The Common Variation in House Price returns

Aurel Hizmo

Preliminary and Incomplete

Abstract

I show that a real estate counterpart to the Fama-French Three Factor model fits the annual house price returns very well. Using annual house price return and average wage data at the metropolitan area level I construct three risk factors. The first factor is the annual house price returns for the whole US housing market. The second factor replicates a diversified portfolio that holds houses in low priced metropolitan areas and shorts houses in high price ones. The third factor replicates a diversified portfolio that holds houses in metropolitan areas with high price to wage ratios and shorts houses in areas with low price to wage ratio. Remarkably, these three factors explain a nearly 90 percent of the time series and cross-sectional variation in returns for twenty five diversified housing portfolios constructed by sorting metropolitan areas on price level and price over wage ratios. As these portfolios are well diversified, I find that idiosyncratic risk is not priced in the cross-section. These results mean that an investor would not have to worry about location specific house price risk if they could hold these portfolios of houses instead of only owning in one particular metropolitan area. On the other hand, when the same analysis is carried out using individual metropolitan areas instead of portfolios, the three factors explain a much lower share of the time series and cross-sectional variation in returns. In addition, idiosyncratic risk is priced in the cross-section. Households that own only in one metro area are exposed to a significant amount of local idiosyncratic risk and this is reflected in house price returns.

1 Introduction

Characterizing and understanding the workings of the housing market has remained a challenge both in the economics and the finance literature. What makes this market especially hard to study from an asset pricing point of view is that residential real estate is a very a unique asset class. Similarly to financial assets, homes provide households with returns from price changes and dividends in the form of utility from living in a particular home. These utility dividends are mainly derived from housing services, the consumption of local amenities, and participation in the local labor market. While financial assets pay out the same dividend to every investor, housing dividends do depend on residents' tastes and their match with the local labor market. Therefore, heterogeneity is important for homeowners' location decisions and house price determination. Frictions are also significantly larger in housing than in asset markets: for individual households, homes are indivisible, cannot be sold short, and large transaction costs impede frequent trades. Because of these unique complications of housing markets, standard asset pricing theory developed for financial assets is not entirely suitable for studying residential markets.

While making considerable progress in modeling heterogeneity, spatial allocation of individuals, and frictions very carefully, the urban economics literature treats homes as a consumption good and ignores any risk associated with owning a home. Since most homeowners live near their workplace, they are exposed to a considerable amount of location specific income and house price risk. This risk is particularly hazardous since households cannot reoptimize very frequently due to large reallocation costs and the indivisible nature of homes. From a portfolio management point of view, households are especially concerned about location specific risk since a disproportionate share of their wealth is invested in one particular house. What exacerbates this problem even more is that much of the local income and house price risk may not be easily diversified away by individual homeowners. The riskiness of a particular location can be an important factor that simultaneously affects house prices, and households' location and portfolio choice decisions.

The national US housing market has been rather uneventful historically with very mild booms and busts. As it can be seen in Figure 1, in the last 30 years the market has been very steadily increasing to a total of about fifty percent over the whole period. However many households do not live in areas that behave like the national housing market. There is much more volatility and heterogeneity in returns across different metropolitan areas. The booms and the busts across different markets do not always coincide, with some markets booming while others declining. If we think of the national house price returns as the aggregate or market returns, it is clear from Figure 1 that there is quite a bit of idiosyncratic volatility across different metropolitan areas. By living in a particular metropolitan area, households are holding all of this idiosyncratic volatility. Households would potentially benefit from owning shares of homes in many markets to diversify this idiosyncratic risk away. A more practical way to hedge this risk is to use financial assets that correlate with local housing returns. Creating a separate financial assets for each housing market can also be difficult to implement. This is not necessary however since there is quite a bit of common variation in housing markets. In principle only assets that correlate with the risk factors that span housing market volatility are needed for diversification or hedging.

The goal of this paper is to study the common variation in housing markets and to find common factors that drive the time-series and cross-sectional returns in different housing markets. In a quest to find common risk factors that drive house price returns, I show that a real estate counterpart to the Fama-French Three Factor model fits the yearly house price returns very well. Using yearly housing return and average wage data at the metropolitan area level I construct three risk factors. The first factor is the yearly house price returns for the whole US housing market. The second factor replicates a diversified portfolio that holds houses in low priced metropolitan areas and shorts houses in high price ones. The third factor replicates a diversified portfolio that holds houses in metropolitan areas with high price to wage ratios and shorts houses in areas with low price to wage ratio. Similarly to Fama-French factors, we can think of the first factor as the market factor,the second factor as small minus big, and the third as high minus low.

Remarkably, these three factors explain a very large fraction of the time series and cross-sectional variation in returns for twenty five diversified housing portfolios constructed by sorting metropolitan areas on price level and price over wage ratios. The magnitudes of the estimated R-squares are comparable to those found in Fama-French models of stock returns. As these portfolios are well diversified, I find that idiosyncratic risk is not priced in the cross-section. These results mean that an investor would not have to worry about location specific house price risk if they could hold a portfolio of houses instead of only owning in one particular metropolitan area. On the other hand, when the same analysis is carried out using individual metropolitan areas instead of portfolios, the three factors explain a much lower share of the time series and cross-sectional variation in returns. In addition idiosyncratic risk is priced in the cross-section. Households that own only in one metro area are exposed to a significant amount of local idiosyncratic risk and this is reflected in house price returns.

Even within metropolitan areas there is heterogeneity in growth rates for homes of different price levels. The small minus big factor can explain some of the heterogeneity in returns for different types of homes even within a metropolitan area. I construct separate indexes for different quartiles of house prices for thirteen metropolitan areas. In the time series, cheaper homes are more volatile and have sharper boom and bust cycles than expensive homes. Some of the difference in returns between these types of homes can be captured by the small minus big factor, which lends further

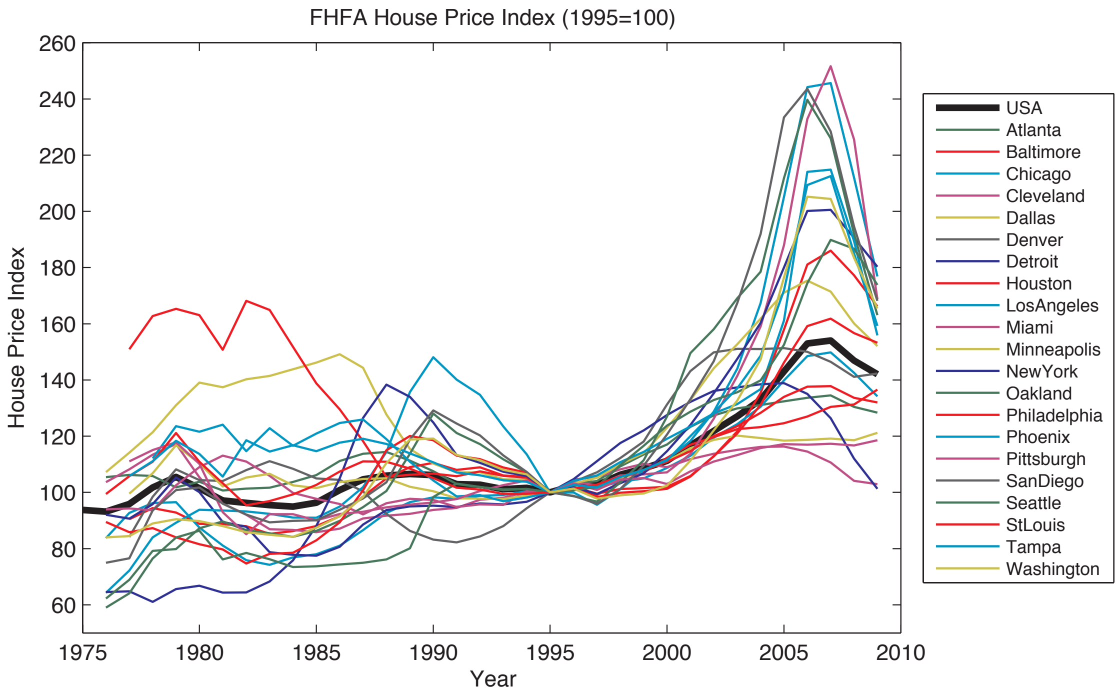

Figure 1: The Heterogeneity Across Housing Markets

support to the conjecture of it being an important risk factor in housing markets as well as in the equity markets.

2 A Three Factor Model for House Price Returns

In this section, I estimate a three factor model for house price returns in the spirit of the popular Fama-French three factor model. Using yearly housing return and average wage data at the metropolitan area level I construct three risk factors, which are then used in time-series and cross-sectional regressions to predict housing price returns. The price returns data considered in this analysis are the OFHEO home price indices at the metropolitan area level. The wage data used to construct one of the factors is the personal income per capita measure made available by the Bureau of Economic Analysis. The final sample analyzed here consists yearly data for the period from 1980 to 2008 for 216 metropolitan areas (MSAs hereafter).

The three factors considered here are constructed very similarly to the Fama-French factors. The first factor, denoted housing market (HMKT hereafter), is the yearly house price returns for the whole US housing market. The second factor, denoted housing small-minus-big (SMBH), is defined as the average returns in MSAs in the bottom half of the price level distribution in a given year minus and the average return in MSAs in the top half. This factor replicates a self-financing diversified portfolio that holds houses in low priced metropolitan areas and shorts houses in high price ones. The third factor, denoted housing high-minus-low (HMLH), is defined as the average returns in MSAs in the bottom 30 percent of the price level distribution in a given year minus and the average return in MSAs in the top 30 percent. This factor replicates a self-financing diversified portfolio that holds houses in metropolitan areas with high price-to-wage ratios and shorts houses in areas with low price to wage ratio. Similar to the small-minus-big Fama-French factors, SMBH intends to capture size effects in MSA price returns. On the other hand, HMLH is intended to capture growth effects since a high price to wage ratio can be an indicator of high expected growth.

For ease of interpretation I orthogonalize the three factors through a series of regressions. First, I regress SMBH on HMLH and HMKT and redefine SMBH as the regression residual. Then I regress HMLH on HMKT and redefine HMLH as the regression residual. This procedure gives three factors that are orthogonal to each other. The qualitative nature of the results is not affected by this orthogonalization.

The empirical analysis is conducted both by using individual MSAs and portfolios of them constructed by sorting MSAs on price and price-to-wage ratios. To construct the twenty five portfolios used in the empirical exercises, in each year, MSAs are grouped by price level quintiles. Then, for each price quintile, a subgroup of MSAs is created for every price-to-wage ratio quintile. The described procedure results in twenty five portfolios each containing MSAs with similar prices and price-to-wage ratios.

2.1 Time series regressions

Following Fama and French (1993), I conduct a series of time-series regressions to determine whether the proposed risk factors explain a good portion of variation in price returns. The empirical model estimated in Table 1 takes the form:

$$Ret_t^i - Rf_t = \alpha^i + \beta_{HMKT}^i \left(HMKT_t - Rf_t\right) + \beta_{SMBH}^i \cdot SMBH_t + \beta_{HMLH}^i \cdot HMLH_t + \varepsilon_t^i \quad (1)$$

where Ret_t^i is the return of MSA or portfolio i at time t, and Rf_t is the one month T-bill rate. Equation 1 is estimated for each portfolio or MSA separately and the resulting mean coefficients are displayed in Table 1. The number of MSAs for which the coefficients are statistically significant at the ten percent level are shown in parenthesis.

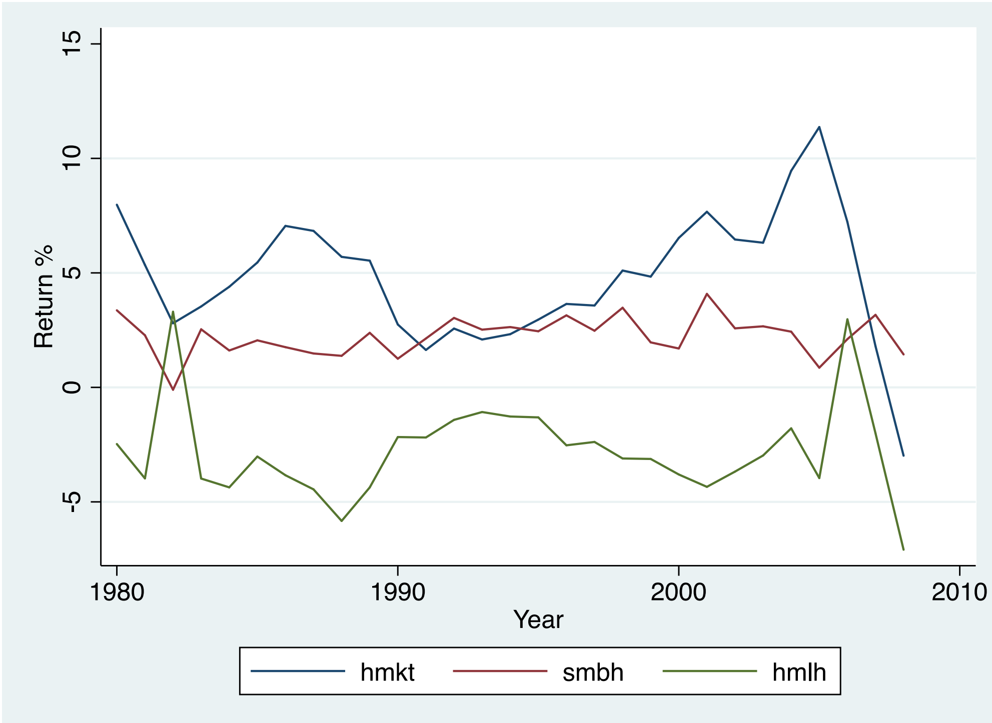

Figure 2: The Three Housing Factors Over Time

The first three specifications of Table 1 estimate equation 1 for twenty five MSA portfolios. Specification (1) shows that the excess market returns explains on average about 75 percent of the time-series variation in portfolio returns. The coefficient on market excess returns is very close to one and statistically significant for all of the 25 portfolios. In specification (2), when only SMBH and HMLH are included as factors, the R-squared drops on average to about eleven percent. The R-squared is low here since the SMBH and HMLH factors have been orthogonalized and only capture variation not present in the HMKT factor . In specification (3), all of the three factors are included. The market beta is still very close to one on average and most of the estimated coefficients are statistically significant for all of the factors. The three factors combine to explain about 85 percent of the time series variation in portfolio excess returns on average. This high R-squared is lower but comparable to what Fama and French (1993) find when using portfolios of US stocks.

The last three specifications of Table 1 estimate equation 1 separately for a sample of 216 MSAs.[1] The magnitudes of the coefficients are very similar to those found when using housing portfolios. The main difference is that the R-squared estimates found here are much lower in every specification. The market factor alone explains on average about 44 percent of the excess return

[1]Appendix Table 1 displays that factor loading and the R-squared for each MSA separately.

Table 1: Time Series Regressions of House Price Excess Returns on Three Risk Factors

	25 Housing Portfolios			Individual MSAs		
	(1)	(2)	(3)	(4)	(5)	(6)
HMKT-Rf	.9923		.9944	.9790		1.004
	(25)		(25)	(209)		(213)
SMBH		.3210	.1729		.1405	.1941
		(7)	(20)		(121)	(165)
HMLH		.0382	.1540		.1764	.1212
		(2)	(10)		(45)	(85)
R^2 distribution						
Mean	.7527	.1103	.8532	.4449	.1848	.6376
Min	.5339	.0205	.6790	.0103	.0007	.2490
Max	.8855	.2745	.9281	.8625	.6524	.9333
Groups	25	25	25	216	216	216

Note - The dependent variable in all of the regressions is the house price returns minus the one month T-bill rate. The T-bill rate is also subtracted from the housing market factor HMKT. Specifications (1)-(3) show the mean coefficients from time-series regressions that are run separately for twenty five housing portfolios constructed by sorting MSAs by price and price-to-wage ratios. Specifications (4)-(6) show the mean coefficients from time-series regressions that are run separately for each MSA. In parentheses is shown the number of times a coefficients is found to be significantly different from zero at the 10% level. The sample consists of yearly data from 1980 to 2008.

variation for MSA returns. SMBH and HMLH combined explain about 18 percent of variation on average. The three factors account on average for about 64 percent of the time series variation in MSA excess returns. That the average R-squared estimates are lower when using individual MSAs is not surprising since individual MSA carry idiosyncratic risk that is washed out on average when they are combined in portfolios.

Table 2 shows similar results when the same regressions are estimated using returns instead of excess returns. The R-squared estimates are lower for all of the specifications and the significance of the estimated coefficients is decreased for many of them. When using portfolios, the market factor explains on average about 57 percent of the variation, while including all three factors explain about

Table 2: Time Series Regressions of House Price Returns on Three Risk Factors

	25 Housing Portfolios			Individual MSAs		
	(1)	(2)	(3)	(4)	(5)	(6)
HMKT	.9647		.9677	.9537		.9527
	(25)		(25)	(134)		(134)
SMBH		.1679	.0440		-.0494	-.0291
		(5)	(12)		(29)	(42)
HMLH		.1975	.2207		.2464	.2336
		(5)	(10)		(68)	(98)
R^2 distribution						
Mean	.5680	.1037	.6717	.2830	.1400	.4214
Min	.1588	.0064	.3096	.0001	0.001	.0310
Max	.8925	.3196	.8981	.8849	.6231	.9104
Groups	25	25	25	216	216	216

Note - The dependent variable in all of the regressions is the house price returns. Specifications (1)-(3) show the mean coefficients from time-series regressions that are run separately for twenty five housing portfolios constructed by sorting MSAs by price and price-to-wage ratios. Specifications (4)-(6) show the mean coefficients from time-series regressions that are run separately for each MSA. In parentheses is shown the number of times a coefficients is found to be significantly different from zero at the 10% level. The sample consists of yearly data from 1980 to 2008.

67 percent of the time series variation. The R-squared estimates are significantly lower when using individual MSA returns. The market factor explains only about 28 percent and the three factors combined explain about 42 percent of the time series variation in returns.

Take together, the above results suggest that there are at least three common factors that drive house price returns in the US market. A professional investor that can hold portfolios of housing can therefore buy housing portfolios that the risk factors replicate and control the amount of risk he is exposed to. On the other hand, typical households that only own a house in one MSA are overexposed to idiosyncratic risk and may not be able to take advantage of the factor structure of the housing returns. Unlike professional investors who have access to large amounts of funds, an individual homeowner will find it very hard to buy the factor portfolios since homes are expensive and indivisible. Even if the three factors were tradable in divisible quantities, an individual homeowner would not be able to hedge as much risk away as professional investors would since the three factors do not explain as much of the variation for individual MSAs as they do for portfolios of MSAs.

2.1.1 Actual Fama-French factors and housing returns

An obvious question is: do the actual Fama-French factors from the stock market explain housing returns? If they did then the housing factors here would be redundant and house price volatility would be easily dealt with by holding portfolios that replicate the factors. To answer this question I repeat the same analysis of Table 1, but this time I use the actual Fama-French factors that are constructed from portfolios of stocks and not houses. The results are presented in Table 3. Across all of the specifications the Fama-French factors do not seem to explain much of the housing market volatility. The factor loadings are almost always insignificant whether we use housing portfolios or individual MSAs. The R-squared is very low for all of the specifications ranging from .02 to about .07. While they explain over 90 percent of the variation in returns for the stock market, the Fama-French factors seem to not have anything in common with the variation in housing markets.

2.2 Cross-sectional regressions

We now turn to analyze whether the factor loadings estimated in the section above can explain cross-sectional expected returns. Table 4 estimates the model:

$$E\left(Ret_t^i - Rf_t^i\right) = a + b_1\hat{\beta}^i_{HMKT-Rf} + b_2\hat{\beta}^i_{SMBH} + b_3\hat{\beta}^i_{HHML} + b_4\hat{\sigma}^i_{ERR} + \upsilon^i \qquad (2)$$

Table 3: Time Series Regressions of House Price Excess Returns on Real Fama-French Factors

	25 Housing Portfolios			Individual MSAs		
	(1)	(2)	(3)	(4)	(5)	(6)
MKT-Rf	.0323		.0441	.0200		.0258
	(4)		(4)	(1)		(1)
SMB		.0072	-.0020		.0614	.0561
		(0)	(0)		(22)	(24)
HML		.0437	.0372		.0219	.0325
		(1)	(2)		(0)	(0)
Mean R^2	.0430	.0307	.0885	.0159	.0542	.0719
Groups	25	25	25	216	216	216

Note - The dependent variable in all of the regressions is the house price returns minus the one month T-bill rate. The independent variables are the three Fama-French factors. Specifications (1)-(3) show the mean coefficients from time-series regressions that are run separately for twenty five housing portfolios constructed by sorting MSAs by price and price-to-wage ratios. Specifications (4)-(6) show the mean coefficients from time-series regressions that are run separately for each MSA. In parentheses is shown the number of times a coefficients is found to be significantly different from zero at the 10% level. The sample consists of annual data from 1980 to 2008.

where the β coefficients are the estimated factor loadings from the previous subsection, and $\hat{\sigma}^i_{ERR}$ is the standard deviation of the residual from the time series regression of excess returns on the factors. Equation 2 is estimated using a panel data between effect estimator for the 25 portfolios and individual MSAs separately.

The first three specifications in Table 4 display the coefficient estimates and the respective standard errors for the 25 housing portfolios. The coefficients on the idiosyncratic error standard deviation are not statistically significant in any of the three specifications. Contrary, the three proposed risk factor seem to be priced and enter with statistically significant coefficients in all specifications. The R-squared is fairly high across all specifications. Most notably, as seen in specification (3), the amount of exposure to the three proposed factors explains about 92 percent of the cross-sectional variation in average returns across portfolios. The estimated constant in specification (3) is also very small in magnitude and statistically indistinguishable from zero. This can be take as a sign that the three factors are capturing most of the cross-sectional variation in expected returns.

The last three specifications of Table 4 conduct a similar analysis for individual MSAs. The R-squared estimates here are about half of those estimated using portfolios. The three risk factors seem to be priced under all the specifications. Contrary to the finding on portfolio returns, idiosyncratic risk seems to be priced when looking at individual MSAs. In specification (3), which includes all of the factors, the coefficient on the idiosyncratic risk standard deviation is positive and statistically significant.

Table 5 estimates similar regressions using returns instead of excess returns. Again the R-squared estimates are fairly high and all of the factors seem to be priced across all specifications. The magnitudes and the signs of some of the estimated coefficients different from those estimated in Table 4. This means that whether investors are concerned with returns or excess returns matters for risk pricing of the three factors. This does not seem to be the case for pricing idiosyncratic error. Even when looking at returns instead of excess returns, idiosyncratic risk is not priced for returns in 25 diversified portfolios but is priced when looking at individual MSAs. In specification (3) we can see that the coefficient on $\hat{\sigma}_{ERR}$ for portfolios is small with a magnitude of 0.056 with a standard error of 0.158. When using individual MSAs the coefficient is 0.215 with a standard deviation of 0.044.

Overall, the cross-sectional results suggest that the three proposed factors are indeed priced factors and exposure to them does explain a large portion of the cross-sectional variation in house

Table 4: Cross-Sectional Regressions of Housing Excess Returns on Factor Loadings

	25 Housing Portfolios			Individual MSAs		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_{HMKT-Rf}$	3.496**		-1.183*	0.826**		-0.542**
	(0.841)		(0.595)	(-0.185)		(0.236)
$\hat{\beta}_{SMBH}$		-1.189**	-1.279**		-0.594**	-0.583**
		(0.129)	(0.136)		(0.059)	(0.067)
$\hat{\beta}_{HHML}$		0.444*	0.415*		0.301**	0.300**
		(0.246)	(0.237)		(0.108)	(0.132)
$\hat{\sigma}_{ERR}$	-0.157	-0.085	0.132	0.192**	0.019	0.203**
	(0.187)	(0.112)	(0.118)	(0.051)	(0.041)	(0.049)
Const.	-4.088**	-0.239	0.086	-2.373**	-0.781**	-0.816**
	(0.657)	(0.547)	(0.563)	(0.218)	(0.232)	(0.283)
R^2	0.512	0.917	0.926	0.249	0.504	0.476
Groups	25	25	25	216	216	216
N. Obs.	725	725	725	5958	5958	5958

Note - The dependent variable is house price returns minus the risk free rate. The independent variables are the factor loadings estimated from time-series regressions of excess returns on the proposed factors. The variable $\hat{\sigma}_{ERR}$ is the standard deviation of the residual from each time-series regression. The coefficients in this table are estimated by a panel data between estimator that only uses cross-sectional variation. The standard errors are shown in parentheses.

* statistical significance at the 90% level

** statistical significance at the 95% level

Table 5: Cross-Sectional Regressions of Housing Returns on Factor Loadings

	25 Housing Portfolios			Individual MSAs		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_{HMKT}$	1.771**		1.072**	0.672**		0.386**
	(0.217)		(0.206)	(0.069)		(0.072)
$\hat{\beta}_{SMBH}$		-0.281**	-0.318**		-0.382**	-0.415**
		(0.122)	(0.126)		(0.054)	(0.0581)
$\hat{\beta}_{HHML}$		-0.632**	-0.469*		-0.307**	-0.217**
		(0.190)	(0.237)		(0.074)	(0.075)
$\hat{\sigma}_{ERR}$	-0.278**	0.412**	0.056	0.226**	0.241**	0.217**
	(0.119)	(0.061)	(0.158)	(0.043)	(0.024)	(0.044)
Const.	3.624**	3.524**	3.711**	3.172**	3.601**	3.610**
	(0.238)	(0.214)	(0.248)	(0.168)	(0.131)	(0.153)
R^2	0.772	0.877	0.878	0.489	0.582	0.599
Groups	25	25	25	216	216	216
N. Obs.	725	725	725	5958	5958	5958

Note - The dependent variable is house price returns minus the risk free rate. The independent variables are the factor loadings estimated from time-series regressions of excess returns on the proposed factors. The variable $\hat{\sigma}_{ERR}$ is the standard deviation of the residual from each time-series regression. The coefficients in this table are estimated by a panel data between estimator that only uses cross-sectional variation. The standard errors are shown in parentheses.

* statistical significance at the 90% level

** statistical significance at the 95% level price returns. The finding that idiosyncratic risk is priced in individual metro areas supports the idea that individual homeowners are overexposed to local risk of one particular MSA that cannot be diversified away. In order to take on this unhedgable risk, households need to be rewarded by higher expected returns and because of this, idiosyncratic risks end up being priced in equilibrium.

3 Within-City Heterogeneity in Returns

Not only is there significant heterogeneity in return across, but also within metropolitan areas. Figure 2 illustrates this for different housing types in San Francisco. To construct this figure, we first divide homes in San Francisco in four quartiles sorted by price level. We then compute the price returns for each group and subtract the total returns for San Francisco from the return of each group. Figure 2 therefore displays the returns of each group detrended by the average returns in San Francisco as a whole. This procedure is repeated for other cities in figures 3-5.

Looking across different cities in Figures 2 through 5 it becomes apparent that lower priced homes are more volatile than high price ones. There is also evidence in the data that the booms and busts are more severe for cheaper homes. There seems to be a clear ordering in the rates of price returns going from cheaper to expensive homes. This observation leads one to think that a version of the small minus big factor would be able to explain some of the heterogeneity in returns across different housing types.

To test this hypothesis I use quarterly data from thirteen metropolitan areas in US that span as far as 1988 to the present for some metropolitan areas.[2] I use transaction level data available from Dataquick to construct four different price indexes for each metropolitan area, each of which corresponding to a different quartile of the price level distribution. Each house type index within a metropolitan area resembles a value-based portfolio that is frequently rebalanced such as the S&P 500.

In Table 6 I present results similar to Table 1. For each housing type i in metropolitan area j I estimate the following time series regression:

$$Ret_t^{ij} - Rf_t = \alpha^{ij} + \beta_{HMKT}^{ij}\left(HMKT_t^j - Rf_t\right) + \beta_{SMBH}^{ij} \cdot SMBH_t^j + \varepsilon_t^{ij} \tag{3}$$

where $HMKT^j$ here is the house price index for the metropolitan area j as a whole. Whether we use returns or excess returns we find similar results. The average metropolitan area index explains

[2]The metropolitan areas are Boston, Chicago, Cleveland, Denver, Las Vegas, Los Angeles, Miami, Orlando, Phoenix, San Diego, San Francisco, Tampa and Tucson.

Table 6: Time Series Regressions of House Price Returns on Risk Factors

	Returns			Returns - Rf		
	(1)	(2)	(3)	(4)	(5)	(6)
HMKT	1.000		1.000	1.000		1.000
	(48)		(48)	(48)		(48)
SMBH		.7655	.0001		.6688	.0001
		(35)	(44)		(34)	(44)
R^2 distribution						
Mean	.7972	.2879	.9012	.8010	.2364	.9065
Min	.1688	.0019	.3777	.2292	.0001	.4190
Max	.9846	.8782	.9913	.9808	.8515	.9903
Groups	48	48	48	48	48	48

Note - The dependent variable in all of the regressions is the house price returns. The regressions are run separately for each quartile of the house price level for each metropolitan area. There are 13 metropolitan areas with 4 groups of types of homes. Averages of the coefficients across all the groups are displayed in this table. The HMKT variable is the house price index for the whole metropolitan area. The 3 month T-bill rate is subtracted from the returns in specifications (4)-(5) . The number of times a coefficients is found to be significantly different from zero at the 10% level is shown in parentheses.

about 80 percent of the time series variance in house price returns. The local SMBH factor explains about 25 percent of the volatility by itself. When both factors are included in specifications (3) and (5) they jointly explain about 90 percent of the time series volatility. In other words the SMBH factor explains about half of the volatility that is left unexplained by the HMKT factor. The fact that the coefficients on SMBH are significant for the majority of the cases, and that the R-squared significantly increases with its inclusion, supports the idea that the "small minus big" idea spans beyond the stock market and can help explain both within and across metropolitan area variation in housing prices.

4 Conclusion

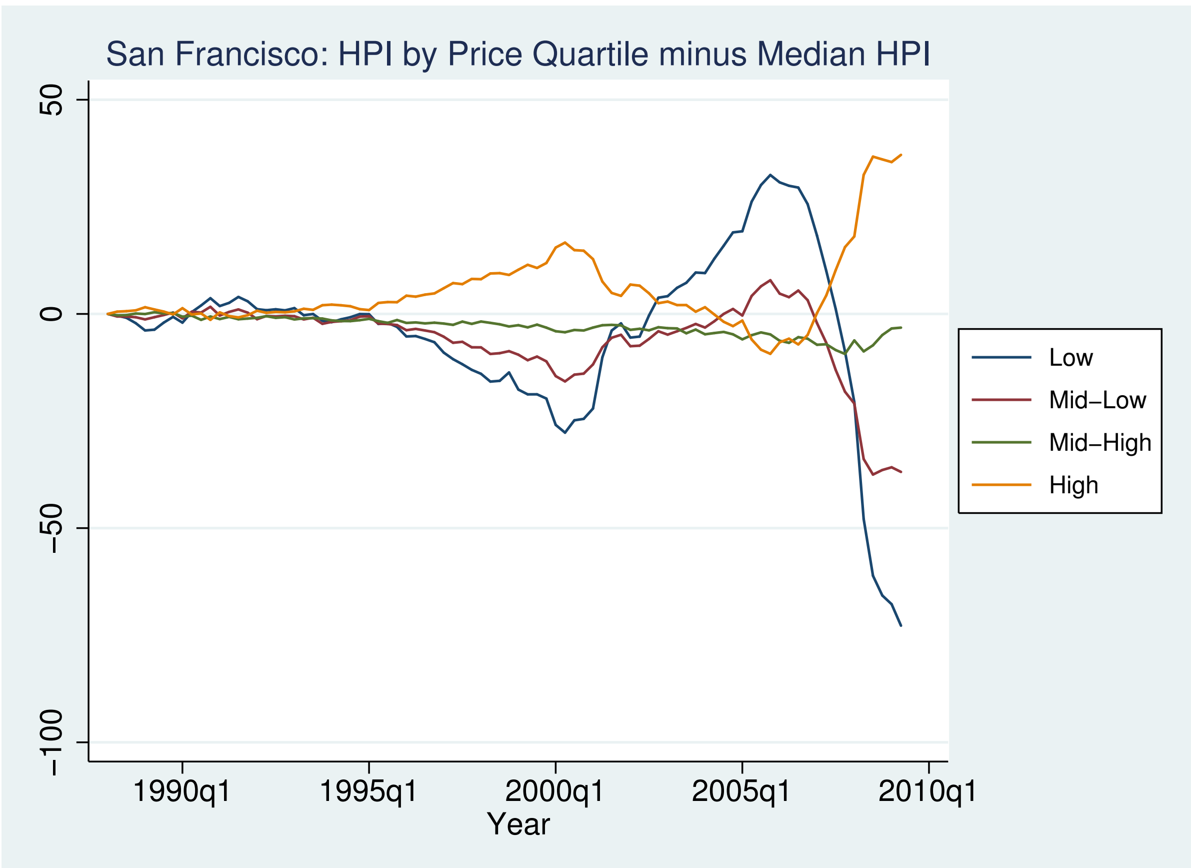

Figure 3: Heterogeneity in house price returns within San Francisco

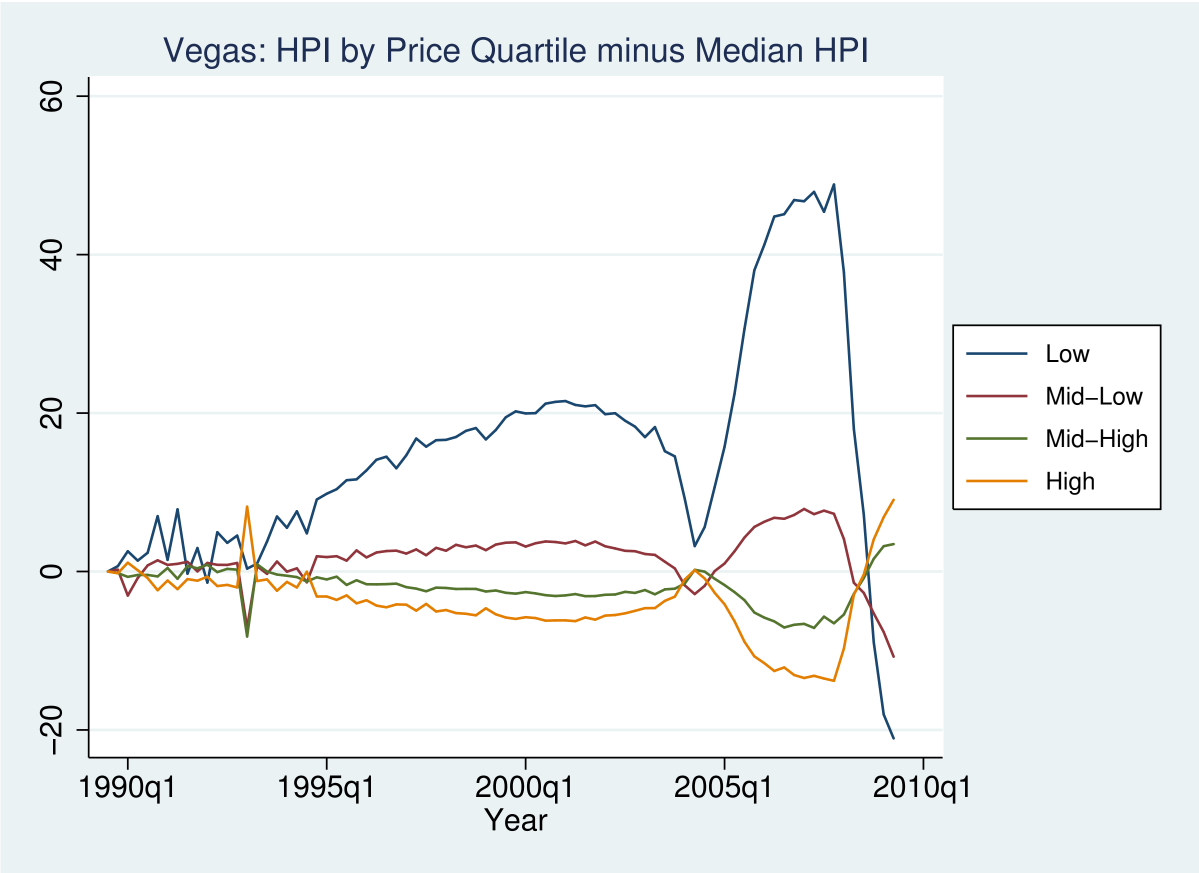

Figure 4: Heterogeneity in house price returns within Las Vegas

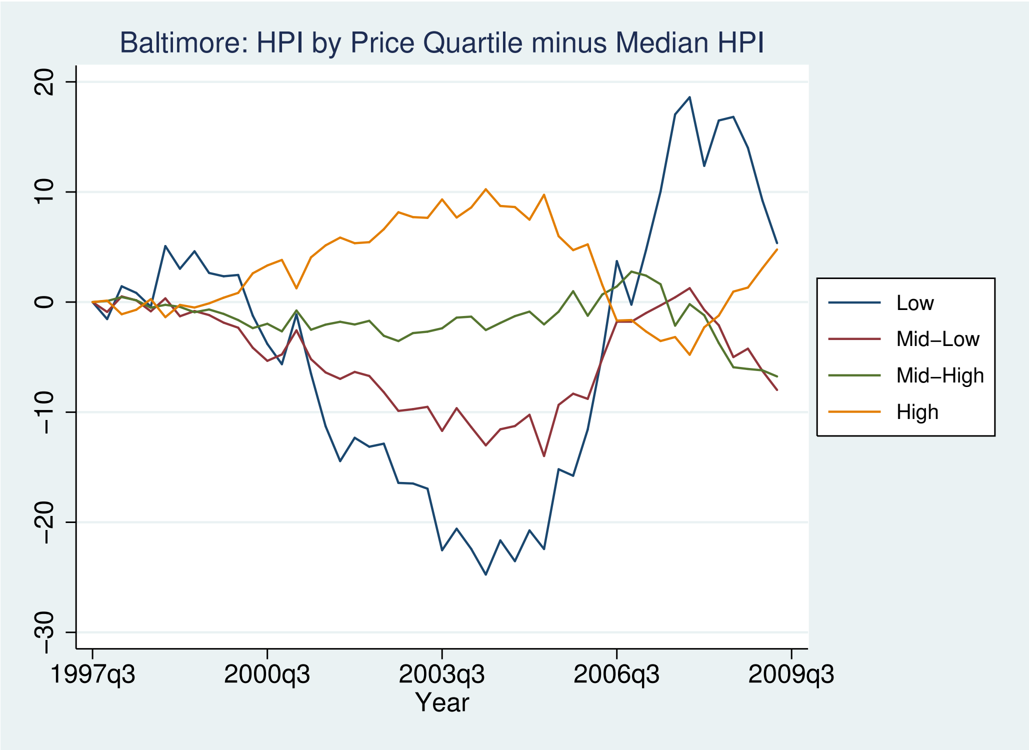

Figure 5: Heterogeneity in house price returns within Baltimore

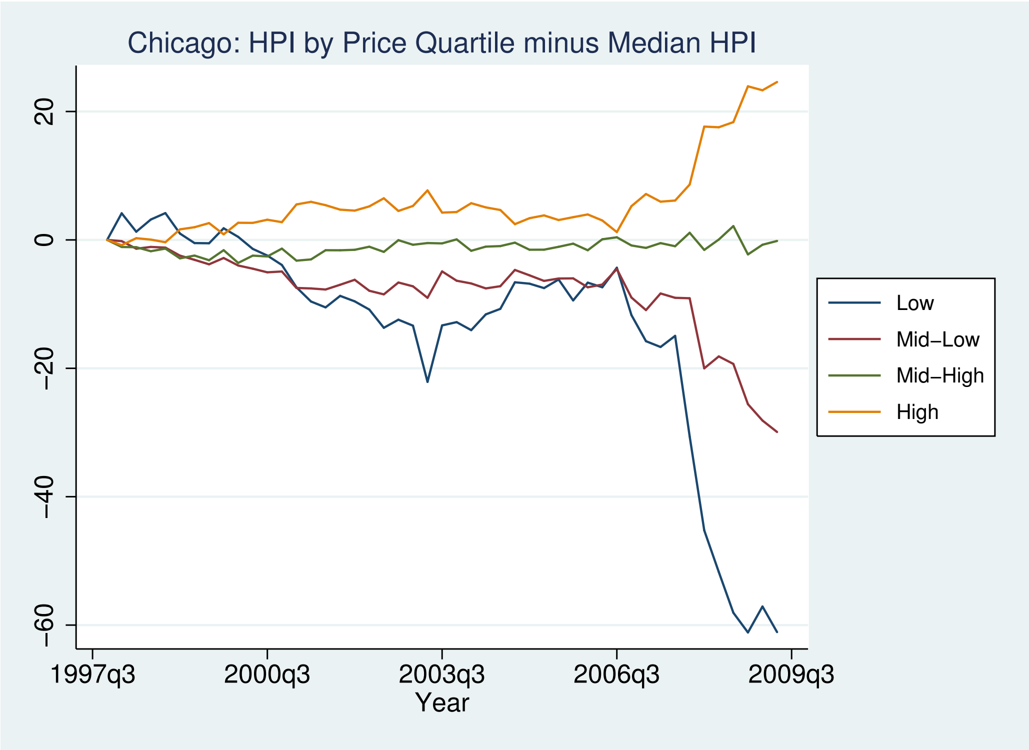

Figure 6: Heterogeneity in house price returns within Chicago

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Appendix

Table 7: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)	1.739308	-1.684288	.3337293	.9333254
Tampa-St. Petersburg-Clearwater, FL	1.497663	-.4346753	1.509949	.8883613
Baltimore-Towson, MD	1.436699	-.9210098	.0785444	.888047
Miami-Miami Beach-Kendall, FL (MSAD)	1.814361	.1475109	1.527967	.8796331
Bethesda-Frederick-Rockville, MD (MSAD)	1.62632	-1.691602	.0029778	.8792134
Sebastian-Vero Beach, FL	2.118671	-.5116773	.9703341	.8773407
Ft. Lauderdale-Pompano Bch.-Deerfield Bch., FL(MSAD)	1.911126	-.9627584	1.474571	.8747436
Burlington-South Burlington, VT	1.156307	-1.080878	-.4205196	.8729107
Orlando-Kissimmee, FL	1.459906	-.6798369	1.613636	.8721479
Richmond, VA	1.081134	.0279757	.1811307	.8705068
Kansas City, MO-KS	.8154212	.8574438	-.2368196	.8684527
West Palm Beach-Boca Raton-Boynton Beach, FL (MSAD)	1.949122	-1.260398	1.181732	.8676999
Cincinnati-Middletown, OH-KY-IN	.7217553	.7190692	-.4900098	.8553255
Naples-Marco Island, FL	2.024173	-1.514975	1.863005	.8550392
Evansville, IN-KY	.8007097	1.535286	-.4473409	.8514798
Jacksonville, FL	1.188899	.0163872	.9847685	.8510042
Milwaukee-Waukesha-West Allis, WI	1.009747	.9632559	-.4994464	.8505163
Cape Coral-Fort Myers, FL	1.989801	-1.410486	1.731332	.8495775
Rockford, IL	.8158908	1.086065	-.3199082	.8444403
Topeka, KS	.7303671	.9775323	-.4640892	.8418379
Fayetteville-Springdale-Rogers, AR-MO	1.142304	1.240988	.0617832	.8401812
Louisville-Jefferson County, KY-IN	.68191	.9566808	-.4102637	.8384024
St. Louis, MO-IL	.9515434	.5587435	-.3589029	.8353294
Indianapolis-Carmel, IN	.5462214	.4988295	-.5754967	.832612
Lakeland-Winter Haven, FL	1.512391	.3120809	1.323639	.8301613
Lubbock, TX	.7083759	1.557587	-.2171553	.829029
Birmingham-Hoover, AL	.7619334	1.08068	-.4064608	.8270332
Port St. Lucie, FL	1.967188	-1.469455	1.320553	.8222526
Columbus, OH	.615291	.5484405	-.4315717	.8205214
Lima, OH	.64823	.69586	-.5138151	.8197289
Deltona-Daytona Beach-Ormond Beach, FL	1.787195	-.4120438	1.367789	.8178752
Philadelphia, PA (MSAD)	1.246428	-1.281691	-.3960994	.8156589
Wilmington, DE-MD-NJ (MSAD)	1.206751	-.9446173	.1423215	.815185
Knoxville, TN	.7421098	.8815386	-.1218146	.8143483
Chicago-Naperville-Joliet, IL (MSAD)	1.026744	-.1422347	-.4816524	.8038828
Minneapolis-St. Paul-Bloomington, MN-WI	1.079635	.5560411	.0469018	.8016554
Tallahassee, FL	1.16147	.6058424	.6325101	.7998915
South Bend-Mishawaka, IN-MI	.5489847	.6219736	-.3689748	.7990227
Des Moines-West Des Moines, IA	.7660007	1.401321	-.5593787	.7984626

Table Continued: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Jackson, MS	.6518641	1.199025	.0084519	.7975181
Bakersfield, CA	1.991107	-1.040892	1.692892	.7917277
Pittsburgh, PA	.7406149	1.095093	-.6054807	.7899842
Stockton, CA	2.020129	-2.757999	1.451765	.789494
Santa Barbara-Santa Maria-Goleta, CA	1.860344	-2.595994	.2703788	.7886921
Charlottesville, VA	1.105693	-.4795941	.0866927	.788562
Omaha-Council Bluffs, NE-IA	.5715273	1.247763	-.002166	.7861776
Riverside-San Bernardino-Ontario, CA	2.050389	-2.186942	1.400772	.7780731
Los Angeles-Long Beach-Glendale, CA (MSAD)	1.921438	-2.650926	.6894765	.7773466
Camden, NJ (MSAD)	1.366554	-1.360979	-.0190126	.7762528
Tyler, TX	1.001905	2.140561	-.3075435	.771041
Oxnard-Thousand Oaks-Ventura, CA	1.875713	-2.804246	.4340868	.7707906
Fresno, CA	1.983159	-.6943497	1.371338	.7665764
Virginia Beach-Norfolk-Newport News, VA-NC	1.35446	-.4373583	.4298752	.764596
Canton-Massillon, OH	.645337	1.350264	-.4059551	.7599728
Fort Wayne, IN	.7169107	.6439775	-.6168843	.757945
Pueblo, CO	.7693724	1.876023	-.0451366	.7572857
Modesto, CA	2.078117	-2.511245	1.391197	.7541206
Shreveport-Bossier City, LA	1.054404	2.123783	-.2499522	.7538227
Santa Ana-Anaheim-Irvine, CA (MSAD)	1.844272	-2.531147	.6129875	.7520804
Racine, WI	.8458657	.6405373	-.0797245	.7492313
Savannah, GA	.9937977	.915508	.1971703	.7454007
New Orleans-Metairie-Kenner, LA	.8364047	1.694388	.3961949	.7435673
San Diego-Carlsbad-San Marcos, CA	1.805525	-1.908512	.0274773	.7425847
Lincoln, NE	.7110559	1.287837	-.4415702	.7385578
Visalia-Porterville, CA	1.813891	-.8271581	1.24551	.738148
Little Rock-North Little Rock-Conway, AR	.6433184	1.089155	-.1777053	.7368505
Columbia, SC	.7054852	.7093366	-.2122757	.7368192
Augusta-Richmond County, GA-SC	.7096264	.7789257	-.090963	.7357413
Salinas, CA	1.873605	-2.697279	.6528514	.7315196
Las Vegas-Paradise, NV	1.721299	-.6481834	1.866821	.7311755
Akron, OH	.6759145	1.012473	-.5674334	.7282528
Dayton, OH	.6465065	.6506191	-.7946156	.7275308
Merced, CA	2.111187	-2.347735	1.818743	.7266911
Cedar Rapids, IA	.8311487	1.628492	-.6329429	.7261147
Oakland-Fremont-Hayward, CA (MSAD)	1.543055	-2.585988	.3737752	.7246303
Las Cruces, NM	1.035634	1.130979	.273275	.7211829
Greensboro-High Point, NC	.5095644	.5468974	-.3719184	.7206948
Baton Rouge, LA	.5737562	2.063165	.4980496	.7186484
Phoenix-Mesa-Scottsdale, AZ	1.61964	-.4817086	1.209447	.717735
Cleveland-Elyria-Mentor, OH	.6914576	.8238608	-.6345518	.7167446
Davenport-Moline-Rock Island, IA-IL	.7023618	1.81427	-.6830581	.7167389
Madera-Chowchilla, CA	1.939422	-.562028	1.542325	.7151922

Table Continued: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Allentown-Bethlehem-Easton, PA-NJ	1.336653	-1.225229	-.1731088	.7146758
Reno-Sparks, NV	1.689274	-.4592462	.7952939	.7137267
Portland-South Portland-Biddeford, ME	1.292113	-1.388818	-.6657466	.7114705
College Station-Bryan, TX	.8578327	2.31608	-.4907193	.7098317
Tucson, AZ	1.410266	.2697997	.4676438	.7080842
Dalton, GA	.7214198	.5270991	-.0385685	.7066731
Atlanta-Sandy Springs-Marietta, GA	.5958056	.2271154	-.061925	.7023659
Monroe, LA	.7493076	1.935249	-.3832749	.7015089
Provo-Orem, UT	.3615704	2.664353	.9528946	.697262
Springfield, MO	.689736	1.249663	-.0024467	.6943635
Vallejo-Fairfield, CA	1.740226	-2.233208	.9873092	.6930622
Macon, GA	.4792249	.5515304	-.0166951	.6903482
Longview, TX	.7395616	1.813538	-.2347972	.6863852
Winston-Salem, NC	.4890127	.4909766	-.4174719	.6849068
Edison-New Brunswick, NJ (MSAD)	1.6337	-1.740719	-.0750091	.683878
Redding, CA	1.780507	-.3187151	.4707254	.6806005
Reading, PA	1.144579	-.0984914	-.3441029	.6805886
Trenton-Ewing, NJ	1.556721	-1.703086	-.2971945	.6782304
Palm Bay-Melbourne-Titusville, FL	1.772163	-1.51054	.8605336	.6767127
Ogden-Clearfield, UT	.4505608	2.59718	.2712373	.6761103
San Francisco-San Mateo-Redwood City, CA (MSAD)	1.378662	-2.489519	-.2840155	.6737127
Gary, IN (MSAD)	.6727179	1.185609	-.4632751	.6732539
Providence-New Bedford-Fall River, RI-MA	1.673406	-1.893564	-.3813959	.6699049
Pensacola-Ferry Pass-Brent, FL	1.323018	-.0684129	.6633518	.6698949
Cheyenne, WY	.8660207	1.641679	-.1513279	.6594113
Lake County-Kenosha County, IL-WI (MSAD)	.8488795	-.1752657	-.5384995	.6564206
Napa, CA	1.491783	-2.05647	.226015	.6512488
La Crosse, WI-MN	.6742157	1.301659	-.1857827	.6444252
Beaumont-Port Arthur, TX	.4876319	1.860963	.0233338	.6383724
Springfield, MA	1.347718	-1.886504	-.7290127	.6382484
Sacramento-Arden-Arcade-Roseville, CA	1.631397	-2.277957	.6184312	.6377586
Toledo, OH	.7143998	.7923267	-.3944279	.6370894
Saginaw-Saginaw Township North, MI	.6767668	.8881786	-.5664833	.6342323
Poughkeepsie-Newburgh-Middletown, NY	1.409224	-2.201568	.1172559	.6323982
Salt Lake City, UT	.52559	2.753828	.633231	.6318843
Kalamazoo-Portage, MI	.6787431	.8879912	-.2601702	.6316655
Santa Cruz-Watsonville, CA	1.278158	-2.479003	.2067656	.631567
Madison, WI	.8467524	1.094781	-.244353	.6313366
Buffalo-Niagara Falls, NY	.7034171	-.0473415	-.7716198	.6298571
Elkhart-Goshen, IN	.485018	.8475485	-.2109199	.6291088
Albany-Schenectady-Troy, NY	1.194681	-1.509796	-.3930397	.6269639
Peoria, IL	.8170562	1.844367	-.6138718	.6263124
Newark-Union, NJ-PA (MSAD)	1.378988	-1.603297	-.1219449	.6259609

Table Continued: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Eau Claire, WI	.77459	1.315956	-.3764178	.6250588
Colorado Springs, CO	.6058795	1.560365	.537026	.6247281
New York-White Plains-Wayne, NY-NJ (MSAD)	1.307997	-1.985643	-.016541	.6167334
Hartford-West Hartford-East Hartford, CT	1.341634	-1.831839	-.7649376	.616543
Portland-Vancouver-Beaverton, OR-WA	1.01516	1.960981	.4738016	.615577
Santa Rosa-Petaluma, CA	1.449629	-2.373837	.1712873	.6152416
York-Hanover, PA	.839407	-.3582635	.1384559	.613829
Springfield, IL	.460801	.7150641	-.2430681	.6135572
Nashville-Davidson–Murfreesboro–Franklin, TN	.6188588	.888057	-.0557535	.609946
Casper, WY	1.509761	3.588137	-.0560974	.6079359
Mobile, AL	.706376	1.77565	.2219398	.6078539
Albuquerque, NM	.7575142	1.13136	.4895241	.6002863
Medford, OR	1.343997	.1110368	.8616053	.5976689
Huntsville, AL	.7017776	.9299185	-.3452248	.5920952
San Luis Obispo-Paso Robles, CA	1.419758	-2.33961	.3095511	.5827718
Charlotte-Gastonia-Concord, NC-SC	.4714094	.5713657	-.2081084	.5782187
Tulsa, OK	.4649238	1.782646	.2430095	.5769485
Fort Collins-Loveland, CO	.5828369	1.774395	-.2874013	.5741873
Bloomington-Normal, IL	.4995199	.9633134	-.1621637	.5724351
Chico, CA	1.483063	-.7509338	.605621	.5723969
Barnstable Town, MA	1.793292	-1.228383	-.6043072	.5716577
Santa Fe, NM	.9259953	1.499676	.2524053	.568601
Grand Rapids-Wyoming, MI	.6137374	.2141422	-.3035836	.5682032
Harrisburg-Carlisle, PA	.7471827	.5512564	.2399148	.5608615
Erie, PA	.4302426	.7506689	-.3238311	.5532143
Rochester, MN	.6874795	.6580055	-.4760609	.5479594
Memphis, TN-MS-AR	.5905951	.6189292	-.1021572	.5458032
Durham-Chapel Hill, NC	.4920477	.4414367	-.2911299	.5450884
Wilmington, NC	.6872642	.1836205	1.051415	.5449303
Lansing-East Lansing, MI	.7329772	.1433742	-.5737608	.5433531
Lexington-Fayette, KY	.6417152	.7060852	-.5456493	.5429359
New Haven-Milford, CT	1.393027	-2.035726	-.4082982	.5397816
Salem, OR	.7250468	1.948333	.5743516	.5346982
Flint, MI	.7672482	.8305301	-.3207991	.5340522
Syracuse, NY	.6899551	-.6944594	-.4288166	.533226
El Paso, TX	.7251959	1.321312	.3214504	.5243231
Odessa, TX	1.033802	3.084394	-.0394553	.5197074
Eugene-Springfield, OR	1.066754	1.435725	.2200429	.5190672
Roanoke, VA	.6677974	.5910771	-.4151526	.5178426
Boise City-Nampa, ID	.9411757	1.506386	.6528531	.5156419
Manchester-Nashua, NH	1.316809	-1.534292	-.3990916	.5137551
Niles-Benton Harbor, MI	.5256685	.0930884	-.3236447	.5053744
Spokane, WA	.9405034	1.623723	.0290905	.5052919

Table Continued: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Tacoma, WA (MSAD)	.9295578	.6373944	.4381441	.503559
Bridgeport-Stamford-Norwalk, CT	1.307849	-1.626335	-.2394837	.5027904
Corpus Christi, TX	.6118565	1.40475	.7813163	.5013151
Nassau-Suffolk, NY (MSAD)	1.088609	-2.275699	.2087466	.4992297
Lafayette, LA	.4937763	2.674303	.6704661	.4976621
Bremerton-Silverdale, WA	1.02068	.6028717	.859329	.4963641
San Jose-Sunnyvale-Santa Clara, CA	1.144956	-2.650034	-.0183004	.4942964
Rockingham County-Strafford County, NH (MSAD)	1.330565	-1.45926	-.4081286	.4939736
Janesville, WI	.5068198	1.314912	.1004011	.4927363
Warren-Troy-Farmington Hills, MI (MSAD)	.8878476	.2355383	-.4371868	.4883039
Springfield, OH	.447158	.6056952	-.4847924	.4834047
Amarillo, TX	.4123472	1.627488	.0501059	.4777049
Oklahoma City, OK	.4591314	1.826705	.3989972	.4725638
Midland, TX	.8360136	2.780784	.8437225	.4678698
Worcester, MA	1.102941	-1.91699	-.2243702	.4559583
Grand Junction, CO	1.002298	2.848661	.3984976	.454966
Raleigh-Cary, NC	.4046108	.7136046	-.2003931	.4528911
Ann Arbor, MI	.8101884	-.17038	-.5188467	.449404
Mansfield, OH	.5319757	1.027042	-.3614577	.4408271
Olympia, WA	.9285134	.8269717	.2848945	.4346703
Chattanooga, TN-GA	.4800681	.3207497	.3632457	.4309074
Greeley, CO	.6227646	1.786674	-.0543916	.4303927
Rochester, NY	.4699604	-.1500427	-.380169	.4261131
Charleston-North Charleston-Summerville, SC	.830126	-.0858982	1.214496	.4182537
Wenatchee-East Wenatchee, WA	.5002186	1.974003	.7142791	.4176424
Detroit-Livonia-Dearborn, MI (MSAD)	.9417439	.2246782	-.3827778	.4140273
Boston-Quincy, MA (MSAD)	.9702687	-2.056921	-.371001	.4091539
Binghamton, NY	.9403079	-.1669429	-.6115076	.4067411
Corvallis, OR	.2418263	1.608958	.8711832	.4050774
Denver-Aurora-Broomfield, CO	.4715832	1.507636	.1316972	.40391
Houston-Sugar Land-Baytown, TX	.5107293	1.472672	.164296	.384208
Holland-Grand Haven, MI	.4732924	.1960437	-.2858527	.3784723
Anchorage, AK	.9774389	1.995599	.0398737	.3573005
Kennewick-Pasco-Richland, WA	.6543217	1.724071	-.133706	.350447
Cambridge-Newton-Framingham, MA (MSAD)	.8098144	-1.767444	-.4109151	.3420412
Bellingham, WA	1.053322	.4531529	.2393851	.3327613
Boulder, CO	.4453126	1.566551	.2013755	.3312142
Dallas-Plano-Irving, TX (MSAD)	.3731183	.900737	.0101809	.3271432
Seattle-Bellevue-Everett, WA (MSAD)	.8994183	.1631877	.2030598	.3267423
Peabody, MA (MSAD)	.9155871	-1.745206	-.3595898	.3256481
San Antonio, TX	.4404857	1.318324	.332029	.316411
Scranton-Wilkes-Barre, PA	.3831452	-.6783717	-.2581123	.2998218
Monroe, MI	.7178025	.5614451	-.2063572	.2984991

Table Continued: The Factor Loadings and the R-squared

Metropolitan Area	HMKT	SMBH	HMLH	R-squared
Honolulu, HI	1.331843	-1.098387	.8759465	.2969043
Longview, WA	.2914874	1.047619	1.019819	.2881624
Austin-Round Rock, TX	.2126772	1.940528	.2324161	.287369
Waterloo-Cedar Falls, IA	.5993633	1.453493	-.3841994	.265759