# Housing and Behavioral Finance

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September 23, 2007

Key words: housing prices, housing rents, user costs, fundamentals, bubbles

Prepared for the Federal Reserve Bank of Boston's "Implications of Behavioral Economics on Economic Policy" conference, September 27-28, 2007. Mayer: Paul Milstein Professor of Real Estate and Director of the Paul Milstein Center for Real Estate, Columbia Business School, Columbia University (email: cm310@columbia.edu). Sinai: Associate Professor, Wharton School of the University of Pennsylvania (email: sinai@wharton.upenn.edu). The authors would like to especially thank Alex Chinco and Rembrandt Koning for extraordinary research support and Richard Peach for helpful comments. The Paul Milstein Center for Real Estate at Columbia and the Zell/Lurie Real Estate Center at Wharton provided funding. The views expressed in the paper are solely those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

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**Abstract**

We examine the relative roles of fundamentals and psychology in explaining U.S. house price dynamics. Using metropolitan area data, we estimate how the house price-rent ratio responds to fundamentals such as real interest rates and taxes (via a user cost model) and availability of capital, and behavioral conjectures such as backwards-looking expectations of house price growth and inflation illusion. We find that user cost and lagged five-year house price appreciation rate are the most important determinants of changes in the price-rent ratio and lending market efficiency also is capitalized into house prices, with higher prices associated with lower origination costs and a greater use of subprime mortgages. We find no evidence in favor of behavioral explanations based on the one-year lagged house price growth rate or the inflation rate. The causes of a house price boom appear to vary over time, with interest rate fundamentals mattering more than backwards-looking price expectations in the house price run-up of the 2000s and vice versa during the 1980s boom.

There has been considerable debate in recent years on the role of behavioral factors in determining housing prices. The question of whether psychology matters in the housing market has been settled long ago: the answer is yes. Rather, economists have debated in what ways psychology impacts behavior and how large is its effect on prices.

One oft-cited example of a clear behavioral bubble in housing is the sharp boom-bust in the Vancouver housing market in the early 1980s. (See Figure 1.) In the 18 months between January 1980 and July 1981, real house prices grew 87 percent. In the subsequent 18 months, real prices fell by nearly 44 percent, plateauing at a level only 6 percent above where prices started at three years earlier. While news about Great Britain's returning Hong Kong to China may have swayed the market, fundamental factors would have great difficulty explaining the sudden boom-bust pattern.

In this paper we examine the relative roles of fundamentals and psychology in explaining U.S. house price dynamics. We begin by considering what proportion of the variation in the house price-rent ratio within metropolitan areas can be explained by fundamentals using a single-period version of the user cost model, as in Himmelberg, Mayer, and Sinai [2005]. We then consider how much additional variation can be explained by a handful of behavioral theories and conjectures, such as backwards-looking expectations of house price growth and inflation illusion. By examining the house price booms of the 1980s and 2000s separately, we can see if the relative weights on fundamental and behavioral explanations varies over time.

Our results suggest that both rational and seemingly behavioral factors explain movements in the price-rent ratio across U.S. metro areas over the last 25 years. We find that user cost, which reflects rational asset pricing fundamentals, is one of the most important factors, especially during the 1995-2006 boom. Lending market efficiency also appears to be capitalized into house prices, with higher prices associated with lower origination costs and a greater use of subprime mortgages.

The other important determinant of price-rent ratios is the lagged five-year house price appreciation rate. This result suggests that backwards-looking expectations likely plays a behavioral role in explaining house price booms, although it is difficult to disentangle backwards-looking expectations with a "rational" model in which households update their beliefs about future house price growth with more recent data. In addition, the results show little evidence in favor of behavioral explanations based on the one-year lagged house price growth rate or the inflation rate.

We begin with a review of the literature on equilibrium models of house price determination and then examine how behavioral economics and lending market inefficiencies may also play a role. Section 2 lays out our simple reduced-form empirical framework. We then describe the data in Section 3, which is followed by a section describing our empirical findings. We conclude with a brief discussion of the factors that might influence the direction of future house prices and avenues for future research.

## *1) Background and Related Literature*

The earliest academic papers on the role of psychology or other non-fundamental factors on real estate prices focused on unexplained serial correlation in real estate prices (see Case and Shiller 1989). Of course, serial correlation itself is not necessarily evidence of irrational markets if underlying rent growth is also serially correlated. Yet data on rents is very hard to obtain, confounding tests of market efficiency. Meese and Wallace [1994] obtained detailed rental data from advertisements and estimated an asset pricing model on houses in the San Francisco area.

The authors concluded that the run-up in prices in the late 1980s was not fully justified by fundamentals.  Both papers concluded that pricing inefficiencies are due to high transaction costs that limit arbitrage opportunities for rational investors.

Theoretical papers have argued that liquidity constraints might also explain the seemingly excess sensitivity of house prices to income shocks (Stein [1995] and Ortalo-Magne and Rady [1999, 2001]).  Lamont and Stein [1999], Engelhardt [1994, 1996], and Genesove and Mayer [1997] present empirical evidence in favor of the liquidity constraints hypothesis.  Yet liquidity constraints are unlikely to explain why volatility differs across markets.

Even after controlling for possible liquidity constraints, evidence suggests that psychological factors still matter, especially in explaining why so few houses transact when house prices fall.  For example, Genesove and Mayer [2001] and Engelhardt [2003] show that loss aversion is a more dominant factor than liquidity constraints in explaining cyclical behavior of trading volumes (and to a lesser extent volatility in prices).

We attempt a systematic analysis of house price dynamics across many different markets. There is great dispersion in house price appreciation rates and volatility over the last three decades.  Some Southern and Midwestern markets like Atlanta, Charlotte, Cleveland, and Houston have shown little long-term appreciation and relatively low volatility in prices (Figure 2A).  By contrast, many primarily coastal markets like Boston, Los Angeles, and San Francisco have shown higher long-term rates of appreciation and also greater peak-to-trough volatility (Figure 2B).  Finally, some markets like Miami, Phoenix, and Las Vegas exhibit recent price spikes despite having little real growth in house prices over previous decades.

One difficulty in this exercise is the lack of a widely-accepted dynamic model of house prices that accounts for changes in economic conditions, risk, and supply constraints at the local level and macro time-series variation in interest rates and inflation. This is a crucial problem, because it is likely that a combination of local and aggregate fundamentals are necessary to explain the wide variation in local house price movements across metropolitan areas. Without a such a model of rational behavior, it is hard to determine the relative contributions of so-called rational factors and psychology in generating the movements in house prices that are in the data.

Recent papers have made some progress in this area. Brunnermeier and Julliard [2007] develop a dynamic rational expectations model of house prices and examine whether inflation is correlated with the residuals. Glaeser and Gyourko [2007] calibrate a dynamic model of housing in a spatial equilibrium. The model does a very good job explaining the impact of local shocks on house prices, but is not able to incorporate shocks to interest rates (or incomes), which the authors concede may explain some of the serial correlation in their data.

Other papers focus on dispersion in long-run price appreciation. Van Nieuwerburg and Weil [2007] calibrate a model that uses productivity differences to explain long-run price dispersion across cities. More relevant for our exercise, Gyourko, Mayer, and Sinai [2006] present evidence suggesting that increasing numbers of households and the growth of income in the right tail of the income distribution, combined with supply constraints in highly some highly desirable cities has led to a 50-year trend of faster house price growth in certain "Superstar Cities." According to the Gyourko et. al. model, households might rationally expect future prices to rise faster in Superstar Cities like San Francisco, Boston, and New York than in other cities around the country.

Himmelberg, et. al. use the standard user cost model (Hendershott and Slemrod [1983], Poterba [1984]) to examine whether house prices relative to rents in 46 metro areas were high in 2004. The authors constructed user cost using long-term interest mortgage rates and historical real appreciation rates, arguing that most households view the purchase of a house not based on a one-year comparison of buying versus owning, but based on a longer-run holding period.

Despite its intuitive appeal, the user cost model contains some simplifying assumptions that abstract from important real world issues. In particular, the user cost model does not characterize how households form their expectations of future price or rent appreciation.

Some authors have argued psychology rather than fundamentals play a key role in explaining how households set their expectations of future price appreciation. Case and Shiller [1988] surveyed recent home buyers in four cities on their expectations of future house price growth. Recent buyers in Los Angeles, a market with strong house price appreciation in the 1980s, reported that they expected much higher long-term returns than households in a control market, Milwaukee, where house prices were flat in the 1980s. In a subsequent survey (Case and Shiller [2004]), recent buyers in Milwaukee raised their reported expected returns in-line with the national housing boom. By 2006, recent home buyers in both Milwaukee and Los Angeles had lowered their reported expected appreciation (Shiller [2007]). Shiller cites the survey evidence and other case studies to support his conclusion that "A psychological theory, that represents the boom as taking place because of a feedback mechanism or social epidemic that encourages a view of housing as an important investment opportunity, fits the evidence better." (than "…fundamentals such as rents or construction costs.")

A second psychological theory proposed by Brunnermeier and Julliard [2007] argues that households cannot fully disentangle real and nominal changes. As a result, when expected inflation falls, home owners take advantage of low nominal interest rates without recognizing that future appreciation rates of prices and rents will fall commensurately. They argue that falling inflation leads to otherwise unjustified price spikes and housing frenzies and can help explain the run-up in US and global prices in the 2000s.

Probably the most direct evidence on the importance of psychology in real estate markets focuses specifically on loss aversion in downturns (Genesove and Mayer [2001], Engelhardt [2003]). Yet loss aversion may have a hard time explaining the current housing boom or even excess volatility in downturns. Since loss averse sellers set higher asking prices when house prices are falling, this particular psychological factor actually leads to lower volatility over the cycle, making the puzzle of possibly excess volatility in cycles an even more difficult problem to explain.

*2) Empirical Model*

Our empirical analysis examines which factors, rational and behavioral, are correlated with house price dynamics within metropolitan areas. As a baseline, we begin with a rational model of asset price equilibrium and see how much of the empirical price volatility such a model can explain. To that baseline, we add proxies for other rational and behavioral factors to see which are correlated with the unexplained residual.

To form the rational market baseline, we assume that housing markets are perfectly competitive and that in equilibrium, risk-adjusted returns for homeowners and landlords should be equated across investments. This yields the usual user cost formula (e.g. Hendershott and Slemrod [1983], Poterba [1984]) where spot rents in a housing market are set such that:

$$R_{it} = P_{it}\left((1-\tau_{it})r_t + m - E\left[\%\Delta P\right]_{it}\right). \tag{1}$$

$R_{it}$ is the rent for one unit of housing services for one year in city $i$ at time $t$, $P_{it}$ is the corresponding price for prepurchasing the entire future flow of $R_i$, $(1-\tau_{it})r_t$ is the after-tax, equivalent-risk opportunity cost of capital, *m* is a measure of carrying costs (such as maintenance) per dollar of house, and $E[\%\Delta P]_{it}$ is the expectation of future house price appreciation in city *i* at time *t*.

To match our empirical work, below, we rearrange equation (1) to obtain the price-rent ratio, P/R. Labeling the terms in large parentheses as user cost, UC(), P/R is:

$$\frac{P_{it}}{R_{it}} = \frac{1}{UC\left(\tau_{it}, r_t, m, E[\%\Delta P]_{it}\right)}. \qquad (2)$$

Examining the price-rent ratio provides a better measure of asset market conditions than does price alone. House prices are determined both by supply and demand for housing services as well as the asset market, making it difficult to empirically identify changes in prices due to the asset changes alone.[1] By conditioning on the spot rent for housing, the price-rent ratio leaves only asset market factors to explain how current and expected future rental values are capitalized into current prices. In the user cost framework in equation (2), home buyers pay a higher multiple to rents when the after-tax opportunity cost of capital is lower. So, for example, when interest rates fall, purchasers of housing will pay a higher price for a given dividend flow (either rental income or the imputed rent from living in the house). Of course, the price-rent ratio also expands when expected future price growth is higher (e.g., when more of the return comes in the form of capital gain).

Re-characterizing the user cost model in the P/R framework also highlights the highly non-linear relationship between changes in the price-rent ratio and user costs. Himmelberg, et. al. [2005] and Campbell et. al. [2007] point out that when user costs are low, convexity implies that relatively small absolute changes in user costs (caused by shocks to long-term interest rates, for example) can cause very large percentage changes in P/R.

[1] See Gallin [2006] who examines the relationship between prices and rents.

The user cost model described in equation (2) provides some empirical guidance, but it is incomplete. For example, the user cost framework does not address how expectations of capital gains are formed. In Poterba's original framework, home buyers are assumed to have perfect foresight. However, Case and Shiller [1988, 2005] provide survey evidence that home owners have price growth expectations that are inconsistent with perfect foresight. Himmelberg et. al. [2005] assume that home owners have static expectations that house prices to grow at their long-run average rate. But another possibility is that home buyers form their expectations based on recent history.

In addition, the measure of the opportunity cost of capital, $r_t$, does not fall out of the user cost model. Himmelberg et. al. [2005] used risk-free interest rates plus a time-invariant risk premium. However, the risk premium required by lenders or equity investors may vary over time, leading them to accept more risk at a given yield. For example, until recently, lenders allowed homeowners to take on more debt as a percentage of the house value (e.g., a higher loan-to-value ratio) and lent to much riskier borrowers (e.g., borrowers who have a worse FICO credit score or who cannot document their current income). In addition, during the 1980s, low capital by government insured savings and loans also led lenders to accept more non-priced risk**.** In these cases, the decline in the true risk-adjusted cost of capital would be greater than what would be reflected in the Himmelberg et. al. measure.[2] In another dimension, Brunnermeier and Julliard [2007] hypothesize that households consider nominal interest rates rather than real.

One way to test for the relevance of these various factors would be to incorporate them into the user cost framework and see which measure(s) of user cost best fit the data. However, a variety of theoretical and practical considerations preclude that approach. For one, the user cost

[2] Also, an increase in mortgage market efficiency that allows mortgages to be more cheaply originated might be capitalized in higher house prices if borrowers are liquidity constrained.

model presumes a rational asset market equilibrium. Embedding parameters in that framework that potentially derive from an underlying model where expected returns do not equate across investments would be inconsistent and difficult to interpret. In addition, if the expected capital gain is high enough, the user cost can be negative, implying that expected price appreciation outstrips the cost of capital. If that were the case, the return on home buying would be infinite and user cost is undefined.

Our empirical approach is to regress the log of the price-rent ratio on the log of the inverse user cost as defined in Himmelberg et. al. and proxies for low risk premia in the capital markets, inflation illusion, and backwards-looking expectations of price growth.:[3]

$$\ln\left(\frac{P_{it}}{R_{it}}\right) = \alpha + \beta \ln\left(\frac{1}{UC\left(\tau_{it}, r_{it}, m, E[\%\Delta P]_{it}\right)}\right) + \delta C_{it} + \gamma B_{it} + \varphi \Pi_t + \kappa_i + \varepsilon_{it}\,. \qquad (3)$$

$C_{it}$ is a vector of proxies for the easy availability of capital, including the average loan-to-value ratio, the fraction of mortgage originations that are adjustable rate, average points and fees, and the fraction of mortgage originations that are subprime. $B_{it}$ is a vector of backwards-looking measures of house price appreciation: the average house price growth in MSA $i$ over the prior year and over the previous five years. To test for the presence of inflation illusion, $\Pi_t$ is a measure of inflation. A set of metropolitan statistical area (MSA) indicator variables, $\kappa_i$, are also included.

It bears mentioning that in most specifications we choose not to include year dummies, instead using the variation over time in UC, C, B, and Π to help identify their effects on P/R. This specification allows us to incorporate two factors inherent in behavioral theories. First,

[3] We include log P/R and log user cost in equation (3) to address an additional problem that is described further in the data section. Our measure of P/R is not comparable across cities and requires that we factor out a multiplicative error term.

[5] More detail on the data used in this paper, as well as updated web links to our sources, can be obtained from the website, http://www0.gsb.columbia.edu/realestate/research/housingcost or in most cases from Himmelberg, Mayer, and Sinai [2005].

inflation illusion can only be considered without national time dummies. Second, Shiller [2007] argues that part of the social epidemics that give rise to housing cycles are due to national and even international influences that are common across regions. However, we include the year effects in a small number of specifications where the sample period is short enough that we believe within-MSA variation is more crucial for empirical identification and where it would be difficult to separately identify national macro factors.

If the user cost model holds and is correctly specified when we use a real opportunity cost of capital and static long-run expectations of house price growth, we would expect $\hat{\beta}$ to equal one. If, in addition, this user cost model were the primary determinant of asset pricing in the housing market, we would expect it to have a high $R^2$. To the degree that easy credit, inflation illusion, or backwards-looking price expectations affect asset pricing in the housing market above and beyond what is already incorporated into this implementation of the user cost model, the estimates of $\delta$, $\gamma$, and $\varphi$ should be statistically significantly different from zero and including $C_{it}$, $B_{it}$, and $\Pi_t$ should increase the explanatory power of the regression.

While the specification in equation (3) is reduced form, we believe it will provide additional evidence on which factors are correlated with the price-rent ratio in the housing market and the relative importance of rational and behavioral components. However, we caution that without a structural dynamic model, our results may be sensitive to misspecification of the functional form, especially if some of the included behavioral factors are correlated with measurement error. Alternatively, a lack of statistical significance might not be taken as evidence that a behavioral factor is unimportant, but may be due to a misspecified model. However, given the absence of models that combine backwards-looking expectations, inflation illusion, and fundamentals such as taxes and forward looking expectations, this stylized approach should provide a starting point.

*3) Data*

The most important variable in our paper is the price index for single family homes.[5] We use the OFHEO repeat sale index in all regressions, as opposed to the two other widely cited alternatives, the median sale price of existing homes from the National Association of Realtors and the S&P/Case-Shiller repeat sale price index. The biggest advantage of the OFHEO index is that it exists reliably for 287 Metropolitan Statistical Areas (MSAs) and Divisions, with most of the MSAs covered since 1975-1979. Yet the index also has two major limitations. First, it includes not only sales transactions, but also appraisals from refinancings that may be less reliable, especially when prices begin to fall. Second, the sample includes only transactions with a mortgage that is sold to Fannie Mae or Freddie Mac, which have an upper limit of $417,000 in 2007 and lower loan limits in previous years (so-called “conforming” loans). However, other indexes also have flaws. The median price index is less useful for our analysis, both because it is available for a shorter time period and, more importantly, because it is quite sensitive to the mix of houses that sell over the real estate cycle. The S&P/Case-Shiller index is arguably more reliable for the MSAs and time periods that it covers because it is based on the universe of all transactions (but not appraisals) and is not subject to a cap on the maximum mortgage amount. Unfortunately, the S&P/Case-Shiller index does not have enough history over time to include the 1980s and parts of the 1990s in many MSAs and has a much more limited coverage of MSAs. When possible, we have compared the results of our analysis using the OFHEO data with those using the S&P/Case-Shiller data, and found no substantive differences.

Reliable data on rental prices are more limited. We are unable to obtain rental costs for single-family homes, so we instead use rents on comparable quality apartments from REIS. The REIS data are available from 1980 to present in 43 metropolitan areas. REIS surveys owners for asking rents on rental units with common characteristics. These are the most comprehensive and reliable rental data available on a historical basis.

An important complication from using the house price indexes from OFHEO and rents based on apartments instead of single-family homes is that we are unable to compute a price-rent ratio that is comparable across markets.[6] The price index is normalized so that one cannot make cross-metropolitan area comparisons, plus we do not know how the quality of the average rental unit compares to average house quality for different metro areas. We address this problem in several steps. First we compute a rent index for each MSA by dividing the actual rent in each year by the rent in a base year for that MSA. Next we divide the price index for each MSA by the rent index for each MSA, and then set that ratio equal to 1 in a base year/quarter (Q1/1998). This allows us to compute the relative price-rent ratio across years within an MSA, but does not allow us to compare the level of P/R across MSAs. These price-rent ratios are only comparable subject to a multiplicative scaling factor for each MSA because we only observe the estimated ratio of P/R.[7]

Our other major challenge is measuring households' expected growth rate of housing prices. For our base measure of static long-term expected future growth rates, we use the average real growth rate of house prices from 1950-2000 from Gyourko, Mayer, and Sinai

[6] Smith and Smith (2006) address this problem in an innovative way by finding a sample of single-family rental units, so that prices and rents are closely matched. However, their estimation procedure did not incorporate differential house price appreciation rates across metro areas and their limited sample appears not to be fully representative of the market. The paper concludes that, based on fundamentals, house prices in some California cities were quite low in 2005 .

[7] We remove the multiplicative error by taking logs of both sides, regressing ln(P/R) on ln(1/user cost) and MSA fixed effects (to pick up the multiplicative scaling factor), plus other covariates. Thus, we can use only within-MSA variation to identify the various parameters of interest.

[2006]. All other calculations based on historical appreciation rates come from lagged appreciation of the OFHEO price indexes.

Other variables come from standard sources. We calculate long-term expected inflation by splicing two series together. From 1998 to present, we compute long-term expected inflation as the difference between the yield on the 30-year US Treasury Inflation-Protected Security (TIPS) and the yield on a 30-year US Treasury security. Prior to the beginning of the TIPS market in 1998, we use the 10-year expected inflation rate from the Livingston Survey of economic forecasters as published by the Federal Reserve Bank of Philadelphia. Interest rates are obtained from constant maturity one-year and ten-year U.S. Treasury securities and mortgage rates from 30-year fixed rate mortgages from the Federal Reserve Board. Per-capita income and inflation (based on the Consumer Price Index less shelter) are obtained from the Bureau of Labor Statistics.

Computing the tax subsidy to owner-occupied housing is a bit more complicated and described in more detail in Himmelberg, Mayer, and Sinai [2005]. We use average property tax rates from Emrath [2002] and income tax rates which we collect from the TAXSIM model of the National Bureau of Economic Research. However, data from the Internal Revenue Service shows that 65 percent of tax-filing households do not itemize their tax deductions and, if they are homeowners, do not benefit from the tax deductibility of mortgage interest and property taxes. To account at least roughly for the higher cost of owning for the non-itemizers, we reduce the tax subsidy in our calculations by 50 percent.

We also assume constant depreciation rates (2 percent) and risk premia (2 percent) for all metro areas in our sample. These assumptions, while simplistic, could bias our calculated user costs in either direction. We might overestimate the spread in user costs between high-priced and low-price metro areas by ignoring the fact that the value of structures is generally small relative to the value of the land in the highest land cost markets such as San Francisco and New York. Thus depreciation might be less important that we assume when we calculate the user cost in low user cost/high appreciation rate cities (Davis and Palumbo [2007]). At the same time, lower depreciation rates in high priced cities like San Francisco might be offset by higher house price risk. Some research has argued that housing in high-priced cities is riskier because the standard deviation of house prices is much higher (Case and Shiller [2004]; Hwang and Quigley [2004]), while other research argues that homeowners can partially hedge this rent and price risk (Sinai and Souleles [2005]). Without further guidance from the literature on this issue, our calculations do not allow for variation in risk across markets.

Finally, we obtain lending covariates from two principal sources. Yearly data on use of adjustable rate mortgages (ARMs), the loan-to-value (LTV) ratio, and average fees/points paid on mortgages comes from the Federal Housing Finance Board and is based on the MIRS survey of rates and terms from conventional mortgages for 32 metro areas and all 50 states. While the MIRS sample has unique data at the metro area level, it is based on a less-than fully comprehensive sample of conventional mortgages that does not include Alt-A and subprime mortgages. In addition, the LTV data are only for primary mortgages and do not include piggyback loans. Thus the MIRS data almost surely understate the usage of ARMs and effective LTV ratios, both of which are more prevalent among subprime loans than the conventional mortgage population. The MIRS data run from 1978 to 2005 for MSAs and thru 2006 for states. We use the MSA data from 1984-2005 and substitute state values for MSA values for 2006. However, the MIRS cities do not completely overlap with the REIS markets. We report regression results using two data samples, listed in Appendix Table 1. The complete sample includes all 43 metro areas with rent data from REIS. When we include the lending covariates, we restrict the sample to 26 cities that are in REIS and the MIRS data. The other results are generally similar across the two sample groups.

Our data on subprime mortgages is reported at the state level and is based on lender-reported mortgage data based on requirements from the Home Mortgage Discrimination Act [HMDA]. While these data are commonly used and reported in research reports and in the press, they have a significant flaw. The definition of "subprime loans" is based on a primary categorization of the lender. So-called subprime lenders sometimes originate conventional or high-quality ("prime") mortgages and some conventional lenders issue appreciable numbers of subprime mortgages. It is impossible to know the overall direction of this bias. We use subprime data from the Mortgage Bankers Association for 2002 to 2005 and from Inside Mortgage Finance for 2000 to 2001. These data are not available prior to 2000, when subprime mortgages were much less widely available.

Summary statistics are reported in Table 1 for all variables used in our analysis. We begin our analysis in 1984, to allow the inclusion of lagged five-year appreciation rate as an independent variable. We report both the aggregate standard deviation as well as the average within-MSA standard deviation, as the latter better reflects our empirical identification. We should also note that the mean values of P/R and ln(P/R) are not meaningful since both are measured as indexes.

There are several instructive facts in the data. While many commentators have reported the seemingly large variation in the ln(P/R) ratio, ln(1/user cost) exhibits the same within-MSA standard deviation. Thus MSA P/R is not *a priori* more volatile than might be expected from a simple user cost model. Second, the five-year lagged nominal growth rate exhibits quite substantial variation, rising as much as 20 percent in the highest-appreciation rate MSA.

### *4) Empirical Results*

We start by establishing a baseline for how much of the variation in the price-rent ratio can be explained by the user cost model with real interest rates and static expectations of capital gains based on long-run real house price growth. The first column of Table 2 reports the results from estimating equation (3) over the 1984-2006 period with only ln(1/user cost) on the right-hand-side. The estimated coefficient on user cost is 0.48 (with a standard error of 0.03), well below (and statistically different from) the value 1.0 that would be expected if the standard user cost model held. Given this estimate, a 10 percent decline in user cost from the sample average would lead to a 5.3 percent increase in house prices, holding rent constant.[8] The $R^2$ is 0.28, so just over one-quarter of the variation in the price-rent ratio is explained by user cost and a set of MSA fixed effects.

Next we split the sample into two periods: 1984-1994 and 1995-2006. We do so to follow-up on the observation in Himmelberg et. al. that the user cost model fit particularly poorly in the 1980s. The sample split shows that the user cost model performs badly in the earlier time period (coefficient of 0.12 on user cost), but there is excess sensitivity in the later period (coefficient of 1.27). Thus between 1984 and 1994, changes in user cost had little effect on the price-rent ratio, while the effect was ten times stronger in the late 1990s and early 2000s. This result is consistent with the view that the run-up in house prices in the 1980s was *not* supported by fundamentals while the price growth in the 2000s was more so. Indeed, it is apparent *a priori*

[8] The average user cost over this sample period is 0.06, from Table 1. A 10 percent decline would yield a user cost of 0.054. In that case, 1/UC would rise from 16.6667 to 18.5185, an 11 percent increase. Multiplying that 11 percent by 0.48 gives a 5.33 percent rise in house prices.

that this should be the case: user costs were high in the 1980s since real interest rates were high, yet prices experienced rampant growth. By contrast, in the 2000s, movements in the price-rent ratio trended with a strong decline in real interest rates. In both periods the $R^2$ is just over 0.55, suggesting that considerable variation in the price-rent ratio remains to be explained.

*a) Capital availability as an explanation for housing booms*

In Table 3, we add proxies ($C_{it}$) for changes in loan terms or mortgage market efficiency over time, including the fraction of loans that are adjustable rate; average points and fees (a proxy for the improved efficiency of the lending market), and the average loan-to-value ratio in an MSA in a given year, since lenders take on more risk when they underwrite with more leverage. Since we do not have these variables for all the cities with price data, we estimate the model on the subset for which we have complete data, which we label as the "MIRS sub-sample." The first column of Table 3 replicates the regression from the first column of Table 2 using the MIRS sub-sample and finds almost identical results, albeit with larger standard errors due to the smaller number of observations.

Adding the fraction ARMs or average points and fees has the expected effect. In column (2) the ARM share is positively correlated with the price-rent multiple, suggesting that when adjustable rate mortgages are more prevalent the price-rent ratio is higher. Similarly, when average points and fees are lower, the price-rent ratio is higher, reflecting the fact that the effective cost of capital is lower when points and fees are reduced. Adding these two variables changes the estimated coefficient on user cost, indicating that they are in part picking up some measurement error in the proxy for the cost of capital used in the user cost formula. In column (4) the estimated coefficient on the average loan-to-value ratio is negative, the opposite sign to what would be predicted if relaxing liquidity constraints leads to a higher P/R. However, LTV as measured by the FHLB falls in house price booms. If so, the variable may not measure the impact of relaxing liquidity constraints for the average buyer or may be measured incorrectly due to missing 2nd mortgages and the lack of high-LTV subprime mortgages. The inclusion of these lending variables generally lowers the coefficient on user cost, suggesting that mis-measurement of the true cost of lending in the user cost might bias our estimation.

When we divide the sample period between the 1980s boom-bust and the 2000s boom, again there are significant differences in the relationship between the capital markets and the price-rent ratio. The estimated coefficient on user cost over the 1984-2006 period when all three credit market variables are included is 0.37 (with a standard error of 0.06). But that masks a coefficient of -0.13 during 1984-1994 and 0.88 for 1995-2006. Some of the credit market variables also have different estimated coefficients during the two periods, with the coefficient on the percent ARM variable approximately zero and insignificant during the early period but positive and significant in the 2000s, and the coefficient on the points and fees variable tripling in magnitude in the latter period. Indeed, with the exception of LTV, credit market conditions seem to have a magnified effect on the price/rent ratio in the 1995-2006 boom and provide little help explaining the 1980s boom-bust.

Next we attempt to examine the impact of growing subprime lending. In Table 4, we examine the extent to which subprime lending is correlated with excess growth in the price-rent ratio. Since data on subprime shares are available only for the 2000-2005 period, we restrict our attention to those six years. The first column of Table 4 shows that the user cost model plus MSA dummies fits quite well during that period, with an estimated coefficient on user cost of 0.95 and an $R^2$ of 0.89. In column (2), we add the share of mortgages originated that were subprime loans. We find that greater fractions of subprime are correlated with higher price-rent ratios, but that the magnitude of the effect is fairly moderate. The estimated coefficient of 0.42 implies that a one standard deviation increase in the subprime mortgage share (five percentage points compared to a mean of 11 percent) yields just over a two percent increase in house prices, holding rents constant. As columns 4 shows, this result is robust to including the other measures of the cost of credit, increasing in magnitude by half when they are added. However, when we include the subprime share, the other lending variables appear to matter much less in explaining P/R, as can be seen by comparing columns 3 and 4.

One might be somewhat skeptical of using changes in subprime share over time to help identify the relationship between subprime share and the price-rent ratio. Since both the price-rent ratio and subprime share were trending upwards between 2000 and 2005, one cannot be sure if the price-rent ratio rose because of lenders taking more risk through subprime loans or if the relationship is spurious. In the last column of Table 4, we add year fixed effects to address this issue. The year effects control for any national trends in the price-rent ratio and subprime share. Thus the estimated coefficient on subprime is identified by whether an MSA's P/R ratio grows faster than the national average when the share of subprime mortgages in an MSA grows faster than the national average. Similarly, the user cost coefficient is identified by whether MSAs with user costs that decline more than the national average in a given year have price-rent ratios that increase more than average in that year. In this specification, percent changes in user cost have an almost one-for-one effect on the price-rent ratio with an estimated coefficient of 0.90 (standard error of 0.22). The estimated effect of the subprime share actually rises fourfold when we restrict our focus to variation within MSA over time. The resulting coefficient of 1.54 (standard error of 0.22) implies that a five percentage point increase in subprime share is correlated with a 10 percent excess increase in the price-rent ratio. The other credit market variables are no longer statistically significant. These results suggest that subprime lending is related to excess growth in price-rent ratios in recent years and are similar in spirit to the findings in prior research (Pavlov and Wachter [2007]).

*b) Behavioral explanations: Backwards-looking expectations*

Collectively, the user cost and credit market variables explain a great deal of the within-MSA variation in the price-rent ratio from 2000 to 2005 – 92 percent without year dummies and 94 percent with. In addition, the estimated coefficient on user cost is very close to one, suggesting that the housing market was pricing rationally given the state of the capital markets. But that leads one to ask: Was the capital that flowed to the housing market motivated by some behavioral response, as suggested by Shiller [2007], even if house purchasers priced the asset correctly?

Discussing behavioral motivations for excessive lending or insufficient risk aversion on the part of lenders is beyond the scope of this paper, but at least we can examine whether subprime mortgage lending followed price growth. In Table 5, we regress the subprime share on recent house price growth rates: the average house price appreciation between six years and one year prior and the house price growth between two and one years prior.[9] Since the regressions contain MSA fixed effects, the identification comes from within-MSA changes in subprime lending relative to the MSA sample period average. The first three columns of Table 5 show that higher past five-year lagged appreciation rates are associated with much a much higher share of subprime loans. The coefficient on lagged five-year growth rate in column (3) shows that a one

[9] We measure the growth rate up through the start of the prior year rather than the current year to avoid a contemporaneous measurement of subprime market share and house price growth. We obtain similar results if we measure price appreciation through the current year.

percentage point increase leads to a 1.29 percentage point greater subprime share. However, the most recent year's appreciation rate has little predictive power for the growth of subprime loans and, if anything, conditional on the five-year lagged growth rate in prices, subprime lending is slightly lower in markets with high price growth over the prior year.

When we include year dummies in the last three columns of Table 5, we see that increases in lagged five-year house price growth are still associated with bigger-than-average increases in the subprime share. However, the magnitude of the effect is about 60 percent as big as without the year fixed effects, with an estimated coefficient on the five-year average prior house price growth ranging from 0.67 to 0.71 with very low standard errors. These results suggest that lenders may have lent more aggressively in booming markets, although no more in markets where just the prior year's house price growth was high than in ones that were booming for half a decade.

Another way in which behavioral factors can enter the housing market is through the formation of expectations about house price growth by home buyers and sellers as suggested by Case and Shiller [1988, 1989, 2004], Shiller [2007], and others. We consider two simple backwards-looking rules for forming expectations: future house price growth is expected to be the average of the last five years and future house price growth is expected to be the same as last year. While these are particularly naïve rules-of-thumb, we have no theory that would give more precise guidance.[10]

As reported in the first column of Table 6 and predicted by the behavioral conjectures, the lagged five-year average of house price growth is positively associated with increases in the

[10] In addition, the five-year-average fit the data better than other approaches, such as overweighting more recent years or estimating an autoregressive price growth process, as in Campbell et. al. [2007]. Ideally, we would have some measure of peoples' actual house price expectations but we are not aware of any source that collects such data for a wide variety of cities.

price-rent ratio. The individual coefficient on lagged five year growth is highly statistically significant and increases the explanatory power of the regression appreciably. [11] When the lagged five-year average house price growth rate is above the MSA average, the price-rent ratio for that MSA is also above its average. In particular, the estimated coefficient in column 1 suggests that a one standard deviation change in the lagged growth rate of three percentage points is associated with more than a six percent increase in the price-rent ratio.

By contrast, the prior year's house price growth rate has little effect on the price-rent ratio (column 2) and what effect it does have is subsumed by the five-year average lagged growth rate (column 3). Neither lagged growth rate affects the estimated coefficient on user cost, which remains between 0.33 and 0.38, very close to the estimate in the fifth column of Table 3. This result is inconsistent with the most behavioral of conjectures in which households set expected growth rates based on very recent changes in house prices.[12]

Of course, backwards-looking expectations are not necessarily behavioral: instead, households might rationally incorporate lagged 5-year price growth when predicting future price growth, especially if there is serial correlation in underlying demand growth.[13] Indeed, all one can say with certainty is that house price growth expectations appear to be dynamic since to the degree that households across MSAs hold different static expectations about future price growth, it is absorbed by the MSA fixed effect. Thus the large and statistically significant coefficient on past house price growth indicates that changes in expected capital gains are correlated with the

[11] We exclude LTV since it appears not to reflect the true degree of leverage. Our conclusions are unchanged if we include it.

[12] This result is not surprising. If very short-run price increases had large impacts on expectations, we would see more bubbles of the form of Vancouver in the early 1980s in which we see quick spikes and declines in house prices.

[13] For example, Gyourko et. al. [2006] show that the rent-price ratio falls as long-run price growth increases, at least using decadal data.

[15] This result is consistent with the last table from Sinai and Souleles (2005) which shows that that markets with higher historical house price growth have higher price-rent ratios and those price-rent ratios expand when past house price growth rises, holding the metropolitan area constant.

price-rent ratio.[15] Even so, the effect of recent house price growth on current price-rent ratios is certainly suggestive of a behavioral component. More work needs to be done so we can better understand how households set expectations of future price growth and how those expectations are capitalized into prices.

*c) Inflation Illusion*

Finally, we examine the evidence on whether households are subject to inflation illusion, confusing nominal interest rates with real ones as suggested by Brunnermeier and Juillard [2007]. To see if inflation has an effect, we add a measure of inflation to the regression. The results, that higher inflation is correlated with a higher price-rent ratio, are reported in column (4) of Table 6. The estimated coefficient of 2.13 (with a standard error of 0.31) suggests that a one percentage point higher inflation rate (the mean is 0.03) is correlated with a 2 percent higher price-rent ratio. This is actually the opposite result that one would expect given the results in Brunnermeier and Juliard. Those authors argue that when actual inflation falls, households think that the cost of capital (the mortgage rate) is lower even as expected house price appreciation has not changed. If lower inflation made housing appear relatively inexpensive in recent years, the price-rent ratio should increase, not fall.

Note that the user cost model predicts that higher *expected* inflation should raise house prices as increases in *expected* inflation raise the value of the nominal mortgage interest deduction. However, with expected inflation already incorporated in the user cost and the relationship between actual and expected inflation unclear, it is quite possible that the positive and significant coefficient on inflation may be due to measurement error in the user cost. As discussed above, it is difficult to accurately compute the value of the tax deduction for nominal interest payments since many households do not itemize deductions when filing their taxes.

Columns 5 and 6 of Table 6 return to the notion that the 1980s boom was perhaps more behaviorally-driven than the housing boom in the 2000s. Between 1984 and 1994 user cost had no effect – and credit market conditions had almost no effect – on the price-rent ratio once one controls for lagged house price growth and inflation, and even those variables had relatively small impacts on the price-rent ratio during that period. But in the 1995 through 2006 period, the user cost coefficient increases to 0.76, much closer to its theoretical value of 1.00. Lagged house price growth also has a larger effect, with an estimated coefficient of 2.08. To give a sense of magnitudes in column (6), a within-MSA one standard deviation decrease in ln(1/user cost) of about 15 percent would lead to an 11.4 percent increase in ln(P/R). By contrast, a within-MSA one standard deviation increase in lagged house price growth (three percentage points) would lead to a 6 percent increase in the price-rent ratio. So, a one standard deviation change in the user cost has about twice as large an effect on ln(P/R) as a one standard deviation change in lagged five-year price appreciation.

We finish by revisiting the recent boom years of 2000-2005 and the impact of subprime mortgages. Column (7) shows that the coefficients estimated over the 2000-2005 period look very similar to those estimated during 1995-2006, except that the coefficient on the inflation rate switches signs and is no longer statistically significant from zero. In column 8, we add the subprime share and see that, once again, that subprime share is strongly correlated with higher price-rent multiples. With a coefficient of 0.32, a one standard deviation increase in the within-MSA share subprime (4 percentage points) is associated with a 1.3 percent increase in the price-rent ratio. The last column of Table 6 incorporates year dummies, using just the variation within

MSA over time to identify the coefficients. The estimated coefficient on user cost of 0.97 is quite close to unity. The coefficient on the five-year lagged appreciation rate is little changed. This specification suggests that in the latest time period, a one standard deviation change in the user cost has almost three times the impact on ln(P/R) as a one standard deviation change in lagged five-year appreciation, and almost six times as much as is explained by a one standard deviation change in percent subprime.

*5) Conclusion*

Our results suggest that both rational and seemingly behavioral factors play an important role in explaining changes in the price-rent ratio across U.S. metro areas since 1984. We began by estimating a standard user cost model with long-term interest rates and expected appreciation equal to its post-war average. We then included other independent variables to control for measurement error and omissions in the standard user cost model. Finally, we added proxies for behavioral explanations of house price growth, including backwards-looking expecations and inflation illusion.

The standard model matched changes across MSAs in house price appreciation after 1994 almost one-for-one , but did a poor job between 1984 and 1994. Backwards-looking expectations, in the form of five-year lagged appreciation rates, were the only factor to have any sizeable correlation with movements in the price-rent ratio between 1984 and 1994, but changes user cost appeared to have a larger effect on P/R in the 1995-2006 period than did the lagged five-year appreciation rate. Mortgage market factors, especially the growing use of subprime mortgages and the decline in lending costs also help explain an additional portion of the variation in price-rent ratios in the later part of the sample period.

The results present a mixed bag when interpreting the magnitude of rational and behavioral effects in explaining house price movements. Fundamentals seem to be important – but only in the 1995-2006 boom. Coefficients on the two most striking behavioral variables, the inflation rate (inflation illusion) and 1-year backwards looking expectations, were the wrong sign in nearly all specifications and these variables showed little explanatory power. However, medium-term, backward-looking expectations (five-year lagged appreciation rate) are quite important in explaining within-MSA variation in price-rent ratios. Overall, these results suggest that the 1980s house price boom was more of a behavioral bubble than the 2000s, where fundamentals dominated in importance but backwards-looking expectations continued to play a sizeable role. Still, there is appreciable scope for additional work exploring how households set their expectations. Without a formal model of expectation setting, it is nearly impossible to determine the extent to which households are rationally updating their beliefs about future house price appreciation or are getting caught up in a "Zeitgeist" or social epidemic (Shiller [2007]).

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TABLE 1: Summary Statistics

| MIRS SUB-SAMPLE | # OBS | YEARS | MEAN | MEDIAN | STD. DEV. | AVG. W/IN MSA STD. DEV. | MIN | MAX |
|---|---|---|---|---|---|---|---|---|
| Price/rent index (P/R) | 520 | 1984-2006 | 1.06 | 1.02 | 0.17 | 0.18 | 0.68 | 2.04 |
| User cost (UC) | 520 | 1984-2006 | 0.06 | 0.06 | 0.01 | 0.01 | 0.02 | 0.08 |
| Ln(P/R) | 520 | 1984-2006 | 0.05 | 0.02 | 0.15 | 0.15 | -0.38 | 0.72 |
| Ln(1/UC) | 520 | 1984-2006 | 2.91 | 2.87 | 0.20 | 0.15 | 2.54 | 3.69 |
| Lagged 5-year growth rate | 520 | 1984-2006 | 0.05 | 0.04 | 0.04 | 0.03 | -0.05 | 0.20 |
| Lagged 1-year growth rate | 520 | 1984-2006 | 0.06 | 0.05 | 0.05 | 0.05 | -0.08 | 0.27 |
| Inflation rate | 520 | 1984-2006 | 0.03 | 0.03 | 0.01 | 0.02 | 0.00 | 0.06 |
| Loan-to-value ratio (LTV) | 520 | 1984-2006 | 0.77 | 0.77 | 0.04 | 0.03 | 0.61 | 0.86 |
| % Adjustable rate mortgages (%ARMs) | 520 | 1984-2006 | 0.27 | 0.24 | 0.16 | 0.12 | 0.04 | 0.77 |
| Points & fees (% of mortgage amount) | 520 | 1984-2006 | 1.15 | 0.95 | 0.73 | 0.81 | 0.07 | 3.44 |
| % of loans that are subprime | 130 | 2000-2005 | 0.11 | 0.10 | 0.05 | 0.04 | 0.03 | 0.29 |

| FULL SAMPLE | # OBS | YEARS | MEAN | MEDIAN | STD. DEV. | AVG. W/IN MSA STD. DEV. | MIN | MAX |
|---|---|---|---|---|---|---|---|---|
| Price/rent index (P/R) | 989 | 1984-2006 | 1.08 | 1.03 | 0.20 | 0.18 | 0.68 | 2.28 |
| User cost (UC) | 989 | 1984-2006 | 0.06 | 0.06 | 0.01 | 0.01 | 0.02 | 0.10 |
| Ln(P/R) | 989 | 1984-2006 | 0.06 | 0.03 | 0.17 | 0.15 | -0.38 | 0.82 |
| Ln(1/UC) | 989 | 1984-2006 | 2.92 | 2.89 | 0.24 | 0.15 | 2.34 | 3.86 |
| Lagged 5-year growth rate | 989 | 1984-2006 | 0.05 | 0.04 | 0.04 | 0.03 | -0.05 | 0.20 |
| Lagged 1-year growth rate | 989 | 1984-2006 | 0.06 | 0.05 | 0.06 | 0.05 | -0.10 | 0.33 |
| Inflation rate | 989 | 1984-2006 | 0.03 | 0.03 | 0.02 | 0.02 | 0.00 | 0.06 |
| Loan-to-value ratio (LTV) | 520 | 1984-2006 | 0.77 | 0.77 | 0.04 | 0.03 | 0.61 | 0.86 |
| % Adjustable rate mortgages (%ARMs) | 520 | 1984-2006 | 0.27 | 0.24 | 0.16 | 0.12 | 0.04 | 0.77 |
| Points & fees (% of mortgage amount) | 520 | 1984-2006 | 1.29 | 1.07 | 0.83 | 0.81 | 0.07 | 3.88 |
| % of loans that are subprime (% Subprime) | 258 | 2000-2005 | 0.12 | 0.11 | 0.05 | 0.04 | 0.03 | 0.29 |

| TABLE 2: | | | |
|---|---|---|---|
| | WHOLE SAMPLE | | |
| | 1984-2006 | 1984-1994 | 1995-2006 |
| Ln(1/user cost) | 0.48 | 0.12 | 1.26 |
| | (0.03) | (0.03) | (0.06) |
| $R^2$ | 0.28 | 0.55 | 0.57 |
| # Obs | 989 | 473 | 516 |
| MSA fixed effects | YES | YES | YES |

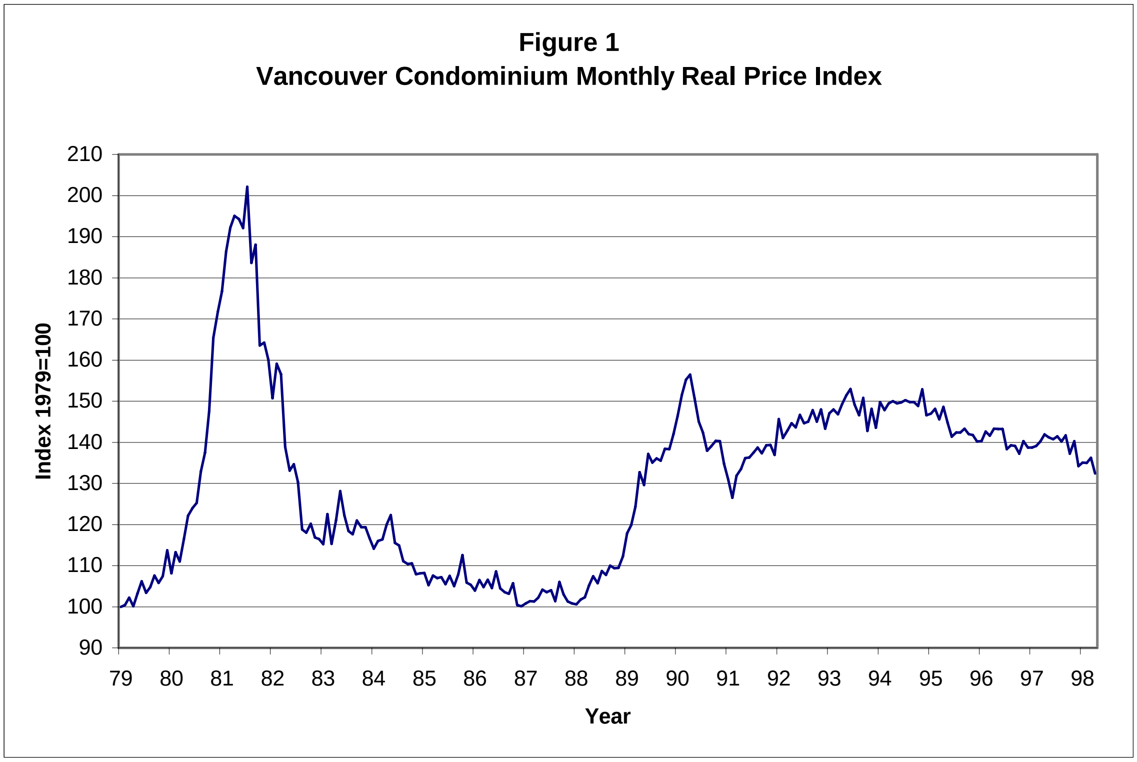
| TABLE 3: | | | | | | | |
|---|---|---|---|---|---|---|---|
| | MIRS SUB-SAMPLE | | | | | | |
| | 1984-2006 | 1984-2006 | 1984-2006 | 1984-2006 | 1984-2006 | 1984-1994 | 1995-2006 |
| Ln(1/user cost) | 0.50 | 0.56 | 0.30 | 0.51 | 0.37 | -0.13 | 0.88 |
| | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.05) | (0.07) |
| %ARMs | | 0.13 | | | 0.19 | -0.04 | 0.23 |
| | | (0.05) | | | (0.05) | (0.04) | (0.06) |
| Points & fees | | | -0.06 | | -0.07 | -0.07 | -0.21 |
| | | | (0.01) | | (0.01) | (0.01) | (0.03) |
| Loan-to-value ratio | | | | -0.98 | -1.11 | -0.99 | -0.56 |
| | | | | (0.20) | (0.18) | (0.25) | (0.25) |
| $R^2$ | 0.20 | 0.21 | 0.28 | 0.24 | 0.35 | 0.72 | 0.66 |
| # Obs | 520 | 520 | 520 | 520 | 520 | 234 | 286 |
| MSA fixed effects | YES | YES | YES | YES | YES | YES | YES |

| TABLE 4: | | | | | |
|---|---|---|---|---|---|
| | SUBPRIME SUB-SAMPLE | | | | |
| | 2000-2005 | 2000-2005 | 2000-2005 | 2000-2005 | 2000-2005 |
| Ln(1/user cost) | 0.96 | 0.82 | 0.81 | 0.65 | 0.90 |
| | (0.04) | (0.06) | (0.08) | (0.08) | (0.22) |
| %Subprime | | 0.43 | | 0.63 | 1.54 |
| | | (0.12) | | (0.15) | (0.22) |
| %ARMs | | | 0.12 | -0.02 | 0.06 |
| | | | (0.05) | (0.06) | (0.07) |
| Points & fees | | | 0.01 | -0.02 | 0.01 |
| | | | (0.05) | (0.04) | (0.04) |
| Loan-to-value ratio | | | -0.81 | -0.75 | -0.23 |
| | | | (0.23) | (0.21) | (0.21) |
| $R^2$ | 0.89 | 0.90 | 0.90 | 0.92 | 0.94 |
| # Obs | 130 | 130 | 130 | 130 | 130 |
| YEAR fixed effects | NO | NO | NO | NO | YES |
| MSA fixed effects | YES | YES | YES | YES | YES |

| TABLE 5: | | | | | | |
|---|---|---|---|---|---|---|
| | SUBPRIME SUB-SAMPLE | | | | | |
| | 2000-2005 | 2000-2005 | 2000-2005 | 2000-2005 | 2000-2005 | 2000-2005 |
| Lagged 5-year growth rate from years -6 to -1 | 1.24 | | 1.29 | 0.67 | | 0.71 |
| | (0.11) | | (0.11) | (0.06) | | (0.06) |
| Lagged 1-year growth rate From years -2 to -1 | | 0.16 | -0.10 | | 0.04 | -0.07 |
| | | (0.09) | (0.07) | | (0.04) | (0.03) |
| $R^2$ | 0.50 | 0.21 | 0.50 | 0.92 | 0.87 | 0.92 |
| # Obs | 258 | 258 | 258 | 258 | 258 | 258 |
| YEAR fixed effects | NO | NO | NO | YES | YES | YES |
| MSA fixed effects | YES | YES | YES | YES | YES | YES |

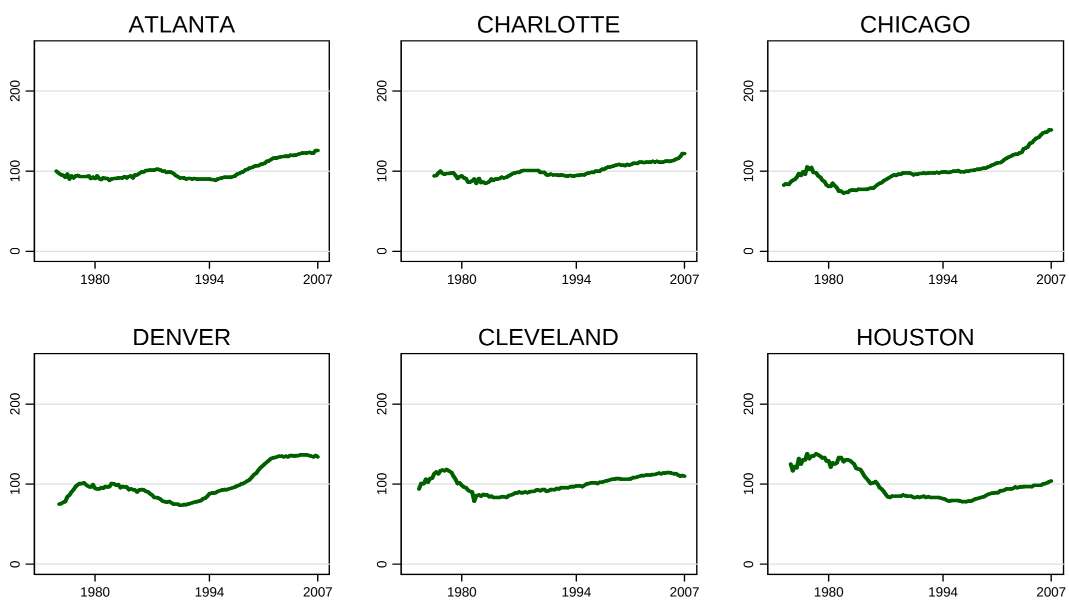
TABLE 6:

| | MIRS SUB-SAMPLE | | | | | | SUBPRIME SUB-SAMPLE | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1984-2006 | 1984-2006 | 1984-2006 | 1984-2006 | 1984-1994 | 1995-2006 | 2000-2005 | 2000-2005 | 2000-2005 |
| Ln(1/user cost) | 0.33 | 0.38 | 0.33 | 0.43 | -0.00 | 0.76 | 0.63 | 0.57 | 0.97 |
| | (0.05) | (0.06) | (0.05) | (0.05) | (0.05) | (0.06) | (0.06) | (0.06) | (0.17) |
| Lagged 5-year growth rate | 2.17 | | 2.20 | 1.99 | 1.57 | 2.08 | 2.35 | 2.16 | 1.80 |
| | (0.13) | | (0.14) | (0.13) | (0.12) | (0.19) | (0.23) | (0.24) | (0.28) |
| Lagged 1-year growth rate | | 0.36 | -0.07 | -0.01 | -0.14 | -0.03 | 0.21 | 0.15 | 0.19 |
| | | (0.12) | (0.10) | (0.10) | (0.07) | (0.13) | (0.10) | (0.10) | (0.09) |
| Inflation rate | | | | 2.12 | 0.57 | 2.49 | -0.19 | -0.34 | |
| | | | | (0.31) | (0.33) | (0.31) | (0.20) | (0.21) | |
| %ARMs | 0.09 | 0.17 | 0.10 | 0.08 | -0.03 | 0.02 | 0.11 | 0.05 | 0.07 |
| | (0.04) | (0.05) | (0.04) | (0.04) | (0.03) | (0.05) | (0.04) | (0.04) | (0.05) |
| Points & fees | -0.05 | -0.06 | -0.05 | -0.05 | -0.02 | -0.08 | 0.01 | -0.01 | -0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.03) | (0.03) | (0.03) |
| %Subprime | | | | | | | | 0.33 | 0.64 |
| | | | | | | | | (0.12) | (0.22) |
| $R^2$ | 0.55 | 0.31 | 0.55 | 0.59 | 0.85 | 0.82 | 0.95 | 0.96 | 0.96 |
| # Obs | 520 | 520 | 520 | 520 | 234 | 286 | 130 | 130 | 130 |
| YEAR fixed effects | NO | NO | NO | NO | NO | NO | NO | NO | YES |
| MSA fixed effects | YES | YES | YES | YES | YES | YES | YES | YES | YES |



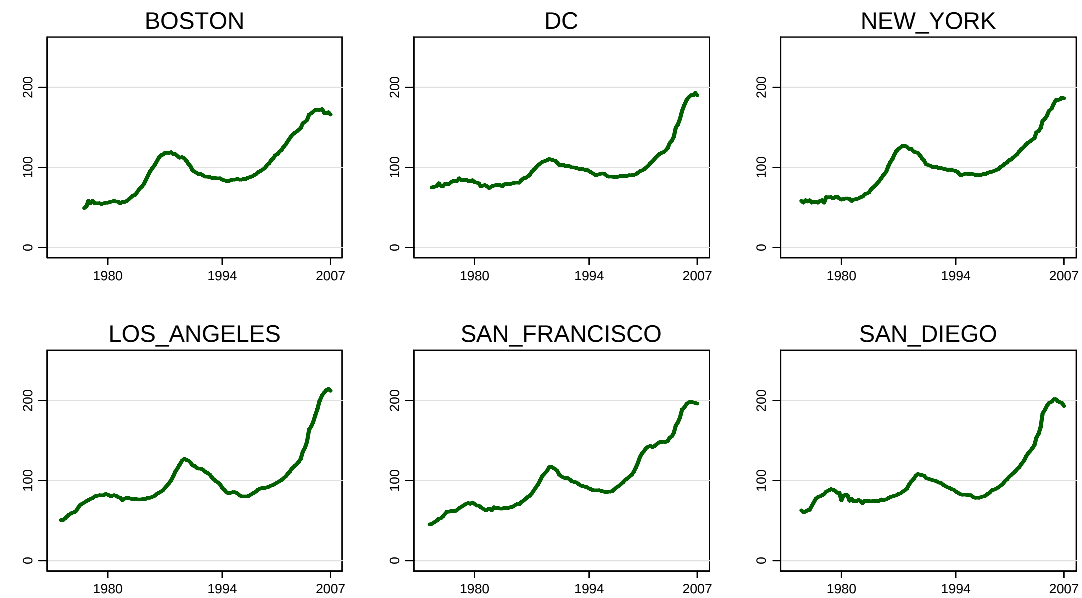

Source: Taken from Figure 2 in Bulan, Mayer, and Somerville (2006).

Figure 2A: Steady Markets



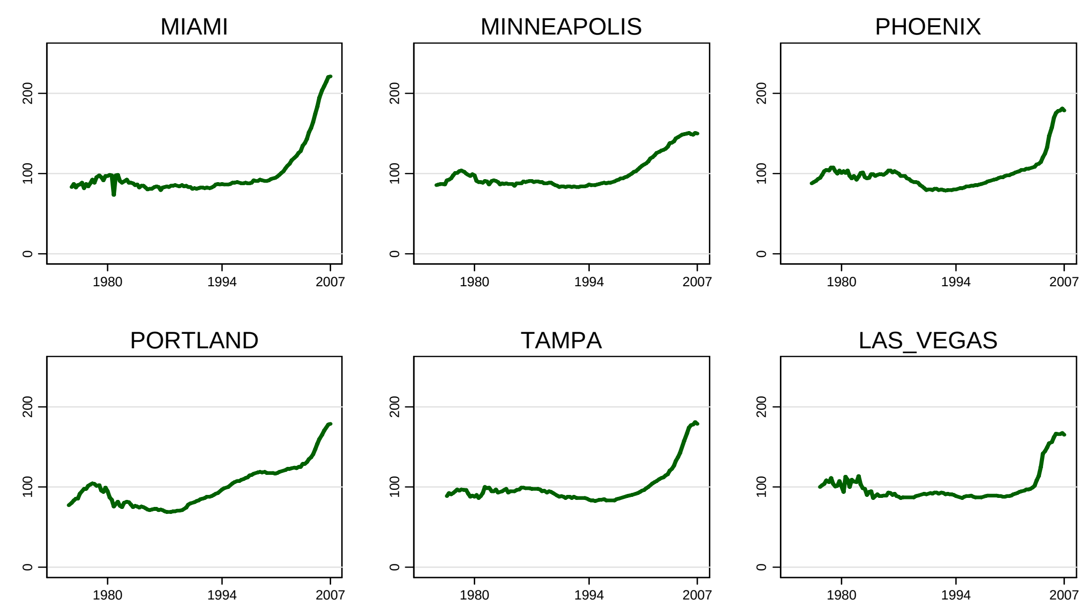

Current as of Quarter 1, 2007
Source: OFHEO and BLS
Real Home Price Index
Index = 1: Sample Average

Figure 2B: Cyclical Markets




Current as of Quarter 1, 2007
Source: OFHEO and BLS
Real Home Price Index
Index = 1: Sample Average

Figure 2C: Recent Boomers




Current as of Quarter 1, 2007
Source: OFHEO and BLS
Real Home Price Index
Index = 1: Sample Average

Source for Figures 2A, 2B, and 2C: Taken from Mayer (2007).

| APPENDIX TABLE 1: | |
|---|---|
| REIS/MIRS MSA's | REIS ONLY MSA's |
| AUSTIN | ATLANTA |
| CHARLOTTE | BALTIMORE |
| CINCINNATI | BOSTON |
| DC | CHICAGO |
| FORTLAUDERDALE | CLEVELAND |
| FORTWORTH | COLUMBUS |
| JACKSONVILLE | DALLAS |
| MEMPHIS | DENVER |
| NASHVILLE | DETROIT |
| OAKLAND | HOUSTON |
| ORANGE COUNTY | INDIANAPOLIS |
| ORLANDO | KANSAS CITY |
| RICHMOND | LOS ANGELES |
| SACRAMENTO | MIAMI |
| SAN ANTONIO | MILWAUKEE |
| SAN BERN-RIVERSIDE | MINNEAPOLIS |
| SAN JOSE | NEW YORK |
| | PHILADELPHIA |
| | PHOENIX |
| | PITTSBURGH |
| | PORTLAND |
| | SAN DIEGO |
| | SAN FRANCISCO |
| | SEATTLE |
| | ST. LOUIS |
| | TAMPA |