covariances. We can then compare the difference in the two groups' homeownership rates to the difference in homeownership rates in the same two industry groups in another city, such as Seattle, who themselves have different expected covariances. The fact that households may be on average more likely to own their houses in Seattle or Philadelphia is absorbed with MSA × year dummies. Any capitalization of the value of the moving hedge into house prices is also captured by these fixed effects. Average differences in homeownership rates across industries can be controlled for with industry dummies. Thus our estimate of β_4 would be identified by industry × MSA variation. Our identification strategy generalizes this example to all MSAs and all industries. We also try a similar strategy using occupation groups rather than industries. We allow for general non-independence of the standard errors within industry × MSA × year (or occupation × MSA × year) groups by clustering the standard errors.

[13] More recently, the theoretical and calibration results of Ortalo-Magne and Prat (2010) and Hizmo (2010) also suggest that housing demand should decline with the volatility of the housing market.

We can identify β_5 separately from β_4, since β_5 is the coefficient on the interaction between the probability of staying (*N*) and the $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ term. Whether or not the expected covariance term alone turns out to be empirically distinguishable from unobserved MSA heterogeneity, the probability of staying varies across households *i* based on their demographic characteristics, so $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}_{i,k} \times g(N)_i$ varies by household within MSA. The same logic applies to the identification of β_3, the coefficient on $f(s_r)_k \times g(N)_i$, since the interaction of the MSA level rent variance and the group-level probability of staying provides MSA × group variation.

In addition to the variables of interest, in all regressions we control for standard household-level covariates: The (uninteracted) imputed P(stay), log real family income, age dummies (in 10-year bins), indicator variables for marital status (single, married, widowed, and divorced), education dummies (less than high school, high school, some college, and completed college), 381 occupation dummies, and the probability of moving within the MSA conditional on moving. We add 243 industry dummies when we use industry for the group *g* in forming the moving weights. MSA-level covariates and aggregate time series effects are subsumed by the MSA × year fixed effects, which we include in all specifications.

As a baseline, the first column of Table 2 uses the average MSA-to-MSA mobility rates by occupation to construct the moving probabilities, so $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ varies both across and within MSAs. The predictions from Section 2 are supported by the data. In column (1), the first row reports the effect of the expected price covariance on the likelihood of owning (β_4) and the second row reports how the effect changes as the probability of staying increases (β_5). Because the specification includes an interaction term with P(stay), the coefficient in the first row can be interpreted as the effect of the covariance for the polar case household who expects to move right away. We find that such a household is more likely to own when the covariance is greater, as predicted. The estimated coefficient β_4 of 2.042 (0.252 standard error) implies that a one standard deviation increase in the square root of the expected covariance (0.015 on a base of 0.041) would yield a 3.1 percent increase in the probability of home ownership (2.04 × 0.015). This represents a sizeable increase in the ownership rate (the average is 65.4 percent), though a small fraction of the cross-sectional standard deviation in the likelihood of owning (the standard

deviation is 47.6 percent). However, this extrapolation to an expected horizon of zero years is well outside of the variation in the sample.

To assess the effect for households with a longer expected horizon, we need to turn to the interaction term, P(stay) × $E(cov(P_A, P_B))^{\frac{1}{2}}$, in the second row. The negative estimated coefficient for β_5 of −2.039 (0.283) implies that the effect of house price covariance on the probability of owning attenuates as a household's expected horizon increases and the value of the moving-hedge falls, again as predicted. Since the estimated coefficient on the interaction term is of similar magnitude but opposite sign to the coefficient on $E(cov(P_A, P_B))^{\frac{1}{2}}$, the net effect of higher covariance declines to effectively zero for the polar case household who is imputed to never move, i.e. whose P(stay)=1. This result, too, is consistent with the framework in Section 1, since non-movers have no need for a moving hedge. To be precise, the estimates show that households with short expected durations and high expected covariances are more likely to own their houses than otherwise equivalent households with short expected durations and low expected covariances in the same MSA and year. As the expected duration increases, the gap in the probability of ownership declines to zero.

We can combine the estimates for these two polar cases to estimate the effect of a one standard deviation higher expected covariance on the probability of owning for households with an intermediate expected duration. For a household with the lowest expected horizon in the sample, two years (imputed P(stay)=0.5), a one standard deviation higher expected covariance raises the probability of owning by 1.6 percentage points (0.2 percentage points standard error), which is a large and significant effect. Households with a longer, five-year expected horizon (with P(stay)=0.8, approximately the sample average), are 0.63 percentage points (0.15) more likely to own a house when the expected covariance rises by one standard deviation. By the time households have a one-in-ten chance of moving in any given year (P(stay)=0.9), the effect on the probability of owning approaches zero (0.32 percentage points) and is barely statistically significant (a standard error of 0.16).

In the third row of Table 2, the effect of rent volatility in the current MSA on the likelihood of owning (β_3) becomes more positive as the horizon increases, since the coefficient on the interaction term, P(stay) × s_r, is positive. This interaction effect was one of the main

empirical results in Sinai and Souleles (2005), and it is robust throughout all the specifications in this paper.

We include P(stay) separately to control for expected horizon and related factors like the fixed costs of buying or selling a house. The estimated coefficient is positive as expected: households with longer expected lengths of stay on average are more likely to own.

The second column of Table 2 reports the estimated coefficients when we impute the pattern of where households expect to move based on industry groups and MSA. The results are very similar to those using occupation groups.

In the third column, we eliminate the within-MSA group-based variation by imputing mobility based on where other households in the same MSA move. Because the weighting matrix in this specification varies only by MSA, the estimated coefficients on the uninteracted expected covariance and rent volatility terms cannot be identified separately from the unobserved MSA-level heterogeneity that is absorbed by MSA × year effects. In this case, only the interaction terms with expected horizon (P(stay)) can be identified, since they vary by MSA × household. Despite the difference in the source of variation, the estimated coefficients on the interaction terms are very close to those in columns (1) and (2).

The last two columns of Table 2 provide the average effect of the expected covariance on home owning, across households of all expected durations, by leaving out the interaction term P(stay) × $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$. These estimates are identified solely from the within-MSA variation (by occupation or industry) and are not dependent on the P(stay) imputation. Because $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ in this specification is not interacted with P(stay), the estimated elasticity corresponds to the household with the average expected length-of-stay in the sample, which is about five years (P(stay)=0.80). The estimated coefficient in the top row of column (4) is 0.367 (0.99), which suggests that if the expected covariance were to rise by one standard deviation, the probability of home owning would go up by 0.367 × 0.015, or almost 0.6 percentage points. Similar results are found using industry groups in column (5).

5) Robustness

One potential complication for our analysis is that if households need the wealth from selling their prior house to afford their next house, they might be constrained to move between

markets that have correlated house price changes. If this effect happens to vary with the MSA-level homeownership rate, it could spuriously link the probability of owning with the expected covariance since our measure of expected covariance is constructed using actual moves. However, we control for the expected covariance in house prices at the MSA level. Any moving based on liquidity constraints should affect all homeowners in a MSA, since they face the same house prices, and should therefore be absorbed by the MSA-level control. There is little reason to think that this constraint would bind differentially *within* MSAs for the various industries or occupations *and* be correlated with differences in their homeownership rates, and so it should not affect our analysis.[14]

Nonetheless, to confirm that our results are robust to this potential complication, we instrument for expected covariance with a covariance constructed using mobility weights that proxy for where a household would like to move if it were unconstrained. Our instrument assumes that, conditional on moving, households' choices of MSA are influenced by where other households in their current occupation or industry are located. In particular, our instrument assigns household *i*'s (currently living in MSA *k*) probability of moving to MSA *l* to be the share of household *i*'s occupation (or industry) in MSA *l* relative to all other MSAs excluding *k*. This set of probabilities differs by occupation (industry) within an MSA, but most of the variation in this instrument is across occupations (industries), not across MSAs. However, when those moving probabilities are used to weight the MSA covariance vectors, which differ across MSAs, the resulting expected covariance varies both within and across MSAs. To instrument for P(stay) $\times\ E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$, we interact P(stay) with the expected covariance instrument. Since P(stay) is imputed using exogenous household demographics, we do not need an instrument for it. (The first stages of the IV regressions are reported in Appendix Table C.)

The results of this IV strategy are reported in Table 3. In column (1), the IV-estimated coefficients for $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ and its interaction with P(stay) nearly double relative to the OLS estimates in the first column of Table 2, to 4.209 (1.271) for the expected covariance and −3.813 (0.387) for the interaction term. Despite the larger standard errors, the IV coefficients remain statistically significant. Since the estimates continue to be close in magnitude with

[14] The theoretical argument of this paper does not require that a household's moving between markets be unconstrained. If a household knows in advance that, when it moves, it would need to move to a housing market where house prices had covaried positively, it should take that into account when making its initial house purchase decision. This is why we address just the empirical implications of this potential mechanism.

opposite signs, at every expected length-of-stay the estimated effect of higher expected covariance on the probability of homeownership is about twice what was found in Table 2. As expected, those households who we impute would never move still have no differential response to changes in expected covariance. For households with P(stay)=0.5, a one standard deviation greater expected covariance leads to a nearly 4 percentage point increase in the probability of home owning. At the sample average P(stay), 0.8, the same increase in expected covariance would raise the probability of owning by just under 2 percentage points. Despite the statistical significance of the individual reported coefficients, for levels of P(stay) observed in the data, the combined effect of $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ and $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}} \times$ P(stay) becomes statistically indistinguishable from zero when instrumenting.

Column (2) of Table 3 uses industry groups rather than occupation to construct the instrument. The estimated coefficients on $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}}$ and $E\left(cov(P_A, P_B)\right)^{\frac{1}{2}} \times$ P(stay) are slightly smaller in absolute value than in column (1), yet still statistically significant. Their combined effects are also statistically different from zero as long as P(stay) is lower than 0.65. At P(stay)=0.5, a one standard deviation greater expected covariance leads to a 3 percentage point increase in the probability of owning.

Column (3) uses just the MSA-level variation to construct the expected covariance, and for the instrument uses the occupation distribution of the MSA to construct where the MSA residents on average would move to. As in Table 1, the level effect of expected covariance cannot be identified in this particular specification. However, the interaction term has the same estimated magnitude as in columns (1) and (2), with about a 50 percent smaller standard error. In sum, the interaction term β_4 remains consistently significantly and economically negative, even across all the IV specifications. Thus we can reject the null hypothesis of no attenuation (with expected horizon) of the effect of the moving hedge on the probability of owning on average over the sample.

Our baseline empirical specification estimated in Table 2 was selected, in part, for its parsimony. In Table 4, we show that our results are robust to the key choices we made. In all cases, we show just the specification corresponding to column 1 of Table 2, which uses MSA × occupation variation to compute the expected covariance. However, the conclusions are the same no matter which specification from Table 2 we replicate.

The first robustness check is to use within-MSA moves for empirical identification. In the specification in equation (5), the expected covariance variable is constructed over the set of possible out-of-MSA moves. We controlled for the possibility that owning a house could hedge against house price changes within the same MSA by including separately an estimate of the household's probability of moving within the same MSA. Alternatively, we could have included the within-MSA moving probability as another element in the weighting vector for expected covariance. That approach would require restricting the effect of within-MSA covariance on housing demand to be the same as across-MSA covariance. It would also require an assumption about the expected covariance of house prices within the MSA since we do not observe within-MSA house prices. We prefer our less restrictive identification strategy that uses just the variation in expected covariance conditional on moving. Nonetheless, treating within-MSA covariance the same as out of MSA covariance yields estimates that are quite similar to our baseline estimates. In the first column of Table 4, we assume that the covariance for within-MSA moves is equal to the MSA's variance – i.e.: the house price correlation is equal to one for within-MSA moves – and weight within-MSA moves in the expected covariance variable by the probability of moving within the MSA. The estimated coefficient on the expected covariance term declines from 2.04 in the first column of Table 2 to 1.53. However, the standard error increases enough (to 0.41) that the these estimated coefficients are statistically indistinguishable. All the other coefficients of interest are basically unchanged.[15]

Another covariate that has little or no effect on the estimates is a control for the expected variance in the destination housing market. To control for housing market volatility in the destination, we simply add $E[var(P_B)]^{1/2}$, which is our proxy for s_B, as a covariate in our baseline specification. The expected variance is the weighted average variance in house prices across the possible destination MSAs, conditional on moving out of the MSA. The results are reported in column 2 of Table 4. The estimated coefficient on $E[var(P_B)]^{1/2}$ is negative and not statistically significant. Including it also has virtually no effect on the other estimated coefficients. These results are consistent with the theoretical framework in Section 2, where the effect of the variance in house prices in the destination cities on housing demand in the origin is ambiguous,

[15] We also have tried testing whether the estimated coefficient on within-MSA covariance is equal to that on the across-MSA covariance. They are not. However, the within-MSA expected covariance – which is just the MSA's price variance times the probability of moving within the MSA conditional on moving at all – is difficult to identify separately from the effect of the MSA's rent variance alone.

due to the offsetting influences of rent risk and house price risk, and attenuated, due to the discounting of future uncertainty.

The third column of Table 4 makes sure that the estimated coefficient on the interaction of $P(stay)_i \times E[cov(P_A,P_B)]^{1/2}$ is not due to a spurious correlation between household characteristics, the expected length of stay, and the expected covariance, by interacting all X_i covariates with P(stay). The estimates on the coefficients of interest are virtually unchanged – they decline by about 10 percent but are statistically indistinguishable from the baseline estimates – when we saturate the regression with P(stay) interactions.

One final potential complication concerns house price formation. The model in Section 2 assumes that common housing demand shocks across MSAs induce house price covariance. However, it is possible that a housing demand shock in one MSA could propagate to other MSAs when households move and spend their housing capital gains, inducing a correlation between household mobility and house price covariance. If this process of price formation occurred at the MSA × occupation × household mobility level, it would raise the issue of reverse causality contaminating our estimates of β_4 and β_5. However, this possibility is not supported by the data. First, even at the MSA × occupation (or MSA × industry) level, the number of households moving from any given MSA × occupation cell to another MSA is small and thus unlikely to influence the house price index at the destination. The median share of the inflow of households into one MSA in a given year that comes from a single MSA × occupation group is less than three-hundredths of one percent. The 95th percentile is still less than three-tenths of a percent. Even if an entire origin MSA were populated by home owners who moved to just one destination – which in any case would be subsumed by our MSA fixed effects – the median origin MSA's share of in-migrants to a particular destination would be just 1.5 percent. In addition, including a control for the weighted average share of movers to the destination accounted for by households in each MSA × occupation group has no effect on the parameter estimates in our baseline regression.

Second, if households moved when they had housing capital gains, and those gains contributed to housing market covariance, then the mobility-weighted covariance should be higher in housing booms. However, Table 1 shows that is not the case.

Lastly, in order for there to be reverse causality at the full MSA × occupation × <u>household mobility</u> level that we use to identify our estimate of β_5, migrants with relatively high

predicted mobility would have to move between relatively high-covariance MSA pairs (as compared to households in the same occupation × origin MSA cell with relatively lower predicted mobility). We tested this implication in the IPUMS by regressing the covariance of the MSA pairs a household moved between (the ex post $\text{cov}(P_k, P_l)$) on its predicted mobility (P(stay)). We found that households with a higher predicted mobility moved between slightly less covarying MSA pairs, rejecting concerns of reverse causality.[16]

6. *Conclusion*

This paper established two novel results. First, because households tend to move among correlated housing markets, the effective covariance of house prices across housing markets is much higher than analysts have previously assumed. We find that half of households' moves in the U.S., excluding within-MSA moving, are between MSAs with correlations in annual real house price growth rates of 0.60 or greater, and 25 percent are between MSAs with more than a 0.89 correlation. When five-year house price growth rates are used, the median correlation rises to 0.74.

Second, households' tenure decisions appear to be sensitive to the moving-hedge benefit of home owning. Households with higher expected covariances between house prices in their current market and their possible future markets are more likely to own. This effect attenuates with a household's expected length of stay in the house: less mobile households place less weight on future housing markets than do more mobile households. For a household who is likely to move in the next two years, having a one standard deviation higher expected covariance leads to a 2 to 4 percentage point higher homeownership rate. That relationship diminishes with the expected length of stay in the house and is indistinguishable from zero for households who appear unlikely to move. The results are robust to instrumenting for the expected covariances by assuming households move proportionally to their industry shares.

The analysis in this paper suggests that the natural hedge provided by owning a house may be quite valuable, and for many households home owning (absent leverage) may actually reduce the risk of the total lifetime cost of obtaining housing services. As noted in Sinai and

[16] The estimated coefficient was statistically significant, but economically tiny. A household with a one standard deviation lower probability of staying (so, more mobile) would have moved between an MSA pair with between a 0.03 and 0.07 standard deviation lower covariance. This result is robust to the inclusion of all the covariates we use in Table 2, as well as complete origin and destination MSA × year fixed effects.

Souleles (2005), home owners who expect never to move are in effect hedged against housing cost risk, since they locked in their housing costs with their initial house purchase. In this paper, we find that even home owners who expect to sell their house and move to another market may be partially hedged, because the volatility in their current house price often undoes the volatility in the price of their next house, reducing their lifetime risk on net. By contrast, renters are exposed to volatility in housing costs in both their current market and any future markets they might move to.

The argument that households should manage the uncertainty of their total lifetime housing costs, not the volatility of their current house price, has important implications for evaluating the efficacy of various methods of controlling households' housing risk, including house price derivatives. For most households, the positive expected covariance between house prices in their current city and prices in possible future cities provides at least a partial hedge against house price risk when they move. Because of that, households who use housing derivatives to lock in the sale price of their current house may actually unhedge themselves by reducing the covariance to zero.

This analysis may help explain why the house price derivatives market has failed to take off. [Shiller (2008)] It may simply be less expensive, easier, and nearly as effective to hedge by owning a home. While the natural hedge provided by owning a house is, in most cases, a partial one, providing a supplemental financial hedge against total housing risk might be complex. Households would need to obtain a complicated portfolio of derivatives that would hedge their total housing costs, including their future housing costs in different markets. This important distinction is neglected in analyses that implicitly assume that the covariances between the current and potential future housing markets are low (e.g., Case *et al.* (1993), Geltner *et al.* (1995), Shiller (2008), Voicu (2007)).[17]

This analysis may also help explain why there are so few long-term leases in the U.S. [Genesove (1999)] A long-term lease avoids rent risk and leaves the sale price risk with the

[17] de Jong *et al.* (2007) point out another reason that housing derivatives might provide a poor hedge is that MSA-level house price indices do not explain much of the variation in individual house prices. This point applies to within-MSA moves as well. Even Hizmo [2010], who finds that in some cities stocks of local companies track local house prices, concludes that the correlation is not enough to significantly reduce house price volatility. Even if one could assemble a portfolio of local stocks to short to hedge the sale price of the current home, this paper shows that a household would also need to acquire an offsetting long portfolio of stocks local to other cities it might move to.

landlord. But for many mobile households there is a potential benefit of retaining exposure to the sale price as a hedge against the uncertainty of the cost of future housing services.

In addition, the results in this paper suggest that, for many households, the marginal propensity to consume out of changes in house prices could be small. To illustrate, if an increase in house prices reflects the fact that a household's implicit short position in future housing costs has become commensurately more expensive, then the household's real wealth is effectively unchanged by the housing capital gains. Unless the capital gains alleviate liquidity/collateral constraints, the consumption response should accordingly be small. Prior research emphasized this argument for home owners with long expected stays in their current housing markets. [Sinai and Souleles (2005), Campbell and Cocco (2007)] In this paper, the high expected house price covariances that we find imply that even home owners with short expected stays in their current housing markets can face similarly small real wealth effects as home owners with long horizons. That is, the high covariances lengthen the effective horizon of households that are likely movers, and so the wealth effect from a change in house prices will often be largely offset by changes in housing costs in both current and expected future housing markets.[18] These results can help explain the small marginal propensities to consume out of housing wealth estimated by Calomiris *et al* (2009) and Attanasio *et al* (2009), among others. Instead, our results suggest that the main channels for housing wealth effects on non-housing consumption would be collateral or liquidity constraints. [Hurst and Stafford (2004), Lustig and Van Nieuweburgh (2005), Ortalo-Magné and Rady (2006)]

[18] This is especially true for households who expect to change location but consume similar amounts of housing service flow. In contrast, households that are net long housing, such as seniors who expect to trade down to smaller houses and who have a discounted bequest motive, will still have a marginal propensity to consume out of housing capital gains, but it will be more attenuated for a household who faces high covariances. Conversely, households that are short housing, such as young households who would like to purchase more housing, could demonstrate a *negative* marginal propensity to consume out of housing capital gains because, with high covariances, increases in future housing costs could exceed the increase in wealth from a higher home sale price. This is a potential explanation for the differences by age in the marginal propensity to consume out of housing wealth found in Campbell and Cocco (2007) and Calomiris, Longhofer, and Miles (2011).

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Table 1: Distributions of correlations in house price growth across MSAs

Correlation:	One-year growth rates of real house prices						Five-year growth rates
			Migration weighted				
Weighting scheme:	Unweighted	Population weighted	Average migration rates	Conditional on house price growth differences	During booms	During busts	Average migration rates
Average	0.34	0.37	0.57	0.55	0.59	0.56	0.64
5th percentile	-0.17	-0.16	-0.02	-0.004	0.04	-0.05	-0.06
25th percentile	0.15	0.18	0.34	0.36	0.44	0.32	0.44
50th percentile	0.35	0.39	0.60	0.58	0.64	0.60	0.74
75th percentile	0.54	0.58	0.89	0.79	0.80	0.84	0.94
95th percentile	0.82	0.86	0.97	0.96	0.96	0.97	0.99
Average difference: 95th−75th percentile	0.26	0.23	0.08	0.14	0.12	0.15	0.07
Average interquartile range	0.37	0.35	0.37	0.20	0.16	0.15	0.41
Average difference: 25th−5th percentile	0.27	0.27	0.33	0.39	0.31	0.33	0.45

Notes: This table reports the distribution of weighted average house price growth correlations across MSAs. MSA *k*'s weighted average correlation is between its real house price growth and that in all other MSAs, with weights varied as listed in the table. Correlations are constant over time within MSA pairs, but the weights can vary over time. A 'boom' is an MSA x year when nominal house price growth in MSA *k* was positive; a 'bust' is an MSA × year when nominal house price growth was negative or zero.

Table 2: The relationship between expected house price covariance and the probability of owning (OLS)

	(1)	(2)	(3)	(4)	(5)
$E[cov(P_A,P_B)]^{½}$	2.042 (0.252)	1.950 (0.265)		0.367 (0.099)	0.298 (0.115)
$P(stay)_i \times E[cov(P_A,P_B)]^{½}$	-2.039 (0.283)	-2.016 (0.292)	-2.135 (0.151)		
$P(stay)_i \times s_r$	2.430 (0.140)	2.468 (0.152)	2.464 (0.081)	1.856 (0.130)	1.902 (0.143)
$P(stay)_i$	0.887 (0.019)	0.870 (0.019)	0.889 (0.010)	0.838 (0.017)	0.821 (0.016)
Probability weights for $E[cov(P_A,P_B)]$:	MSA x occupation	MSA x Industry	MSA	MSA x occupation	MSA x Industry
MSA × year dummies?	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2965	0.2993	0.2964	0.2965	0.2993
Clustering of standard errors	MSA x year x occupation	MSA x year x industry	None	MSA x year x occupation	MSA x year x industry

Notes: N = 3,326,113. Sample period covers the 1980, 1990, and 2000 Censuses. The dependent variable is an indicator variable that takes the value of one if the respondent owns its home and zero if the respondent rents. The probability of staying (not moving), P(stay), is imputed using occupation × marital status × age category cells. The square root of the expected covariance of house prices, $E[cov(P_A,P_B)]^{½}$, is a moving-probability weighted average of the covariances between the MSA of residence and possible future MSAs. The standard deviation of detrended log rent, s_r, is a MSA (k) characteristic and is subsumed by the MSA × year dummies. The standard deviations and covariances are not time-varying. All regressions include as covariates: MSA × year dummies, age dummies, occupation dummies, marital status dummies, education dummies, log real family income, and the share of moving households who remain in the MSA. Columns (2) and (5) add a detailed set of industry dummies.

Table 3: The relationship between expected house price covariance and the probability of owning (IV)

	(1)	(2)	(3)
$E[cov(P_A,P_B)]^{½}$	4.209 (1.271)	3.757 (0.743)	
$P(stay)_i \times E[cov(P_A,P_B)]^{½}$	-3.813 (0.387)	-3.741 (0.377)	-3.718 (0.162)
$P(stay)_i \times s_r$	2.911 (0.155)	2.946 (0.171)	2.908 (0.083)
$P(stay)_i$	0.930 (0.021)	0.912 (0.021)	0.927 (0.010)
Probability weights for $E[cov(P_A,P_B)]$:	MSA x Occupation	MSA x Industry	MSA
MSA × year dummies?	Yes	Yes	Yes
Instrument?	MSA x Occupation instrument	MSA x Industry instrument	MSA x Occupation instrument
Adjusted R-squared	0.2965	0.2993	0.2964
Clustering of standard errors	MSA x year x Occupation	MSA x year x industry	None

Notes: N = 3,326,113. Sample period covers the 1980, 1990, and 2000 Censuses. The dependent variable is an indicator variable that takes the value of one if the respondent owns its home and zero if the respondent rents. The probability of staying, P(stay), is imputed using occupation × marital status × age category cells. The square root of the expected covariance of house prices, $E[cov(P_A,P_B)]^{½}$, is a moving-probability weighted average of the covariances between the MSA of residence and possible future MSAs. The standard deviation of detrended log rent, s_r, is a MSA (k) characteristic and is subsumed by the MSA × year dummies. The standard deviations and covariances are not time-varying. The instrument replaces the actual moving rates between MSAs with each destination MSA's share of the occupation (industry). All regressions include as covariates: MSA × year dummies, age dummies, occupation dummies, marital status dummies, education dummies, log real family income, and the share of moving households who remain in the MSA. Column (2) adds a detailed set of industry dummies.

Table 4: Additional specifications for the relationship between expected house price covariance and the probability of owning

	(1)	(2)	(3)
	Include within-MSA moves in E[cov]	Control for $E[var(P_B)]^{1/2}$	Fully interact covariates with p(stay)
$E[cov(P_A,P_B)]^{1/2}$	1.534 (0.411)	2.107 (0.256)	1.823 (0.242)
$P(stay)_i \times E[cov(P_A,P_B)]^{1/2}$	−2.121 (0.285)	−2.046 (0.283)	−1.782 (0.274)
$P(stay)_i \times s_r$	2.648 (0.152)	2.431 (0.141)	2.504 (0.126)
$P(stay)_i$	0.910 (0.021)	0.887 (0.019)	
$E[var(P_B)]^{1/2}$		−0.570 (0.618)	
E[share of movers-in]			
Probability weights for $E[cov(P_A,P_B)]$:	MSA × occupation	MSA × occupation	MSA × occupation
Adjusted R-squared	0.2966	0.2966	0.2980
Clustering of standard errors	MSA × year × occupation	MSA × year × occupation	MSA × year × occupation

Notes: N = 3,326,113. Sample period covers the 1980, 1990, and 2000 Censuses. The dependent variable is an indicator variable that takes the value of one if the respondent owns its home and zero if the respondent rents. The probability of staying (not moving), P(stay), is imputed using occupation × marital status × age category cells. The square root of the expected covariance of house prices, $E[cov(P_A,P_B)]^{1/2}$, is a moving-probability weighted average of the covariances between the MSA of residence and possible future MSAs. The standard deviation of detrended log rent, s_r, is a MSA (k) characteristic and is subsumed by the MSA x year dummies. The standard deviations and covariances are not time-varying. All regressions include as covariates: MSA × year dummies, age dummies, occupation dummies, marital status dummies, education dummies, log real family income, and the share of moving households who remain in the MSA.

Figure 1:

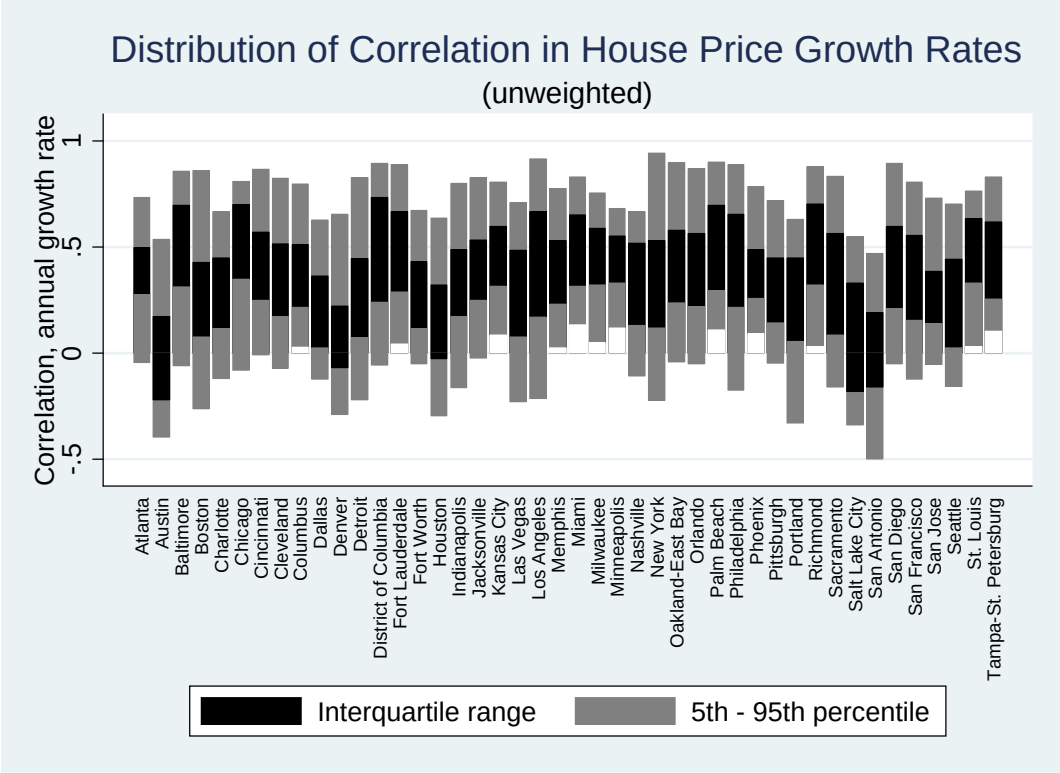


Figure 2:

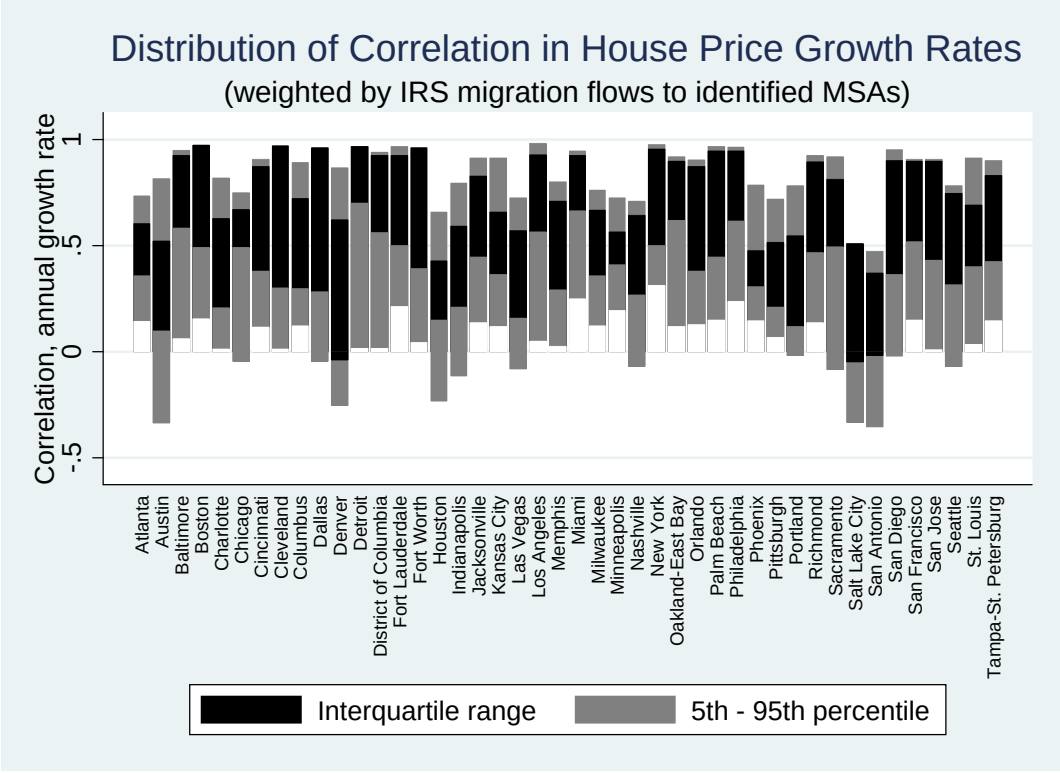
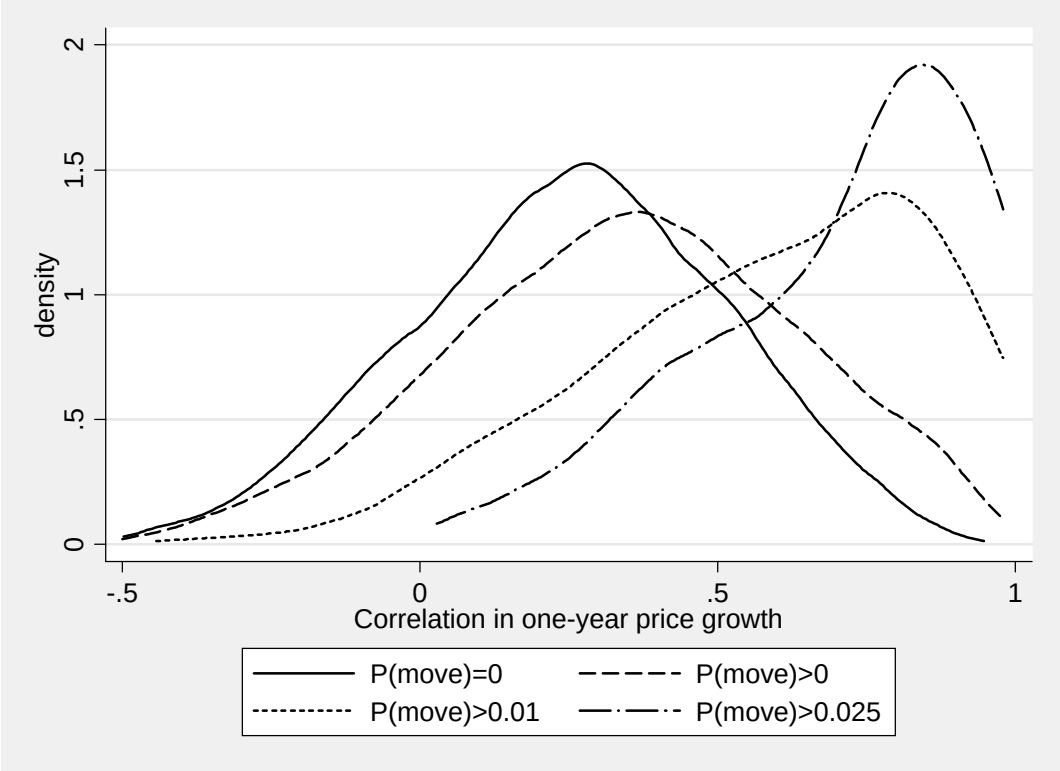


Figure 3: The distributions of house price growth correlations across housing markets, by probability of moving



Appendix Table A: IPUMS Data Construction

	Observations deleted	Observations left
Starting observations		37,925,632
Exclude age<25	14,159,970	23,765,662
Keep only heads of household	10,670,270	13,095,392
Keep only single-family households	877,100	12,218,292
Drop if were military households 5 years prior	61,092	12,157,200
Drop if were in college 5 years prior	192,144	11,965,056
Migration sample:		
Starting observations		11,965,056
Not asked about prior residence in 1980 Census	1,626,943	10,338,113
Regression sample:		
Starting observations		11,965,056
Cannot match MSA to REIS or HPI data[1]	6,765,722	5,199,334
Exclude MSAs with incomplete HPI data[2]	41,261	5,158,073
Missing log(family income)	64,204	5,093,869
Unable to impute P(stay)	494	5,093,375
Missing sd(rent)	764,579	4,328,796
Cannot impute out-of-town moves	22,830	4,281,924
Cannot impute expected moves based on occupation or industry shares	32,019	4,249,905
Drop if P(stay)<=0.5	21,292	4,228,613
Final sample:		4,228,613
Sample with age<=65:		3,326,113

[1]Reasons for a lack of a match are either that the household did not live in an MSA that was identified in the IPUMS data or the identified MSA could not be matched to the MSAs contained both in the REIS and HPI data. [2]MSAs with incomplete HPI data are Greenville, SC and New Haven, CT.

Appendix Table B: Summary Statistics

Variable	Mean	Standard Deviation
Own	0.654	0.476
Probability of staying	0.810	0.113
SD(real rent growth)	0.068	0.028
SQRT(IPUMS MSA × industry-weighted average price covariance) – actual	0.041	0.015
SQRT(IPUMS MSA × industry-weighted average price covariance) – imputed	0.038	0.011
Average annual rent ($2000)	10,290	3,738
Average house price ($2000)	170,235	87,066
Rent growth rate (real)	0.011	0.008
Price growth rate (real)	0.017	0.013
Age	44.0	11.1
Family income ($2000)	64,534	58,857
Fraction married	0.64	0.48
Fraction widowed	0.05	0.21
Fraction divorced	0.19	0.39
Fraction with less than high school ed.	0.16	0.37
Fraction with high school diploma	0.28	0.45
Fraction who attended some college	0.26	0.44
Fraction with college diploma	0.30	0.46
Share of moves that are within-MSA	0.75	0.04

Appendix Table C: First stages of the IV regressions (Table 3)

Column of Table 3:	(1)		(2)		(3)
Original covariate	$P(stay)_i \times E[cov(P_A,P_B)]^{½}$	$E[cov(P_A,P_B)]^{½}$	$P(stay)_i \times E[cov(P_A,P_B)]^{½}$	$E[cov(P_A,P_B)]^{½}$	$P(stay)_i \times E[cov(P_A,P_B)]^{½}$
Constructed $E[cov(P_A,P_B)]^{½}$	-0.950 (0.0003)	0.324 (0.002)	-0.681 (0.002)	0.393 (0.002)	-0.614 (0.001)
$P(stay)_i \times$ constructed $E[cov(P_A,P_B)]^{½}$	1.173 (0.0002)	0.067 (0.002)	1.217 (0.001)	0.027 (0.001)	1.166 (0.001)
Adjusted R-squared	0.9984	0.9520	0.9558	0.9628	0.9651
Probability weights for $E[cov(P_A,P_B)]$:	MSA × Occupation		MSA × Industry		MSA × Occupation
Instrument?	MSA × Occupation		MSA × Industry		MSA × Occupation
Clustering of standard errors	MSA × year × occupation		MSA × year × industry		none

Notes: N = 3,326,113. Sample period covers the 1980, 1990, and 2000 Censuses. The covariance of house prices is a probability-weighted average of the covariances between the MSA of residence and possible future MSAs. The dependent variable is the expected covariance weighted by the actual probability of staying (not moving). The instrument replaces the actual moving rates with each destination MSA's share of the industry or occupation group. The probability of staying is imputed using occupation × marital status × age category cells. The standard deviations and covariance are not time-varying. All regressions include MSA × year dummies, P(stay), the standard deviation of real rents, age dummies, occupation dummies, marital status dummies, education dummies, log real family income, the share of moving households who remain in the MSA, and a detailed set of industry dummies.