Spatial Variation in the Risk of Home Owning

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To casual observers, home owning often appears risky. They note that the typical pre-retirement household (in the 2004 Survey of Consumer Finances) has about 45 percent of their net worth tied up in housing wealth and those house values can be volatile. In fact, 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. Even expert analysts of housing markets typically concern themselves with the risk of house price declines. Indeed, two papers in this volume [Shiller (2008), Caplin *et al* (2008)] address ways to mitigate the asset price risk of housing through the use of house price derivatives or home equity insurance.

Recent research has emphasized that this focus on asset price volatility yields an incomplete picture of the risk of home owning. Sinai and Souleles (2005) highlight two additional components of that risk. First, renting, which is the alternative to owning, is itself risky. While home owners take on asset price risk, they avoid uncertainty about the total rent they would have to pay as renters. Second, households face uncertainty about the cost of future housing if they ever move. When an owner sells their house and purchases another, the risk they face is due to uncertainty about the *difference* in the prices of the two houses. If the two houses were in independent markets, there would be risk both from selling in the current market and purchasing in the next. If the housing markets moved together, any change in price of a house in a household's current city could net out the price changes of the house purchase in a subsequent city, reducing the sale/repurchase risk. That is, owning one house can hedge against uncertainty in the price of a household's next house if the prices of the two houses covary positively. [Ortalo-Magné and Rady (2002), Sinai and Souleles (2005), Han (2008), Cocco (2000)]

In this paper I consider all three of these determinants of housing risk—rent volatility, price volatility, and the average covariance of house price growth with other housing markets—

document where and for whom home owning might be risky, and discuss the conditions under which hedging housing price risk through the use of housing derivatives would or would not be valuable for a homeowner. One source of variation in the riskiness of home owning is location: the volatility of the housing market varies widely across metropolitan areas (MSAs). This volatility is reflected both in rents and house prices because they are endogenously related, as stressed by Meese and Wallace (1994) and Sinai and Souleles (2005). I first provide suggestive evidence as to why some housing markets are more volatile than others, showing that it results from more variable underlying demand combined with an inelastic supply of housing. I then estimate the rent and house price volatilities across MSAs, using the standard deviation of an MSA's log annual rents or log prices after removing its time trend. That standard deviation for log rent ranges from 0.011 in a low volatility market such as Pittsburgh to 0.136 in a high volatility market such as San Jose. The estimated standard deviation for log prices follows a similar pattern, ranging from 0.012 (Indianapolis) to 0.146 (San Jose). Indeed, I find that rent volatility and house price volatility are highly correlated across MSAs, as would be expected if house prices are determined endogenously by rents. All of these facts are robust to computing the standard deviation using the annual growth rate of rents or prices or the growth rate over longer horizons, such as five years. Although the estimated standard deviations decline as the horizon lengthens, the relative magnitudes across MSAs remain the same.

Another factor in housing risk that varies across MSAs is the covariance between an MSA's house price changes and those in the rest of the country. I estimate that almost every MSA in the data has house price growth that over the 1990 through 2002 period on average covaried positively with the house price growth in the other MSAs. This implies the asset price risk is of owning is mitigated by the natural hedge between the sale price of the current house and the purchase price of a future house. This point has long been recognized for within-market moves where the covariance is assumed to be high [e.g., Cocco (2002)], but the positive cross-MSA covariances indicate that there is a hedging value even when a household may move out of its MSA. While this empirical point was made in Sinai-Souleles (2005), in this paper I estimate how the covariances differ across MSAs. The average correlation in real house price growth with other MSAs ranges from 0.034 (Seattle) to 0.636 (Richmond), with covariances between 0.015 (Seattle) and 0.046 (Boston). In addition, I find that MSAs with higher price volatilities tend to have higher covariances of house price growth with other MSAs. Thus, the MSAs with the highest house price volatilities have the most valuable natural hedge against house price risk in future MSAs. That pattern indicates that the hedging property of home owning reduces the net house price volatility especially for the most volatile markets. Because of this, buying a house in a more volatile market might *reduce* lifetime housing risk on net if that house is a better hedge against house price uncertainty in some future market.

Since the net risk of home owning involves trading off the three different sources of risk, they should not be considered in isolation. Indeed, since rent volatility and house price volatility are positively correlated within MSAs, the relative risk of owning is usually mitigated since taking on greater sale price risk typically entails avoiding commensurately larger rent risk. And, since higher volatility markets covary more with future markets, the asset price risk is attenuated. The element that links these risks is a household's probability of moving. A household that plans never to move has a greater weight on avoiding rent risk whereas mobile households should care more about sale price volatility and the natural hedge owning a house provides for future houses. Thus, I combine the risk parameters to illustrate how the difference between the volatility of renting and the volatility of owning varies across MSAs for households with different expected mobilities. I conclude that when expected lengths of stay are short and the correlation of house prices with the next residence is low, the risk of renting could dominate that of owning.

The evidence in this paper has important implications for the role of housing derivatives for homeowners and may help explain some of the low utilization of house price hedges documented in Shiller (2008) and Caplin *et al* (2008). Since every household has to live somewhere, the natural hedge provided by the house undoes risk—the risk of the cost of obtaining housing—that households are 'born' with. For a household that might move, whether to another MSA or within the same housing market, owning a home typically provides at least a partial hedge against the cost of a future house. In fact, households who use housing derivatives or home equity insurance to lock in their current house prices may actually unhedge themselves because they would reduce to zero the covariances of their current house price with their subsequent house price. Such households would face less risk than renters since they would lock in rental costs in their current markets but more risk than owners because, like renters, they would be unhedged against the costs of future houses. And among households who plan never to move, many face low house price volatilities in the first place, they may have heirs who value the hedge against their own housing costs embodied in their parents' house, or they may place little weight on the sale price of their house since the sale is so far in the future. Instead, the best use of housing derivatives by existing homeowners may be to enhance the hedging benefit of owning a house rather than substitute for it. This could be done by supplementing the natural hedge owning a house provides by raising the house price covariance for mobile households in low-covariance markets or by locking in house prices for immobile households without children.

This point, which applies most when the quantity of housing consumption is held constant, is not intended to minimize the other potentially valuable uses of housing derivatives.

[Case et al (1993), Geltner et al (1995), Voicu (2007), de Jong et al (2007)] For example, households that are short future housing, such as renters or the underhoused, could use derivatives to hedge their future increases in housing consumption. Households that have sold one house but not yet purchased their next one could use derivatives to lock in the relative house prices. Households who plan never to move and whose heirs live in uncorrelated markets, or seniors who need to lock in wealth for retirement consumption or intend to downsize, could be a market for home equity insurance. Investors, such as developers or institutions exposed to housing market risk, might wish to hedge their exposure, and speculators seeking diversification may wish to increase theirs.

The rest of this paper proceeds as follows: I outline a simple conceptual framework for thinking about housing risk in section 1. Section 2 delves into why housing markets differ in their volatilities. Section 3 estimates rent and house price volatility by MSA then turns to the covariances in house price growth across MSAs. In section 4, I incorporate household mobility to estimate the net risk of owning versus renting and discuss the findings in section 5. Section 6 describes what the results from this paper imply for the market for housing derivatives. Section 7 briefly concludes.

1. *Conceptual Framework*

To provide some intuition behind how various sources of volatility contribute to housing risk, I adapt the conceptual framework from Sinai and Souleles (2005). That framework starts with the notion that every household needs a place to live. The decision the household faces is how to obtain their desired level of housing services at the lowest risk-adjusted cost: either rent, or own. The total cost of renting a house is the present value of the annual rents paid. The total cost of owning is the present value of the purchase price less the present value of the sale price when the owner moves out.

In a riskless, frictionless equilibrium, the market would set house prices so that the present value of owning and renting were equal. [Meese and Wallace (1994)] But housing costs are far from certain. Annual rent is determined by the intersection of household demand for housing services and the supply of housing. It fluctuates because of shocks to local housing demand that, in concert with the elasticity of housing supply, determine the rent level that clears the housing market.

Because of this rent volatility, renting yields an uncertain total cost of obtaining housing services. Renting is akin to purchasing housing services on the spot market. Since renters do not know what future rents will be, the present value of their rental payments is uncertain. But the total cost of home owning is uncertain as well. Although a homeowner essentially prepays the present value of expected future rents and thus avoids the uncertainty over the spot housing market, the future sale value of the house is unknown.

In the Sinai-Souleles framework, households live in two houses, the first in city 'A' and the second in city 'B'. (Both cities A and B could be the same.) A household stays in each house for *N* years and after 2*N* years it dies. Both future rents and house prices are uncertain, although they are correlated with each other and across MSAs, as I will discuss below. To choose between renting and owning, households compare their lifetime risk-adjusted cost of renting to the risk-adjusted cost of buying.

From a homeowner's perspective, the lifetime *ex post* cost of owning is $C_O \equiv P_0^A + \delta^N\left(\widetilde{P}_N^B - \widetilde{P}_N^A\right) - \delta^{2N}\widetilde{P}_{2N}^B$. The P_0^A term is the initial purchase price in city A, which is known with certainty. The middle term, $\delta^N\left(\widetilde{P}_N^B - \widetilde{P}_N^A\right)$, 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. The tilde denotes that both prices are uncertain. Since the move from A to B occurs N years in the future, the sale and subsequent purchase prices are discounted at rate δ^N. The last term, $\delta^{2N}\widetilde{P}^B_{2N}$, is the uncertain residual value of the house at the time of death. It, too, is discounted since death occurs *2N* years in the future.

For a renter, the lifetime cost of obtaining housing services is the present value of all future rents, $C_R \equiv r_0^A + \sum_{n=1}^{N-1}\delta^n \widetilde{r}_n^A + \sum_{n=N}^{2N-1}\delta^n \widetilde{r}_n^B$. The first year's rent, r_0^A, is known with certainty. The remaining rents in city A are uncertain, and so the *ex-post* present value is $\sum_{n=1}^{N-1}\delta^n \widetilde{r}_n^A$. The move to city B occurs after year N, and thus those rents are discounted yet further, yielding an *ex-post* present value of $\sum_{n=N}^{2N-1}\delta^n \widetilde{r}_n^B$.

From this initial setup, we can derive two key measures of housing risk. The risk of renting comes from not having locked-in the future price of housing services, so the present value of the future rent stream is unknown. It turns out that the cost of the risk of renting is proportional to the present value of the sum of the variance of rent innovations:

$$\pi_R \approx \frac{\alpha}{2}\left(s_A^2 \sum_{n=1}^{N-1}\delta^{2n} + s_B^2 \sum_{n=N}^{2N-1}\delta^{2n} \right), \qquad (1)$$

where s_A^2 is the variance of the rent risk in market A, s_B^2 is the variance of the rent risk in market B, and α is a proportional scaling factor.

For owners, risk comes from uncertainty over the sale price of the first house and the purchase price and sale price of the second house.

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

where ρ is the correlation in house price shocks between cities A and B and σ_A^2 and σ_B^2 are respectively the variance in house prices in those two cities. The first house is sold *N* years in the future for some uncertain amount. However, at the same time, the household has to purchase a house in B. Because of that, the net risk is due to the difference between the sale price in A and the purchase in B. However, since the sale/repurchase occurs *N* periods in the future, and the terminal sale another *N* periods after that, the risk is discounted.

If city A and city B have highly correlated house prices, so ρ is close to one, the first sale and subsequent purchase is nearly a wash since $\frac{(1-\rho)^2}{1+\rho^2}=0$ when ρ=1. If the two markets are relatively uncorrelated, the sale and subsequent house repurchase are more risky. In that case, the magnitude of the risk depends on the variances of house prices in city A and city B. In the extreme case of completely uncorrelated housing markets, ρ=0, we see that $\frac{(1-\rho)^2}{1+\rho^2}=1$: the owning risk depends solely on the sum of the variances. When ρ=−1, so the house prices in the two markets are perfectly negatively correlated, the sale/repurchase volatility is twice as large as the sum of the variances.

As we turn to the data, it will be convenient to rewrite equation (2)

as: $$\pi_O \equiv \frac{\alpha}{2}\left[\delta^{2N}\left(\sigma_A^2+\sigma_B^2-2g(\mathrm{cov}(A,B))\right) \quad + \quad \delta^{4N}\left(\sigma_B^2\right)\right] \qquad (3)$$

In equation (3), g() is increasing.

For ease of exposition, these equations assume rents and prices follow separate white noise processes. This requires two simplifications. First, the risks of renting and owning should be correlated because house prices are endogenously determined by rents in a given market when households equate the expected utilities of renting and owning. Sinai and Souleles (2005) show that, assuming inelastic supply, house prices should capitalize the expected present value of future rents plus a premium for the hedging value of homeownership. Because of this endogenous relationship, house price volatility should be a function of rent volatility and the two should be correlated. In any case, the endogeneity of rents and house prices does not affect the intuition that households trade off the two sources of risk when making their tenure choice. Rather, it affects the likelihood that the risk of renting outweighs the house price risk or vice versa. In the end, these are empirical questions that will be examined below.

Second, shocks to rents (or prices) are likely to be persistent. Persistent rent shocks lead to a larger effective risk of renting since an early rise or fall in rent is more likely to be sustained throughout a household's entire stay. However, since the persistence is capitalized into house prices, the volatility of house prices would increase as well. On the other hand, the resulting greater persistence in house prices implies a higher correlation between the purchase and sale prices of the house in city B, reducing the net volatility of owning that second house. The qualitative discussion of the sources of risk does not depend on the degree of persistence. However, the empirical analogs to the rent and price variance and covariance terms in the equations above may. We will turn to that question in Section 3.

It also bears mentioning that this framework assumes away a number of interesting complications, such as whether income and rents covary [Davidoff (2006)] or whether there are time-varying discount rates. However, the hedging intuition exposited here operates in addition to these other issues.

In the remainder of this paper, I will show how the underlying parameters—rent variance, price variance, and house price correlations and covariances—vary across MSAs. In addition, I will compare the risk of renting in equation (1) to the risk of owning in equations (2) and (3) as a way of illustrating how the interaction of the parameters varies across MSAs.

2. *Why does rent variance differ across metropolitan areas?*

In the framework in Section 1, housing markets have varying degrees of volatility that are expressed in rents and endogenously through prices. The cross-MSA variation in rent volatility should be due to differences in demand volatility and housing supply elasticities. We expect MSAs with volatile housing demand, presumably caused by shocks to local economic growth, to have more rent variance. MSAs with more inelastic housing supply should also exhibit higher rent variance as the housing or apartment stock is less able to adjust to demand fluctuations.

This view is supported by Table 1, where we regress the standard deviation of de-trended rents in an MSA on a proxy for the volatility of demand for space and proxies for the elasticity of housing supply. The rent variable we use comes from surveys of Class A apartment buildings conducted quarterly by REIS and reported as an annual average by housing market. For each market, we de-trend the 1989-1998 rent series by MSA and compute the standard deviation of the residual. The demand proxy is the de-trended standard deviation in aggregate employment for the Metropolitan Statistical Area (MSA) that corresponds to each REIS housing market. We proxy for the inelasticity of supply of living space with two variables from Mayer and Somerville (2000): Whether the MSA charges impact fees to developers and the number of months it takes to obtain a building permit. The former raises construction costs so that developers would wait for a larger increase in rents before adding more housing stock. The latter reduces the speed in which developers can respond to demand shocks and adds uncertainty to the development process, which is another cost of construction.

Variation in demand for space has a strong effect on rent variance. In the first column, we include only the standard deviation of MSA employment on the right-hand-side. This leaves us with a sample of 43 MSAs in 1998, which is the entire REIS sample during this period. The coefficient on employment volatility is positive and significant, with a coefficient of 0.52 (0.17) and the regression has an R-squared of 0.19. Thus an MSA with a one standard deviation higher employment volatility (0.008 on a mean of 0.019) has a one-half standard deviation higher rent volatility.

Our proxies for whether supply is inelastic in the MSA also appear to affect rent volatility. In column two, we use the indicator variable for whether the MSA charges impact fees and the time-to-obtain-permit variable as covariates. Our sample size falls to 38 since the supply elasticity variables are not available for all MSAs in the REIS sample. The impact fee dummy has a strong and statistically significant effect on rent variance with an estimated coefficient of 0.0084 (0.0026). Presumably, our impact fee variable proxies for other deterrents to development in the market, as well. The estimated coefficient on the length of time to obtain a development permit variable has the expected positive sign, 0.00069 (0.00036), and is significant at the 93 percent confidence level.

In column 3, we show that both the demand- and supply-side factors have an effect on rent variance in the MSA by including all three covariates. The point estimate on the standard deviation of employment changes only slightly, falling to 0.42 (0.18). The impact fee dummy remains statistically significant: its estimated coefficient of 0.0061 (0.0027) implies that the standard deviation of rent is about 30 percent higher than the mean of 0.020 in markets where impact fees are charged. The coefficient on the development permit variable falls in magnitude to 0.00040, reducing its t-statistic to just over one so it is not statistically distinguishable from zero. The R-squared increases to 0.38, suggesting that we are able to account for a substantial portion of the variation across MSAs in rent variance with this small set of explanatory variables.

While the regression in column three suggests that both demand variance and supply inelasticity contribute to rent variance in a market, we anticipate that both factors must work in concert to create high rent variance. In other words, demand fluctuations may be innocuous if housing supply can easily adjust and inelasticity of supply would be moot if demand were not volatile. We provide a crude test of that hypothesis in column 4 by interacting the impact fee dummy variable with the employment variance variable. Indeed, only the interaction term is statistically significant in that regression, showing that the standard deviation of employment affects rent variance only in markets with impact fees. The point estimate of 0.63 (0.35) is significant at the 90 percent confidence level. Of course, these regressions are intended only to be suggestive, given the small number of MSAs, limited proxies for the elasticity of supply, and our inability to control for unobserved heterogeneity across MSAs.

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3. *How the risks of owning and renting vary across metropolitan areas*

Due to the factors described in Section 2, the volatility of rents and house prices varies considerably across MSAs. The covariances and correlations with other MSAs vary as well, likely due to the extent that an MSA is exposed to national demand shocks.

In this section, we estimate each MSA's real rent and real house price volatilities, and their average correlation and covariance of house price growth with the other MSAs. As in Table 1, the annual rent data comes from REIS. Our annual house price data comes from an index of repeat sales of houses with conforming mortgages available from the Office of Federal Housing Enterprise Oversight (OFHEO). Combining the two yields 42 MSAs for which we have consistent data in both data sets. We convert from nominal to real values using the CPI less shelter. Both the rent and house price series are believed to understate true housing market volatility because the liquidity of the housing market declines with rents and prices in a downturn. [Stein (1995)] That reduced liquidity is costly, but is not capitalized into market prices because only a selected sample of properties trade. Fisher *et al* (2006) construct a constant-liquidity apartment rent index and show that at the national level, the volatility of the latent rent is greater than the volatility of the observed rent. However, the data sets we use cover a long time period (1980 to the present) and a large number of MSAs (44 in the REIS data and 136 in the OFHEO data) so they are the best options for our application. Since in the end we are concerned with the relative risk of owning and renting, as long as the percent bias in the estimated volatility is about the same across MSAs and for both the rent and house price series, it should net out.

That rent risk varies considerably across MSAs is documented in Table 2, which reports several different estimates of rent volatility by metropolitan area. A low standard deviation of rent in an MSA implies that fundamentals are not that volatile. In that case, there is less inherent uncertainty about total rental costs. Since rent risk should reflect unanticipated changes in rents, each column reflects a slightly different assumption about the underlying rent process.

The first column lists the standard deviation of log real rent after the MSA-specific trend has been removed. Implicit in this specification is a model of rents where they have a constant expected growth rate within an MSA with i.i.d. deviations around the trend. 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 this column the underlying rent variance is calculated over the 1990-2002 period. Some MSAs, such as Palm Beach (0.017), Detroit (0.019), and Pittsburgh (0.011) have very low standard deviations of rent. Others, such as San Jose (0.136), San Francisco (0.121), Oakland (0.102), or New York (0.082) exhibit high rent volatility.

In the second column, we estimate the standard deviation of annual real rent growth. Implicit in this measure is that households expect rents to be the same as last year, so rents follow a random walk. In general, the estimated volatility is lower than in the previous column, especially in the most cyclical markets, such as Boston, New York, and Los Angeles, since sustained deviations from the trend lead to a higher estimated standard deviation in the first column but can yield a relatively lower estimated standard deviation in the second column. In Los Angeles, for example, the estimated standard deviation of real rents fell from 0.080 in the first column to 0.026 in the second. By contrast, San Jose's estimated standard deviation of real rents rose from 0.136 in the first column to 0.170 in the second.

In the third column, we take a different approach to estimating the rent volatility. Rather than estimating the volatility of the underlying rent shocks (which we would then aggregate up to total rent volatility over the entire residence spell using equation 1), we estimate the volatility of the present value of the rents over a five-year horizon. Using a discount rate of 1/0.96, we compute the present value of the rental cost over the prior five years for each year in each MSA. We then compute the standard deviation of the annual growth in that rent total. This approach estimates the volatility of apparent rent, rather than the underlying rent shocks. To the extent that rents mean-revert at a high frequency, the volatility of the total rent should be lower than the sum of the rent volatilities.

This approach typically yields a lower estimated rent volatility than in either of the prior two columns. The declines in the San Francisco bay area MSAs are especially notable, with the estimated standard deviations falling by as much as one-third. For example, in San Jose, the estimated standard deviation of rent falls from 0.170 to 0.056 between the second and third columns. In most other MSAs, the decline is much more muted.

Despite the declines in the estimated rent volatility in the second and third columns, the relative volatility across MSAs stays fairly constant across the two columns. The correlation between the first two measures of rent volatility is 0.85, between the second and third measures is 0.91, and between the first and third measures is 0.86.

The pattern of rent risks across MSAs can also differ over time, as can be seen in the last column of Table 2, which reports the standard deviation of the detrended log real rents estimated over the 1981–1993 period. During that era, Texas cities such as Austin, Houston, and San Antonio had much higher rent volatilities. The Bay Area cities had considerably lower rent volatility.

In Table 3, we repeat this exercise for real house prices, with the first column reporting the standard deviation of detrended (by MSA) log real house prices over the 1990 to 2002 period. The California cities again have the highest estimated volatilities. For example, the estimated house price volatility in San Jose is 0.146 and in Los Angeles it is 0.132. By contrast, Cincinnati has an estimated 0.015 standard deviation; in Indianapolis it is 0.012. Mid-range cities include those in Florida (Miami, for example, comes in at 0.50), the Northwest (Seattle has a 0.057 estimated volatility), and the Mid-Atlantic (Baltimore's is 0.051).

The second column of Table 3 reports the estimated standard deviation of annual house price growth. For many cities, this estimate is similar to the first column. For others, where house prices tend to have sustained deviations from trend rather than higher frequency fluctuations, the estimated volatility falls considerably. Such cities include those in California, plus Boston and New York. Even so, the correlation between the estimated standard deviations in the first two columns is 0.97.

The third column uses a longer difference—five years—when calculating the average annual growth to try to mimic the longer holding period of a home owner. According to the framework in Section 1, within-holding period fluctuations in house prices should not matter. Thus for someone with a longer holding period, high-frequency house price changes that net out with each other may be less important than sustained deviations. The estimated annual standard deviations using five-year average growth rates are typically lower than those using one-year growth rates. However, the relative degree of volatility across MSAs remains stable. The estimates in the third column are highly correlated with those in the second column—0.91—and even columns 1 and 3 have a 0.88 correlation.

As with rents, we see that the time period over which the standard deviation is estimated can matter quite a bit. The last column of Table 3 follows the same estimation procedure as column 1, but uses the 1981-1993 time period. The estimated standard deviation of house prices rises from 0.037 to 0.141 in Austin, Texas, 0.039 to 0.067 in Dallas, and 0.061 to 0.110 in Philadelphia, for example. However, in many cities the estimated standard deviation remains unchanged over the time periods.

Since house prices should be determined endogenously from rents, in MSAs with low rent risk there should also be low house price volatility. In a simple model of rents, even if there is persistence in the rent process, the standard deviation of rents and prices should be the same when measured in percentages. Even so, there are a number of practical reasons why rent and price volatility might differ within MSA. For example, changes in the discount rate might affect the pricing multiple applied to rents differentially across markets, as argued in Himmelberg *et al* (2005), Mayer and Sinai (2008), and, in the commercial real estate context, Mei and Geltner (1995). Or, the differences could be the result of speculative bubbles, as in Case and Shiller (2004); inefficiencies, as in Case and Shiller (1989); capital markets, such as in Pavlov and Wachter (2007); or an unspecified overpricing, as in Campbell *et al* (2007).

More prosaically, differences between rent and house price volatility could be due to the underlying samples in the rent and house price series. REIS surveys "class A" apartments in each market, which are the nicest available, to obtain rents. OFHEO uses transaction and appraisal-based valuations from repeat observations of properties with conforming mortgages. As Smith and Smith (2006) point out, these two samples potentially are not comparable since houses and apartments are very different. This issue might lead us to find differences between the observed rent volatility and the observed house price volatility whereas there should be no difference in the underlying true risks. Even with that handicap, we observe highly correlated rent and price volatilities.

To the Smith and Smith (2006) argument, Glaeser and Gyourko (2008) add that differences in tax treatment of home owners and landlords among other factors leads to an inability to arbitrage rents and house prices. If this were the case, the true rent volatility could deviate from the true house price volatility. In the analysis that follows, I will use the actual rent and house price volatilities, thus allowing the two risk concepts to differ.

House price volatility indeed is highly correlated with rent volatility. The correlation between rent volatility and price volatility, as reported in the first columns of Tables 2 and 3, is 0.87. The second columns, which use the higher frequency variation of annual growth rates, have a 0.72 correlation. This close relationship can be seen in Figure 1, where the data from the first columns of Tables 2 and 3 are plotted against each other. MSAs with a higher standard deviation of detrended log real rent also have a higher standard deviation of detrended log real house prices over the 1990-2002 period. The slope of the regression line that is plotted through the data is 1.2 (with a standard error of 0.11) and the adjusted R-squared is 0.74.

Even so, there are some notable MSAs where price risk diverges from rent risk. In Miami, the standard deviation of detrended log rent is 0.026 but the standard deviation of detrended log price is almost twice as high, at 0.050. In San Diego, the standard deviation of rents is 0.077 while for prices it is 0.137. And in Fort Lauderdale, the standard deviation is just 0.014 for rents but 0.071 for prices.

It is important to note that we are considering only how the estimated rent volatilities and price volatilities are correlated across metropolitan areas and not whether year-to-year rent and price changes covary within a MSA. The framework in Section 1 shows that households trade off rent and price volatility when making their tenure decisions, and the high frequency comovement of rent and price changes does not enter their decisions. That parameter may be more relevant in other contexts, such as in Davidoff (2006).

From equation (3), we know that selling a house in city A is risky only to the extent that house prices there do not covary much with house prices in city B. If they covaried perfectly, there would be no house price risk upon leaving city A since all the sale proceeds would be used to purchase the house in B. If the covariance were zero, a household would be exposed to the uncertainty of the sale price in A plus the purchase price in B.

Indeed, it is possible that if both the price variance in city A and the covariance between cities A and B increased together, on net the risk of buying a home in A could be *reduced*. That occurs because the sale price volatility in A affects net risk only to the extent it is independent of the house purchasing risk in B.

It turns out that the correlation in house prices with the market varies widely across MSAs, so to assess the true risk of renting versus owning one needs to consider the particular MSA they are living in. Table 4 reports several estimates of the average of the correlations of each MSA's house prices with the other MSAs in the sample over the 1990 to 2002 period. In the first column, the correlation is computed using the annual real house price growth from the OFHEO index. Some MSAs—such as Richmond with 0.636, Chicago with 0.595, and Miami with 0.550—have relatively high correlations. Others are much lower: Austin has a 0.243 correlation, Seattle's is 0.034, and Portland's is negative.

In the second column we estimate the correlations using average house price growth rates over a five year period. The longer time period is intended to better correspond to the holding period for some owners. That is, owners may not care about the year-to-year correlation in house prices as long as prices are correlated at the time of sale/repurchase. The pattern of correlations across MSAs is similar whether we use one-year or five-year growth rates, with a correlation of 0.89.

As equation 3 showed, the covariance in house prices should be more relevant to the hedging value of owning a house than the correlations. A pair of cities can be highly correlated, but one could have more volatility than the other, making them poor hedges for each other. The covariance better measures whether the benefit of house price movements in one city undoes the cost of house price movements in another.

In Table 5, we provide estimates of the average of the square roots of each MSA's covariances with all the other MSAs. We use the same underlying concepts to measure house price growth as in Table 4. In the first column of Table 4, cities like San Diego, Boston, and New York have high average covariances and thus houses there have more value as a hedge against the price of houses if the household were to move. The hedging value is low in Cleveland, Seattle, and Portland. In fact Portland's average covariance over the 1990 to 2002 time period was negative, hence the square root is not listed. Using five-year growth rates, we obtain lower estimates of the square root of the covariances but the correlation between columns 1 and 2 is 0.94.

This wide range of average covariances means that a city like Austin can have a larger effective price risk even if its actual rent and price volatilities are not high because the sale price is unhedged. By contrast, in Washington DC where the average correlation is 0.591 and the average covariance is 0.039, the high price volatility hedges the home owner in part against house price movements in other cities.

4. *The net volatility of renting*

It is becoming apparent that the parameters that enter equation (3) are not independent of each other across MSAs. For example, metros with high rent volatility also have high house price volatility. These correlations mean that the volatility of owning net of the volatility of renting needs to take into account how the parameters interrelate.

One important correlation from the perspective of the hedging value of owning is that the very MSAs that have higher house price volatility (and thus a greater risk of owning) also tend to have higher pairwise covariances with other markets, providing a hedge against subsequent house purchases that mitigates the initial house price risk. Figure 2 plots MSAs in risk-covariance space. On the Y-axis is the standard deviation of detrended log house prices, computed over the 1990-2002 period. On the X-axis is the average of the square root of the MSA's pairwise covariances in its log real house price growth with each of the other MSAs' log real house price growth, computed for 126 metropolitan areas from the OFHEO data. The relationship is strongly positive with a tight clustering of MSAs (the dots) around the fitted regression line. The estimated slope on the line is 1.77 (standard error of 0.081) and the adjusted R-squared is 0.78. We obtain quantitatively similar results using covariances computed using five-year growth rates.

In some sense, the result in Figure 2 is not surprising since only MSAs with high variances can have high covariances. But it emphasizes a crucial point: house price volatility inherently hedges a home owner against house price volatility in other markets. Without it, a homeowner is exposed to the vagaries of house prices wherever he moves.

In order to evaluate the relative volatilities of renting and owning, we need to combine the various risk and correlation parameters at the MSA level, since there is so much cross-MSA heterogeneity, and the parameters interact nonlinearly. In Table 6, we take the difference of equations (1) and (2) to compute the net volatility of renting. A more positive coefficient means that renting has more volatility relative to owning. Larger numbers (in absolute value) mean that there is more overall volatility. The intent is not to measure the actual cost of the risk of owning versus renting, but to provide an index that incorporates several MSA-specific parameters into one. The only parameters that do not vary across MSAs are δ and α. We assume δ=0.96 and α=2, and use the parameters estimated using the one-year growth rates in rents and house prices.

Results from Sinai and Souleles (2005) suggest that on average the risk-based demand for home owning increases with expected length of stay in the house and with greater intensity when housing market risk is larger. That is because a short-duration home owner avoids few rent risks but has asset price risk arriving early in time and thus is large in present value whereas a long-duration home owner avoids many rent risks—frontloaded in time and thus more significant in present value—and takes one price risk far in the future. The greater the market volatility, the more emphatic is that tradeoff. That is, when the rent and price volatilities are small, there is little risk from either owning or renting and the net risk does not vary much with expected length of stay. Conversely, in MSAs with high rent risk, prices will be volatile as well, and there will be considerable risk from owning for a short duration or renting for a longer duration.

In keeping with the notion that expected length-of-stay affects the relative risks of renting and owning, we evaluate each MSA at five different expected durations. As can be seen in Table 6, the volatility of renting increases relative to the volatility of owning as expected duration increases. Beyond that, there is considerable heterogeneity across MSAs in the magnitude of the risks and the slope with duration. Sacramento and Seattle, for example, are the most volatile MSAs in which to own for a short duration, with a net volatility of -0.004. While Seattle has only moderate rent and house price volatility, its price growth has a low covariance with other MSAs, so a short duration owner risks changes in house prices both in Seattle and in the city he moves to without being able to offset them against each other. Sacramento has a very high house price volatility (0.079 standard deviation) which the natural hedge of its moderate covariance (root-covariance is 0.037) cannot undo. As expected durations rise, the expected price volatility declines and the expected rent volatility increases, so the relative volatility of owning falls. Given the greater volatility of Sacramento's housing market, the net volatility changes more rapidly with duration there.

Another example is San Jose, which has extremely high rent and price volatility. In San Jose, the net volatility of renting increases very rapidly with expected duration in the house, from

0.02 at two years' duration to 0.27 at 20 years' expected duration. By contrast, low volatility places like Memphis experience little change in the net volatility of renting as expected duration increases. In Memphis, the net volatility ranges from -0.001 to 0.002.

5. *Where and when is there risk of owning?*

This low relative volatility of home owning arises in part because owning a house hedges the consumption need for a place to live. In equilibrium, when the present value of housing costs rise, so must house prices, exactly undoing the increases. Empirically, it appears that this linkage between rents and prices more-or-less holds at the MSA level. Because of this linkage between the price of housing and the consumption value, there is no net gain in household net worth, holding consumption constant, when house prices rise. While the housing wealth increases, so does the future rent liability, on net leaving no change in net worth. To see why that is, consider a household whose house has appreciated in value. Could it increase its lifetime consumption while holding housing service consumption constant? If it sold its house, it would have to repurchase one that provided the same level of housing services in the same market—and that house would have gone up in price just as much as the existing house, leaving the household no better off. If it sold and did not repurchase, the household would have to rent, which risk-adjusted would be just as costly in present value as owning. And if it borrowed against its now-higher housing equity to finance consumption, the borrowing would have to be paid back, merely resulting in changing the timing of consumption. This may be the reason many researchers find a low marginal propensity to consume out of housing wealth.[1] [Skinner (1989, 1996)]

One category of households who potentially could gain from this increase in house prices are homeowners who anticipate moving. However, if their house prices covary with other

[1] One notable exception is Case, Quigley, and Shiller (2003), who find a high MPC out of housing wealth.

markets', their house price capital gain is offset by an increase in the purchase price of their next house.

Indeed, the households who could gain the most from an increase in house prices are the elderly—for whom the present value of the residual value of their house when they expect to die is greater than zero—if they have a limited bequest motive. [Li and Yao (2007)] Such households can transfer wealth from their heirs to themselves by spending housing capital gains. For example, if they sold their houses and rented instead, the present value of future rents would be less than their sale price because they had relatively few years left to live. Or, they could borrow against their houses leaving their heirs to settle the debt position. Consistent with this possibility, Campbell and Cocco (2007) find the largest marginal propensity to consume out of housing wealth among older homeowners and a zero MPC for younger homeowners. However, for elderly households with children the bequest motive can yield a positive hedging value of home owning if the children live in a housing market that covaries positively with the parents'.

Still, the largest risk from home owning comes toward the end of life when more of the value of the house could be extracted from the estate and used for current consumption. Sinai and Souleles (2008) estimate how much housing equity could be used for non-housing consumption, depending on a household's age. They find that the median 62-69 year old could extract almost 50 percent of their housing equity as long as they did not want to leave a bequest, although 40 percent of households could not extract any equity at all. By contrast, by age 90-94 almost all home owning households could extract housing equity, with a median value of 76 percent. Considering that national house prices rose 50 percent between 2000 and 2007, the amount of equity available for consumption by older households increased significantly. Should house prices decline, there would be commensurately less residual value of the house to consume. This uncertainty of house prices even makes the timing of the decision to extract equity risky. [Sun *et al* (2006)]

6. *The implications for house price derivatives*

Using house price derivatives to lock in house prices looks appealing at first glance because it could eliminate one of the risks in equation (2), the volatility of the sale price. By buying a house and using such derivatives to effectively lock in its value, one could avoid both rent risk and sale price risk.

However, as can be seen in equations (2) and (3), eliminating asset price fluctuations in city A does not necessarily reduce the risk of owning and possibly could increase it. That is, house price risk in both the current and the *future* markets affect the risk of owning, attenuated by their covariance. Hedging the volatility of house prices in the current market eliminates a portion of the aggregate uncertainty, but also reduces the covariance which makes the effective volatility higher.

Consider, for example, a homeowner who intends to move to a new house in the same market. If her housing value is unhedged, then the volatility in her sale price exactly offsets the volatility in her purchase price, at least to the degree that the volatility is due to market-wide demand shocks rather than idiosyncratic factors, resulting in a volatility-free wash sale. But if she locks in the value of her current house to avoid sale price uncertainty, she is exposed to all the changes in the market cost of housing services. A similar thing happens if the homeowner intends to move to another market. Owning a house, in most cases, would at least partially hedge the uncertainty about house prices in the future city. But locking in the current house price would undo the natural hedge of home owning. The only way to truly avoid house price risk is to lock in the asset value until one dies (assuming any children do not value a hedge against housing costs in their bequest). That would require hedging house prices in both the current and future locations, as in Voicu (2007).

This counterproductive aspect of the derivatives-based hedge may 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.

The greatest value of a housing derivatives-based hedge, then, may be to complement the natural hedging aspect of house price volatility rather than trying to undo it. One such way may be to use such derivatives to lock in the *relative* price of two locations, either in the short run to eliminate risk in between selling in one market and buying in the next (or vice versa) or in the long run if the household knows their sequence of housing locations and are not completely hedged by owning a house. This application would enhance the hedging aspect of homeownership by eliminating risk from the timing of the buy/sell transaction. Another use may be for households who are too short or too long future housing consumption, such as renters or the underhoused who would like to trade up to larger houses, or the overhoused who would like to downsize to smaller houses in the future. Of course, housing derivatives can still provide a hedging benefit for investors and lenders, since they are not naturally hedged through the consumption value of ownership.

7. *Conclusion*

Fluctuations in housing markets manifest themselves in uncertain rents and house prices. This paper considered how that volatility varies across metropolitan areas. Using several measures, we found considerable heterogeneity across MSAs in rent and house price volatility. The two volatilities are highly correlated, as would be predicted by a model where house prices were determined endogenously by rents. That correlation in volatilities implies that for a household with a long enough expected length of stay in a house, owning will involve less volatility than renting because home owners can avoid the uncertainty of future rents and the risk of the future sale price is smaller in present value.

In addition, in many MSAs, the house price volatility provides a natural hedge for the price of housing in other MSAs. In fact, the greater the house price volatility in the housing market, the better it hedges prices in other MSAs. This hedging benefit of home owning helps to mitigate the house price risk in the current market.

The implication of these results is that the role for housing derivatives to lock in asset values for home owners is limited. That is because, for most households, home owning provides a natural hedge due to the implicit short position in housing all households are born with. Putting a collar on house price volatility would actually unhedge a home owner.

This analysis has ignored two important features of housing market risk. The first is that households control whether to adjust their housing consumption. In that case, if a homeowner uses derivatives to hedge her housing price volatility and market housing costs fall, she can choose to move to a larger house whereas if housing costs rise she can remain instead in her current house at her current level of consumption. The second is leverage. In the presence of housing debt and liquidity constraints, the risks of house price volatility may be exacerbated. [Chan (2001), Stein (1995), Genesove and Mayer (1997, 2001), Hurst and Stafford (2004), Lustig and Van Nieuwerburgh (2005)] Even so, the risk hedging benefits of home ownership that we have outlined in this paper should remain even with these other risks of home owning.

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Table 1: Factors that affect rent variance

	(1)	**(2)**	**(3)**	**(4)**
Standard deviation of MSA employment	0.52 (0.17)		0.42 (0.18)	0.08 (0.29)
Impact Fees		0.0084 (0.0026)	0.0061 (0.0027)	-0.0061 (0.0068)
Months for permit		0.00069 (0.00036)	0.00040 (0.00037)	
SD employment X use impact fees				0.63 (0.35)
Constant	0.010 (0.003)	0.011 (0.003)	0.011 (0.003)	0.014 (0.005)
Adjusted R^2	0.19	0.29	0.38	0.41
Observations	43	38	37	38

Notes: Dependent variable is the de-trended standard deviation of real rents, as defined in the text. Standard errors in parentheses. Sample year is 1998.

Table 2: Real rent volatility by MSA

Metro	1990-2002 Standard deviation of detrended log real rent	1990-2002 Standard deviation of growth rate of annual rent	1990-2002 Standard deviation of growth rate of 5-year sum of rent	1981-1993 Standard deviation of detrended log real rent
Atlanta	0.035	0.019	0.012	0.052
Austin	0.042	0.040	0.015	0.127
Baltimore	0.038	0.013	0.009	0.048
Boston	0.085	0.048	0.020	0.099
Charlotte	0.046	0.011	0.017	0.044
Chicago	0.022	0.019	0.006	0.059
Cincinnati	0.019	0.012	0.005	0.048
Cleveland	0.017	0.011	0.006	0.044
Columbus	0.020	0.014	0.008	0.030
Dallas	0.034	0.020	0.017	0.038
Denver	0.024	0.028	0.015	0.066
Detroit	0.019	0.016	0.005	0.033
District of Columbia	0.069	0.030	0.013	0.041
Fort Lauderdale	0.014	0.010	0.003	0.016
Fort Worth	0.030	0.018	0.014	0.037
Houston	0.028	0.014	0.009	0.083
Indianapolis	0.014	0.010	0.007	0.023
Jacksonville	0.026	0.015	0.007	0.015
Kansas City	0.026	0.015	0.009	0.086
Los Angeles	0.080	0.026	0.014	0.075
Memphis	0.032	0.011	0.011	0.034
Miami	0.026	0.017	0.006	0.026
Milwaukee	0.016	0.015	0.004	0.023
Minneapolis	0.039	0.021	0.012	0.055
Nashville	0.044	0.011	0.013	0.077
New York	0.082	0.041	0.025	0.038
Oakland-East Bay	0.102	0.109	0.031	0.060
Orlando	0.034	0.007	0.005	0.035
Palm Beach	0.017	0.015	0.002	0.026
Philadelphia	0.029	0.014	0.004	0.039
Phoenix	0.039	0.009	0.013	0.054
Pittsburgh	0.011	0.016	0.002	0.020
Portland	0.015	0.017	0.010	0.041
Richmond	0.034	0.013	0.007	0.045
Sacramento	0.077	0.040	0.012	0.075
St. Louis	0.027	0.016	0.002	0.034
San Antonio	0.029	0.012	0.003	0.076
San Diego	0.077	0.027	0.009	0.066
San Francisco	0.121	0.103	0.048	0.055
San Jose	0.136	0.170	0.056	0.058
Seattle	0.047	0.027	0.020	0.055
Tampa-St. Petersburg	0.029	0.009	0.007	0.028
Corr. with column 2:	0.846		0.909	
Corr. of cols 1 and 3:		0.863		

Table 3: Real house price volatility by MSA

Metro	1990-2002 Standard deviation of detrended log real HPI	1990-2002 Standard deviation of annual growth of HPI	1990-2002 Standard deviation of 5-yr growth rate of HPI	1981-1993 Standard deviation of detrended log real HPI
Atlanta	0.040	0.035	0.026	0.042
Austin	0.037	0.038	0.047	0.141
Baltimore	0.051	0.038	0.022	0.079
Boston	0.112	0.079	0.057	0.204
Charlotte	0.028	0.023	0.016	0.044
Chicago	0.028	0.023	0.015	0.066
Cincinnati	0.015	0.015	0.010	0.031
Cleveland	0.013	0.013	0.003	0.045
Columbus	0.014	0.014	0.008	0.033
Dallas	0.039	0.032	0.033	0.067
Denver	0.043	0.037	0.039	0.064
Detroit	0.050	0.028	0.021	0.121
District of Columbia	0.083	0.055	0.033	0.093
Fort Lauderdale	0.071	0.054	0.027	0.026
Fort Worth	0.031	0.026	0.028	0.051
Houston	0.046	0.032	0.024	0.087
Indianapolis	0.012	0.015	0.007	0.052
Jacksonville	0.049	0.037	0.029	0.044
Kansas City	0.032	0.031	0.026	0.023
Los Angeles	0.132	0.078	0.059	0.157
Memphis	0.021	0.028	0.018	0.037
Miami	0.050	0.047	0.019	0.041
Milwaukee	0.015	0.014	0.006	0.041
Minneapolis	0.055	0.041	0.030	0.017
Nashville	0.040	0.031	0.025	0.055
New York	0.090	0.066	0.043	0.182
Oakland-East Bay	0.143	0.081	0.056	0.122
Orlando	0.052	0.038	0.022	0.026
Palm Beach	0.071	0.052	0.028	0.030
Philadelphia	0.061	0.045	0.030	0.110
Phoenix	0.031	0.038	0.033	0.041
Pittsburgh	0.022	0.024	0.007	0.021
Portland	0.049	0.029	0.016	0.085
Richmond	0.029	0.025	0.015	0.039
Sacramento	0.131	0.079	0.050	0.129
St. Louis	0.030	0.029	0.021	0.047
San Antonio	0.020	0.032	0.030	0.081
San Diego	0.137	0.079	0.054	0.110
San Francisco	0.142	0.085	0.060	0.154
San Jose	0.146	0.098	0.060	0.149
Seattle	0.057	0.044	0.027	0.108
Tampa-St. Petersburg	0.057	0.043	0.028	0.031
Corr. with column 2:	0.974		0.914	
Corr. of cols 1 and 3:		0.879		

Table 4: Average house price correlations between an MSA and the others, 1990-2002

	Mean correlation	
Metro	in real annual HPI growth	in real 5-year HPI growth
Atlanta	0.598	0.536
Austin	0.243	0.225
Baltimore	0.563	0.336
Boston	0.597	0.562
Charlotte	0.469	0.464
Chicago	0.595	0.379
Cincinnati	0.578	0.530
Cleveland	0.479	0.416
Columbus	0.549	0.483
Dallas	0.596	0.447
Denver	0.339	0.352
Detroit	0.366	0.474
District of Columbia	0.591	0.396
Fort Lauderdale	0.599	0.554
Fort Worth	0.620	0.446
Houston	0.508	0.459
Indianapolis	0.554	0.498
Jacksonville	0.601	0.535
Kansas City	0.555	0.488
Los Angeles	0.564	0.316
Memphis	0.490	0.461
Miami	0.550	0.505
Milwaukee	0.483	0.445
Minneapolis	0.594	0.539
Nashville	0.369	0.321
New York	0.611	0.550
Oakland-East Bay	0.476	0.427
Orlando	0.612	0.548
Palm Beach	0.621	0.555
Philadelphia	0.607	0.343
Phoenix	0.535	0.441
Pittsburgh	0.383	0.268
Portland	-0.398	-0.452
Richmond	0.636	0.517
Sacramento	0.287	0.262
St. Louis	0.609	0.540
San Antonio	0.489	0.265
San Diego	0.555	0.418
San Francisco	0.440	0.436
San Jose	0.385	0.445
Seattle	0.034	0.148
Tampa-St. Petersburg	0.628	0.551
Corr. with column 2:	0.893	

Table 5: Average house price covariances between an MSA and the others, 1990-2002

	Mean square root of the covariance	
Metro	in real annual HPI growth	in real 5-year HPI growth
Atlanta	0.029	0.020
Austin	0.020	0.014
Baltimore	0.031	0.017
Boston	0.046	0.031
Charlotte	0.020	0.014
Chicago	0.025	0.014
Cincinnati	0.019	0.012
Cleveland	0.015	0.006
Columbus	0.017	0.010
Dallas	0.029	0.020
Denver	0.023	0.018
Detroit	0.021	0.017
District of Columbia	0.039	0.022
Fort Lauderdale	0.038	0.021
Fort Worth	0.026	0.018
Houston	0.027	0.018
Indianapolis	0.017	0.010
Jacksonville	0.032	0.021
Kansas City	0.026	0.018
Los Angeles	0.045	0.027
Memphis	0.022	0.014
Miami	0.033	0.016
Milwaukee	0.017	0.008
Minneapolis	0.033	0.022
Nashville	0.019	0.013
New York	0.042	0.027
Oakland-East Bay	0.044	0.029
Orlando	0.032	0.019
Palm Beach	0.038	0.022
Philadelphia	0.035	0.019
Phoenix	0.028	0.019
Pittsburgh	0.020	0.008
Portland	.	.
Richmond	0.026	0.016
Sacramento	0.037	0.023
St. Louis	0.028	0.018
San Antonio	0.025	0.013
San Diego	0.046	0.028
San Francisco	0.043	0.030
San Jose	0.043	0.030
Seattle	0.015	0.014
Tampa-St. Petersburg	0.035	0.021
Corr. with column 2:	0.935	

Table 6: Net Rent Volatility by MSA and Expected Length of Stay

	Expected Length of Stay				
Metro	2	5	10	15	20
Atlanta	-0.001	0.002	0.003	0.004	0.005
Austin	-0.001	0.005	0.010	0.014	0.016
Baltimore	-0.001	0.001	0.002	0.002	0.003
Boston	0.001	0.008	0.015	0.020	0.022
Charlotte	-0.001	0.001	0.002	0.002	0.002
Chicago	-0.001	0.002	0.004	0.004	0.005
Cincinnati	-0.001	0.001	0.002	0.003	0.003
Cleveland	-0.001	0.001	0.002	0.002	0.002
Columbus	-0.001	0.001	0.002	0.003	0.003
Dallas	-0.001	0.002	0.004	0.005	0.005
Denver	-0.001	0.002	0.006	0.007	0.008
Detroit	-0.002	0.001	0.002	0.003	0.003
District of Columbia	-0.001	0.003	0.006	0.008	0.009
Fort Lauderdale	-0.002	0.000	0.002	0.002	0.002
Fort Worth	-0.001	0.002	0.003	0.004	0.004
Houston	-0.001	0.001	0.002	0.003	0.003
Indianapolis	-0.001	0.001	0.002	0.002	0.002
Jacksonville	-0.001	0.001	0.003	0.003	0.003
Kansas City	-0.001	0.001	0.003	0.003	0.003
Los Angeles	-0.002	0.002	0.005	0.006	0.007
Memphis	-0.001	0.001	0.002	0.002	0.002
Miami	-0.002	0.001	0.003	0.004	0.004
Milwaukee	-0.001	0.001	0.003	0.003	0.003
Minneapolis	-0.001	0.002	0.004	0.005	0.005
Nashville	-0.002	0.000	0.002	0.002	0.002
New York	0.000	0.006	0.011	0.015	0.017
Oakland-East Bay	0.008	0.038	0.072	0.095	0.110
Orlando	-0.002	0.000	0.001	0.002	0.002
Palm Beach	-0.001	0.001	0.002	0.003	0.003
Philadelphia	-0.001	0.001	0.002	0.003	0.003
Phoenix	-0.002	0.000	0.001	0.002	0.002
Pittsburgh	-0.001	0.001	0.003	0.003	0.003
Portland	-0.006	-0.003	0.000	0.002	0.002
Richmond	-0.001	0.001	0.002	0.003	0.003
Sacramento	-0.004	0.002	0.009	0.012	0.015
San Antonio	-0.001	0.001	0.002	0.002	0.002
San Diego	-0.002	0.002	0.005	0.007	0.008
San Francisco	0.007	0.034	0.065	0.086	0.099
San Jose	0.023	0.093	0.177	0.232	0.269
Seattle	-0.004	0.000	0.004	0.006	0.007
St. Louis	-0.001	0.001	0.003	0.003	0.004
Tampa-St. Petersburg	-0.001	0.001	0.002	0.002	0.002

Figure 1: The relationship of house price volatility to rent volatility

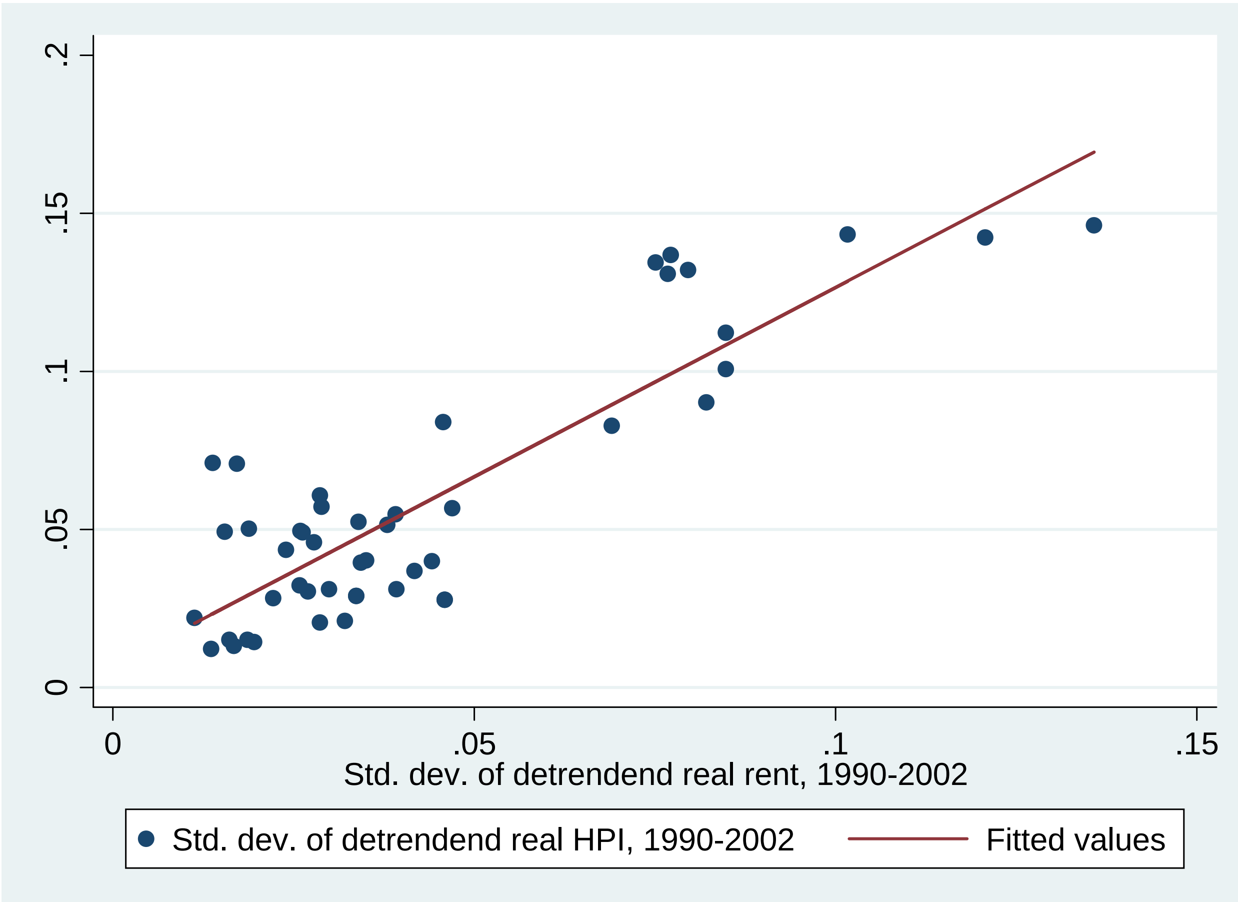

Figure 2: Standard Deviation of Real Annual House Price Growth vs.
Average Covariance of Real Annual House Price Growth with Other MSAs