

PERE  
7/22/08  
2:00 pm

## Can Owning a Home Hedge the Risk of Moving?

July 14, 2008

Todd Sinai  
The Wharton School  
University of Pennsylvania  
and NBER

and

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

We are grateful to Dimo Primatov for helpful research assistance and participants in the Wharton Summer Applied Economics Workshop and at Stanford University for useful feedback. Sinai thanks the Research Sponsors Program of the Zell-Lurie Real Estate Center at Wharton for financial support. Contact: Todd Sinai, 1465 Steinberg Hall – Dietrich Hall, 3620 Locust Walk, Philadelphia, PA 19066. (215) 898-5390. [Sinai@wharton.upenn.edu](mailto:Sinai@wharton.upenn.edu).

## ABSTRACT

Conventional wisdom holds that one of the riskiest aspects of owning a house is the uncertainty surrounding its sale price, especially if one moves to another housing market. We show instead that for many households, home owning hedges their net exposure to housing market risk because the sale price is expected to covary with house prices in the likely new markets. That expected covariance is much higher than previously realized because households tend to move between highly correlated housing markets and there is considerable heterogeneity across city pairs in how much house prices covary. Taking these two considerations into account increases the estimated median expected correlation in real house price growth across MSAs from 0.36 to 0.67. Moreover, we show that households' tenure decision (whether to own or rent) is sensitive to this "moving-hedge" value. We find that the likelihood of home owning is five to 10 percentage points higher for a highly mobile household when the effective covariance between markets rises by 38 percent (one standard deviation). This effect attenuates as a household's probability of moving diminishes and the hedging value declines.

Conventional wisdom holds that one of the riskiest aspects of owning a house is the uncertainty surrounding its sale price, especially if one moves to another housing market. It is now well appreciated that house prices can be quite volatile. Between the end of 2005 and the end of 2007, real house prices fell by more than 15 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. Since the primary residence comprises about two-thirds of the median homeowner's assets (2004 Survey of Consumer Finances), realizing a gain or a loss on its house could have a sizeable effect on its balance sheet.

Historically, academics have concluded that this volatility in house prices makes home owning risky. Case *et al* (1993) argue for using house price derivatives to help households to offset house price volatility. In some cities, home equity insurance products have been created, enabling households to guarantee (for a fee) that their house values will not fall below some threshold. [Caplin *et al* (2003)]

However, once a household sells its house, it still has to live somewhere. In this paper, we show that for many households, home owning is not as risky as conventionally assumed because their house's sale price commoves with the purchase price of their next house. In effect, owning a house provides a hedge against the uncertain purchase price of a future house, reducing the volatility in the net cost of selling one house and buying another.

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

is low, which implies that owning a house provides a poor hedge for households who face some chance of moving to a different market. The literature has instead emphasized that home owning can be a good hedge against buying a larger house in the *same* market. [Cocco (2000), Ortalo-Magne and Rady (2002)]<sup>1</sup>

While it is correct that house prices do not covary much when one considers the U.S. as a whole, that unconditional 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. Second, households do not move to random locations; instead, they tend to move between highly covarying housing markets. Our first contribution is to show that, because of these two considerations, many households' expected covariance in house prices, where the expectation is weighted by the household's probability of moving from one location to another, is quite high. For example, the simple unweighted median correlation in house price growth across U.S. metropolitan statistical areas (MSAs) is 0.36. When we account for where households are likely to move, the effective correlation faced by the median household rises substantially, to 0.67.

Because households' effective expected covariances are quite high, owning a house can provide a valuable hedge against house price risk, especially for those households who are likely to move. This includes households who do not know exactly where they are going to move. As

---

<sup>1</sup> This 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 against volatility in housing costs within the current housing market. In fact, they implicitly assume that within-market moves have highly correlated house prices and out-of-market moves do not. Han (2008) distinguishes between 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.

long as they are likely to move to positively covarying markets, home owning hedges their expected purchase price risk.

Our second contribution is to show that households' tenure decision (to rent versus own) appears to be sensitive to this "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 their 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 expected house price covariance should matter less for households whose probabilities of moving to another MSA are smaller.

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 the probability of moving for each household. We impute the odds of a household moving to various 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 notional household that anticipates moving immediately the likelihood of home owning increases by five to 10 percentage points when the effective covariance rises by 38 percent, which is one standard deviation. In addition, this effect attenuates as the probability of moving across MSAs diminishes. That is, the covariance of

house price growth with the house price growth in other MSAs has little or no effect on the likelihood of home ownership for a household that expects never to move out of its MSA. But the expected covariance has a larger effect as the probability of moving increases. These results are robust to our 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 across MSAs.

In the next section, we present a simple theoretical framework to illustrate the moving-hedge benefit of owning and to motivate our empirical tests. In Section 2, 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. Section 3 describes the various data sources we use. The empirical identification strategy and results are covered in Section 4. Section 5 briefly concludes.

### *1. Theoretical Framework*

In this section, we illustrate how owning a house can hedge against the house price risk from future moves. This will also provide guidance for the empirical tests that follow. Our exposition generally follows Sinai and Souleles (2005). To simplify, and focus attention on the moving-hedge benefit of owning, we abstract from some other important issues, such as leverage and down payment requirements, taxes, and moving costs, which would operate in addition to the hedging benefit. (Such issues will be taken into account in our empirical work.)

Since our focus is on how owning a house in one city can hedge against house price volatility in the next city, we will consider a representative (price-setting) household that 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  $B$ , 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 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 to rent in both locations.<sup>2</sup> 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.

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 housing demand and supply. To allow for correlation in rents 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,  $\mu^A$  and  $\mu^B$  measure the expected level or growth rate of rents (depending on  $\varphi$ ), and the shocks  $\eta^A$  and  $\eta^B$  are independently distributed  $\text{IID}(0, \sigma_A^2)$  and  $\text{IID}(0, \sigma_B^2)$ .  $\rho$  parameterizes the spatial correlation in rents (and, endogenously, in house prices) across the two locations, with  $\rho=0$  implying independence and  $\rho=1$  implying perfect correlation. To control the total magnitude of housing shocks incurred as  $\rho$  varies, the scaling constant  $\kappa$  can be set to  $1/(1+\rho^2)^{1/2}$ . For simplicity in this exposition, we will set the persistence term  $\varphi$  to 0. We find

---

<sup>2</sup> 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 & Souleles (2005).

similar qualitative results with the more realistic assumption of  $\phi > 0$  [e.g., Case and Shiller (1989)].

From a homeowner's perspective, the lifetime *ex post* cost of owning, discounted to year 0, is  $C_O \equiv P_0^A + \delta^N (\tilde{P}_N^B - \tilde{P}_N^A) - \delta^{2N} \tilde{P}_{2N}^B$ . 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,  $\delta^N (\tilde{P}_N^B - \tilde{P}_N^A)$ , 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  $N$ .

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

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

Sinai and Souleles (2005) derive house prices in this setting assuming they endogenously adjust to leave households indifferent between owning and renting. The 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:

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

The risk premium for owning,  $\pi_O$ , measures the risk associated with the cost  $C_O$  of owning, which in equilibrium reduces the price  $P_0^A$ , ceteris paribus (c.p.). The risk premium for renting,  $\pi_R$ , measures the risk associated with the cost  $C_R$  of renting. Since owning avoids this risk,  $\pi_R$  increases  $P_0^A$ , c.p.  $P_0^A$  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,  $\pi_o$  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:

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

where  $s_A^2 \equiv \text{var}(r_A)$  and  $s_B^2 \equiv \text{var}(r_B)$  are the variance of rents in cities A and B, respectively, and  $\alpha$  is household risk aversion. Since house prices are endogenously related to rents, 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.<sup>3</sup>

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  $2N$ .

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,  $(\tilde{P}_N^B - \tilde{P}_N^A)$ . The net risk depends on the correlation  $\rho$  between house prices in A and B.

If prices in the two markets are uncorrelated, with  $\rho=0$ , then  $f(\rho) \equiv \frac{(1-\rho)^2}{1+\rho^2} = 1$ , so the net risk

from the two transactions is the sum of the risks of the individual transactions  $(s_A^2 + s_B^2)$

(appropriately discounted). But as the two markets become increasingly correlated, the net risk declines. That is, owning a house in A helps to hedge against the uncertainty of the purchase in

---

<sup>3</sup> If  $\rho>0$ , the variance of observed rents in a given city includes the contribution of the underlying housing market shocks  $\eta$  from the other city as well:  $s_A^2 = \kappa(\sigma_A^2 + \rho^2 \sigma_B^2)$  and  $s_B^2 = \kappa(\sigma_B^2 + \rho^2 \sigma_A^2)$ . With  $\rho=0$  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  $\rho>0$ , the prices would also include the persistent effect of the preceding rent shocks. [Sinai and Souleles (2005)]

B. In the polar case when  $\rho=1$ , then  $f(\rho)=0$ , and so the sale and subsequent purchase are expected to fully wash each other out. By contrast, if  $\rho=-1$  and the prices in the two markets are perfectly negatively correlated, 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  $\rho$ , in our empirical work it will be useful to use the approximation

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

where  $\text{cov}(A, B)$  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:

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

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:

$$(\pi_R^B - \pi_O^B) \approx \frac{\alpha}{2} s_B^2 \left( \sum_{n=1}^{N-1} (\delta^n)^2 - (\delta^N)^2 \right). \quad (4)$$

Finally, the present value of expected rents in A increases with the trend  $\mu^A$ :

$$PV(r_0^A) \equiv \left( r_0^A + \mu^A \frac{\delta}{1-\delta} \right) \quad (5)$$

For our empirical work, which will allow for heterogeneity in households (in particular in  $N$  and  $\rho$ ),  $P_0^A$  can be thought of as measuring a household's demand for owning. If this value is above the market-clearing price determined by the marginal owner, the household will own, otherwise it will rent.

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 price  $P_0^A$  and the demand for owning should increase with the covariance, c.p.

Second, that hedging value should diminish as the likelihood of moving falls. As the 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, a household that expects to be mobile (small  $N$ ) should be more attuned to a house's natural hedge when it chooses its tenure mode since its move will occur sooner and thus the uncertainty has a higher present value. Conversely, a household that anticipates never moving has no need to worry about future markets. Thus the demand for owning should decline with the interaction of  $N$  and  $COV(A,B)$ .<sup>4</sup>

These cross-market implications operate in addition to the within-market implications already empirically established in Sinai and Souleles (2005). The key implication they tested is that the effect of local rent volatility  $s_A^2$  on demand generally increases with the horizon ( $N$ ).

---

<sup>4</sup> These results generalize to the case when  $\varphi > 0$ . First,  $P_0^A$  still increases with  $\rho$ ,  $\partial P_0^A / \partial \rho > 0$ :  $\partial \pi_0 / \partial \rho$  remains negative, and  $(\pi_R^B - \pi_O^B)$  is independent of  $\rho$ . When  $\varphi > 0$ ,  $\pi_R$  is no longer independent of  $\rho$ , 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  $N$  for realistic parameters and  $N$  not too small ( $N > 4$ ).

Households with longer expected horizons are exposed to a larger number of rent shocks (in  $\pi_R$ ), whereas the expected sale price risk (in  $\pi_O$ ) comes further in the future and hence is discounted more heavily. Thus the demand for owning should increase with the interaction of  $s_A^2$  and  $N$  – an implication they confirm empirically.

## 2. *The covariance of house prices across MSAs*

The previous section established that the value of owing a house as a hedge against future moving depends on how much house prices covary across cities. Most researchers have concluded that there is little covariance in prices across housing markets because the national average covariance when MSAs are equally weighted 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 masks this heterogeneity. Second, households do not move at random. Instead, they are more likely to move among more highly covarying housing markets. The framework in Section 1 assumed that households knew with certainty that they would move from city A to city B. In practice, households likely have a number of cities to which they might move with some probability. For them, the value of the moving hedge depends upon their expected covariance, the probability-weighted average of the covariances of house prices in their current market with each of their other possible subsequent housing markets. Because of the non-random moving, the average household's expected covariance is higher than the national average.

Third, the distribution of the expected covariances is skewed, with a longer lower tail. Because of this, the median household's expected covariance is higher than the average. Thus,

many households have high expected covariances with a minority having very low expected covariances, bringing the average down.

The heterogeneity across and within housing markets can be seen in Figure 1, which graphs each MSA's distribution of correlations, for a subsample of the largest MSAs. (The figure uses the correlation rather than the covariance because the former is easier to interpret visually. The conclusions are the same no matter which measure one uses.) We compute 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 the effective house price volatility because it fails to take into account differences in liquidity between booms and busts in the housing market, it is available for a long period for many different MSAs, making it the best data set 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 correlations with each of the other MSAs, where each MSA is equally weighted and the correlation of an MSA with itself (which would equal one) is excluded. The bar turns from grey to black at the 25<sup>th</sup> percentile, then from black to grey at the 75<sup>th</sup> percentile, and the grey portion ends at the 95<sup>th</sup> percentile. Thus the black bar covers the interquartile range of correlations across MSAs and the grey/black bar covers from the 5<sup>th</sup> percentile to the 95<sup>th</sup>. An MSA whose vertical bar is higher has a higher distribution of correlations with other MSAs in the data.

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 grey bars for some start and end higher than the others. For example, consider the distribution of correlations between house

prices in Atlanta and all the other cities  $j$ ,  $\rho_{ATL,j}$ . The 5<sup>th</sup> percentile correlation is  $-0.05$ , and the 95<sup>th</sup> percentile correlation is  $0.77$ . By contrast, for the second city, Austin, the corresponding percentiles are  $-0.40$  and  $0.54$ . San Antonio has the lowest correlations, ranging from  $-0.50$  to  $0.47$ . The highest among the 5<sup>th</sup> percentiles is in Palm Beach ( $0.10$ ) and the highest of the 95<sup>th</sup> percentiles is in New York ( $0.94$ ).

While the 5<sup>th</sup> through the 95<sup>th</sup> percentile correlations always overlap with the other cities, the same cannot be said for the interquartile range (the black bars). In Atlanta, the interquartile range of the correlations runs from  $0.28$  to  $0.51$ , which does not overlap at all with the interquartile range in Austin, which runs from  $-0.22$  to  $0.18$ . The highest interquartile range is in Richmond, where it runs from  $0.33$  to  $0.71$ .

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 can be seen by the height 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 some other MSAs and relatively highly correlated with others. For example, New York has a  $-0.22$  correlation with its 5<sup>th</sup> percentile correlation city, but a  $0.94$  correlation with its 95<sup>th</sup> percentile city. There is relatively less heterogeneity within Minneapolis, where the corresponding correlations range from  $0.12$  (5<sup>th</sup> percentile) to  $0.71$  (95<sup>th</sup> percentile). There is also significant heterogeneity in the sizes of the interquartile ranges (the black bars). However, the cities with the widest 5<sup>th</sup> to 95<sup>th</sup> percentile ranges are not necessarily the same ones with the widest interquartile ranges. For example, New York's interquartile range runs from  $0.13$  to  $0.54$ , about the same as Nashville, even though Nashville's 5<sup>th</sup> to 95<sup>th</sup> range is much tighter. San Jose's

interquartile range is fairly tight at 0.15 to 0.40, even though the 5<sup>th</sup> to 95<sup>th</sup> percentile range is middle-of-the-road.

In Figure 2, we take into account where households are likely to move and estimate a probability of moving-weighted distribution of correlations. In this Figure, we use data from the U.S. Department of the Treasury's County-to-County Migration Patterns to impute a household's likelihood of moving from one MSA to another. 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 for each county pair, the number of tax returns annually where the taxpayers moved from the origination to the destination. We aggregated the counties into MSAs, computed the fraction of an MSA's taxpaying households moving from each MSA to each of the others, and used the fractions as the probabilities of all the households in the MSA making a similar transition. These moving-shares are the weights for computing the distributions in Figure 2. Once again, the Figure considers only out-of-MSA moves.

When we weight by where households typically move, it is clear that most households face much higher effective correlations than indicated in the first Figure because they are more likely to move to more highly correlated MSAs. In Figure 2, the mass of the distributions of the correlations shifts upwards in every MSA. In many MSAs the black bars shift to the very top of the distribution, so there is little-to-no grey bar at the top. This implies that the entire top 25 percent of the probability mass in the MSA has a correlation close to one. (It is impossible to reach a correlation of 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 75<sup>th</sup> percentile shifts upward to 0.95 from 0.54 in Figure 1 and its 25<sup>th</sup> percentile shifts from 0.13 to 0.50. Even its 5<sup>th</sup> percentile correlation rises to 0.28

from  $-0.22$ . Similar shifts occur in San Francisco, Dallas, and Philadelphia, among many others. In Baltimore, fully 75 percent of the moves have correlations of at least 0.64.

Not every metro area experiences such a shift in their correlation distributions when we weight by where households move. Atlanta and Phoenix, for example, change little. And, in many MSAs, the 5<sup>th</sup> percentile correlation is still fairly low or negative. Instead, those MSAs experience an upwards shift in their distributions, but their lower tail gets longer.

To provide a sense as to just how high the expected correlations across MSAs in real house price growth actually faced by households can be, Table 1 compares some summary statistics for the unweighted and weighted correlations. When we treat all MSAs equally, the unweighted average pairwise correlation is just 0.35. However, when we weight the correlations by the odds of a household actually making that move, the average correlation rises to 0.60.

This comparison of averages misses much of what makes the effective correlation so high, and that is the upper tail of the distribution. While the median is close to the mean – it increases from 0.36 to 0.67 – the 75<sup>th</sup> percentile correlation rises from 0.56 to 0.90 when we weight by the probability of moving. The 95<sup>th</sup> percentile goes up from 0.83 to 0.98. Thus, the U.S. population as a whole expects a correlation of at least 0.90 between the annual house price growth in the MSA they live in and the house price growth in an MSA they would move to 25 percent of the time. Indeed, more than one-third of the MSAs in our data have a 75<sup>th</sup> percentile correlation of 0.90 or above. Evidence of this compression at the top end of the correlation distribution can be seen at the bottom of Table 1. Unweighted, the difference between the average 95<sup>th</sup> percentile correlation (across MSAs) and the average 75<sup>th</sup> percentile correlation was 0.25. When we weighted by the probability of moving, it fell to 0.08 since in many MSAs, the weighted distribution was compressed against the maximum of 1.



In addition, after weighting, very little of the probability mass is on moves between markets where the correlations are negative. The 5<sup>th</sup> percentile correlation increases from  $-0.16$  (unweighted) to  $0.01$  (weighted). This is significant because a positive correlation indicates that owning a house provides at least some of a moving hedge.

Investigating why households tend to move between MSAs with correlated house price growth is beyond the scope of this paper. However, one can surmise that the very demand shocks that induce the correlation in rent shocks in the framework in Section 1 also lead to 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. It is relatively common for a household to move between Dallas and San Antonio, and their house prices are highly correlated. But it is relatively rare for the household to move between Dallas and Milwaukee, and their house prices are not correlated much at all. Likewise, it is more common for a household to move between correlated Los Angeles and San Diego than between uncorrelated Los Angeles and Cincinnati.

Alternatively, households may move between correlated cities precisely because the house prices covary. For example, if a household lived in a city where house prices grew less than the national average, it might be able to afford to move only to where house prices grew similarly little – or less. While we will not worry about this potential endogeneity for the illustrative Figures 1 and 2, we will use an instrumental variables strategy in the next section when estimating the demand for home ownership induced by the moving hedge.

### 3. *Data*

We use the 1992 through 2002 waves of the Current Population Survey (CPS) as our base data set. The CPS is a representative, annual, repeated cross-section survey of households conducted by the Bureau of Labor Statistics. It is well-suited for our purpose in that it has many observations (55,000 – 85,000 per year), contains MSA identifiers, reports whether the household owns its home, and contains a host of income and demographic characteristics we use as controls.

The main variables of interest – the expected covariance, rent risk, and expected length-of-stay – need to be imputed to the CPS. The expected covariance is comprised of two parts: the matrix of covariances between each pair of MSAs, and the probability weights that a household living in MSA  $k$  would apply to the likelihood of moving to each of the MSAs. The covariance matrix is constructed using real annual house price growth based on the OFHEO index described earlier. The covariances are estimated over the 1980 to 2002 period.

We use several different approaches to estimate the moving weights. The Integrated Public Use Microsample of the 1980, 1990, and 2000 U.S. Censuses reports the current MSA of residence and the MSA of residence five years earlier. Pooling the household-level data from these three surveys, and using the provided household weights, we construct the average annual rate of moving from each MSA to each of the other MSAs. We then repeat the exercise allowing the MSA-to-MSA moving matrix to differ for each of the Census's detailed industry groups, and again with a different matrix for each 10-year age bin: 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and 85-90.

We construct expected duration and rent volatility in the same manner as Sinai and Souleles (2005). We proxy for the expected duration with the probability of not moving, imputed using exogenous demographic characteristics. The CPS reports whether each household

has moved in the last year. To generate the probability of moving, using the CPS we take the average rate of moving over the last year in the age (in 10-year bins)  $\times$  marital status  $\times$  major occupation cell that matches the household in question, but excluding that household from the cell, and impute the average as the expected probability of moving. We subtract that average from one to obtain the probability of staying,  $N$ . We will control separately for age, marital status, and major occupation in a vector of demographic controls, so the probability of staying will be identified off of the fact that households have a different mobility profile over their lifetimes depending on whether they are married and their occupations, or both.

To estimate rent volatility,  $\sigma_r$ , we use data from REIS, a commercial real estate data provider that 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 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 risk is not affected by the level or average growth rate of rents.

In all regressions, we restrict our sample to CPS households where the head is age 25 or over and who live in one of the 42 MSAs we can match to the REIS data. When we use MSA-based or industry-based moving to estimate the expected covariance, we exclude households over age 65 from the sample but not when we use age-based moving.

#### 4. *Estimation strategy and results*

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

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

where ‘OWN’ is an indicator variable for home ownership,  $\sigma_r$  is the measure of the rent volatility,  $N$  is the imputed probability of not moving, and  $E\left(\text{cov}(P_A, P_B)^{\frac{1}{2}}\right)$  is the square root of the household’s expected covariance. The remaining variables are controls:  $X$  is a vector of household-level characteristics,  $Z$  controls for time-varying MSA-level characteristics, and  $\zeta$  is a set of year dummies. We will use OLS.<sup>5</sup>

The predictions from the framework in Section 1 are that  $\beta_1 < 0$ ,  $\beta_3 > 0$ ,  $\beta_4 > 0$ , and  $\beta_5 < 0$ . One way to identify the effect of  $E\left(\text{cov}(P_A, P_B)^{\frac{1}{2}}\right)$  is to make use of the fact that it applies a set of weights to a MSA  $\times$  MSA covariance matrix. That covariance matrix itself does not vary within MSA and thus we cannot separately identify the effect of the unweighted covariance from MSA-level unobserved heterogeneity. But different types of households in each MSA apply differing weights to that same covariance matrix, yielding variation in *expected* covariances within MSA. Since we allow the moving weights to differ by industry or age groups, our variation is at the industry  $\times$  MSA or the age  $\times$  MSA level. Thus we can include MSA  $\times$  year dummies and a complete set of industry dummies and still identify  $\beta_4$ , the effect of the expected covariance on the decision to own.

It is more straightforward to identify  $\beta_5$  and  $\beta_3$  since they make use of the interaction between the probability of staying and  $E\left(\text{cov}(P_A, P_B)^{\frac{1}{2}}\right)$  or  $\sigma_r$ , respectively. While the covariance and variance terms alone may be indistinguishable from unobserved MSA

---

<sup>5</sup> The marginal effects from a probit regression are similar to the OLS results reported here. We use OLS in this table for consistency with the linear IV regressions reported below. We are in the process of trying an instrumental variables probit model.

heterogeneity, the probability of staying varies across households  $i$  based on their demographic characteristics, so both  $E\left(\text{cov}(P_A, P_B)^{\frac{1}{2}}\right)_{i,k} \times g(N)_i$  and  $f(\sigma_r)_k \times g(N)_i$  vary by household within MSA.

The standard deviation of rent variance,  $\sigma_r$ , is indistinguishable from MSA-level unobserved heterogeneity. Typically, we will include MSA  $\times$  year dummies, subsuming  $\sigma_r$  and will not try to identify its effect on the demand for owning.

As a baseline, the first column of Table 2 uses the IPUMS average MSA-to-MSA mobility rates to construct the moving probabilities, so  $E\left(\text{cov}(P_A, P_B)^{\frac{1}{2}}\right)$  varies only across MSAs. In the first column, we use a set of MSA-level covariates – average real rent, average real house prices, annual real rent growth, and annual real house price growth – to control for MSA-level heterogeneity. We also include year dummies and household-level demographic controls: age dummies, occupation dummies, marital status dummies, race dummies, and controls for income.

The predictions of the framework from Section 1 are supported by the data. The first row reports the effect of the expected covariance on the likelihood of owning and the second row reports how the effect differs as the probability of staying increases. Because the interaction term is in the estimation, the estimated coefficient in the first row can be interpreted as the elasticity for a household who expects to move right away. Such a household is more likely to own when the expected covariance – and hence the value of the moving hedge – is greater. The estimated coefficient of 3.41 (0.57 standard error) implies that a one standard deviation increase in the square root of the expected covariance (0.012 on a base of 0.042; see Appendix Table A) would yield a 4.1 percent increase in the probability of home ownership, a sizeable increase in the ownership rate (the average is 0.605) but a tiny fraction of the cross-sectional standard deviation in the likelihood of owning (the standard deviation is 0.488). As the expected length of

stay increases, the value of the moving hedge declines, as indicated by the estimated coefficient in the second row of  $-5.37$  ( $0.70$  standard error). We control for  $P(\text{stay})$  separately, so the interaction of  $P(\text{stay})$  and the expected covariance reflects how the hedging value increases with  $P(\text{stay})$  and the covariance, controlling for the covariance when  $P(\text{stay})$  is zero and the effect of  $P(\text{stay})$  when the covariance is zero. While we do not report the coefficient, the estimated effect of  $P(\text{stay})$  is positive: households with longer expected lengths of stay on average choose ownership more, presumably because the fixed costs are amortized over a longer stay.

The opposite pattern can be seen with the current market's rent risk in the third and fourth rows. Greater rent risk for a short-duration household reduces the probability of owning, but the effect of rent risk on the likelihood of owning becomes more positive with duration. This is the main result from Sinai and Souleles (2005) and it is robust throughout all the specifications in the paper.

Because the weighting matrix we are using in this specification varies only by MSA, the estimated coefficients on the expected covariance and rent risk terms cannot be identified separately from unobserved MSA-level heterogeneity. In column (2), we add  $\text{MSA} \times \text{year}$  dummies to absorb such MSA effects. In that case, only the interaction terms with  $P(\text{stay})$ , since they vary by  $\text{MSA} \times \text{household}$ , can be identified. The estimated coefficients on the interaction terms are very close to what we found in column (1).

In columns (3) through (6), we allow the moving probabilities to vary within MSA, first by industry and then by age. In other words, we assume that a household's chances of moving to various MSAs do not so much match the average moving rates from their MSA to other MSAs, but rather the average moving rates by members of their industry in their MSA to other MSAs. In essence, we can compare (for example) the homeownership rates of electricians and lawyers

in Philadelphia since those two groups, despite living in the same MSA, are likely to move to different cities and thus experience different covariances. We can then compare their difference in homeownership rates to the difference between people in the same two industries in another city, such as Seattle, who themselves expect different covariances. The fact that households may on average be more likely to own their houses in Seattle or Philadelphia is absorbed with MSA  $\times$  year dummies. Constant differences in homeownership rates across industries can be controlled for with industry dummies. Thus our estimate of  $\beta_4$  will be identified by industry  $\times$  MSA variation. A similar strategy can be applied using age groups rather than industries. We allow for general non-independence of the standard errors within industry  $\times$  MSA  $\times$  year (or age  $\times$  MSA  $\times$  year) groups by clustering the standard errors.

In columns (3) and (4), by omitting the interaction with the P(stay) term, we estimate the effect of the moving hedge on the average duration household. The estimate is identified by some of those households having a greater expected covariance than others, but since the average expected duration in the CPS data is about 6 years ( $1/(1-0.83)$ ) and even longer for homeowners alone, one might expect that the value of the hedge for a move that far in the future would be small.

In column (3), which imputes the probability of moving using MSA  $\times$  industry cells, that appears to be the case since the estimated coefficient is just 0.40 and not significant. In column (4), which makes use of MSA  $\times$  age, we find a statistically significant positive effect of 2.87.

Columns (5) and (6) use within-MSA variation to identify the estimate of  $\beta_4$  and interacts the expected covariance with the imputed P(stay) to estimate  $\beta_5$  as well, even in the presence of MSA  $\times$  year dummy variables. The estimated effect of the moving hedge is slightly larger than before – the estimated coefficients of 4.69 to 6.69 correspond to 7.5 and 10.7

percentage point increases in the demand for home owning for someone who planned to move right away. Of course, that is an extreme example and, as the expected duration rises, the value of the moving hedge declines (second row). On net, someone who planned never to move would not demand to own their house more if the covariance were higher ( $P(\text{stay}) = 1$ , so in column (5) the effect of  $E[\text{COV}]$  is  $4.69 - 5.33 = -0.64$ ). However, in column 6, which uses the  $\text{MSA} \times \text{age}$  variation, although the value of the moving hedge falls as the expected stay rises, it does not fully offset the value of the hedge when  $P(\text{stay})=1$  (the net effect of  $E[\text{COV}]$  is  $6.69 - 3.81 = 2.88$ ).

One might worry that households' moving decisions are endogenous if they move primarily to where they can afford to go – homeowners might have to move to markets that have correlated house prices. If that were true, the weights that were applied to the covariance matrix would be biased, leading to an overestimate of the expected covariance in house prices especially for those MSAs, industries, or age groups that have a higher homeownership rate.<sup>6</sup>

To surmount this problem, we instrument for the expected covariance with a covariance constructed using probability weights imputed using plausibly exogenous factors. In particular, we impute household  $i$ 's (living in MSA  $k$ ) odds of moving to MSA  $m$  as its share of household  $i$ 's detailed industry, excluding MSA  $k$  from the denominator. This set of probabilities differs by industry within an MSA. The resulting imputed expected covariance is our instrument.

The results of this IV strategy are reported in Table 3. The first column corresponds to the second column of Table 2: the endogenous expected covariance uses actual MSA-to-MSA mobility so it varies across MSAs but not within, we include  $\text{MSA} \times \text{year}$  dummies, and we interact the moving hedge variable with  $P(\text{stay})$ . We instrument for the expected covariance with

---

<sup>6</sup> It would be reasonable for a household that knew in advance that it would choose to move to a housing market where house prices had covaried positively *ex post*, to take that into account when making their house purchase decision. Instead, our worry is about the mechanical relationship between an exogenously higher home ownership rate and an endogenously higher expected covariance.



the variable described above, which does vary by industry within MSA, and interact it for use as an instrument for the interaction terms.. The estimated coefficient on the expected covariance interacted with the probability of staying changes little, increasing in magnitude from  $-5.65$  to  $-6.15$  (0.78). As before, the  $MSA \times year$  dummies absorb the across-MSA variation so we cannot identify the level of the expected covariance variable. Overall, the industry  $\times$  MSA-based instrument generates IV estimates that are similar to but somewhat larger than the OLS estimates. (The first stage estimates are reported in Appendix Table B; the instrument yields a good fit and the expected positive coefficient.)

Column (2) allows for within-MSA variation in the expected covariance, based on  $MSA \times industry$  cells. When we instrument, the estimated coefficient on the expected covariance increases from 0.40 to 3.18, but it is still not statistically significant with a standard error of 2.14.

Column (3) contains the IV versions of column (5) from Table 2. Using industry  $\times$  MSA variation, the IV estimate of the coefficient on the expected covariance term is 8.34 (2.29), almost double the OLS estimate. The interaction of the expected covariance with  $P(stay)$  is still negative,  $-6.30$  (0.82), and slightly larger in magnitude than before. In this specification, the effect of a one standard deviation increase in the moving hedge for a household that expects to move right away is a 10 percentage point increase in their likelihood of home owning. However, this diminishes to 6 percentage points for a household that expects to move in two years and 5 percentage points if the household expects to move in three years.

The estimated coefficient on the interaction of the standard deviation of log rents and  $P(stay)$  changes little from Table 2 – in this specification, or any of the others.

We take a slightly different approach in Column (4), using CPS data to construct the moving likelihoods rather than the IPUMS. Unlike the IPUMS, the CPS does not report where households moved from, so we cannot determine what the actual moving probabilities are. However, we can still impute the odds of moving for a household in industry  $j$  to MSA  $m$  as the share of industry  $j$ 's employment that is located in MSA  $m$ , using the CPS employment data to form the shares. We apply these probability weights to the usual covariance matrix to obtain a proxy for the expected covariance.

We use this proxy directly in the regression in Column (4), and interact it with  $P(\text{stay})$  in the second row. The expected covariance variable is identified even with  $\text{MSA} \times \text{year}$  dummies because it uses  $\text{MSA} \times \text{industry}$  variation. The results look very similar to the OLS results in Table 2.

## 5. *Conclusion*

In this paper, we established two novel facts. First, the effective covariance among housing markets is much higher than people have historically realized. Because households tend to move among correlated housing markets, their subjective expected covariance is much higher than the equally weighted covariance. We find that half of the moves in the U.S. are between MSAs with correlations of 0.67 or greater, and 25 percent are between markets with more than a 0.90 correlation – and that excludes within-MSA moving.

Second, households act as if they take the ‘moving hedge’ aspect of home owning into account when they make their tenure decision. Households with higher expected covariances between a house in their current market and their possible future markets – where the expected covariance is determined by the household’s likelihood of moving to various cities and their

MSA's covariances with those cities – are more likely to own. This effect diminishes with the household's imputed expected length of stay in the house; more mobile households place more weight on future housing markets than do less mobile households. For a household who planned to move right away, having a one standard deviation higher expected covariance leads to a five to 10 percentage point higher homeownership rate. That relationship diminishes rapidly and is indistinguishable from zero for households who plan never to move. The results are robust to instrumenting for the expected covariances by assuming households would move proportionally to their industry shares and applying that to each MSA's vector of covariances.

The analysis in this paper has important implications for the role of housing derivatives for home owners. Since every household has to live somewhere, the natural hedge provided by the house may be quite valuable, actually undoing risk – the risk of the cost of obtaining housing – that households are 'born' with. For many households, the positive expected covariance between house prices in their current city and prices in the set of 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 their current house prices may actually unhedge themselves as it would set the covariance to zero. This is counter to the view in Case *et al* (1993), Geltner *et al* (1995), Shiller (2008), Voicu (2007), and even Sinai and Souleles (2005), all of whom implicitly assume that the covariances between the current and any future housing markets are low. One exception is de Jong *et al* (2007) who point out that housing derivatives are a poor hedge because MSA-level house price indices do not explain much of the variation in individual house prices.

Another benefit of using the house as a natural moving hedge rather than a housing derivatives-based approach is that to hedge future housing prices a household needs to know where it is likely to move, as in Voicu (2007), to be able to construct the proper portfolio of

housing futures. When home owning, all a household needs is to recognize that wherever it ends up moving, it is likely to be to a positively covarying housing market.

The strong hedging value of home owning may help explain why the house price futures market has failed to take off [Shiller (2008)]. It may simply be less expensive, easier, and nearly as powerful to hedge by owning a home. It 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 asset price risk with the landlord. But a mobile household should want to retain the asset price uncertainty to hedge future housing costs.

Of course, an important source of housing risk is leverage. Financing a volatile asset with high ratios of debt creates risk. Combined with liquidity constraints, downturns in prices can lead to an inability to move, less consumption, and more volatile pricing. [Chan (2001), Stein (1995), Genesove and Mayer (1997, 2001), Hurst and Stafford (2004), Lustig and Van Nieuwerburgh (2005), Li and Yao (2007)] In this paper, we ignore the effects of leverage and liquidity constraints to highlight the moving hedge, a valuable feature of home owning that exists even with different choices of housing finance.

## References:

- Caplin, Andrew, William Goetzmann, Eric Hangen, Barry Nalebuff, Elisabeth Prentice, John Rodkin, Matthew Spiegel, Tom Skinner, "Home Equity Insurance: A Pilot Project," *mimeo* (2003).
- Case, Karl, and Robert Shiller. "The Efficiency of the Market for Single-Family Homes." *American Economic Review*, vol. 79 (1), March 1989, pp. 125-137.
- Case, Karl, Robert Shiller, and Allan Weiss. "Index-Based Futures and Options Markets in Real Estate," *Journal of Portfolio Management*, vol. 19, no. 2 (Winter 1993), pp. 83-92.
- Chan, Sewin. "Spatial Lock-In: Do Falling House Prices Constrain Residential Mobility?" *Journal of Urban Economics*, vol. 49 (3), May 2001, pp. 567-586.
- Cocco, Joao. "Hedging House Price Risk with Incomplete Markets." *Mimeo, London Business School*, September 2000.
- Davidoff, Thomas. "Labor Income, Housing Prices and Homeownership," *Journal of Urban Economics*, Vol. 59, number 2 (March 2006), pp. 209-235.
- de Jong, Frank, Joost Driessen, and Otto Van Hemert. "Hedging House Price Risk: Portfolio Choice with Housing Futures," *mimeo*, New York University (August 8, 2007).
- Geltner, David, Norman Miller, and Jean Snavely. "We Need a Fourth Asset Class: HEITs." *Real Estate Finance*, vol. 12, no. 2 (Summer 1995), pp. 71-81.
- Genesove, David. "The Nominal Rigidity of Apartment Rents." *NBER Working Paper #7137*, May 1999.
- Genesove, David and Christopher Mayer. 1997. "Equity and Time to Sale in the Real Estate Market." *The American Economic Review*, Vol. 87(3), 255-69.
- Genesove, David and Christopher Mayer (2001): "Loss Aversion and Seller Behavior: Evidence from the Housing Market," *Quarterly Journal of Economics*, v. 116(4), pp. 1233-1260.
- Glaeser, Edward and Joseph Gyourko, "Housing Dynamics," *NBER Working Paper #12787*, December 2006.
- Han, Lu. "The Effects of House Price Uncertainty on Housing Demand: Empirical Evidence from the U.S. Housing Markets." *Journal of Urban Economics*, (forthcoming 2008).
- Hurst, Erik and Frank Stafford (2004) "Home Is Where the Equity Is: Mortgage Refinancing and Household Consumption", *Journal of Money, Credit & Banking*, Vol. 36

- Li, Wenli and Rui Yao. "The Life-Cycle Effects of House Price Changes," *Journal of Money, Credit and Banking*, Vol. 39, No. 6 (September 2007), pp. 1375-1409.
- Lustig, Hanno and Stijn Van Nieuwerburgh. "Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective." *Journal of Finance*, vol. 60, no. 3 (June 2005), pp. 1167-1219.
- Meese, Richard and Nancy Wallace. "Testing the Present Value Relation for Housing Prices: Should I Leave my House in San Francisco," *Journal of Urban Economics*, Volume 35, 1994.
- Ortalo-Magné, Francois and Sven Rady. "Tenure Choice and the Riskiness of Non-Housing Consumption," *Journal of Housing Economics*, 11:266-279, September 2002.
- Shiller, Robert. "Derivatives Markets for Home Prices," *NBER Working Paper #13962*, (April 2008).
- Sinai, Todd and Nicholas Souleles. "Owner Occupied Housing as a Hedge Against Rent Risk," *Quarterly Journal of Economics*, vol. 120, number 2 (May 2005), pp. 763-789.
- Stein, Jeremy (1995). "Prices and Trading Volume in the Housing Market: A Model with Downpayment Effects," *Quarterly Journal of Economics* 110, May, pp. 379-406.
- Voicu, Cristian. "Optimal Portfolios with Housing Derivatives," *mimeo*, Harvard Business School (May 1, 2007).

Table 1: Distributions of Correlations in House Price Growth Across and Within MSAs

	Correlation	
	Unweighted	Migration Weights
Average	0.35	0.60
5 <sup>th</sup> percentile	-0.16	0.01
25 <sup>th</sup> percentile	0.16	0.37
50 <sup>th</sup> percentile	0.36	0.67
75 <sup>th</sup> percentile	0.56	0.90
95 <sup>th</sup> percentile	0.83	0.98
Average 95 <sup>th</sup> -75 <sup>th</sup> percentile	0.25	0.08
Average interquartile range	0.38	0.36
Average 25 <sup>th</sup> -5 <sup>th</sup> percentile	0.28	0.34

Table 2: The relationship between of house price covariance and the probability of owning

	(1)	(2)	(3)	(4)	(5)	(6)
$E[\text{COV}(P_A, P_B)]^{1/2}$	3.41 (0.57)		0.40 (0.33)	2.87 (1.08)	4.69 (0.68)	6.69 (1.50)
$P(\text{stay})_i \times E[\text{COV}(P_A, P_B)]^{1/2}$	-5.37 (0.70)	-5.65 (0.70)			-5.33 (0.71)	-3.81 (0.83)
$\sigma_r^A$	-3.66 (0.33)					
$P(\text{stay})_i \times \sigma_r^A$	3.15 (0.40)	3.27 (0.40)			3.11 (0.40)	3.14 (0.40)
Probability weights for $E[\text{COV}(P_A, P_B)]$ :	IPUMS (by MSA)		IPUMS (MSA x Industry)	IPUMS (MSA x Age)	IPUMS (MSA x Industry)	IPUMS (MSA x Age)
MSA $\times$ year dummies?	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.30	0.30	0.31	0.30	0.31	0.30
Clustering of standard errors			MSA x year x industry	MSA x year x age category	MSA x year x industry	MSA x year x age category
N	166,904	166,904	166,697	202,641	166,697	202,641

Notes: Sample period is 1992 through 2002. LHS variable is an indicator variable that takes the value of one if the respondent owns their home and zero if the respondent rents. The probability of staying is imputed using occupation  $\times$  marital status  $\times$  age category cells. The standard deviation of rent is a MSA (k) characteristic. The covariance of house prices is a probability-weighted average of the covariances between the MSA of residence and possible future MSAs. The standard deviations and covariance are not time-varying. All regressions except column (1) include MSA  $\times$  year dummies,  $P(\text{stay})$ , age dummies, occupation dummies, marital status dummies, race dummies, and controls for income. Column (1) includes the household-level demographic controls, year dummies, and MSA-level controls for average real rent, average real house prices, annual real rent growth, and annual real house price growth. Columns (3) and (5) add a detailed set of industry dummies.



Table 3: The relationship between of house price covariance and the probability of owning, instrumented

	(1)	(2)	(3)	(4)
$E[\text{COV}(P_A, P_B)]^{1/2}$		3.18 (2.14)	8.34 (2.29)	5.67 (0.99)
$P(\text{stay})_i \times E[\text{COV}(P_A, P_B)]^{1/2}$	-6.15 (0.78)		-6.30 (0.82)	-7.22 (0.92)
$P(\text{stay})_i \times \sigma_r^A$	3.47 (0.42)		3.46 (0.42)	2.52 (0.36)
Probability weights for $E[\text{COV}(P_A, P_B)]$ :	IPUMS (MSA)	IPUMS (MSA x Industry)	IPUMS (MSA x Industry)	CPS (MSA x Industry)
MSA x year dummies?	Yes	Yes	Yes	Yes
Instrument?	MSA x Industry instrument	MSA x Industry instrument	MSA x Industry instrument	MSA x Industry proxy
R-squared	0.30	0.31	0.31	0.31
Clustering of standard errors		MSA x year x industry	MSA x year x industry	MSA x year x industry
N	166,207	166,016	166,016	166,904

Notes: Sample period is 1992 through 2002. LHS variable is an indicator variable that takes the value of one if the respondent owns their home and zero if the respondent rents. The probability of staying is imputed using occupation x marital status x age category cells. The standard deviation of rent is a MSA (k) characteristic. The covariance of house prices is a probability-weighted average of the covariances between the MSA of residence and possible future MSAs. The instrument replaces the actual moving rates with each destination MSA's share of the industry. The standard deviations and covariance are not time-varying. All regressions include MSA x year dummies, P(stay), age dummies, occupation dummies, marital status dummies, race dummies, and controls for income. Columns (2), (3) and (4) add a detailed set of industry dummies.

Figure 1:

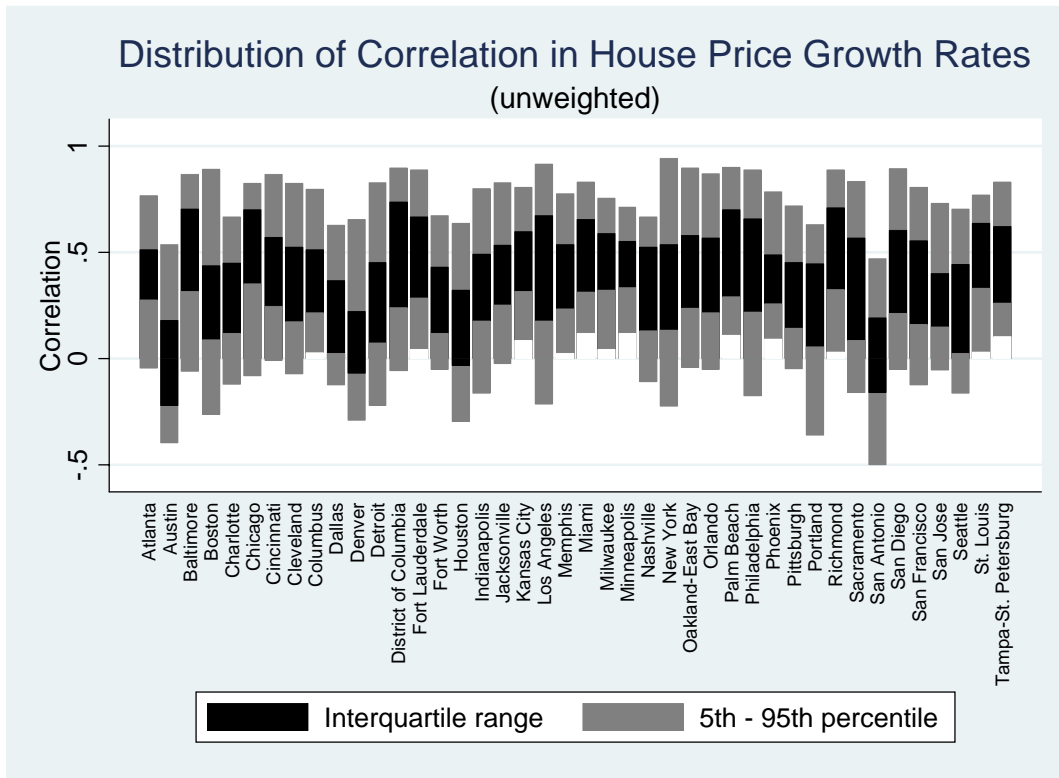
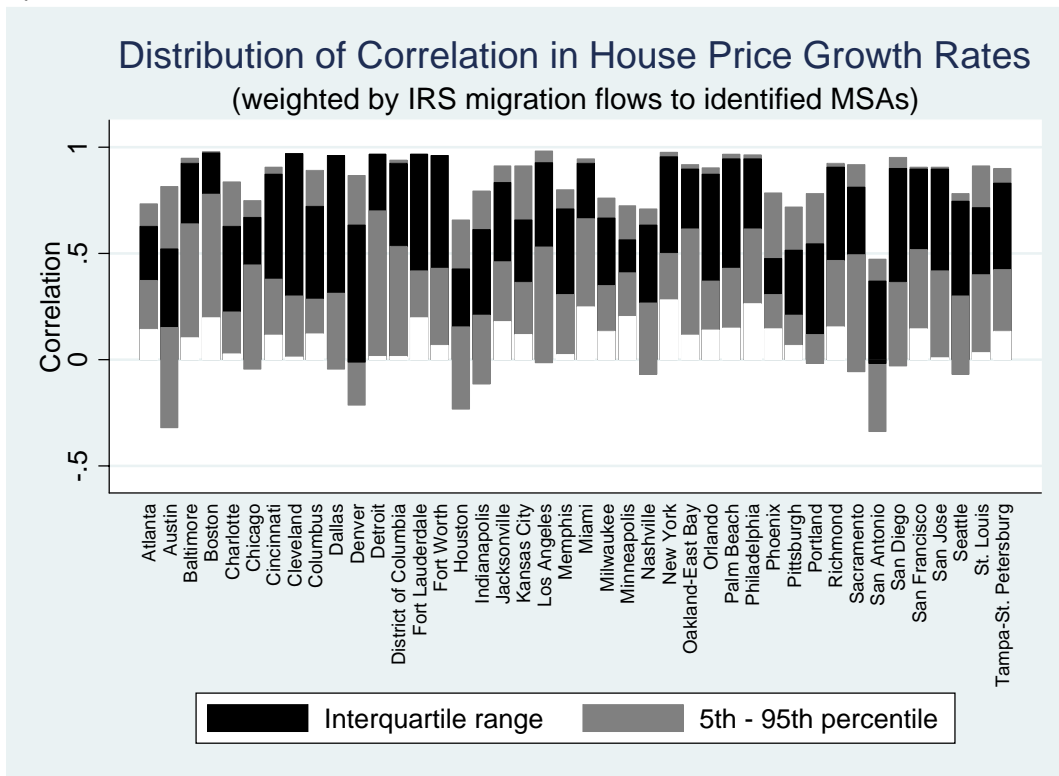


Figure 2:



Appendix Table A: Summary Statistics

Variable	Mean	Standard Deviation
Own	0.605	0.488
Probability of staying	0.827	0.112
SD(real rent growth)	0.0678	0.0285
SQRT(CPS industry-weighted average price covariance)	0.037	0.012
SQRT(IPUMS MSA-weighted average price covariance) – actual	0.042	0.016
SQRT(IPUMS MSA × industry-weighted average price covariance) – actual	0.042	0.016
SQRT(IPUMS MSA × industry-weighted average price covariance) – imputed	0.038	0.012
SQRT(IPUMS MSA × age-weighted average price covariance) – actual	0.042	0.016
Average annual rent (\$2000)	10,407	3,904
Average house price (\$2000)	163,060	74,152
Rent growth rate:	0.012	0.008
Price growth rate:	0.018	0.012
Age	48.0	16.1
Fraction married	0.51	0.50
Fraction widowed	0.11	0.31
Fraction divorced	0.19	0.39
Less than high school	0.19	0.39
High school diploma	0.28	0.45
Some college	0.24	0.43
College diploma	0.29	0.45

Appendix Table B: First stages of the IV regression

	(1)	(2)	(3)
$E[\text{COV}(P_A, P_B)]^{1/2}$		0.316 (0.016)	0.316 (0.016)
R-squared		0.9635	0.9635
$P(\text{stay})_i \times E[\text{COV}(P_A, P_B)]^{1/2}$	0.307 (0.001)		0.690 (0.014)
R-squared	0.9917		0.9626
Probability weights for $E[\text{COV}(P_A, P_B)]$ :	IPUMS (MSA)	IPUMS (MSA x Industry)	IPUMS (MSA x Industry)
Instrument?	MSA x Industry instrument	MSA x Industry instrument	MSA x Industry instrument
Clustering of standard errors		MSA x year x industry	MSA x year x industry
N	166,207	166,016	166,016

Notes: Sample period is 1992 through 2002. The covariance of house prices is a probability-weighted average of the covariances between the MSA of residence and possible future MSAs. The LHS variable is the expected covariance weighted by the actual rate of moving. The instrument replaces the actual moving rates with each destination MSA's share of the industry or age group. The probability of staying is imputed using occupation  $\times$  marital status  $\times$  age category cells. The standard deviations and covariance are not time-varying. All regressions include MSA  $\times$  year dummies,  $P(\text{stay})$ , the standard deviation of real rents, age dummies, occupation dummies, marital status dummies, race dummies, controls for income, and a detailed set of industry dummies. Columns (1) and (3) add  $P(\text{stay}) \times$  the standard deviation of rents as a control.