



Provided by the author(s) and University College Dublin Library in accordance with publisher policies., Please cite the published version when available.

<b>Title</b>	Housing risk and return : evidence from a housing asset-pricing model
<b>Authors(s)</b>	Case, Karl E.; Cotter, John; Gabriel, Stuart A.
<b>Publication date</b>	2009-11
<b>Series</b>	UCD Geary Institute Discussion Paper Series; WP 10 05
<b>Publisher</b>	University College Dublin. Geary Institute
<b>Link to online version</b>	<a href="http://ideas.repec.org/p/ucd/wpaper/201005.html">http://ideas.repec.org/p/ucd/wpaper/201005.html</a>
<b>Item record/more information</b>	<a href="http://hdl.handle.net/10197/2684">http://hdl.handle.net/10197/2684</a>

Downloaded 2019-03-19T21:34:52Z

The UCD community has made this article openly available. Please share how this access benefits you. Your story matters! (@ucd\_oa)



Some rights reserved. For more information, please see the item record link above.





**UCD GEARY INSTITUTE  
DISCUSSION PAPER  
SERIES**

**Housing Risk and Return:  
Evidence from a Housing  
Asset-Pricing Model**

**HOUSING RISK AND RETURN:  
EVIDENCE FROM A HOUSING ASSET-PRICING MODEL**

Karl Case, John Cotter, and Stuart Gabriel\*  
Wellesley College, University College Dublin, and UCLA

November 2009

**Abstract**

This paper investigates the risk-return relationship in determination of housing asset pricing. In so doing, the paper evaluates behavioral hypotheses advanced by Case and Shiller (1988, 2002, 2009) in studies of boom and post-boom housing markets. The paper specifies and tests a housing asset pricing model (H-CAPM), whereby expected returns of metropolitan-specific housing markets are equated to the market return, as represented by aggregate US house price time-series. We augment the model by examining the impact of additional risk factors including aggregate stock market returns, idiosyncratic risk, momentum, and Metropolitan Statistical Area (MSA) size effects. Further, we test the robustness of H-CAPM results to inclusion of controls for socioeconomic variables commonly represented in the house price literature, including changes in employment, affordability, and foreclosure incidence. Consistent with the traditional CAPM, we find a sizable and statistically significant influence of the market factor on MSA house price returns. Moreover we show that market betas have varied substantially over time. Also, we find the basic housing CAPM results are robust to the inclusion of other explanatory variables, including standard measures of risk and other housing market fundamentals. Additional tests of the validity of the model using the Fama-MacBeth framework offer further strong support of a positive risk and return relationship in housing. Our findings are supportive of the application of a housing investment risk-return framework in explanation of variation in metro-area cross-section and time-series US house price returns. Further, results strongly corroborate Case-Shiller behavioral research indicating the importance of speculative forces in the determination of U.S. housing returns.

Keywords: asset pricing, house price returns, risk factors

JEL Classification: G10, G11, G12

\*Case is Katherine Coman and A. Barton Hepburn Professor of Economics, Department of Economics, Wellesley College, Wellesley, Massachusetts, tel (781)283-2178, e-mail: [kcase@wellesley.edu](mailto:kcase@wellesley.edu); Cotter is Associate Professor of Finance, Director of Centre for Financial Markets, UCD School of Business, University College Dublin, Blackrock, Co. Dublin, Ireland, tel 353 1 7168900, email [john.cotter@ucd.ie](mailto:john.cotter@ucd.ie) and Research Fellow, Ziman Center for Real Estate, UCLA Anderson School of Management. Gabriel is Arden Realty Chair and Professor of Finance, Anderson School of Management, University of California, Los Angeles, 110 Westwood Plaza C412, Los Angeles, California 90095-1481, tel: (310) 825-2922, email: [stuart.gabriel@anderson.ucla.edu](mailto:stuart.gabriel@anderson.ucla.edu). This research was funded by the UCLA Ziman Center for Real Estate. The authors thank Stuart Myers, Matthew Spiegel, and Richard Roll for comments. The authors are grateful to Ryan Vaughn for excellent research assistance.

## 1. Introduction

Speculation has arguably been important to the recent and extreme swings in housing markets. However, few existing analyses have explicitly tested the risk-return framework in explanation of housing investment returns. As is broadly appreciated, the CAPM provides a simple risk-return relationship whereby an asset's or portfolio's returns are predicted by the market return. However, the CAPM is typically applied to the pricing of equities. This paper applies the CAPM to evaluate the risk-return relationship in housing asset pricing.<sup>1</sup> Further, the research seeks to determine whether other measures of house price risk have explanatory power for housing returns. Moreover, we seek to evaluate the robustness of the risk-return relationship to the presence of non-risk characteristics.<sup>2</sup> We examine the relation both in the metropolitan cross-section and time-series of house price returns. Results of estimation of housing CAPM (H-CAPM) provide evidence of a strong positive relationship between housing risk and returns. This relationship remains after accounting for well-known fundamentals including affordability, employment, and foreclosure effects. The findings are robust both in the cross-sectional and time-series relation between metropolitan-specific returns and aggregate housing market returns. Using the Fama-MacBeth framework to test the H-CAPM, we find strong support for the basic premise of the CAPM for housing, that there is a positive risk and return relationship. However we also find evidence of a non-linear CAPM.

Our research seeks new insights as regards the extreme boom-bust cycle in house prices evidenced in many U.S. metropolitan markets over the current decade. As is widely appreciated, recent substantial reductions in house values have figured importantly in the implosion of capital markets, reverse wealth effects, and global economic contraction. Neither analysts, regulators, nor other players in housing markets well anticipated the depth of the house price movements, their geographical contagion, or their broader macroeconomic impact.

In the economics literature, market and demographic fundamentals are often employed in assessment of housing market fluctuations. Often, those models pool cross-location and time-series data in reduced form specifications of supply- and demand-side fundamentals, including controls for labor market, nominal affordability, and other cyclical terms (see, for example, Case and Shiller (1988, 1990), Case and Quigley (1991), Gabriel, Matthey and Wascher (1999), Himmelberg, Mayer, and Sinai (2005)). While house price determination has been a popular topic of economics research, (see, for example, Case and Shiller (1989, 2003)), existing models often have failed to capture the substantial time and place variability in housing returns.

---

<sup>1</sup> Housing is analogous to equities in that it can pay two forms of compensation to investors. For equities, compensation is composed of price returns and dividends, whereas for housing compensation is comprised of house price returns and rents. Similar to the standard approach taken in the equity pricing literature, (e.g. Fama and French, 1992) we focus on modelling only the price return compensation of housing investment.

<sup>2</sup> The legitimacy of the CAPM with the single market variable has been questioned (Fama and French, 1996). Further, additional factors have been found to explain the variation in equity returns (see for example Fama and French, 1992; 1993). In defence of the CAPM, however, the market factor has been found to be the most important factor that predicts equity returns.

Behavioral research (e.g. Case and Shiller (1988, 2003)) suggests that market fundamentals are insufficient to explain house price fluctuations and that speculation plays a role.<sup>3</sup> Early surveys of recent homebuyers in San Francisco, Los Angeles, Boston, and Milwaukee, Case and Shiller (1988) concluded that “without question, home buyers [in all four sampled areas] looked at their decision to buy as an investment decision.”<sup>4</sup> More recent survey findings point to the growing importance of investment motivations for home purchase. For example, results of the 2002 survey, published in Case, Quigley, and Shiller (2003), indicate that investment returns are a consideration for the vast majority of buyers. Further, the pattern of survey findings reveals both geographic and temporal variations in investment demand for homeownership. In discussion of recently released 2009 Case-Shiller survey results (see New York Times, October 11, 2009) Bob Shiller suggests that “the sudden turn in the housing market probably reflects a new homebuyer emphasis on market timing.” Shiller concludes that “it appears the extreme ups and downs of the housing market have turned many Americans into housing speculators.”<sup>5</sup>

To assess the dynamics underpinning house price returns, we specify and test a Housing Capital Asset Pricing Model (H-CAPM). Despite the fundamental importance of the CAPM to empirical asset pricing (see, for example, Fama and MacBeth (1973), Merton (1973), Fama and French (1992), Fama and French (1993), Roll (1977)), few papers have undertaken comprehensive tests of the investment asset pricing framework in applications to housing.<sup>6</sup> In this paper, we equate expected returns in metropolitan housing markets to the market return as proxied by aggregate

---

<sup>3</sup> As suggested by Case and Shiller (1988) “Home buyers in the boom cities had much higher expectations for future price increases, and were more influenced by investment motives. In both California cities, over 95 percent said that they thought of their purchase as an investment at least in part. In Boston, the figure was 93.0 percent and In Milwaukee, 89.7 percent. A surprisingly large number in San Francisco, 37.2 percent, said that they bought the property "strictly" for investment purposes.”

<sup>4</sup>Case and Shiller (1988) conclude that “All of this suggests a market for residential real estate that is very different from the one traditionally discussed and modeled in the literature. In a fully rational market, prices would be driven by fundamentals such as income, demographic changes, national economic conditions and so forth. The survey results presented here and actual price behavior together sketches a very different picture. While the evidence is circumstantial, and we can only offer conjectures, we see a market driven largely by [investment] expectations.”

<sup>5</sup> Case, Quigley, and Shiller (2003) suggest that even after a long boom, home-buyers typically had expectations that prices over the next 10 years would show double-digit annual price growth, apparently only with a modest level of risk. Results from 2008 and 2009 Case and Shiller surveys provide strong evidence that homebuyers remains housing bulls in the long-run. Further, they suggest that “it seems reasonable to conjecture that an expectations formation process such as this could well be a major contributor to the substantial swings seen in housing prices in some US regions.”

<sup>6</sup>While homeownership user cost computations account for expected housing investment returns, standard reduced form house price models focus largely on fundamentals associated with housing consumption demand.

US housing market returns. The traditional application of the CAPM uses aggregate stock equity market returns, for example the S&P500 index returns, to proxy the market portfolio and to estimate a market beta. Accordingly, a first consideration is to assess the appropriateness of alternative proxies for the market factor, including both the national house price series and the S&P500 equity return series.

Moreover we augment the model by examining the impact of other risk factors including idiosyncratic risk, momentum, and MSA size effects. Idiosyncratic risk is not included in the traditional CAPM world as market risk is taken to be the sole predictor of returns. In that context, investors are assumed to hold the fully diversified market portfolio. Unlike the CAPM for equities, however, investment in housing is usually not associated with a diversified portfolio, as investors typically hold a small number of location-specific properties (for example, a single property) in private ownership. This suggests that the housing pricing model should not only include a reward in expected returns for systematic (market) risk, but also provide compensation for diversifiable risk.<sup>7</sup> Thus, housing investors seek compensation for total risk, encompassing both systematic (market) risk and unsystematic (idiosyncratic) risk (see Merton's (1987) model for a theoretical framework). In the empirical asset pricing literature, however, evidence on the role of idiosyncratic risk in equity pricing is mixed. Ang, Hodrick Xing and Zhang (2006) find the relationship between idiosyncratic risk and expected returns is negative. In contrast, Goyal and Santa-Clara (2003) find a positive relationship, whereas Bali, Cakici, Yan, Zhang (2001) find an insignificant relationship. For real estate, the issue is overlooked somewhat although Plazzi, Torous and Valkonov (2008) find a positive relationship between commercial real estate expected returns and idiosyncratic risk.<sup>8</sup> We use the most commonly applied measure of idiosyncratic risk by taking the standard deviations of the squared residuals from the CAPM model. Regardless, idiosyncratic risk is an important component of total risk for equities (Campbell, Latteau, Makiel, Xu, 2000) and given the lack of diversification may also be prominent for housing investment.<sup>9</sup>

In the equity pricing literature, research has confirmed the existence of a size effect whereby small firms earn higher risk-adjusted returns than large firms (using firm market capitalization as a measure of firm size). Banz (1981) was among the first to document the size effect-- suggesting that returns on small firms were high relative to their betas. The prevalence of this effect led Fama and French (1992) to incorporate size as a risk factor in the CAPM. Known as Small Minus Big (SMB), this control

---

<sup>7</sup> Of course idiosyncratic risk may also have an influence on house prices for different reasons. For instance if there is mispricing of housing it will attract economic agents such as arbitrageurs who try and exploit this and earn non-market risk related returns.

<sup>8</sup> The mixed evidence may result from the modelling of idiosyncratic risk where a number of alternative measures are driven by different econometric assumptions (eg. see Lehmann, 1990).

<sup>9</sup> As in the case of equities, idiosyncratic risk associated with housing investment may have changed over time. For example, as shown by Campbell, Latteau, Makiel, and Xu (2000), idiosyncratic risk trended upwards up during the 1990s, but this trend has reversed in more recent times (Bekaert Hodrick Zhang, 2008).

tests for a zero cost investment strategy based on size whereby investors short large firms to finance their ownership of small firms. Fama and French (1992) find a positive relationship between the SMB factor and expected returns and show that it predicts future asset returns. In housing research, Cannon, Miller and Pandher (2007) find a positive cross-sectional relationship between the SMB factor and housing returns. We construct a similar SMB term for metropolitan housing by subtracting the 75<sup>th</sup> quartile return based on median MSA house prices from the 25<sup>th</sup> quartile return for each time interval.

Carhart (1997) has provided evidence in support of the inclusion of a momentum term in the pricing of equities. The momentum term seeks to identify past winners and losers in asset returns and specifies a trading strategy by assuming that these outcomes will continue in the future. In that trading strategy, the investor buys past winners and sells past losers with the expectation that the overall return is positive. In a key known study, Jegadeesh and Titman (1993) sort past returns into decile portfolios and assume the investor buys the best return ranking portfolio and sells the worst return ranking portfolio for each period. The authors find that their momentum factor has significant positive explanatory power for equity returns, and remain seven in the presence of the control for market risk. In addition, an extensive literature has used variations on this definition with similar results. Momentum has been generally overlooked in the housing literature although momentum trading has been found to have a positive influence on future real estate investment trust (REIT) returns (Chui, Titman, and Wei, 2003; Derwall, Huij, Brounen, and Marquering, 2009). For our asset pricing model, winning and losing MSAs are identified in every time period by sorting all previous period's MSA returns and the highest (lowest) returns are associated with winners (losers). In specification of this housing spatial arbitrage term, we take an average of the highest quartile returns less the lowest quartile returns.

Finally, the augmented CAPM model is tested against the inclusion of controls for socioeconomic variables commonly represented in the house price literature, including changes in income, employment, and affordability. Those controls seek to link house price fluctuations to local fundamentals, notably including proxies for nominal ability-to-pay, supply-side shocks, and demographic controls (see, for example, Case and Shiller (1988, 1990), Goodman and Gabriel (1996), Case and Quigley (1991), Gabriel, Matthey and Wascher (1999), and Himmelberg, Mayer, and Sinai (2005).

Our focus on the cross-sectional and intertemporal dynamics of US house prices is facilitated via the application of quarterly house price indices from the Office of Federal Housing Enterprise Oversight (OFHEO) for the 1985-2007 timeframe and across over 150 MSAs.<sup>10</sup> The national house price series is identified as the market

---

<sup>10</sup> The Case-Shiller data uses a similar methodology in incorporating repeat sales for a number of US cities (currently 20). While the OFHEO data derives from sales of homes using conforming loans, that data offers a substantially greater cross-sectional spread in addition to a much longer time series than the Case-Shiller series, which is only available since 1987. In ongoing work, we seek to test the robustness of our results to the Case-Shiller time-series.

return for housing investment.<sup>11</sup> The study first uses a pooled cross-section and time-series approach to fit the asset pricing model. We generate betas for each MSA's returns with respect to movements in the OFHEO national house price index. Each beta represents the market risk-adjusted sensitivity of the per-period change in MSA-specific house prices to movements in the aggregate housing market. High betas represent high risk housing markets whereas low betas represent low risk housing markets. For example, as expected, we find high housing betas in metropolitan areas of the east and west coasts, notably including coastal California and Florida, whereas areas of the upper mid-west and Great Plains are characterized by low betas. In general, we find that investment in high (low) risk markets is compensated by high (low) returns.

We also undertake cross-sectional analysis at quarterly intervals for our large sample of MSAs to examine the temporal evolution of our asset pricing variables. Assessment of the time-series of our model coefficients indicates that the relative importance of explanatory factors has varied across time and over the housing cycle. Specifically we find that the positive influence of the market factor on MSA-specific asset returns has been marked by substantial cyclical variability in some metropolitan areas; in other areas, betas have evidenced little increase or decrease. However, as expected, the model explanatory power does vary substantially across MSAs, suggesting the housing CAPM investment framework is more relevant to an explanation of house price returns in some MSAs than in others. To illustrate, we find that market betas increase substantially through the sample period for Milwaukee, where those estimates are estimated at close to zero through much of the 1990s, but then rise to about 1 toward the end of the sample period. In contrast, the opposite occurs in Boston, where market betas are estimated at greater than 2 early in the time-series but trend down to less than 1 during the mid-2000s, only to jump again precipitously during the subsequent housing boom years. However there are a large set of MSAs where the market betas remain relatively high or low throughout the sample. Also the asset pricing model explanatory power varies across MSAs; for example, model fit is particularly high for coastal California MSAs such as Los Angeles, CA ( $R^2 = 0.846$ ), but relatively low for central areas such as Cedar Rapids, IA ( $R^2 = 0.132$ ).

We also run separate time-series models for each MSA. We find strong evidence of a risk-return relationship that varies across MSAs. In particular our CAPM market betas vary substantially and are strongly related to the relative explanatory power of the models in the cross-section. The average correlation across MSAs between the  $R^2$  and betas for our H-CAPM model with only 1 factor, the OFHEO National series, is 0.739. In terms of specific MSAs we find that Raleigh-Cary, NC has a very low explanatory power ( $R^2 = 0.108$ ) coupled with a low beta (0.074) whereas in contrast Tampa-St.Petersburg-Clearwater, FL has a relatively high  $R^2$  (0.886) and market beta (1.567).

To avoid a potential error-in-variable problem from using a single asset CAPM we also examine the pricing relationship using portfolios of MSA returns. Using

---

<sup>11</sup> In contrast aggregate stock market returns have a negligible influence on the variation of house price returns with low explanatory power, and is supportive of previous evidence (Case, 2000).

portfolios we test the validity of our H-CAPM model using the Fama-MacBeth (1973) framework. Note, however, that using portfolios is not without its challenges. Roll (1977) finds that portfolio averages may conceal relevant information on assets, so as to make it difficult to determine the impact of variables on asset returns.<sup>12</sup> This issue is particularly relevant to studies of metropolitan housing markets (relative to equity markets), in that limited cross-sectional housing data may give rise to portfolios containing few assets. That notwithstanding, we find a strong risk and return relationship for the housing portfolios. Further, we find the basic housing CAPM model is robust to the addition of other explanatory variables, including standard measures of risk and other housing market fundamentals. Our findings corroborate survey findings by Case and Shiller and are supportive of the application of a housing investment risk-return model in explanation of variation in metro-area cross-section and time-series of US house price returns. Further, our results suggest the markedly elevated importance of a housing investment asset pricing framework to certain MSAs over the course of the recent house price cycle.

The plan of the paper is as follows. The following section describes our house price data and characterizes temporal and cross-sectional variability in house price returns. Section 2.2 defines model explanatory variables and reports on summary characteristics in the data. Section 2.3 reports on the estimation results of alternative specifications of the housing CAPM, inclusive of assessment of cross-sectional and temporal variation in the housing market betas. Section 2.4 focuses on Fama-MacBeth analysis and other robustness checks. Section 3 provides concluding remarks.

## **2. Analysis**

### **2.1 Housing Market Returns**

In our H-CAPM the dependent inputs include MSA-specific house price returns as proxied by the OFHEO metropolitan indices. Regression analysis is undertaken on 151 MSAs for which we have obtained quarterly price index data from 1985:Q1 – 2007:Q4. The house price time-series are produced by the U.S. Office of Federal Housing Enterprise Oversight (OFHEO). The OFHEO series are weighted repeat-sale price indices associated with single-family homes. Home sales and refinancing activity included in the OFHEO sample derive from conforming home purchase mortgage loans purchased by the housing Government Sponsored Enterprises—the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac). The OFHEO data comprise the most extensive cross-sectional and time-series set of quality-adjusted house price indices available in the United States. However, due to exclusion of sales and refinancing associated with government-backed and non-conforming home mortgages, the OFHEO series likely understates the actual level of geographic and time-series variability in U.S. house prices.<sup>13</sup>

---

<sup>12</sup> However, the portfolio sort criteria has an impact on the findings for portfolio returns with Brennan, Chordia and Subrahmanyam (1998) showing that the impact on returns change significantly from using 6 versus 7 portfolios.

<sup>13</sup> For a full discussion of the OFHEO house price index, see “A Comparison of House Price Measures”, Mimeo, Freddie Mac, February 28, 2008.

While some of the MSA-specific OFHEO series are available from 1975, our timeframe (1985-2007) is chosen so as to maximize representation of U.S. metropolitan areas.<sup>14</sup> Our 151 time-series include all major U.S. markets. As suggested below, the average of our 151 MSA-specific time-series is closely correlated to the OFHEO national house price index (corr = .953). We calculate house price returns for each MSA in our sample as the log quarterly difference in its repeat home sales price index<sup>15</sup>

Figure 1 provides an initial review of the house price series incorporating time series plots and summary details at quarterly frequency. Here, for illustrative purposes, we distinguish movements in house prices for the 4 metropolitan areas identified in ongoing Case-Shiller survey research, relative to that of the U.S. market overall. As suggested above, the OFHEO national series is computed over a large number of sampled areas for the 1985-Q1 through 2007-Q4 period.<sup>16</sup> In each case, the time-series of index levels are normalized to 100 in Q1 1995.

Figure 1 provides evidence of considerable temporal and cross-sectional variation in the house price series. As shown, the rate of increase in aggregate market returns accelerated markedly during the post-recession years of the early 2000s. Among the 4 identified locations, extreme house price run-ups are identified for coastal metropolitan areas, with the highest rates of mean price change and risk (standard deviation of index changes) shown for California coastal markets. In Los Angeles, for example, house prices moved up from an index level of 100 in 1995 to a peak level of almost 350 in 2007! One quarter's returns almost reached 10%. Similar price movements, although somewhat less extreme, were evidenced in San Francisco and Boston. In marked contrast, house price trend and risk were substantially muted in Milwaukee, at levels close to the US market average. The summary data presented in Figure 1 suggest marked variability in house price risk and returns across US metro areas as is consistent with earlier Case-Shiller behavioral characterization.

---

<sup>14</sup> The Case-Shiller house price indices provide the primary alternative to the OFHEO series. While the Case-Shiller price indices are not confined only to conforming mortgage transactions, they include a substantially smaller (N=20) set of cities over a much shorter timeframe (2000-present).

<sup>15</sup> In principle, it would be desirable to model house prices at higher frequencies. Unfortunately, monthly quality-adjusted house price indices are available from OFHEO only for Census Divisions (N=18) and only for a much shorter time-series.

<sup>16</sup> OFHEO actually provides data for a larger number of MSAs (384 in total for 2009) which is used to create the National house price index. However many of those MSAs are associated with a lack of trading activity and so the full set of MSAs are not included as rankable according to the definition provided by OFHEO. Moreover our sample is restricted to include only those MSAs with data available between 1985 and 2007 resulting in 151 individual MSAs. However we are confident that we have captured a very large proportion of US housing market as measured by OFHEO with the average of individual MSA series very strongly correlated with the National series (corr = 0.953).

## 2.2 Inputs to the Regressions

### Explanatory Variables

Table 1 provides definitions and summary information on model variables. While empirical modelling is undertaken at a quarterly frequency, this information is displayed at an annual frequency. As shown, the cross sectional average return for all MSA housing markets ( $R_{HPI}$ ) is substantial at almost 1% with an average deviation of just less than this. Moreover we see strong cross sectional variation with returns ranging from 0.295% to 2.530%. This is similar to the national OFHEO series ( $R_{OFHEO}$ ). The alternative market return series, the S&P 500 ( $R_{SP}$ ), is characterized by substantially elevated risk relative to that of housing markets and the return performance is relative poor with average negative returns in excess of 1%.

The small minus big term (SMB) is defined as the quarterly return associated with the 25<sup>th</sup> percentile house price MSA less that associated with the 75<sup>th</sup> percentile house price MSA. As suggested above, SMB has been found to be an important determinant of equity returns, as small (market capitalization) firms earn higher returns than large firms (see, for example, Banz, 1981 and Fama and French, 1992). For US housing markets, the average SMB return is a positive 0.175 (Table 1): however, SMB does exhibit substantial variation and is not significantly different from zero. Consistent with the equity asset pricing literature, idiosyncratic risk ( $s^2$ ) is defined as the standard deviation of squared CAPM model residuals (see Ang, Hodrick, Xing and Zhang, 2006). Accordingly,  $s^2$  provides a proxy for diversifiable risk. In marked contrast to equities, a typical housing investor trades in a very small number of location-specific properties, suggesting that diversification in housing investment is substantially more difficult to achieve. Again, relative to equities, idiosyncratic risk should be relatively more important to housing investment (as has been found by Plazzi, Torous and Valkanov (2008) in the case of commercial real estate). As shown in Table 1, we find substantial idiosyncratic risk on average (4.590%) with considerable cross sectional variation in this variable.

Consistent with the finance literature (e.g. Jegadeesh and Titman, 1993), our momentum term reflects average house price return differentials between the 10 highest and lowest return sample MSAs in each quarter. This formulation tests the hypothesis that investors identify the best performing MSAs in the country and fund investments in those areas via sales of property in the worst performing areas. The average return from the momentum strategy is large (6.350%) and is statistically greater than zero. Accordingly, the momentum term seeks to identify speculative spatial strategies among housing investors.

The final three variables, quarterly proxies for change in employment ( $\Delta Emp$ ), change in foreclosures ( $\Delta Forc$ ), and log of lagged affordability, ( $\log(Afford_{t-1})$ ), are socio-economic factors commonly cited in the housing literature. In that regard, nominal affordability is particularly important to mortgage qualification and related demand for housing. Further, as suggested by above citations, housing returns are taken to vary with fluctuations in local employment and foreclosure activity. As indicated in Table 1, all terms are presented at yearly frequency. The employment variable represents the one quarter log change in MSA employment using data supplied by the Federal Reserve Bank of St. Louis. On average employment fell by about 0.7 among

MSAs in the sample. Affordability is defined as the log of the one quarter lagged ratio of MSA mean household income to mean house price. In our sample, housing affordability averaged 0.241% and is statistically significant in 47 of the 151 MSAs. Foreclosure information is provided by the Mortgage Bankers Association and is defined as the 1-quarter change in foreclosures in the MSA. Average foreclosures are substantial and average over 1% per MSA. These levels are significant across housing markets.

Table 2 provides a matrix of simple correlations among the time-varying variables. As evident, there exists little correlation between the housing market ( $R_{HPI}$ ) and equity return ( $R_{SP}$ ) series. In marked contrast, and as would be expected, the correlation between the MSA cross-sectional average housing market return ( $R_{HPI}$ ) and that of the OFHEO index ( $R_{OFHEO}$ ) exceeds .95. The table further reveals a relatively strong correlation between the housing market return series ( $R_{HPI}$ ) and the Small minus Big (SMB) term. Otherwise, simple correlations between the remaining explanatory variables are of limited magnitude with the exception of the Affordability and Foreclosures terms. As evaluated below, the table is suggestive of the importance of the national housing return series ( $R_{OFHEO}$ ) in determination of returns at the MSA level ( $R_{HPI}$ ). Generally we also note a lack of correlation between the explanatory variables. In general, the OFHEO series returns have very low correlation with the other explanatory variables, although SMB, Foreclosures and Affordability tend to have higher correlation suggesting we can isolate the impact of these variables for the variation of house prices.

## Estimating Housing Market $\beta$ s

### 2.3 $\beta$ Estimates

Table 3 presents results of our basic H-CAPM models. The table provides summary evidence on regressions estimated for each of the 151 MSAs included in the analysis. For each explanatory variable, Table 3 presents the average estimated coefficient value. The number of MSAs with significant estimated coefficients is indicated in parentheses below the coefficient values. Models (1) – (6) present variants of the basic model; those specifications are indicated in a memo item to the table. In addition, the tables provide additional summary information based on estimation results for the 151 MSAs on model coefficients and model explanatory power. Model (1) consists of the single factor housing CAPM; here we equate the returns in each MSA ( $R_{HPI}$ ) with national housing market returns ( $R_{OFHEO}$ ). In model (2), we estimate an alternative single factor housing CAPM, whereby a proxy for equity market returns ( $R_{SP}$ ) is used to represent the market variable.<sup>17</sup>

We separately generate betas for each MSA with respect to movements in the market return. Each beta represents the sensitivity of the quarterly change in the MSA-

---

<sup>17</sup> As is common to the empirical asset pricing literature, we also estimate the H-CAPM in an excess return specification, whereby the MSA and national house price return series are adjusted by the risk-free rate. In that specification, we use the 3-month Treasury Bill to proxy the risk-free rate. Research findings are robust to the excess return transformation of the model. Those results are contained in Tables 6 and 7.

specific OFHEO index to movements in the specified market factor. High betas represent high risk MSA housing markets, whereas low betas represent the opposite. In the basic CAPM pricing framework of model (1), a MSA's quality-adjusted house price returns are generated by market risk only. In this model, investment is assumed to be in a market portfolio, such that investors get compensated only for non-diversifiable risk. In equity markets, the market factor is typically proxied by a broad market portfolio such as the S&P500. We examine two alternative proxies of the market factor, the log difference of the OFHEO national house price index, and the log difference of the S&P500 index, both at quarterly frequency. The OFHEO national series is an equally weighted index of the individual MSA house price indices, whereas the stock market index is a value-weighted series.<sup>18</sup>

To begin, we identify the relevant market factor as the National OFHEO series. As shown in model (1), the average estimated market beta is close to .8; further, the housing market return proxy is statistically significant in 103 MSAs. Note also that the mean  $R^2$  in the OFHEO series single factor model is almost 20 percent. Those results stand in marked contrast to findings associated with the equity market return series. Results from model (2) indicate the lack of power or significance of the equity market return series in explaining MSA-specific housing return series. In particular, the equity return series is statistically significant in only 2 of the sampled MSAs; further, the estimated coefficient magnitudes are negligible. Table 3 also provides evidence of substantial cross-sectional variability in model explanatory power and estimated housing return betas, which range upwards to about 75 percent and 2.6, respectively, from a low of near zero. In sum, results of models (1) and (2) suggest the appropriateness of the national housing return series to proxy market returns in the housing CAPM. The findings for model (1) are strongly supportive of the Case-Shiller behavioral studies. Here we find widespread evidence in support for non-fundamental variables in explanation of cross-sectional variations in house price returns. Per the CAPM, the market variable is an investment variable with its estimated beta coefficient representing the magnitude of market risk. The strong findings in model (1) for the market factor suggest a beta risk and return relationship where investment in housing follows a risk and return strategy; investment in high risk areas is compensated by high returns, whereas investment in low risk areas results in a low return reward. Further, as evidenced in Case-Shiller survey results, there exists substantial variation in housing investment behavior among different metropolitan specific markets as identified by variability in the estimated market beta.

Subsequent models augment the single factor market return specification so as to determine whether there are other risk factors that are compensated by additional returns. In model (3), we estimate a two-factor model which controls for size effects associated with differences in returns between low- and high-priced metropolitan housing markets. Here we test the hypothesis that lower-priced MSA housing markets offer higher risk-adjusted returns than higher-priced MSAs. This term bears a relation to the small firm effect evidenced in the equity pricing literature, whereby small firms offer higher risk-adjusted returns than large firms. This effect is

---

<sup>18</sup> The distinct weighting structure of the candidate market factors may have consequences for the inferences of the H-CAPM results. However, given the very strong support for the OFHEO series over the equity series as the market proxy we do not comment on this issue further.

sufficiently prominent so as to be included in standard asset pricing models such as the Fama and French (1993) 3-factor model as a Small minus Big (SMB) firm variable where the returns from large firms are subtracted from those of small firms and the resulting zero-investment variable is included as an explanatory variable. As suggested above, the housing small minus big term (SMB) is defined as the quarterly return associated with the 25<sup>th</sup> percentile MSA house price area less that associated with the 75<sup>th</sup> percentile MSA house price area.<sup>19</sup> Results from Table 3 indicate that the coefficient on the housing small minus big term is precisely estimated only in 19 of the 155 MSAs and is not of the anticipated sign. Accordingly, systematic arbitrage of returns among high- and low-priced MSAs does not appear relevant to housing asset pricing in the vast majority of sampled areas. Note, however, that the estimated market beta is robust to inclusion of this term and the explanatory power of the single factor model increases with its inclusion.<sup>20</sup>

In model (4), we estimate another two-factor model that tests for momentum effects. Consistent with the finance literature (see, for example, Jegadeesh and Titman, 1993), our momentum term is defined as the difference in average house price returns between the 10 highest and 10 lowest return MSAs in each quarter. In the finance literature, this variable has been used to proxy the investment strategy of going long with the previous period's winners while at the same time shorting losers from the prior period in a zero-investment positive return approach. In the housing application, this formulation tests the hypothesis that investors identify the best performing MSAs in the country and fund investments in those areas via sales of property in the worst performing areas. Accordingly, the momentum term seeks to identify speculative spatial strategies among housing investors. Indeed, this formulation of the momentum term derives as well from Case-Shiller survey findings, which indicate higher (lower) levels of speculative home purchase in rising (falling) housing markets. As evidenced in Table 3, the estimated momentum terms are quite small in magnitude, with an average of slightly less than zero as against a positive prediction, and precisely estimated only in 18 MSAs.<sup>21</sup> Results of the housing investment risk-return framework accordingly do not provide much support for geographic arbitrage zero-investment strategy, although including momentum does increase the explanatory power of the housing investment model without impacting the influence of the market beta.

In model (5), we estimate a two-factor model which incorporates idiosyncratic risk. As is broadly appreciated, household investment in housing is typically among a small number of properties and is highly undiversified.<sup>22</sup> Liquidity constraints and

---

<sup>19</sup> We tested this with alternative formulations of the SMB and the results were qualitative similar and are available on request.

<sup>20</sup> Note it is possible that the SMB term provides explanatory power in analysis of housing market returns but that its impact is reduced due to the use of MSA-level time-series rather than property-specific data.

<sup>21</sup> Our H-CAPM findings are qualitatively robust to the inclusion of variations in the specified momentum term and are available on request.

<sup>22</sup> The most common form of housing investment is in a single unit of owner-occupied property.

difficulty in shorting the housing asset further constrain diversification. Accordingly, investment in housing diverges markedly from the usual CAPM world, where market participants are able to invest in a diversified equity portfolio. The unique aspects of investment in housing suggest that our housing asset pricing model compensate investors for total risk, inclusive of both systematic (market) risk and unsystematic (idiosyncratic) risk. Accordingly, our specification follows that of Merton's (1987) model, where both market risk and idiosyncratic risk require risk-return compensation. Our methodology for computing idiosyncratic risk is standard to the asset pricing literature. We use the standard deviation of squared residuals associated with estimation of the simple CAPM for each MSA to proxy for MSA-specific non-market returns. As indicated in Table 3, the idiosyncratic risk proxy enters the asset pricing model with a high level of statistical significance only in 25 of the 151 sampled MSAs. Further, the estimated betas on the market factor appear robust to the inclusion of this term and are very similar to those reported for model (1). Note as well that the inclusion of idiosyncratic risk does increase the explanatory power of the model.

Finally, in model (6), we estimate a four factor model that controls for the market factor, idiosyncratic risk, momentum, and (SMB) size effects. The inclusion of these 4 factors aims to replicate the augmentation of the CAPM in equity pricing, namely additional factors have been found to generate anomalous pricing behaviour (see Fama and French, 1996), and as a consequence have been incorporated into the pricing model as potential risk factors. As evidenced in Table 3 and discussed above, estimation results suggest a very strong relation between MSA specific house price returns and market risk. In addition, there is only limited significance for the idiosyncratic risk, momentum, and size terms in the determination of MSA housing returns. Those controls sometimes enter the estimating models with an unanticipated sign; further, they are significant only for a small number of MSAs. The non-market risk proxy, for example, is significant only in about 25 MSAs. Note, however, that the inclusion of those terms boosts the average explanatory power of the housing CAPM model with the average explanatory rising to almost 30 percent compared to 20 percent for the single factor CAPM model. Notably, the average estimated market beta remains robust to the inclusion of those controls at about 0.8.

Figure 2 provides a further indication of variation in estimated market betas across sampled MSAs. Plotted in Figure 2 are betas sorted by magnitude from lowest to highest MSA-specific estimates. To illustrate the variation in magnitude of betas across MSAs, we plot every 10<sup>th</sup> market beta in the sample. The betas are generated from regression model (1) in Table 3.<sup>23</sup> Also plotted are the 95 percent confidence bands. The housing market betas indicate substantial cross-sectional variation, ranging from -.185 in Provo, UT to a positive 2.61 in Modesto, California. In the case of Modesto, the estimated beta suggests a highly volatile market that moves by 2.61 percent for every percentage point move in the national house price series. Among U.S. metropolitan areas, the California Central Valley boom town of Modesto recorded the greatest house price response to movements in the National OFHEO series. As would be anticipated, elevated betas are estimated for major metropolitan areas on the west coast and Florida. Further, the top 10 betas are all associated with

---

<sup>23</sup> Similar variation for market betas occur for the augmented models and are available upon request.

California markets. In marked contrast, many metropolitan areas in the Midwest are characterized by low housing market betas.

The complete set of estimated market betas by MSA is contained in Appendix Table 1. The table also provides information on average housing market returns for each sample MSA. As evidenced in the Table, the statistical significance of the estimated beta and the overall explanatory power of the simple housing CAPM model tend to be highest in those MSAs with the larger market betas. The large estimated beta associated with Modesto, CA is highly significant; further, national housing market returns alone explain 82 percent of the variations in Modesto housing market returns. Similarly,  $R^2$  values were estimated at about 70 percent or greater for the California MSAs with the 10 highest estimated betas. In marked contrast, the estimated market betas for low beta areas are largely insignificant; typically, the explanatory power of the housing CAPM is quite low in those areas.

Several important conclusions emerge from the MSA-specific results. Firstly, on average, the single factor housing CAPM works well to capture the common variation in MSA housing returns. Results accordingly indicate the relevance of the housing investment framework in an explanation of sampled MSA housing returns. However, as would be expected, the investment asset pricing model is not similarly relevant in all places, as findings indicate a strong geographic dispersion in the magnitude of the estimated market betas and the model fit. For example, consistent with Case-Shiller behavioral survey results, investment considerations, as captured in the housing CAPM, are highly important to the determination of house price returns in many US coastal markets. On the other hand, the investment model has little explanatory power in many smaller, mid-western cities.

Table 4 provides results of an augmented housing asset pricing model that includes additional explanatory variables terms commonly cited in the housing literature (see, for example, Case and Shiller (1988, 1990), Goodman and Gabriel (1996), Case and Quigley (1991), Gabriel, Matthey and Wascher (1999), and Himmelberg, Mayer, and Sinai (2005)). As evident, those variables (defined above) include controls for quarterly changes in MSA employment, log of lagged nominal housing affordability (defined per convention in terms of nominal house price/income ratios), and change of housing foreclosures. Per above, models (1) – (3) add these terms sequentially, starting with the employment growth proxy, to the four-factor housing CAPM framework. As evident in model (1), the employment growth term is significant only in a few metropolitan areas. A similar outcome is evidenced in model (3) for the change in foreclosures term. As is broadly appreciated, nominal affordability is an important input to mortgage qualification and to housing demand. Results of the augmented models indicate that nominal affordability is significant in explanation of house price changes in approximately 50 of the 151 metro areas in our sample. Further, inclusion of the affordability term adds to the explanatory power of the model overall. That notwithstanding, results of the augmented models indicate substantial robustness to the basic CAPM relationship in the determination of housing returns. Indeed, the estimated CAPM market beta remains in the range of .8 - .9 and is significant in some 115 of the 155 MSAs. Overall, consistent with survey research findings, results of the augmented model provide strong support for the housing CAPM investment model, where expected returns to housing are related to market risk and where other fundamentals are of secondary importance.

We now turn to questions of temporal variability in the H-CAPM model results. Figures 3 – 6 plot the temporal variation in market betas and model  $R^2$  for San Francisco, Boston, Milwaukee, and Los Angeles. The respective plots also illustrate the cross sectional variation among the four areas in the boom and bust cycle of US housing. Recall per above that the four markets are the metropolitan areas of focus in the Case-Shiller behavioral research. The estimates displayed in these figures derive from a four-year moving estimation period. Further, the simple model (1) housing CAPM framework is used to compute the estimates. In all cases, both the estimated market betas and the model explanatory power change dramatically over time. The plots are further instructive in discerning the relationship between the magnitude of the estimated market factor and the model explanatory power. In that regard, as noted in memo items to the plots, the simple correlations between  $R^2$  and the estimated market betas range from about .65 in San Francisco and Boston to .81 in Los Angeles and .93 in Milwaukee. Indeed, both the estimated betas and the model explanatory power spike during periods of housing market boom. In San Francisco, the estimated market betas range upwards to 3, with model fit in the range of 80 percent, during the housing booms of the early 1990s and early 2000 periods. As housing booms turn to economic downturn and housing bust, both the investment model explanatory power and estimated market betas fall markedly. The extreme cyclical variability in these terms is evidenced in the Boston market as well, albeit to a lesser degree. Estimated market betas and  $R^2$  trended down markedly during the first half of the current decade—suggesting markedly diminished importance to a risk-return characterization of Boston house price fluctuations during that period. While those trends reversed in the context of the recent housing boom, estimated market betas in Boston failed to reach levels recorded for coastal California. Finally, Milwaukee presents a different case altogether. Consistent with early Case-Shiller behavioral findings (Case and Shiller, 1988), the risk-return housing investment model, as embodied in the CAPM, provides little insight as to Milwaukee house price trends for much of the 1990s. Indeed, in early years, both estimated market betas and model explanatory power approximated zero. For the decade of the 1990s, as described by Case and Shiller, one would be hard-pressed to argue the importance of investment demand as deterministic for housing market fluctuations in Milwaukee. Interestingly, as evidenced by findings from the most recent housing boom, both investment model explanatory power and magnitude of estimated market beta jumped sharply for Milwaukee. Consistent with 2009 Case-Shiller survey findings, results from Milwaukee typify the substantially more widespread ability of the housing risk-return model to explain housing market fluctuations in recent years.

## **2.4 Fama-MacBeth**

The Fama-MacBeth (1973) framework has been extensively applied to test the validity and related implications of the CAPM. In particular, it determines whether the linear market beta risk-return relation holds. Specifically, the Fama-MacBeth approach allows us to examine a number of distinct implications for the CAPM. Of particular importance is assessment of whether there exists a significant positive market beta-return relationship, implying that the market beta can explain the variation in MSA housing returns and that the variation is positively related to beta. Accordingly, the Fama-McBeth framework tests whether beta risk is the important

driver of MSA housing returns. Second, recall that only market risk is rewarded in the CAPM framework. The Fama-MacBeth approach allows us to test whether non-market risk, as proxied by the standard deviation of the CAPM squared residuals, is related to assets returns. For the CAPM to hold in its strictest sense we expect that non-market risk would be an insignificant determinant of MSA returns. Further the CAPM describes a linear risk return relationship. The Fama-MacBeth framework allows us to determine whether there are non linearities in the beta-return relationship.

Similar to much of the asset pricing testing in equity markets the Fama-MacBeth framework uses portfolios. As is broadly appreciated, the use of portfolios helps to avoid problems of errors in variables (see Miller and Merton, 1972). That notwithstanding, the use of portfolios involves choices regarding portfolio composition which can influence the outcome of the analysis (see Brennan, Chordia and Subrahmanyam, 1996). Moreover, the use of portfolios can hide valuable information about the individual assets that comprise the portfolio.

The Fama-MacBeth approach is not without its faults. Some of the challenges are due to estimation of parameters (e.g. see Shanken, 1992), whereas a more fundamental concern is associated with identification of the market portfolio and the use of related proxies. Roll (1977) and Roll and Ross (1984) note that testing the validity of the CAPM may become problematical as the market portfolio may not be observable and its proxy may not be mean-variance efficient. Notwithstanding these faults the Fama-MacBeth framework is the standard approach to testing the validity of the CAPM and related multi-factor models [Brennan, Chordia and Subrahmanyam, 1998].

To motivate the asset pricing tests Figure 7 presents the full set of MSA market betas and their associated mean returns using model (1) in Table 3. There is a clear positive market risk and return relationship with high beta MSAs attached to high return MSAs. For the indentified MSAs in the scatter plot such as Salinas we see a high beta and average returns whereas in contrast for Dallas-Plano-Irving we see a low beta and average returns. However there is not a very precise positive linear beta return relationship with some MSAs having a low beta and high returns. Moreover and alternatively the plot suggests that there may be a role for non-market risk that results in deviations from a positive beta return linear relationship. In the Fama-MacBeth approach the non-market risk is assumed to be unidentified idiosyncratic risk, but it may also involve systematic factors (eg. momentum) other than market risk.

Following the Fama-MacBeth approach we identify 3 steps. First, in each of 67 quarterly periods we identify the CAPM betas implied by model (1) in Table 3. These individual betas are sorted by rank into 10 portfolios in each period to minimise the errors in variable problem associated with using individual asset betas. Second, post-ranking portfolio betas are estimated in each quarter using a simple CAPM model on the constructed portfolios. Finally, we run cross sectional regressions of the full Fama-McBeth specification for each quarter. That final analysis yields estimated parameters for each quarter that are then used to test the implications of the CAPM model. The specification of the Fama-McBeth portfolio model is indicated in the memo below Table 5.

The Fama-MacBeth results for US housing data are presented in Table 5. Overall, estimates of the model provide strong evidence in support of a positive beta-return

relationship in US housing markets. We examine the robustness of these results using data for the full time frame, sub-periods prior to and after 2000 and additional sample sub-periods. In all samples, we obtain strong evidence in support of a positive risk and return relationship for US house prices with an average  $\gamma_1$  parameter significantly greater than zero. However, our evidence on other implications of the CAPM is not as conclusive. Unlike the premise of a linear risk and return relationship in the CAPM, we find strong evidence of a non linear relationship between returns and beta although there is ambiguity regarding the sign on the estimated  $\gamma_2$  parameter. Finally, the Fama-McBeth analysis also provides evidence in support of the non-market (idiosyncratic) risk factor. In that regard, the role of non market risk may thus be masked in our earlier tests, where we present a single set of results for the full period, as results seem to be switching from positive to negative coefficients over time. Overall though the primary premise of the CAPM is strongly supported in application to housing investment, risk, and return.

### **3. Conclusions**

In this research, we apply quality-adjusted house price data from 151 U.S. metropolitan areas over the 1985-2007 period to estimate a housing CAPM. The paper seeks to assess the importance of the risk-return framework in the determination of metropolitan housing returns, as suggested by Case-Shiller survey research. Overall, results indicate a sizable and statistically significant influence of the market factor on MSA house price returns. Further, the basic housing CAPM model is robust to the addition of other explanatory variables, including measures of idiosyncratic risk, momentum, geographic arbitrage among high- and low-priced metropolitan areas, and other housing market fundamentals. Our CAPM market betas vary substantially and are strongly related to the relative explanatory power of the models in the cross-section. Further, our results suggest considerable time-variation in housing CAPM model explanatory power, with markedly elevated importance of the pricing framework over the course of the recent house price cycle. To avoid potential errors-in-variables problems associated with the use of a single asset CAPM, we also examined the pricing relationship using portfolios of MSA returns within the Fama and Macbeth framework. We again find a strong positive risk and return relationship for the portfolios. However, we do find a non linear relationship for our H-CAPM and we are currently investigating this issue further. Overall, our findings are supportive of the application of a housing investment risk-return model in explanation of variation in metro-area cross-section and time-series of US house price returns. The findings strongly corroborate Case-Shiller behavioral findings indicating the importance of speculative forces in the determination of U.S. housing returns.

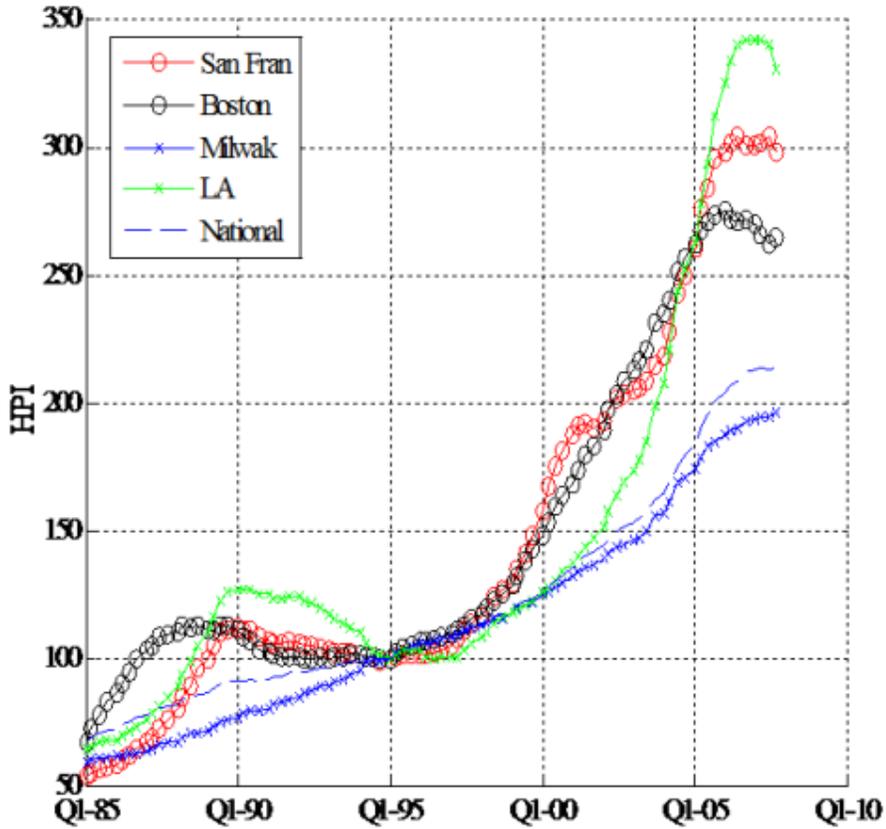
## References

- Ang, Andrew., Robert J. Hodrick, Ying. Xing and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance*, 61, 259-299.
- Bali, Turan, Nusret Cakici, Xuemin Yan and Zhe Zhang, 2005, “Does Idiosyncratic Risk Really Matter?” *Journal of Finance*, 60(2), 905—929.
- Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.
- Bekaert, Geert, Robert J. Hodrick, Xiaoyan Zhang, 2008, Is There a Trend in Idiosyncratic Volatility?, Working Paper Columbia University.
- Brennan, Michael J., Tarun Chordia, and Avanindhar Subrahmanyam, 1998, Alternative Factor Specifications, Security Characteristics, and the Cross-section of Expected Stock Returns, *Journal of Financial Economics*, 49, 345-373.
- Brunnermeier, Markus and Christian Julliard, 2008, Money Illusion and Housing Frenzies, *Review of Financial Studies*, 21: pp. 135 - 180.
- Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1-43.
- Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52, pp. 57–82.
- Cannon, S., Miller, Norman and Gurupdes S. Pandher, 2006, A Cross-Sectional Asset-Pricing Analysis of the U.S. Metropolitan Real-Estate Market at the Zip Code Level, *Real Estate Economics*, 34 (4), 519-552.
- Case, Bradford and John Quigley 1991. The Dynamics of Real Estate Prices, *Review of Economics and Statistics* 73(1): 50-58
- Case, Karl E., 2000, Real Estate and the Macroeconomy, *Brookings Papers on Economic Activity* 2, 119–162.
- Case, Karl & Robert J. Shiller, 1988. The behavior of home buyers in boom and post-boom markets, *New England Economic Review*, Federal Reserve Bank of Boston, Nov, pp 29-46.
- Case, Karl E. and Robert J. Shiller 1988. Prices of Single-Family Homes Since 1970: The Experience of Four Cities, *New England Economic Review*.
- Case, Karl E. and Robert J. Shiller 1990. Forecasting Prices and Excess Returns in the Housing Market, *Journal of the American Real Estate and Urban Economics Association* 18(3): 253 – 273.

- Case, Karl E. & Robert J. Shiller, 2003. Is There a Bubble in the Housing Market?, *Brookings Papers on Economic Activity, Economic Studies Program*, 34(2003-2), pp 299-362.
- Chui, Andy C.W., Sheridan Titman, and K.C. John Wei, 2003, Intra-Industry Momentum: The Case of REITs, *Journal of Financial Markets*, 6, pp 363–387.
- Derwall, Jeroen., Joop Huij, Dirk Brounen, and Wessel Marquering, 2009, REIT Momentum and the Performance of Real Estate Mutual Funds, *Financial Analysts Journal*, 65, 5, 24-34.
- Fama, Eugene F. and James MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81, 607-636.
- Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance*, 47, 427-465.
- Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stock and Bonds, *Journal of Financial Economics*, 33, 3-56.
- Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.
- Freddie Mac, 2008, A Comparison of House Price Measures, Mimeo, February 28.
- Gabriel, Stuart A, Joe Matthey and William Wascher 1999. House Price Differentials and Dynamics: Evidence from the Los Angeles and San Francisco Metropolitan Areas. *Economic Review*, Federal Reserve Bank of San Francisco, 3 – 22.
- Goodman, John and Stuart Gabriel, 1996, “Why Housing Forecasts Go Awry”, in J. Stein (ed.) “Classic Readings in Real Estate and Development, Urban Institute Press, Washington, D.C. 1996.
- Goyal, Amit, and Pedro Santa-Clara, 2003, “Idiosyncratic Risk Matters!” *Journal of Finance*, 58(3), 975-1007.
- Himmelberg, Charles, Chris Mayer and Todd Sinai 2005. Assessing High House Prices: Bubbles, Fundamentals, and Misperceptions, *Journal of Economic Perspectives* 19(4): 67-92.
- Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.” *Journal of Finance*, 48, pp. 65–91.
- Lehmann, Bruce N., 1990, Residual Risk Revisited, *Journal of Econometrics*, 45, 71-97.
- Merton, Robert C., 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica* 41, 867–887.

- Merton, Robert C. 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance*, 42, 483-510.
- Miller, Merton. H. and Myron Scholes, 1972, Rates and Return in Relation to Risk: A Reexamination of Some Recent Findings, in Michael C. Jensen, ed.: *Studies in the Theory of Capital Markets*, Praeger: New York, pp. 47-78.
- Plazzi, A., W. Torous and R. Valkanov, 2008, The Cross-Sectional Dispersion of Commercial Real Estate Returns and Rent Growth: Time Variation and Economic Fluctuations, *Real Estate Economics*, 36, pp. 403-439.
- Roll, Richard, 1977, A Critique of the Asset Pricing Theory's Tests: Part I, *Journal of Financial Economics*, 4, pp. 129-176.
- Roll Richard., and Stephen Ross, 1994, On the Cross-Sectional Relation between Expected Returns and Betas, *Journal of Finance*, 49, pp. 101-122.
- Shanken Jay., 1992, On the Estimation of Beta-Pricing Models, 1992, *Review of Financial Studies*, 5, pp. 1-33.
- Shiller, Robert, 2009, "A Bounce? Indeed. A Boom? Not Yet." *Economic View*, New York Times, October 11, 2009.

**Figure 1**  
**National and Individual MSA House Price Indices**



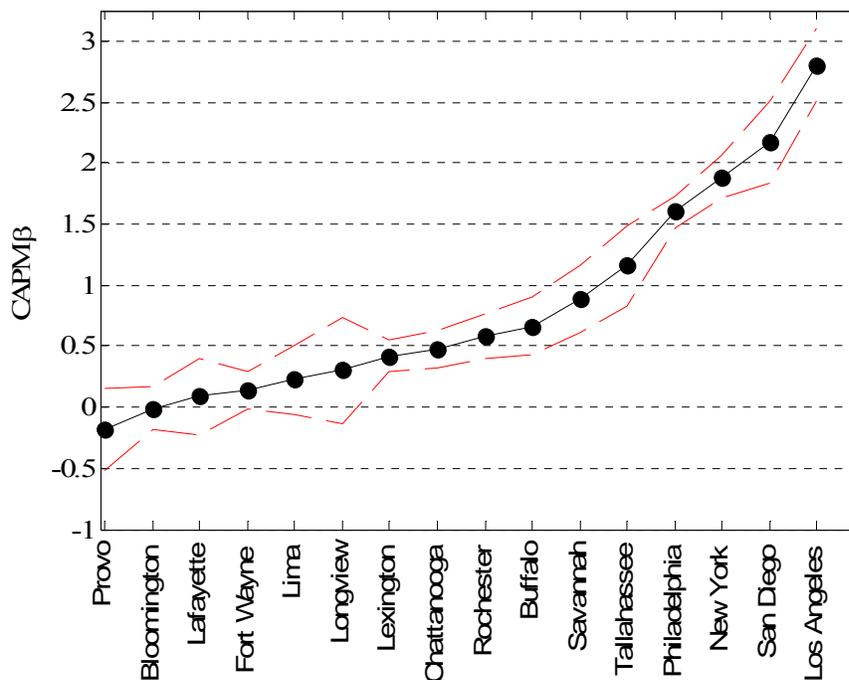
**R<sub>HPI</sub> Summary Statistics by Select MSA**

	Mean	Std Dev	Min	Max
<b>San Francisco</b>	1.883	2.217	-2.378	6.691
<b>Boston</b>	1.503	2.071	-3.274	7.114
<b>Milwaukee</b>	1.31	0.801	-0.333	4.707
<b>Los Angeles</b>	1.798	2.549	-4.333	9.953
<b>National</b>	1.257	0.781	-0.391	3.742

The plot details the time series of quarterly index levels for 4 individual MSAs and for the National OFHEO series between 1985 and 2007. The table contains quarterly summary statistics of percentage returns for 4 individual MSAs and for the National OFHEO series between 1985 and 2007.

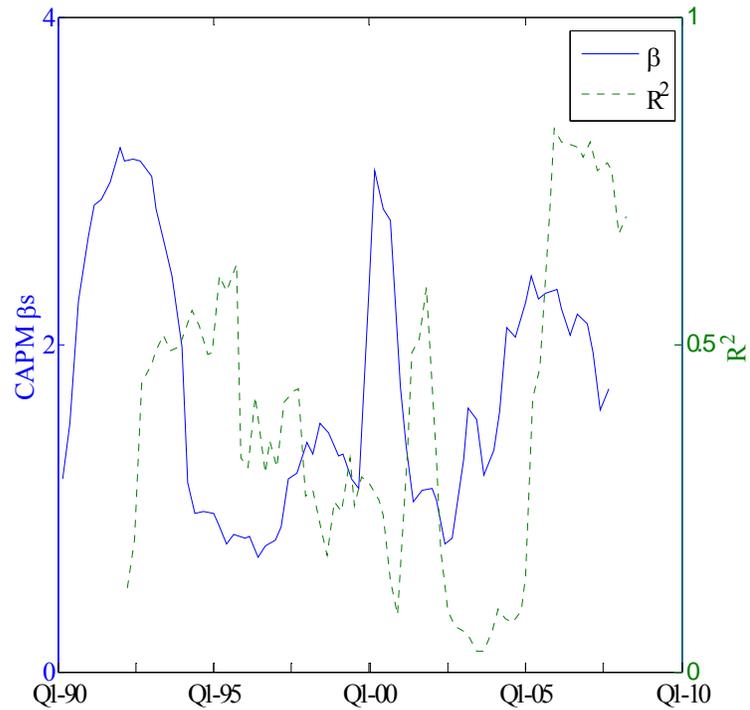
Figure 2

Plot of Select CAPM  $\beta$ s



The plot is based on a sort of betas by magnitude from lowest to highest and where every 10<sup>th</sup> beta is selected for presentation. The betas are obtained from model (1) in Table 3. The 95 percent confidence bands of the identified MSA betas are also given (dashed lines).

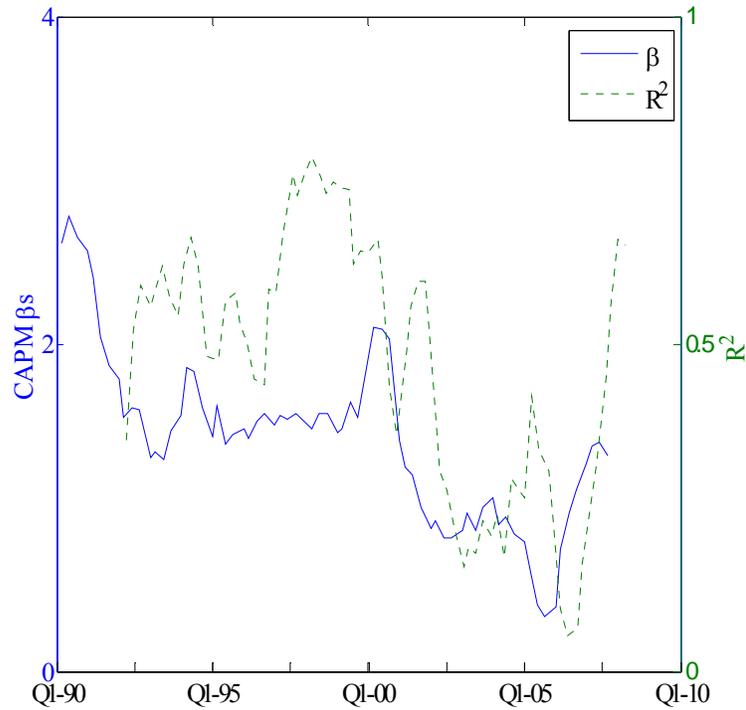
**Figure 3**  
**Temporal Variation in CAPM  $\beta$  and Model Explanatory Power**  
**San Francisco**



	<b>Mean</b>	<b>Std Dev</b>	<b>Min</b>	<b>Max</b>
<b><math>\beta</math></b>	1.75	0.763	0.695	3.197
<b><math>R^2</math></b>	0.389	0.235	0.031	0.83
<b><math>\text{Corr}(\beta, R^2)</math></b>	0.633			

The plot details the time series of quarterly market betas and model  $R^2$  for San Francisco using model (1) in Table 3. The timeframe is between 1985 and 2007 based on a moving four-year moving window and where the initial betas are obtained for 1990. The table contains quarterly summary statistics of the associated market betas and model  $R^2$  for San Francisco using model (1) in Table 3. The correlation between market betas and  $R^2$  is also given.

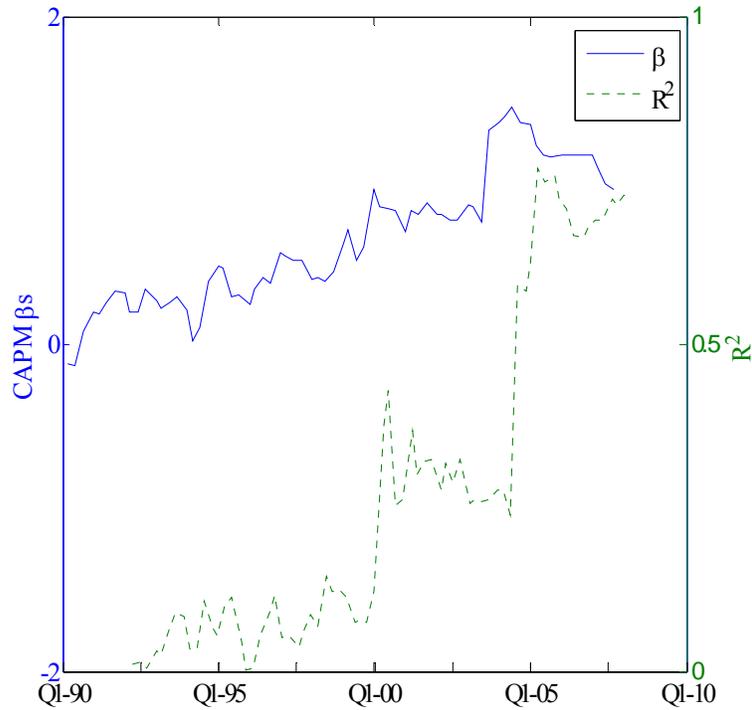
**Figure 4**  
**Temporal Variation in CAPM  $\beta$  and Model Explanatory Power**  
**Boston**



	Mean	Std Dev	Min	Max
$\beta$	1.416	0.518	0.328	2.773
$R^2$	0.471	0.198	0.055	0.785
$\text{Corr}(\beta, R^2)$	0.643			

The plot details the time series of quarterly market betas and model  $R^2$  for Boston using model (1) in Table 3. The timeframe is between 1985 and 2007 based on a moving four-year moving window and where the initial betas are obtained for 1990. The table contains quarterly summary statistics of the associated market betas and model  $R^2$  for San Francisco using model (1) in Table 3. The correlation between market betas and  $R^2$  is also given.

**Figure 5**  
**Temporal Variation in CAPM  $\beta$  and Model Explanatory Power**  
**Milwaukee**

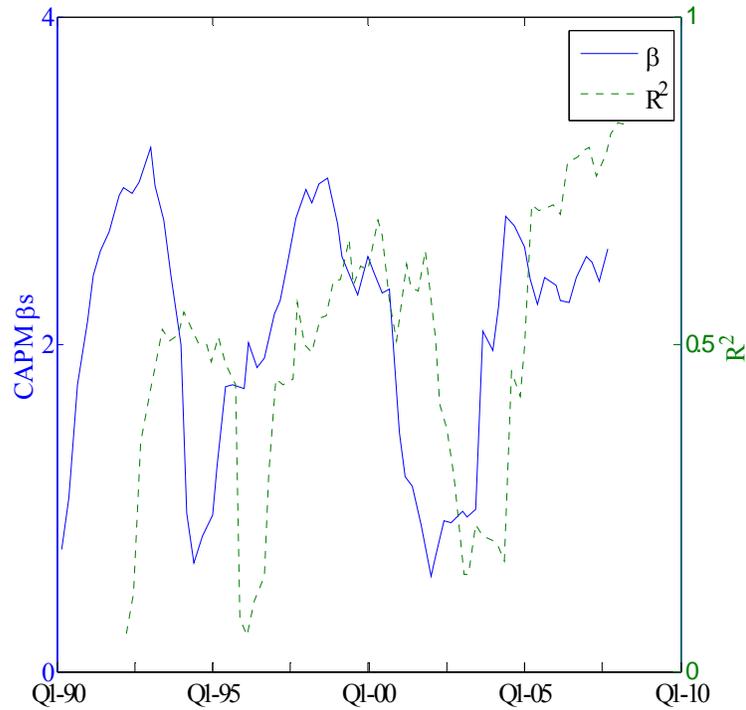


	<b>Mean</b>	<b>Std Dev</b>	<b>Min</b>	<b>Max</b>
<b><math>\beta</math></b>	0.633	0.405	-0.135	1.445
<b><math>R^2</math></b>	0.278	0.257	0.000	0.767

**$\text{Corr}(\beta, R^2) = 0.933$**

The plot details the time series of quarterly market betas and model  $R^2$  for Milwaukee using model (1) in Table 3. The timeframe is between 1985 and 2007 based on a moving four-year moving window and where the initial betas are obtained for 1990. The table contains quarterly summary statistics of the associated market betas and model  $R^2$  for San Francisco using model (1) in Table 3. The correlation between market betas and  $R^2$  is also given.

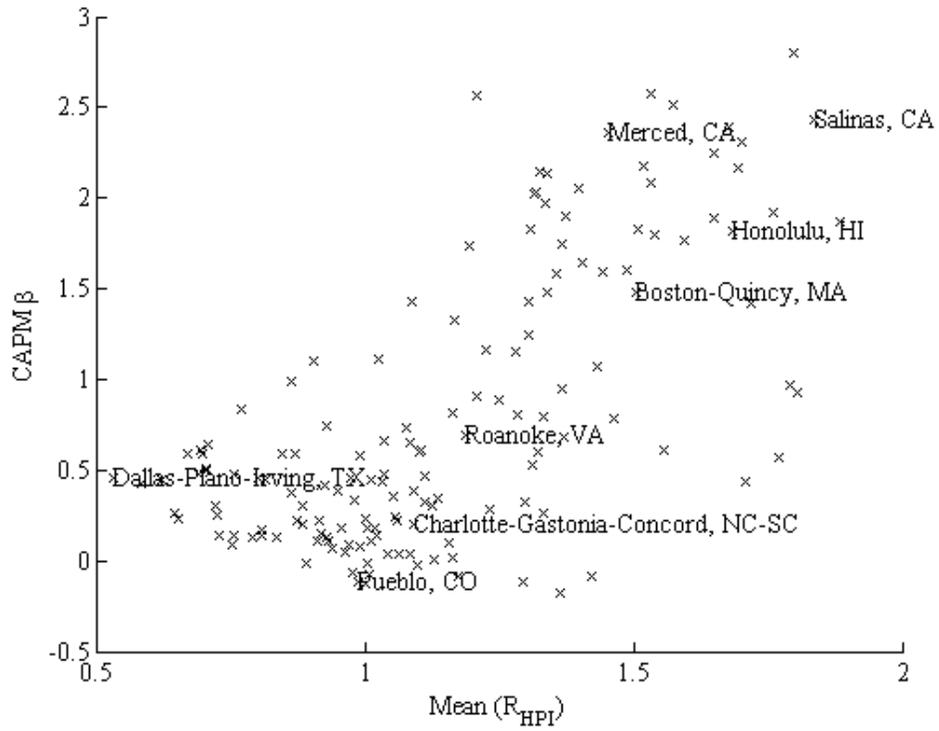
**Figure 6**  
**Temporal Variation in CAPM  $\beta$  and Model Explanatory Power**  
**Los Angeles**



	Mean	Std Dev	Min	Max
$\beta$	2.63	0.735	0.583	3.193
$R^2$	0.494	0.21	0.053	0.837
<b>Corr(<math>\beta, R^2</math>)</b>	0.808			

The plot details the time series of quarterly market betas and model  $R^2$  for Los Angeles using model (1) in Table 3. The timeframe is between 1985 and 2007 based on a moving four-year moving window and where the initial betas are obtained for 1990. The table contains quarterly summary statistics of the associated market betas and model  $R^2$  for San Francisco using model (1) in Table 3. The correlation between market betas and  $R^2$  is also given.

**Figure 7**  
**MSA Housing Market Risk and Return**



The scatter plot shows the full sample of MSA market betas and their respective mean returns. The timeframe is between 1985 and 2007 where the betas are obtained from model (1) in Table 3 and the mean returns are in Appendix Table 1.

**Table 1**  
**Summary Statistics Presented at Yearly Frequency**

	<b>Mean</b>	<b>SD</b>	<b>Min</b>	<b>Median</b>	<b>Max</b>
<b>R<sub>HPI</sub></b>	0.924	0.738	-0.295	0.854	2.530
<b>R<sub>OFHEO</sub></b>	1.150	0.754	-0.391	1.190	2.870
<b>R<sub>SP</sub></b>	-1.330	8.030	-19.400	1.850	9.350
<b>SMB</b>	0.175	0.406	-0.882	0.135	0.827
<b>Mom</b>	6.35	2.97	2.98	5.51	12.7
<b>s<sup>2</sup></b>	4.590	4.530	0.693	3.170	19.700
<b>ΔEmp</b>	-0.764	0.329	-1.270	-0.563	-0.120
<b>Log(Afford<sub>t-1</sub>)</b>	0.241	0.011	0.216	0.244	0.257
<b>ΔForc</b>	1.090	0.217	0.802	1.060	1.720

R <sub>HPI</sub>	1 Quarter Asset Return from each MSA: $100 * [\text{Log}(\text{HPI}_t) - \text{log}(\text{HPI}_{t-1})]$
R <sub>OFHEO</sub>	1 Quarter Market Return: $100 * [\text{Log}(\text{NatHPI}_t) - \text{log}(\text{NatHPI}_{t-1})]$
R <sub>SP</sub>	1 Quarter Market Return: $100 * [\text{Log}(\text{SP500}_t) - \text{log}(\text{SP500}_{t-1})]$
SMB	Small Minus Big in each quarter: (25th Return Quartile) - (75th Return Quartile)
Mom	Mean Price at 75th Quartile of HPI – Mean Price at 25th Quatile of Price
s <sup>2</sup>	Idiosyncratic Risk: The standard deviation of squared CAPM model residuals
ΔEmp	1 Quarter change in employment for each MSA: $100 * [\text{Log}(\text{Emp}_t) - \text{log}(\text{Emp}_{t-1})]$
ΔForc	1 Quarter Change in Foreclosures for each MSA
Afford <sub>t</sub>	Income/Price in each quarter in each MSA: $\text{Income}_t / \text{Price}_t$

Annual summary statistics are presented for H-CAPM model variables with the associated definitions for the timeframe between 1985 and 2007. Time series summary statistics are provided for the variables with no MSA specific data (R<sub>OFHEO</sub> and R<sub>SP</sub>) whereas cross sectional summary statistics are provided for the other variables with MSA specific data.

**Table 2**  
**Correlation Matrix of Time Varying Terms**

	<b>R<sub>HPI</sub></b>	<b>R<sub>OFHEO</sub></b>	<b>R<sub>SP</sub></b>	<b>SMB</b>	<b>Mom</b>	<b>s<sup>2</sup></b>	<b>ΔEmp</b>	<b>Afford<sub>t-1</sub></b>	<b>Log(Forc)</b>
<b>R<sub>HPI</sub></b>	1.000								
<b>R<sub>OFHEO</sub></b>	0.953	1.000							
<b>R<sub>SP</sub></b>	-0.029	-0.023	1.000						
<b>SMB</b>	0.402	0.300	-0.019	1.000					
<b>Mom</b>	0.287	0.234	0.103	0.660	1.000				
<b>s<sup>2</sup></b>	0.047	-0.106	0.024	0.652	0.424	1.000			
<b>ΔEmp</b>	0.092	0.028	0.047	0.184	-0.091	0.091	1.000		
<b>Log(Afford<sub>t-1</sub>)</b>	-0.499	-0.412	0.063	-0.509	-0.522	-0.179	0.038	1.000	
<b>ΔForc</b>	0.431	0.512	-0.210	0.038	0.108	-0.135	-0.040	-0.352	1.000

R <sub>HPI</sub>	1 Quarter Asset Return from each MSA: 100*[Log(HPI <sub>t</sub> )-log(HPI <sub>t-1</sub> )]
R <sub>OFHEO</sub>	1 Quarter Market Return: 100*[Log(NatHPI <sub>t</sub> )-log(NatHPI <sub>t-1</sub> )]
R <sub>SP</sub>	1 Quarter Market Return: 100*[Log(SP500 <sub>t</sub> )-log(SP500 <sub>t-1</sub> )]
SMB	Small Minus Big in each quarter: (25th Return Quartile) - (75th Return Quartile)
Mom	Mean Price at 75th Quartile of HPI – Mean Price at 25th Quatile of Price
s <sup>2</sup>	Idiosyncratic Risk: The standard deviation of squared CAPM model residuals
ΔEmp	1 Quarter change in employment for each MSA: 100*[Log(Emp <sub>t</sub> )-log(Emp <sub>t-1</sub> )]
ΔForc	1 Quarter Change in Foreclosures for each MSA
Afford <sub>t</sub>	Income/Price in each quarter in each MSA: Income <sub>t</sub> /Price <sub>t</sub>

A correlation matrix is presented for H-CAPM model variables with the associated definitions for the timeframe between 1985 and 2007.

**Table 3**  
**Housing CAPM**  
**Investment Models**

$R_{HPI} = \alpha_0 + \beta R_m + x'\delta + \varepsilon$						
	(1)	(2)	(3)	(4)	(5)	(6)
<b>R<sub>OFHEO</sub></b>	0.785 (103)		0.809 (104)	0.809 (105)	0.792 (103)	0.810 (109)
<b>R<sub>SP</sub></b>		-0.001 (2)				
<b>SMB</b>			-0.046 (19)			0.224 (18)
<b>Mom</b>				-0.003 (18)		-0.019 (9)
<b>s<sup>2</sup></b>					-0.012 (25)	0.011 (15)
<b>Distribution of CAPM <math>\beta</math></b>						
<b>mean</b>	0.785	-0.001	0.809	0.809	0.792	0.810
<b>min</b>	-0.185	-0.102	-0.058	-0.056	-0.135	-0.075
<b>median</b>	0.473	0.003	0.538	0.533	0.495	0.535
<b>max</b>	2.610	0.067	2.580	2.570	2.600	2.610
<b>Distribution of R<sup>2</sup></b>						
<b>mean</b>	0.191	0.007	0.240	0.243	0.236	0.277
<b>min</b>	0.000	0.000	0.000	0.001	0.005	0.012
<b>median</b>	0.098	0.003	0.161	0.075	0.156	0.208
<b>max</b>	0.752	0.055	0.799	0.163	0.783	0.810

**Model (1):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \varepsilon$

**Model (2):**  $R_{HPI} = \alpha_0 + \beta R_{SP} + \varepsilon$

**Model (3):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta SMB + \varepsilon$

**Model (4):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta Mom + \varepsilon$

**Model (5):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta s^2 + \varepsilon$

**Model (6):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta_1 SMB + \delta_2 s^2 + \delta_3 Mom + \varepsilon$

The mean coefficients values for variables of the models listed are presented for the 151 MSAs. The numbers of MSAs from the sample with significant coefficients at the 5% level follow in parentheses. Summary details of the distribution of model betas and the distribution of R<sup>2</sup> follow. All models include an unreported constant. The timeframe is between 1985 and 2007 using quarterly data. The variables are defined in Table 1.

**Table 4**  
**Housing CAPM**  
**Augmented Models**

$R_{HPI} = \alpha_0 + \beta R_{OFHEO} + x'\delta + z'\gamma + \varepsilon$			
	(1)	(2)	(3)
<b>R<sub>OFHEO</sub></b>	0.809 (104)	0.882 (112)	0.878 (112)
<b>SMB</b>	-0.015 (19)	0.087 (19)	0.088 (20)
<b>Mom</b>	0.013 (19)	-0.017 (20)	-0.012 (19)
<b>s<sup>2</sup></b>	0.032 (28)	0.041 (31)	0.038 (33)
<b>ΔEmp</b>	0.037 (10)	0.032 (7)	0.032 (7)
<b>Log(Afford<sub>t-1</sub>)</b>		2.340 (47)	2.390 (43)
<b>ΔForc</b>			0.002 (14)
<b><u>Distribution of CAPM β</u></b>			
<b>mean</b>	0.809	0.882	0.878
<b>min</b>	-0.814	-1.350	-1.440
<b>%50Q</b>	0.714	0.725	0.411
<b>max</b>	2.400	2.450	0.723
<b><u>Distribution of R<sup>2</sup></u></b>			
<b>mean</b>	0.404	0.450	0.466
<b>min</b>	0.012	0.072	0.089
<b>%50Q</b>	0.345	0.382	0.393
<b>max</b>	0.902	0.907	0.908

All models including a unreported constant

Number of MSAs (out of 151) with significant coefficients at 5% level in parantheses

s<sup>2</sup> represents standard deviation of squared errors from Investment model (1)

Subscript "t-1" indicates a lagged term

**Model (1):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta_1 SMD + \delta_2 Mom + \delta_3 s^2 + \delta_4 \Delta Emp + \varepsilon$

**Model (2):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta_1 SMD + \delta_2 Mom + \delta_3 s^2 + \delta_4 \Delta Emp + \delta_5 \log(Afford_{t-1}) + \varepsilon$

**Model (3):**  $R_{HPI} = \alpha_0 + \beta R_{OFHEO} + \delta_2 SMD + \delta_2 Mom + \delta_2 s^2 + \delta_3 \Delta Emp + \delta_4 \log(Afford_{t-1}) + \delta_5 Forc + \varepsilon$

The mean coefficients values for variables of the models listed are presented for the 151 MSAs. The numbers of MSAs from the sample with significant coefficients at the 5% level follow in parentheses. Summary details of the distribution of model betas and the distribution of R<sup>2</sup> follow. All models include an unreported constant. The timeframe is between 1985 and 2007 using quarterly data. The variables are defined in Table 1.

**Table 5**  
**Fama-Macbeth CAPM Validity Test Statistics**

<b>Period</b>	<b>Mean(<math>\gamma_1</math>)</b>	<b>Mean(<math>\gamma_2</math>)</b>	<b>Mean(<math>\gamma_3</math>)</b>
<b>Full Period</b>	8.1582 (136.0575)	17.4433 (13.2112)	2.7763 (23.7613)
<b>Post 2000</b>	7.9525 (94.6832)	24.9397 (13.4848)	3.6183 (22.1082)
<b>Pre 2000</b>	8.3463 (97.8313)	10.5895 (5.6369)	2.0064 (12.0696)
<b>Mar - 91</b> <b>Sep - 93</b>	8.0446 (135.1141)	18.8176 (14.3530)	1.4406 (12.4169)
<b>Jan - 94</b> <b>Jun - 96</b>	8.4853 (142.5156)	6.7263 (5.1304)	2.4426 (21.0532)
<b>Sep - 96</b> <b>Mar - 99</b>	8.5707 (143.9497)	5.7737 (4.4039)	1.9852 (17.1110)
<b>Jun - 99</b> <b>Jan - 02</b>	8.2378 (138.3584)	9.7057 (7.4030)	3.6616 (31.5609)
<b>Mar - 02</b> <b>Sep - 04</b>	8.0573 (135.3270)	22.8809 (17.4523)	3.6903 (31.8082)
<b>Jan - 05</b> <b>Jun - 07</b>	7.5837 (127.3726)	39.1123 (29.8326)	3.3566 (28.9317)

t-statistics in parantheses

The included gammas are the average of the estimated gammas in each period from the following model:  $R_{\text{portfolio},i,t} = \gamma_{\text{The}}\beta_{it} + \gamma_{2t}\beta_{it}^2 + \gamma_{3t}S_t^2 + u_t$ . The time-series averages of the estimated gammas are presented and average t-statistics follow in parentheses. The Fama-MacBeth results use 10 portfolios. In each of the 67 quarterly periods we identify the CAPM betas as given by model (1) in Table 3 and these are sorted into portfolios. We obtain post-ranking portfolio betas for each quarter using a model (1) in Table 3. We then run cross section regressions of the full Fama-MacBeth specification for each quarter.

**Table 6**  
**Housing CAPM**  
**Excess Return Investment Models**

$R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + x'\delta + z'\gamma + \varepsilon$						
	(1)	(2)	(3)	(4)	(5)	(6)
<b>R<sub>OFHEO</sub></b>	0.94 (151)		0.960 (151)	0.940 (151)	0.953 (151)	0.992 (151)
<b>R<sub>SP</sub></b>		-0.288 (1)				
<b>SMB</b>			-0.190 (30)			-0.269 (25)
<b>Mom</b>				0.022 (33)		-0.026 (12)
<b>s<sup>2</sup></b>					0.037 (34)	0.064 (32)
<b>Distribution of CAPM <math>\beta</math></b>						
<b>mean</b>	0.94	-0.288	0.96	0.94	0.953	0.992
<b>min</b>	0.601	-0.631	0.48	0.602	0.547	0.571
<b>median</b>	0.868	-0.299	0.943	0.869	0.878	0.978
<b>max</b>	1.55	0.417	1.35	1.55	1.63	1.38
<b>Distribution of R<sup>2</sup></b>						
<b>mean</b>	0.777	0.106	0.802	0.798	0.797	0.825
<b>min</b>	0.27	0.000	0.324	0.314	0.303	0.355
<b>median</b>	0.804	0.102	0.829	0.823	0.821	0.845
<b>max</b>	0.967	0.287	0.971	0.972	0.97	0.976

Model (1):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + \varepsilon$

Model (2):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{SP} - R_0) + \varepsilon$

Model (3):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + \delta \text{SMB} + \varepsilon$

Model (4):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + \delta \text{Mom} + \varepsilon$

Model (5):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + \delta s^2 + \varepsilon$

Model (6):  $R_{HPI} - R_0 = \alpha_0 + \beta(R_{OFHEO} - R_0) + \delta_1 \text{SMB} + \delta_2 s^2 + \delta_3 \text{Mom} + \varepsilon$

The mean coefficients values for variables of the models listed are presented for the 151 MSAs. The numbers of MSAs from the sample with significant coefficients at the 5% level follow in parentheses. Summary details of the distribution of model betas and the distribution of R<sup>2</sup> follow. All models include an unreported constant. The timeframe is between 1985 and 2007 using quarterly data. R<sub>0</sub> represents the 3-month US Treasury Bill rate and other other variables are defined in Table 1.

**Table 7**  
**Housing CAPM**  
**Excess Return Augmented Models**

$R_{HPI} - R_o = \alpha_0 + \beta(R_{OFHEO} - R_o) + x'\delta + z'\gamma + \varepsilon$			
	(1)	(2)	(3)
<b>R<sub>OFHEO</sub></b>	0.9920 (151)	1.0200 (151)	1.0200 (151)
<b>SMB</b>	-0.2440 (27)	0.0830 (26)	0.0669 (28)
<b>Momentum</b>	-0.0320 (9)	-0.0390 (14)	-0.0878 (26)
<b>s<sup>2</sup></b>	0.0680 (31)	0.0670 (30)	-0.0368 (13)
<b>ΔEmp</b>	0.0440 (9)	0.0370 (7)	0.0369 (7)
<b>Log(Afford<sub>t-1</sub>)</b>		2.2700 (47)	2.3900 (48)
<b>ΔForc</b>			0.0018 (10)
<b>Distribution of CAPM β</b>			
<b>mean</b>	0.992	1.020	1.020
<b>min</b>	0.535	0.522	0.634
<b>%50Q</b>	0.973	0.994	1.000
<b>max</b>	1.380	1.500	1.490
<b>Distribution of R<sup>2</sup></b>			
<b>mean</b>	0.829	0.842	0.846
<b>min</b>	0.386	0.387	0.407
<b>%50Q</b>	0.849	0.856	0.859
<b>max</b>	0.977	0.977	0.977
<b>Model (1): <math>R_{HPI} - R_o = \alpha_0 + \beta(R_{OFHEO} - R_o) + \delta_2 SMD + \delta_2 Momemtum + \delta_2 s^2 + \varepsilon</math></b>			
<b>Model (2): <math>R_{HPI} - R_o = \alpha_0 + \beta(R_{OFHEO} - R_o) + \delta_2 SMD + \delta_2 Momemtum + \delta_2 s^2 + \delta_3 \Delta Emp + \delta_4 Log(Afford_{t-1}) + \varepsilon</math></b>			
<b>Model (3): <math>R_{HPI} - R_o = \alpha_0 + \beta(R_{OFHEO} - R_o) + \delta_2 SMD + \delta_2 Momemtum + \delta_2 s^2 + \delta_3 \Delta Emp + \delta_4 Log(Afford_{t-1}) + \delta_5 \Delta Forc + \varepsilon</math></b>			

The mean coefficients values for variables of the models listed are presented for the 151 MSAs. The numbers of MSAs from the sample with significant coefficients at the 5% level follow in parentheses. Summary details of the distribution of model betas and the distribution of R<sup>2</sup> follow. All models include an unreported constant. The timeframe is between 1985 and 2007 using quarterly data. R<sub>o</sub> represents the 3-month US Treasury Bill rate and other other variables are defined in Table 1.

**Appendix Table 1**  
**Housing CAPM Investment Model for Individual MSAs**

MSA	$R_{OFHEO}$			
	$R^2$	$\beta$	SE ( $\beta$ )	mean( $R_{HPI}$ )
Akron, OH	0.435	0.423	0.135	1.0572
Albany-Schenectady-Troy, NY	0.710	1.678	0.253	1.339
Albuquerque, NM	0.328	0.408	0.245	1.1294
Allentown-Bethlehem-Easton, PA-NJ	0.838	1.583	0.158	1.1506
Amarillo, TX	0.421	1.118	0.264	1.416
Anchorage, AK	0.672	1.251	0.346	1.3434
Atlanta-Sandy Springs-Marietta, GA	0.805	1.029	0.083	1.1117
Atlantic City-Hammonton, NJ	0.726	1.856	0.277	1.0665
Augusta-Richmond County, GA-SC	0.530	1.668	0.256	1.0458
Austin-Round Rock, TX	0.457	0.790	0.224	0.8995
Bakersfield, CA	0.824	1.862	0.277	1.299
Barnstable Town, MA	0.736	2.168	0.278	0.8431
Baton Rouge, LA	0.296	0.458	0.178	0.9941
Beaumont-Port Arthur, TX	0.144	0.150	0.324	1.0793
Bellingham, WA	0.458	0.673	0.365	1.1096
Binghamton, NY	0.239	1.313	0.526	0.762
Birmingham-Hoover, AL	0.359	0.475	0.168	1.0487
Bloomington-Normal, IL	0.221	0.197	0.159	0.9036
Boise City-Nampa, ID	0.508	0.943	0.295	0.8777
Boston-Quincy, MA	0.831	1.906	0.180	1.114
Buffalo-Niagara Falls, NY	0.560	1.331	0.229	0.8782
Canton-Massillon, OH	0.476	0.718	0.185	0.6668
Casper, WY	0.199	0.816	0.420	0.92
Cedar Rapids, IA	0.132	0.144	0.181	1.1479
Charleston-North Charleston-Summerville, SC	0.485	1.461	0.274	0.7596
Charlotte-Gastonia-Concord, NC-SC	0.410	0.374	0.114	0.8176
Chattanooga, TN-GA	0.409	0.481	0.143	0.8927
Cheyenne, WY	0.212	0.506	0.297	0.9769
Chicago-Naperville-Joliet, IL	0.838	0.750	0.076	0.9821
Chico, CA	0.676	1.572	0.304	0.7407
Cincinnati-Middletown, OH-KY-IN	0.393	0.330	0.073	0.7391
Cleveland-Elyria-Mentor, OH	0.418	0.593	0.116	0.9966
Colorado Springs, CO	0.256	0.275	0.191	1.0912
Columbia, SC	0.383	0.499	0.150	0.8038

**Appendix Table 1 (continued)**

<b>MSA</b>	<b>R<sub>OFHEO</sub></b>			
	<b>R<sup>2</sup></b>	<b>β</b>	<b>SE (β)</b>	<b>mean(R<sub>HPI</sub>)</b>
Columbus, OH	0.228	0.290	0.092	0.8021
Corpus Christi, TX	0.220	0.907	0.379	0.7072
Dallas-Plano-Irving, TX	0.766	1.005	0.098	1.3007
Davenport-Moline-Rock Island, IA-IL	0.367	0.361	0.147	0.7276
Dayton, OH	0.089	0.268	0.148	0.7095
Deltona-Daytona Beach-Ormond Beach, FL	0.808	1.781	0.229	0.7694
Denver-Aurora, CO	0.338	0.707	0.216	1.2064
Des Moines-West Des Moines, IA	0.196	0.252	0.156	0.9168
Detroit-Livonia-Dearborn, MI	0.323	0.389	0.175	1.147
Eau Claire, WI	0.373	0.589	0.288	0.9843
El Paso, TX	0.323	1.439	0.379	1.0644
Elkhart-Goshen, IN	0.215	0.472	0.221	1.0589
Eugene-Springfield, OR	0.557	0.201	0.248	0.9337
Evansville, IN-KY	0.137	0.291	0.239	1.0188
Fayetteville-Springdale-Rogers, AR-MO	0.338	0.587	0.237	0.8549
Fort Collins-Loveland, CO	0.349	0.123	0.259	1.1658
Fort Wayne, IN	0.255	0.421	0.142	0.6735
Fresno, CA	0.740	1.457	0.296	1.0541
Grand Junction, CO	0.309	1.012	0.305	0.9354
Grand Rapids-Wyoming, MI	0.203	0.358	0.142	0.8329
Greensboro-High Point, NC	0.208	0.393	0.133	1.2584
Greenville-Moultrie-Easley, SC	0.257	0.450	0.166	0.8208
Harrisburg-Carlisle, PA	0.513	1.236	0.209	0.9429
Hartford-West Hartford-East Hartford, CT	0.866	1.884	0.159	1.0086
Honolulu, HI	0.662	1.250	0.383	1.0602
Houston-Sugar Land-Baytown, TX	0.582	0.967	0.144	1.1855
Huntsville, AL	0.418	1.067	0.215	1.0944
Indianapolis-Carmel, IN	0.237	0.417	0.117	0.6723
Jackson, MS	0.368	0.651	0.252	1.3117
Jacksonville, FL	0.746	1.122	0.183	0.8367
Janesville, WI	0.342	0.318	0.250	0.7472
Kalamazoo-Portage, MI	0.161	0.438	0.221	0.9528
Kansas City, MO-KS	0.682	0.685	0.085	0.8275
Knoxville, TN	0.388	0.779	0.166	0.9297
La Crosse, WI-MN	0.272	0.495	0.221	1.0272
Lafayette, LA	0.378	0.115	0.262	0.8962
Lancaster, PA	0.786	0.914	0.124	0.9361

Appendix Table 1 (continued)

MSA	R <sub>OFHEO</sub>			
	R <sup>2</sup>	β	SE (β)	mean(R <sub>HPI</sub> )
Lansing-East Lansing, MI	0.279	0.598	0.165	0.8255
Las Cruces, NM	0.379	1.076	0.381	0.7691
Las Vegas-Paradise, NV	0.657	1.154	0.361	1.1377
Lexington-Fayette, KY	0.416	0.434	0.122	0.9061
Lima, OH	0.185	0.399	0.265	0.9898
Lincoln, NE	0.281	0.113	0.172	0.9559
Little Rock-North Little Rock-Conway, AR	0.299	0.855	0.213	1.2105
Longview, TX	0.125	0.564	0.419	0.9554
Los Angeles-Long Beach-Glendale, CA	0.846	2.423	0.271	0.7647
Louisville-Jefferson County, KY-IN	0.171	0.288	0.126	0.7858
Lubbock, TX	0.171	0.623	0.342	0.9269
Macon, GA	0.282	0.896	0.341	0.9929
Madison, WI	0.411	0.165	0.230	0.9358
Mansfield, OH	0.134	0.573	0.459	0.8078
Medford, OR	0.642	1.080	0.271	1.0171
Memphis, TN-MS-AR	0.294	0.532	0.200	1.0581
Merced, CA	0.751	1.349	0.340	0.9529
Miami-Miami Beach-Kendall, FL	0.834	1.117	0.202	1.024
Milwaukee-Waukesha-West Allis, WI	0.581	0.473	0.136	1.0952
Minneapolis-St. Paul-Bloomington, MN-WI	0.665	1.142	0.141	1.2384
Mobile, AL	0.232	0.462	0.248	1.3253
Modesto, CA	0.828	2.204	0.258	1.1743
Monroe, LA	0.258	0.459	0.267	1.0984
Nashville-Davidson--Murfreesboro--Franklin, TN	0.354	0.361	0.154	1.2139
New Orleans-Metairie-Kenner, LA	0.367	0.433	0.203	1.292
New York-White Plains-Wayne, NY-NJ	0.864	1.831	0.160	1.1556
Odessa, TX	0.320	-1.443	0.737	1.0838
Oklahoma City, OK	0.335	0.667	0.160	1.6593
Omaha-Council Bluffs, NE-IA	0.308	0.227	0.139	1.127
Orlando-Kissimmee, FL	0.883	1.780	0.167	1.0958
Pensacola-Ferry Pass-Brent, FL	0.522	0.881	0.313	0.9333
Peoria, IL	0.131	0.328	0.188	1.0466
Philadelphia, PA	0.883	1.497	0.128	1.0173
Phoenix-Mesa-Scottsdale, AZ	0.762	1.111	0.267	1.047
Pittsburgh, PA	0.358	0.965	0.201	0.805
Portland-South Portland-Biddeford, ME	0.746	1.344	0.223	1.0064
Portland-Vancouver-Beaverton, OR-WA	0.590	0.254	0.216	1.2385

Appendix Table 1 (continued)

MSA	R <sub>OFHEO</sub>			
	R <sup>2</sup>	β	SE (β)	mean(R <sub>HPI</sub> )
Provo-Orem, UT	0.117	0.262	0.340	1.1399
Pueblo, CO	0.170	0.335	0.366	0.8566
Raleigh-Cary, NC	0.108	0.074	0.144	1.2643
Reading, PA	0.734	1.736	0.203	1.2323
Redding, CA	0.697	1.626	0.318	1.2162
Reno-Sparks, NV	0.779	0.858	0.235	1.4882
Richmond, VA	0.854	1.105	0.117	1.3934
Roanoke, VA	0.343	0.723	0.215	1.5619
Rochester, MN	0.449	0.999	0.180	1.2028
Rochester, NY	0.503	0.997	0.189	1.0864
Rockford, IL	0.363	0.070	0.138	1.0411
Sacramento-Arden-Arcade-Roseville, CA	0.767	1.976	0.306	1.0926
Saginaw-Saginaw Township North, MI	0.236	0.664	0.233	1.2592
Salinas, CA	0.757	2.038	0.323	1.2281
Salt Lake City, UT	0.124	-0.147	0.319	1.1049
San Antonio, TX	0.368	1.292	0.253	1.1072
San Diego-Carlsbad-San Marcos, CA	0.699	1.904	0.332	0.9676
San Francisco-San Mateo-Redwood City, CA	0.735	1.944	0.290	1.0826
San Luis Obispo-Paso Robles, CA	0.763	2.231	0.280	1.323
Santa Barbara-Santa Maria-Goleta, CA	0.689	2.439	0.354	1.5065
Savannah, GA	0.430	0.754	0.281	1.0317
Scranton-Wilkes-Barre, PA	0.352	2.021	0.459	1.1283
Seattle-Bellevue-Everett, WA	0.729	1.100	0.183	1.2558
Shreveport-Bossier City, LA	0.378	0.089	0.209	0.8385
South Bend-Mishawaka, IN-MI	0.244	-0.009	0.196	1.0376
Spokane, WA	0.233	0.398	0.320	1.1786
Springfield, IL	0.163	0.001	0.183	1.1349
Springfield, MA	0.858	1.675	0.159	1.2382
Springfield, MO	0.172	0.269	0.213	1.1083
St. Louis, MO-IL	0.830	0.653	0.070	0.7992
Stockton, CA	0.818	1.947	0.282	0.9443
Syracuse, NY	0.518	1.258	0.251	0.8166
Tallahassee, FL	0.494	1.165	0.291	0.8829
Tampa-St. Petersburg-Clearwater, FL	0.886	1.567	0.148	1.4276
Toledo, OH	0.339	0.605	0.153	1.2064
Topeka, KS	0.297	0.708	0.258	1.2281
Tucson, AZ	0.722	0.906	0.224	1.0605

**Appendix Table 1 (continued)**

MSA	R <sub>OFHEO</sub>			
	R <sup>2</sup>	β	SE (β)	mean(R <sub>HPI</sub> )
Tulsa, OK	0.309	0.601	0.189	1.2278
Tyler, TX	0.174	0.448	0.351	1.7807
Visalia-Porterville, CA	0.729	1.638	0.325	1.0256
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.908	1.967	0.159	0.941
Waterloo-Cedar Falls, IA	0.321	1.261	0.322	0.7847
York-Hanover, PA	0.655	1.370	0.220	0.8517

Market CAPM β estimates from model (1) in Table 3 with the associated standard errors of betas and the R<sup>2</sup> are presented for each MSA. The mean return for each MSA is also presented. The timeframe is between 1985 and 2007 using quarterly data.