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**House Prices and Credit Constraints:
Making Sense of the U.S. Experience**

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Abstract

Inverting the effective demand for housing implies home prices depend on credit constraints (Meen (2001), Muellbauer and Murphy (1997) and Cameron, Muellbauer and Murphy (2006)), a theoretical result also demonstrated in Kim's (2007) home price-to-rent framework. Previous U.S. home price models lack data on credit constraints facing first-time home-buyers (and regional housing stocks), likely accounting for the poor performance of home price models based on interest rates and income (Gallin, 2006). We incorporate such omitted data into home price models which yield stable long-run relationships, more precisely estimated income and interest rate coefficients, reasonable speeds of adjustment, and improved model fits.

JEL Codes: R31, G21, E51, C51, C52.

Key Words: home prices, credit standards, subprime mortgages

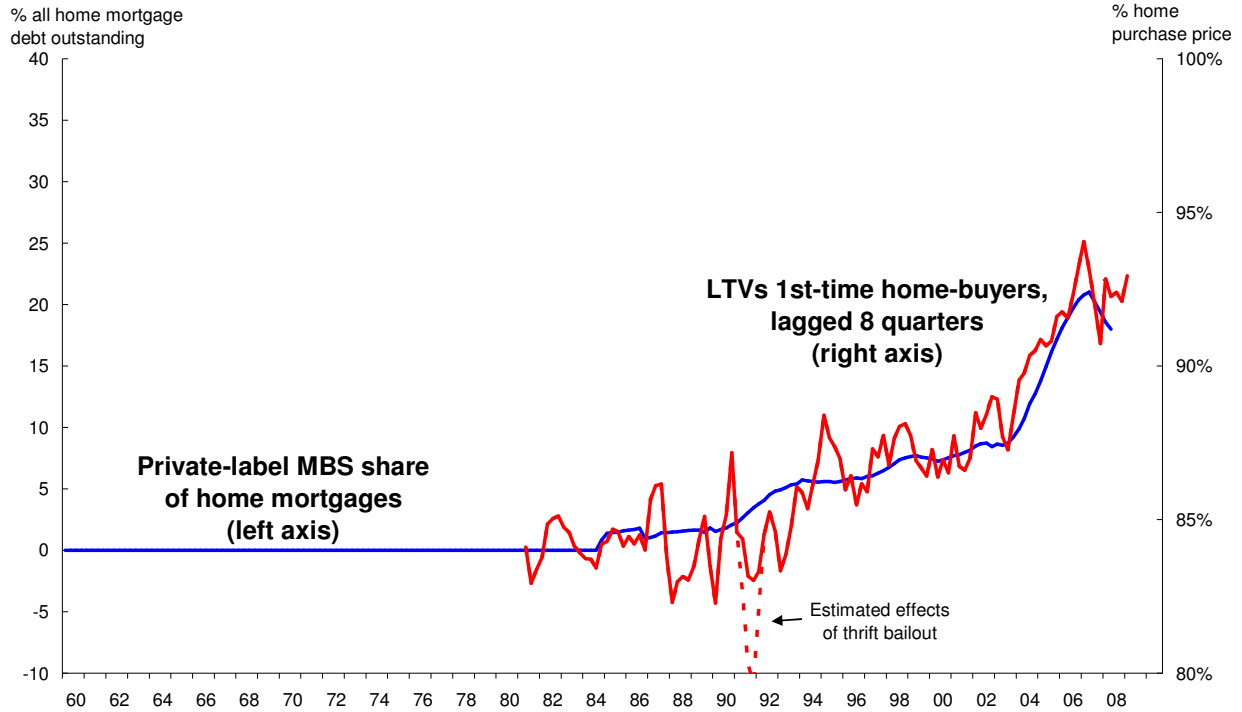
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The recent boom and bust in U.S. housing and mortgage markets has rekindled interest in modeling home prices and examining their links to changes in credit standards, the subject of this study. As Meen (2001), Muellbauer and Murphy (1997) and Cameron, Muellbauer and Murphy (2006) stress, inverting the effective demand for housing services implies that home prices are a function of credit constraints, as well as income, the housing stock, and real user capital costs. Kim (2007) shows theoretically that down-payment or loan-to-value (LTV) constraints also help determine home prices using the home price-to-rent approach to model home prices. Previous models of U.S. home prices have been hindered by a lack of consistent time series measures of the credit constraints affecting the marginal, first-time home-buyer and—at least at the regional level—of the housing stock. This shortcoming implies that estimates of U.S. home price and consumption models may suffer from omitted variable bias.

This study focuses on national home prices and addresses the lack of data on mortgage availability by using Duca and Johnson's (2008) new data on average LTV ratios over 1979-2007:H1 for first-time home-buyers, the marginal buyers most likely affected by down-payment constraints. Derived from the American Housing Survey, this LTV series implies that down-payment constraints were eased early this decade, in line with Doms and Krainer's (2007) finding that the largest rise in U.S. homeownership by age group occurred among the young. Consistent with views that the subprime boom reflected a weakening of credit standards, LTVs for the young are positively correlated with the share of mortgages outstanding that were securitized into private-label mortgage-backed securities (MBSs, Figure 1). MBSs issued by Fannie Mae and Freddie Mac were generally conforming loans, which met credit standards that were generally applied to most mortgages in earlier years. In contrast, the bulk of nonprime mortgages were financed by being packaged into "private label" MBSs because they did not

meet the credit standards typically used by Fannie Mae or Freddie Mac, or were too risky to be held by regulated depository institutions (Credit Suisse, 2007). Because our LTV series reflects loan originations, it leads the private MBS share of home mortgages by roughly 2 years.

Figure 1: Share of Mortgages Packaged into NonConforming Mortgage-Backed Securities



The rise in LTV ratios from 2000 to 2005 likely reflects the combination of two financial innovations: the adoption of credit scoring technology that enabled the sorting and pricing of nonprime mortgages and funding of such loans by selling them to investors in the form of collateralized debt obligations (CDOs) or with protection from credit default swaps (CDSs). The subsequent failure of CDOs to protect investors from unanticipated default losses and the soaring cost of using CDSs have induced a reversal of the earlier easing of credit standards. Abstracting from the 8-quarter lag, the peak in the LTV series occurs in 2005q2, with a modestly lower level seen through 2007:q2, just before subprime difficulties put financial markets into the crisis that

started in August 2007. Given widespread reports that lenders have tightened credit standards on new home mortgages, the LTV series will likely show a further and a greater decline, after we can update the series with the release of the 2009 AHS data base.

Including LTV data on first time home-buyers notably improves home price models by yielding stable long-run relationships, sensible and more precisely estimated income and user cost coefficients, reasonable speeds of adjustment, and better model fits. This is true even before the post-2001 subprime explosion raised LTVs and appears to reflect an earlier, more modest rise in LTV ratios enabling us to identify such an effect in pre-2002 samples. Before including LTV data in our models, we regressed them on variables to remove the estimated effects of cyclical and other variables, such as changes in the overall unemployment. In a related study, we find that adding data on LTVs and regional housing stocks qualitatively improves regional home price models, paralleling the UK regional results of Cameron, Muellbauer and Murphy (2006).

This study is organized as follows. The next section presents the estimation frameworks and the data. The third section reviews cointegration results using the inverted demand and house-price-to-rent approaches. Then it sheds evidence on more general, one-stage models of home prices where the specifications used are less constrained by the practical need to minimize the number of long-run variables to run cointegration tests. The fourth section builds off the estimation results to assess to what extent and why U.S. home prices are over-valued. The last section concludes with a discussion of the links between credit and asset market bubbles.

II. House Price Models and Data

(a) House Price Models Using the Inverted Demand Approach

Perhaps the simplest theory of what determines house prices is to treat supply—the stock of houses—as given in the short run, with prices driven by the inverted demand for housing services (h) that are proportional to the housing stock (hs).¹ Let log housing demand be given by

$$\log h = -\alpha \log hp + \beta \log y + z$$

where hp = real house price, y = real income and z = other demand shifters. The own price elasticity of demand is $-\alpha$ and the income elasticity is β . Solving yields

$$\log hp = (\beta \log y - \log h + z) / \alpha$$

Reasonable priors for the values of the key long run elasticities are the “central estimates” set out in Meen (2001) and Meen and Andrews (1998), *inter alia*. For example, many estimates of the income elasticity of demand suggest that β is in the region of 1, in which case the income and housing stock terms in above equation simplify to log income per house, i.e., $\log y - \log h$.

The demand shifters included in z cover a range of other drivers. Since housing is a durable good, inter-temporal considerations imply that expected or ‘permanent’ income and ‘user cost’ are important drivers. The user cost takes into account that durable goods deteriorate, but may appreciate in price and incur an interest cost of financing as well as tax. The usual approximation is that the real user cost is $uc = hp(r + \delta + t - hp^e / hp)$, where r is the real after-tax interest rate of borrowing, possibly adjusted for risk, δ is the depreciation rate, t is the property tax rate, and hp^e / hp is the expected real rate of capital appreciation.

Ex-post user costs can be negative if appreciation rates in house price booms exceed nominal user costs. An important issue is how to track expectations of house price appreciation. Many studies find that lagged rates of appreciation are good proxy, suggesting an extrapolative element in household expectations. Our real user cost measure (*RUSER*) uses the lagged annual

¹ Inverse demand functions have a long history, particularly in the analysis of markets for natural resources. Their

rate of appreciation in the US house price index over the prior 4 years. Given assumptions on transactions costs, $RUSER$ is always positive making $\log RUSER$ defined over the sample. The log transformation implies that at low values, variations in $RUSER$ have a more powerful effect than at high values, reflecting the idea that when appreciation is high relative to tax and interest costs, the market gets into a ‘frenzied’ state. Hendry (1984) and Muellbauer and Murphy (1997) capture similar effects using a cubic in the recent or fitted rate of appreciation. In results not shown, we found that models using $\log(RUSER)$ and models linear in $RUSER$ but which include a cubic in lagged appreciation, yield similar long run solutions and adjustment speeds.

Other factors could be relevant, given that many mortgage borrowers face limits on their borrowing and may be risk averse. These could include nominal as well as real interest rates, credit supply conditions, demography, and proxies for risk, particularly of mortgage default.

In the dynamics, lagged price adjustment is plausible, given the inefficiency of house prices.² The rate of change in the housing stock relative to the population, as well as the per capita stock, are also likely relevant in helping explain house price movements. One interpretation is through expectations: households observing much new construction might lower expectations of future appreciation. Another interpretation is in terms of prices adjusting both to stock and flow disequilibria, for which error or equilibrium correction models are well suited.

(b) Models Using the House Price-to-Rent Ratio Approach

Home prices have also been modeled using the house price-to-rent approach, particularly in the U.S., where regional measures of the housing stock are not readily available, rental markets are well-developed, and rents are generally market-determined, in contrast to the heavily

(1976) refers to a 1909 Danish study as the first empirical study of inverse demand functions.

² Hamilton and Schwab (1985), Case and Shiller (1989, 1990), Poterba (1991) and Meese and Wallace (1994) find that house price changes are positively correlated over time and past information on housing fundamentals can

regulated rental markets of the UK. This approach is more grounded in finance and assumes that, absent substantial frictions and credit restrictions, arbitrage between owner-occupied and rental housing markets implies the house rent-to-price ratio is a function of the real user cost of capital, defined as the nominal user cost of mortgage finance (*NOMUSER*) minus expected appreciation:

$$RENT/HP = NOMUSER - (\text{expected home price appreciation}) = RUSER,$$

where *NOMUSER* is tax-adjusted and can reflect tax effects on rents relative to home prices. As shown by Kim (2007), this result also obtains when agency costs make renting housing services more expensive than owning a home. Inverting and taking logs implies:

$$\log(HPRENT) = -\log(RUSER),$$

where the elasticity of the price-to-rent ratio equals -1 and the price-to-rent ratio is invariant to the housing stock and deviations of income from trend.

However, Kim (2007) has recently theoretically demonstrated in an equilibrium model that when rental agency costs are accompanied by binding, maximum LTV ratios on marginal home buyers, the equilibrium log price-to-rent ratio is more complicated:

$$\log(HPRENT) = f(\log(RUSER), \text{max LTV}, \text{income deviations}),$$

where income deviations equal actual minus permanent income, and the size of the negative real user cost elasticity can be smaller than 1 in line with empirical results (e.g., Gallin, 2006). We also test the price-to-rent approach using error or equilibrium correction models initially using log specifications (variables in logs are denoted with an “L” before their level names).

(c) Comparison of the Two Approaches

Theoretically, the price-to-rent approach is more grounded in finance and arbitrage, whereas the inverted demand approach is more grounded in consumer demand theory.

forecast future excess returns. Hamilton and Schwab (1985), Capozza and Seguin (1996), and Clayton (1997), find significant evidence against the hypothesis of rational home price expectations.

Empirically, the relative advantages of the price-rent approach are that this framework is applicable where rental markets are flexible (e.g., U.S.), does not require housing stock data, and uses rents which may reflect many factors special to housing that are not controlled for by variables in the canonical inverted-demand approach. Conversely, the inverted demand approach has relative advantages in being practical for countries where rental markets are regulated; not ignoring that income shocks can drive rents and home prices; and being helpful in tracking home prices in markets where both rents and home prices might be equally over- or under-valued. It is a priori unclear which is the better approach for the U.S. and for robustness, we test whether to include LTV data on first-time homebuyers using both approaches.

(d) Data

The variables used fall into the following categories: home prices and rents, real user cost, household income, housing stock, mortgage credit standards, capital gains and depreciation taxes, monetary/regulatory, and household expectation variables. So far, shifts in demographics variables were not found to be statistically or economically significant in regressions not shown, perhaps reflecting a number of breaks in the population data stemming from diennial censuses. We plan to further investigate adding demographic effects in subsequent versions of this paper.

Home Prices and Rents

We use Freddie Mac data on nominal home prices from repeat sales of homes and omit prices from mortgage refinancings, which are distorted by appraisers' incentives to inflate prices. We seasonally adjusted these data and then deflated them using the personal consumption expenditures (PCE) deflator to measure real home prices (*HP*). To construct the house price-to-rent ratio (*HPRENT*), we deflated nominal home prices with the PCE index for renting fixed dwellings, which closely parallels the owner-equivalent rent series from 1983-present.

Real User Cost of Mortgage Capital

The real user cost of capital (*RUSER*) is the after-tax sum of the effective conventional mortgage interest rate (*NOMRMORT*) and the property tax rate from the Federal Reserve Board (FRB) model plus the FRB depreciation rate for housing minus the annualized growth rate of home prices over the four prior years adjusted for an assumed 8 percent cost of selling a home. This resulting real rate exceeds zero throughout the sample, allowing real user costs to enter in logs, an appealing aspect stressed by Meen (2001). Some models split the user cost term into separate nominal user cost (*NOMUSER*) and appreciation (*APP*) terms to assess the period over which appreciation is defined and issues related to speculation.

Household Income

As in the FRB-US model, per capita income (*Y*) equals the tax adjusted sum of labor and transfer income, deflated by the overall personal consumption expenditures (PCE) deflator. Non-property income is used because it accords with standard consumer theory and avoids simultaneity bias by omitting property income, which includes rents that reflect property values.

Housing Stock

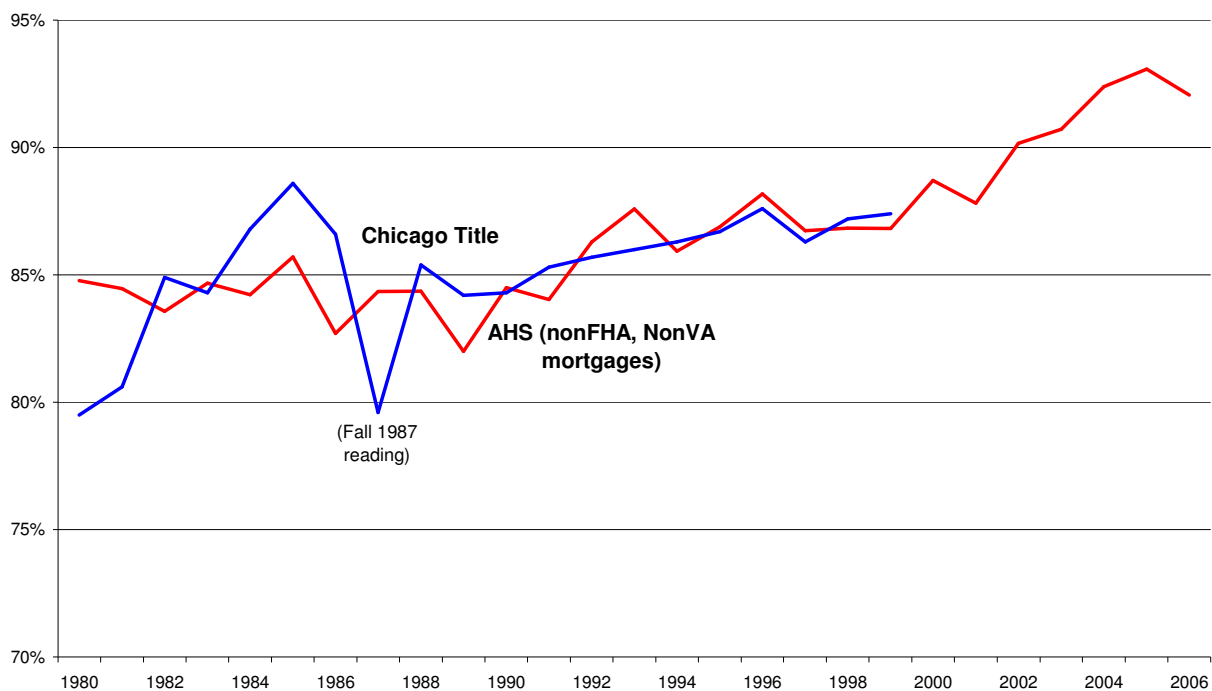
For the inverted demand approach, we tracked the real, per capita housing stock (*HSTOCK*) using Federal Reserve estimates of the replacement cost of residential housing structures owned by households deflated by the price index for housing construction.

Mortgage Credit Standards

Changes in mortgage credit standards are tracked by the average loan-to-value (*LTV*) ratio for homes bought by first-time home buyers (Duca, Johnson, and Muellbauer, 2008). This series is constructed using data from the American Housing Surveys since 1979, and is a consistent measure of LTV ratios on conventional mortgages, which corresponds to the Freddie

Mac home price series that is based on homes bought with conforming conventional mortgages. This LTV series shifted up slightly, from fluctuating in a range around 85% in the late 1970s and the 1980s to a range around 87 percent in the 1990s (Figure 1). Then LTVs jump sharply after 2002. Although a discontinued series from the Chicago Trust and Title company is less representative, it is reassuring that the series moved in a similar range before 2000 (Figure 2).³

Figure 2: Average First Time Homebuyer LTV Ratios, Chicago Title vs. AHS



We adjust raw quarterly AHS data for two reasons. First, we adjust the raw quarterly data for shifts in average age, seasonality, some unusually small quarterly samples, and regional composition that introduce noise and debt demand factors from which we wish to abstract. Second, we examined whether LTVs were endogenous to several macroeconomic variables over 1979-2007, finding no significant link with income and interest rates, but a statistical link with

³ Other disadvantages are that the Chicago Title data are not broken out by age and are from one month per year, November. Thus the 1987 survey, following the October 1987 stock crash seems unrepresentative.

changes in the overall unemployment rate (U). To estimate these effects, Duca, Johnson, and Muellbauer also regressed the raw, simple mean average LTV ratio on the above variables in the presence of the Hodrik-Prescott filtered LTV ($LTVHP$) to control for LTV trends and controlling for two unusual episodes which would otherwise distort estimates of other coefficients. The latter were the quarter following the September 11, 2001 terrorist attacks ($SEPT11$), which apparently induced a temporary plunge, and a dummy equal to one during the quarter of and following the passage of thrift bailout legislation in 1989:q3, which temporarily disrupted lending as savings and loan institutions were initially seized before being later closed ($FIRREA$).

$$\begin{aligned}
 LTV(\text{raw}) = & 0.082622 - .017889*\Delta U + 0.002296*AGE + 0.074932*WEST - 0.061997*SEPT11 \\
 & (1.37) \quad (-3.02) \quad (-2.44) \quad (2.67) \quad (-6.20) \\
 & + 0.977258*LTVHP - 0.047266*FIRREA + 0.082512*\Delta LTV_{t-1} \\
 & (15.66) \quad (-3.70) \quad (1.42)
 \end{aligned}$$

where t-statistics are in parentheses, $R^2 = 0.866$, standard error = 01145, $LM(2) = 1.64$, and the estimation was done in the presence of quarterly seasonal dummies and dummy variables for quarters with less than 20 observations. $WEST$ is the western share of first-time buyers in a quarter, which was the only regional share variable that was close to being statistically significant. The positive coefficient on $WEST$ plausibly reflects the impact of higher home prices in that region on preferences with respect to LTV ratios and the tendency for faster home price appreciation in that region, which may make lenders feel comfortable with smaller down-payment cushions. The positive coefficient on age plausibly reflects that older households have somewhat more wealth, and would either be able to or would prefer to borrow at a lower LTV.

The adjusted series equals the raw series minus all of the above effects except that of the lagged dependent variable, $FIRREA$, and the H-P filtered LTV. To keep the adjusted LTV near its equilibrium, $(1 - \text{coefficient on } LTVHP)*LTVHP$ was also deducted from the raw series. We

then took a three-quarter, weighted average moving average of the resulting series using quarters t through $t-2$, where weights are the relative share of observations in each of the three quarters. This smoothes the series, with the observation weights treating individual borrowers equally.

There are several reasons to interpret the rise in the resulting LTV ratio (“LTV”) as being largely exogenous to income, interest rates, or home prices. First, much of the recent run-up in LTV ratios coincides with a surge of subprime and Alternative A mortgages, from 9 percent of mortgage originations in 2001 to 40 percent by 2005, a jump linked to the increased adoption of new financial technology and a change of practices by rating agencies. In particular, improvements in credit scoring technology used earlier in subprime auto lending were adapted to mortgage lending. In addition, the increased use of derivatives and collateralized debt obligations allowed subprime mortgages to be more easily securitized by enabling investors to purchase instruments whose risk characteristics *appeared* closer to their preferences. Second, this decade has seen an increased adoption of new mortgage instruments, such as interest-only and low/no documentation mortgages, and the greater use of multiple mortgages by buyers, which rose from 5 percent of recent movers in the mid-1990s to 10% by 2000 to 25% in 2005 (American Housing Survey, see Duca 2006, p. 7). Indeed, the rise of LTV ratios for first-time buyers owes mainly to the greater use of multiple mortgages than to bigger primary mortgages. We tested the robustness of results to the inclusion of short-run or exogenous variables that control for changes in taxes, monetary/regulatory policy, and household expectations.

Capital Gains and Depreciation Taxes

The impact of federal income taxes is largely taken into account in the user cost of capital variable. Nevertheless, two changes in capital gains taxes had notable effects on home prices, as did changes in tax depreciation for rental housing (which may affect market rents) on the ratio of

home prices to rents. Before 1998, realized, net capital gains on the sale of homes were subject to taxation for households under age 55 if the seller did not purchase a home of equal or greater value. The Tax Reform Act of 1997 largely eliminated this tax by exempting the first \$500,000 of gains for married couples (\$250,000 for single filers), thereby raising the after-tax value of housing and encouraging turnover (Cunningham and Englehardt, 2007). To control for any such effects, we included a dummy (*CAPGAIN*TAX) equal to 1 since 1998:q1 and 0 before then. Another tax term is the time over which rental properties can be depreciated for taxes (*TAXDEP*), which changed much before 1987 (Poterba, 1990), with longer depreciation periods raising the after-tax cost of renting and depressing the price-to-rent ratio.

Monetary/Regulatory Variables

One monetary/regulatory variable is a dummy (*MONEYTARGET*) equal to 1 over the money targeting regime of 1979:q4-1982:q4, which may have reduced the supply or demand for mortgages by raising interest rate uncertainty. Another is Duca's (1996) measure of how much Reg Q ceilings on deposit interest rates were binding (*REGQ*), which was included to control for unusual, negative short-run disintermediation effects that are not always consistently reflected in interest rate or real user cost of capital variables (see Duca and Wu, forthcoming).

Household Expectation Variables

Expectations of employment and household assessments about whether economic conditions are good for buying homes could have short-run effects on or marginal information about home prices that may not be captured by income, mortgage rates or the non-price terms of housing finance. From the Conference Board survey of consumer confidence, we include the log of an index equaling 100 plus the percent of households who expect more minus fewer jobs over the next six months, (*LCONFLABOR*). We also include the percent of households

(*BUYPROSPER*) who thought it was a good time to buy a home because, “times were good and there was prosperity.” This variable may control for housing demand shocks not picked up by other interest rate, income, house price or credit availability variables.

III. Long-Run and Short-Run Results from Cointegration Models

We first present findings using cointegration methods given the nonstationarity of long-run variables, starting with specifications based on the inverted-demand approach and then the price-to-rent approach. In the following section, we relax some of the cointegration restrictions and employ simpler one-stage OLS models containing lagged levels and first differences of housing variables. One commonality in both sections is that our models control for tax effects beyond including simple income and property tax rates in calculating the user cost of mortgage capital, as well as the monetary policy targeting regime of 1979-1982 which imparted more interest rate risk to house prices beyond that simply reflected in simple user cost of capital variables. By addressing these important influences, we try to avoid omitted variable bias that can obscure long-term, qualitative relationships and lead to poorly estimated coefficients.

(a) Results Based on the Inverted Demand Approach

As we saw in Section 2, the long run solution for log real house prices is

$$\log hp = (\beta \log y - \log h + z) / \alpha .$$

In our model, the only long-run demand shifters in z are log real user cost, log LTV and step dummies representing shifts in tax rates and in monetary policy.

Long-Run Results

This long-run solution implied by theory involves the variables in the unique, estimated cointegrating vectors in Table 1. Results are from models with and without the LTV measure of credit supply conditions. The first two vectors shown are for models 1 and 4 which only include the monetary targeting regime variable as an additional exogenous variable and are estimated over a full common sample 1981:q3-2007:q2. This sample reflects the number of lags of first difference variables needed to obtain a unique and significant cointegrating vector and which minimized the AIC statistic under time series assumptions allowing for possible time trends in the endogenous variables but not a time trend in the cointegrating vector. The second set of two vectors from models 3 and 6 also include the four extra tax and expectations variables, and are estimated over a full common sample 1980:q3-2007:q2. The earlier sample start date reflects that four fewer lags on the first difference terms are needed to obtain unique and significant cointegrating vectors. The third set of vectors also include the same set of exogenous variables, but have a common end date of 2001:q4, which ends just before LTV ratios jumped during the subprime boom that started in 2002. The common start date is one quarter latter than the full sample set owing to the need to include one more lag to obtain significant cointegrating vectors.

For both the nonLTV and LTV models, unique cointegrating vectors are obtained with the expected signs. However, the LTV models yield better results in several respects. First, the vectors obtained have a higher degree of statistical significance for the full sample LTV models (99% confidence level) than for the full sample nonLTV models. Second, in the simplest vectors that only include the monetary targeting variable as an extra term, the log housing stock is not statistically significant in the nonLTV model. Third, in terms of interpreting the estimated coefficients, the inclusion of the LTV measure results in more plausible values particularly for

the full sample: the coefficient on log housing stock is interpretable as the inverse of the long run price elasticity of demand, which ranges between -1.3 and -1.0 for the LTV models, depending on the other variables included, whereas they lie in a less plausible range from -3.79 to -1.52 for the nonLTV models. Furthermore, the ratio of coefficients on log income and log housing stock estimates the long run income elasticity of demand, which reasonably ranges between 1.33 and 1.69 for the LTV models, versus an implausible range of 2.19 to 3.08 in the nonLTV models. Finally, comparing the models including a full set of short-run variables, the LTV models have coefficients that are very similar in the pre-subprime boom and full samples. Overall, the inclusion of the LTV ratio yields more plausible long-run elasticities and relationships.

Short-Run Results

Table 2 reports results from ECM models of the first difference in real home prices, where the error-correction terms equal the gap between actual and equilibrium house prices, where the latter are based on correspondingly numbered vectors in Table 1. In several ways the LTV models outperform corresponding nonLTV models. First, LTV models yield corrected R squares that are .05 to .21 higher than from corresponding nonLTV models. Second, unlike the nonLTV models, the speeds of adjustment for LTV models are around 20 percent per quarter, whereas there is no evidence of statistically significant error-correction in nonLTV model 1. Perhaps more relevantly, for full sample models including all the expectations and tax variables, the speed of error-correction is a higher 17 percent in model 6 versus 13 percent in model 3.

In Table 2, the coefficients on lagged changes in the log per capita housing stocks tend to be negative, as expected and in line with UK results (Cameron et al., 2006). The income dynamics are consistent with a moving average of income. The dynamics in log real user cost

also suggest a moving average. Short run dynamics in lagged house price changes suggest a positive short term momentum effect, aside from that embedded in the real user cost term.

We checked the robustness of these results in one-step estimation with alternative lag lengths, confirming the long-run solutions and estimated adjustment speeds. Furthermore, results are generally unaffected by breaking the log real user cost into its two main elements, the tax adjusted interest rate and the annualized rate of home price appreciation over the prior four years. One exception is when we added a new non-linear term, the cubic of home price appreciation over the last four quarters. Without this extra term, the estimated speed of adjustment drops and the residuals suffer from serial autocorrelation. These results are available on request.

Exogeneity

A natural question is whether the LTV series is driven by house prices, which would greatly complicate the interpretation of the above findings. In a vector-error correction system using the lag length of model 6 in Tables 1 and 2, the error correction term is highly insignificant (t statistic of 0.54) in modeling the LTV ratio, indicating that the LTV ratio is weakly exogenous to the other variables, as is the case for the real user cost (t-statistic of 0.02) and income (t-statistic of -0.27). In contrast, house prices are not weakly exogenous (t-statistic of -6.26 on the EC term), as is the case for the stock of housing (t-statistic of -4.64). These results point to an asymmetry to how the vector components adjust to disequilibria, with house prices and the housing stock making the significant adjustments. Thus, consistent with theory, equilibrium house prices and the housing stock are driven by income, user costs, and credit availability.

(b) Results Using the Home Price-to-Rent Ratio Approach

For robustness, we assess the importance of mortgage availability using a home price-to-rent approach. In this approach, exogenous increases in mortgage availability, that are unrelated

to income and interest rate movements, alter the relative demand for owner-occupied versus rental housing by increasing the effective demand for owner-occupied housing of the credit constrained and lowering their effective demand for rental housing.⁴ Such a relative demand shift can alter the equilibrium price-to-rent ratio by affecting the land intensity of housing since the supply of land is not as price elastic as is the cost of building structures (Davis and Heathcote, 2005). Home price-to-rent models generally estimate a long-run relationship between mortgage interest rates and a price-to-rent ratio, and often find that U.S. home prices are over-valued. Exceptions to the latter are regional or city models that either (1) use unusually low user cost of capital rates arising from assumptions that unusually high rates of past local price appreciation will persist (e.g., Himmelberg, Mayer, and Sinai, 2006) or (2) argue that rental rates are higher in high cost locales than implied by official rent data (Smith and Smith, 2006). Following convention, we use standard measures of rents and use national price appreciation rates to construct real user cost of capital measures. We depart from published models by including our cyclically adjusted measure of LTV ratios for first-time home buyers. We add this variable to cointegrating vectors containing the home price-to-rent ratio (HPRENT) and user cost of mortgage and compare long-run and short-run results to models that omitting LTV ratios.

Long-Run Results

Table 3 reports cointegrating vectors of national price-to-rent ratios estimated over the long-run sample (data from 1979-2007) under assumptions allowing for deterministic trends in the long-run variables, but not in the cointegrating vector. As before, the lag lengths were long enough to yield statistically significant unique vectors and minimize the AIC statistic for the LTV models. For the nonLTV models, this was also done when possible, and when not, the vector minimizing the AIC statistic was selected. The first two vectors (numbered 1 and 4)

⁴ Higher LTV ratios in the early 2000's coincided with a jump in subprime mortgages and the homeownership rate.

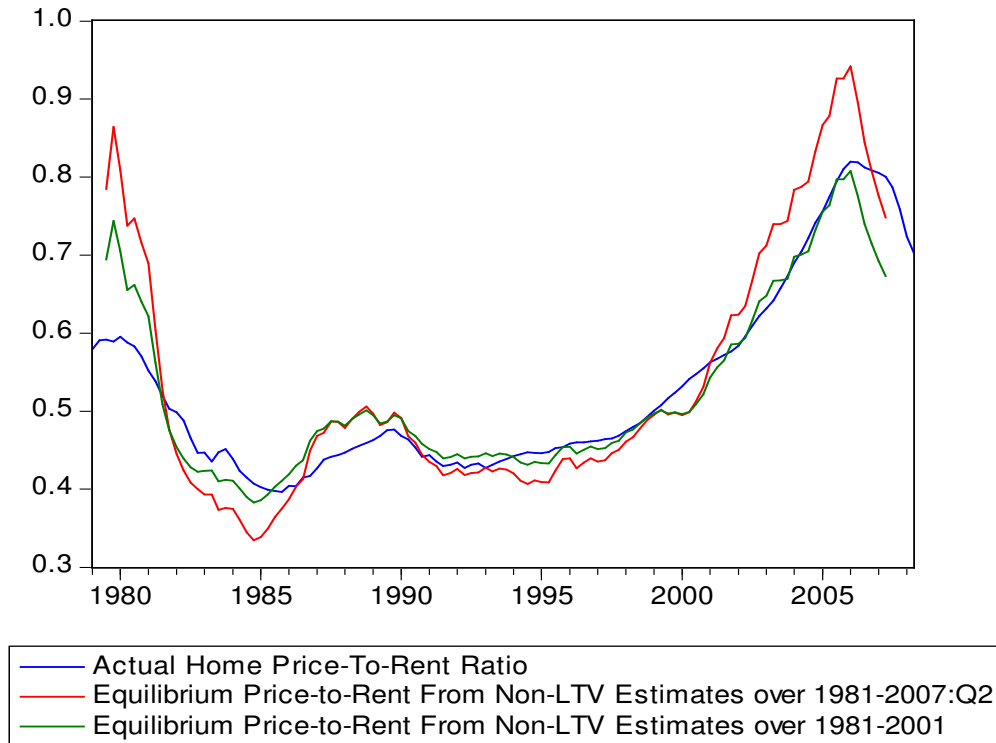
include the monetary targeting dummy, and respectively omit and include the LTV ratio. The third and fourth vectors (numbers 3 and 6) also include terms for the other tax effects, job expectations, and whether prosperity made it good time to buy a home. The fifth and sixth vectors also use these variables, but in a shorter sample ending in 2001:4 prior to the subprime boom starting in 2002.

As implied by trace and maximal eigenvalues, unique cointegrating vectors were found in each of the LTV vectors, with either mixed or less strong evidence of cointegration in models omitting the LTV ratio. In addition, in vector error correction models, the error-correction term was significant in the price-to-rent equation and was insignificant in the income and user cost models. As in the inverted demand models, these two findings are consistent with the view that LTV ratios are largely exogenous drivers of home prices. Consistent with priors, the estimated long-run coefficients in all the vectors indicated that home prices are negatively and significantly related to real user cost of capital, and are positively and significantly related to the LTV ratio.

The LTV models also show less parameter instability when the sample is extended from 2001:q4 to 2007:q2, where the former quarter precedes the large jump in LTV ratios over 2002-05. In non-LTV models, the long-run coefficient on real user costs rises notably as the end of sample is extended from 2001 to 2007. Indeed, the equilibrium price to rent ratios implied by the full non-LTV model (vector 3) differ notably using model estimates through 2001 instead of through 2007, with a tendency for the earlier period coefficients to under-predict home prices in the mid-2000s (Figure 3).⁵ In contrast to the parameter instability for models omitting LTVs, models inclusive of LTVs exhibit parameter stability given the large rise in the both the LTV and price-to-rent ratio in recent years. The equilibrium price-to-rent ratios implied by the full LTV

⁵ Note that equilibrium is defined using the current value of real log user cost, reflecting the annual rate of lagged house price appreciation. A plausible alternative is to use historical average appreciation, as discussed in Section IV.

Figure 3: Implied Equilibrium Home Price-To-Rent Ratios Differ for Models
Omitting LTV Ratios Estimated with and Without 2002-2007



model (vector 6) do not differ much using parameters estimated through 2001 rather than through 2007:q2 (Figure 4). A plausible interpretation of this result, as well as the tendency for the real mortgage rate coefficients to rise in the non-LTV models, is that non LTV models omit important information and that the rise in LTV ratios is an important driver, along with low real interest rates, of the large increases in U.S. home prices over the period 2002-2005.

Short-Run Results

An easing of mortgage credit standards also has large short-run effects on home prices, as shown in Table 4 which reports the error-correction model results for the change in the home price-to-rent ratio which use the long-run equilibrium relationships corresponding to vectors in

Figure 4: Implied Equilibrium Home Price-To-Rent Ratios Similar for LTV Models Estimated with and Without 2002-2007

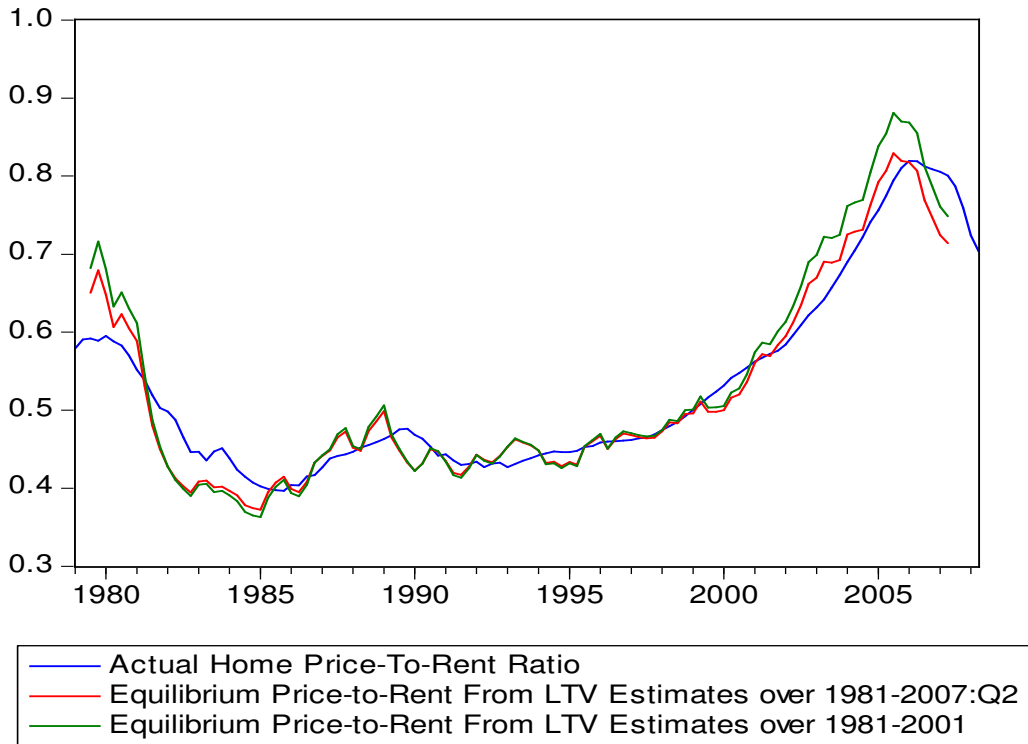


Table 3. In each LTV model, the error-correction term is very significant with plausible speeds of error-correction of 9-19 percent per quarter. By contrast, the error-correction speeds of the noncredit models range between 2 and 8 percent, reflecting the lower ability of nonLTV models to track long-run relationships. This is particularly the case in the full sample models that include all the tax, monetary policy, and expectations variables, where the speed of error-correction is 19 percent in the LTV model versus only 8 percent in the nonLTV model. Comparing conventional with credit models that contain the same short-run exogenous variables indicates that including the LTV ratio and its lagged first-difference improves the R-squares of corresponding models by 4-10 percentage points and lowers standard errors by 5-14 percent. Estimates suggest some short term persistence in the dynamics, in that last quarter's change in

the log house price to rent ratio has a significantly positive effect on the current log price to rent ratio, though lagged house price appreciation over a longer period is incorporated in log RUSER.

Overall, the LTV models outperform their nonLTV counterparts in yielding stronger and more stable long-term home price-to-rent relationships. Furthermore, with respect to explaining short-run changes in the price-to-rent ratio, LTV models yielded better model fits, faster speeds of adjustment, better behaved residuals, and more significant estimated effects from tax changes regarding capital gains and the depreciation of rental properties. In short, the nonLTV models appear to suffer from symptoms of omitted variable bias, consistent with the view that an easing of mortgage credit standards significantly helped fuel the home price boom of the mid-2000s. Consistent with this interpretation, in a vector-error correction system using the lag length of model 6 in Tables 4 and 5, the error correction term is highly insignificant (t statistic of 0.42) in modeling the LTV ratio and the real user cost (t-statistic of -0.61), indicating that the LTV and real user cost variable are weakly exogenous to other variables. In contrast, the house price-to-rent ratio is not weakly exogenous (t-statistic of -4.60 on the EC term).

(c) Results Using One-Step Models

Using the inverted demand approach, we performed robustness checks on these models with similarly satisfying results: one-step estimates and the alternative specification of a non-linearity in the dynamics give similar long-run solutions and estimated speeds of adjustment. In particular, one-step estimation results for samples through 2007 using the inverted demand approach show that, relative to corresponding nonLTV models, LTV models have better fits, have faster speeds of adjustment over the full sample, imply long-run price elasticities of the housing stock that are near unity, and generally have more plausible income elasticities as well. (Compare models 1 vs. 4, and models 3 vs. 6 in Table 5).

We also examined whether the qualitative results from the house price-to-rent approach were similar in one-step estimation models and in alternative specifications allowing for nonlinearity in the dynamics. Using one-step models, we needed to include lags of the first difference of the Regulation Q, disintermediation variable to obtain residuals that were not serially correlated. Results show that, relative to corresponding nonLTV models, LTV models have better fits (.02 to .04 higher corrected R²'s) and faster speeds of adjustment reflecting the statistical significance of the LTV ratio. And in contrast to the LTV models, the lagged log-level of the price-to-rent and the real user cost term are not always significant in the nonLTV models.

IV. How Much Are U.S. Home Prices Overvalued?

To throw light on how much U.S. home prices may be overvalued, we now examine the implications of the two home price models incorporating LTV terms for the deviations of prices from their 'equilibrium' or 'long-run' values. As noted in section III there is more than one concept of equilibrium. The narrow concept is conditional on the observed log real user cost as used in our econometric models. Consider model 6 (Tables 3 and 4) for the home price-to-rent approach as an example. The long run solution is $LHPRENT = 0.9 - 0.17*LRUSER + 0.81*LLTV +$ fitted effects of persistent terms or step dummies for tax variables and the 1979-82 monetary policy regime. Then, conditional on LRUSER, the deviation from equilibrium is:

$LHPRENT - 0.9 + 0.17 LRUSER - 0.88 \log LTV -$ fitted step function dummies, which reflects I(0) variables (e.g., lagged changes in LHPRENT, residuals, and other variables).

Using this metric, U.S. home prices were over-valued by 9% using LTV model 6 versus 5% using nonLTV model 3. Similar deviations between actual and equilibrium log real home prices can be computed from inverted demand models, such as models 3 and 6 from Tables 1 and 2, which suggest 15 and 13 percent overvaluations at in 2007:q2, respectively.

However, these calculations suffer from a shortcoming: RUSER contains the average annual percentage change in (nominal) house prices over the previous 16 quarters. This cannot be regarded as permanent and clearly it is part of the 'bubble builder' represented in the model's dynamics, as discussed by Abraham and Hendershott (1996). We address this issue, as well as alternative assumptions about post-2007:q2 values of LTV. Then we calculate various measures of the extent to which U.S. home prices are over-valued and how much of the over-valuation may be directly attributable to unsustainable credit practices and how much to home price appreciation effects (which include indirect effects of credit conditions on home price expectations).

(a) Whither Credit Conditions?

American Housing Survey data are currently available up through the 2007 biennial survey, which limited our estimation samples to end in 2007:q2. This subsection examines alternative credit tightening scenarios to forecast home prices through 2008:q3.

MORE RESULTS ARE FORTHCOMING

V. Conclusion

Our findings provide a theoretically appealing and empirically consistent account of the behavior of U.S. home prices. Changes in credit standards affecting first-time home-buyers can be an important determinant of home prices in the two main theoretical approaches to modeling home prices - the inverted demand and home price-to-rent approaches. Our results indicate that a substantial easing of U.S. mortgage standards, as reflected in the LTV ratios for first-time home-buyers, led to a rise in the effective demand for housing in the first half of the decade. Between early 2005 and mid-2007, there was a partial reversal of that easing, which has likely intensified

with the beginnings of the mortgage-related turmoil showing up in August 2007 and the more severe market turmoil during the Fall of 2008.

Most empirical models of US home prices do not include a measure of mortgage credit conditions and thus suffer from a meaningful omitted variable bias, rendering them less capable of tracking the earlier surge of home prices during the mortgage boom and the unwinding of much of that appreciation during the early phases of the subprime bust. In contrast, models including a cyclically adjusted LTV measure for first time home-buyers yield sensible and statistically significant long-run relationships, and in models of short-run movements in home prices, more precise estimates of key coefficients, reasonable speeds of adjustment, and better model fits. Furthermore, our credit-augmented models imply that much of the boom-bust cycle in U.S. home prices largely stemmed from an easing and subsequent tightening in U.S. mortgage standards affecting potential marginal home-buyers. From a broader perspective, our results are consistent with the view that many asset bubbles are linked to an unsustainable easing of credit standards or adoption of risky financial practices that eventually unwind during a subsequent bust.

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Table 1: Cointegration Results for Home Prices, Inverted Demand Approach, 1980-2007:q2

Model #	Sign. & Vec. Vectors	Cointegrating Equilibrium Relationship (assumption: no trend in vector or in variables)				Log Likelihood (AIC)	Eigenvalue (Trace Statistic, Max-Eigen Statistic)	
							0 vectors	1 vector
<i>Sample: 1981q3-2007q2 (only monetary policy regime variable added)</i>								
1	1	LHP = 3.386880+0.814500LY*-.217862LRUSER**-.263814LHS				1683.836	0.199863	0.121000
		(2.61)	(-17.05)	(-1.06)	(-28.36066)	(48.79386*)	(24.26688)	
						(24.52698*)	(14.18671)	
4	1	LHP = 4.265519+1.319210LY**-.175825RUSER**-.0755788LHS**+0.990389LLTV**				2019.415	0.412926	0.199804
		(7.58)	(-25.56)	(-5.31)	(6.03)	(-35.18106)	(98.19839**)	(41.2926)
						(55.39081**)	(23.18140)	
<i>Sample: 1980q3-2007q2 (all tax, monetary policy, and expectations variables present)</i>								
3	1	LHP = 3.505681+1.442648LY**-.200143LRUSER**-.658091LHS**				1655.966	0.230940	0.130620
		(4.97)	(-15.36)	(-2.74)	(-28.96233)	(49.55113*)	(21.19176)	
						(28.35937*)	(15.11730)	
6	1	LHP = 4.064860+1.473664LY**-.159792LRUSER**-.842816LHS**+.872428LLTV**				2007.293	0.425066	0.208021
		(5.45)	(-13.75)	(-3.55)	(3.91)	(-35.50542)	(101.9708**)	(42.19284)
						(59.77798**)	(25.18777)	
<i>Sample: 1980q4-2001q4 (all tax, monetary policy, and expectations variables present)</i>								
2	1	LHP = 3.733716+1.207294LY**-.148087LRUSER**-.556711LHS**				1349.631	0.411492	0.123657
		(6.65)	(-11.46)	(-3.65)	(-29.96778)	(65.26009**)	(20.19602)	
						(45.06407**)	(14.09674)	
5	1	LHP = 4.114899+1.602328LY**-.146580LRUSER**-.0995839LHS**+0.544678LLTV**				1654.002	0.533787	0.179171
		(7.60)	(-10.81)	(-5.29)	(3.16)	(-36.21181)	(100.5803**)	(35.71566)
						(64.86466**)	(16.78249)	

	<i>Level (AIC lag in parentheses)</i>	<i>5% Critical level for lag</i>	<i>1% Critical level for lag</i>	<i>First Diff. SIC lag in parentheses)</i>	<i>5% Critical level for lag</i>	<i>1% Critical level for lag</i>	<i>Assumptions</i>
ln(HP)	-1.868602 (4)	-3.449716	-4.040532	-3.741875* (7)	-3.449716	-4.040532	constant/trend
ln(RUSER)	-2.389194 (2)	-3.449716	-4.040532	-4.124070** (1)	-3.449716	-4.040532	constant/trend
ln(LTV)	-2.060300 (3)	-3.451959	-4.045236	-10.78284** (3)	-3.451959	-4.045236	constant/trend
ln(Y)	-2.292525 (1)	-3.449716	-4.040532	-13.50677** (0)	-3.449716	-4.040532	constant/trend

Notes. (**) denotes significant at the 95% (99%) level. t-statistics in parentheses except when AIC statistic is reported. For vectors numbered 1-6, lag lengths of (7, 4, 5, 7, 3, and 3), respectively, minimized the AIC and yielded significant and unique vectors allowing time trends in the variables. Lag lengths in the ADF unit root tests based on the Schwartz Information Criterion. Data used span 1979-2007:2.

Table 2: 2nd-Stage ECMs of the Percent Change in Real U.S. Home Prices

Variable	<i>No LTV Terms</i>			<i>LTV Terms</i>		
	81:3-07:2 <u>Model 1</u>	80:4-01:4 <u>Model 2</u>	80:3-07:2 <u>Model 3</u>	81:3-07:2 <u>Model 4</u>	80:4-01:4 <u>Model 5</u>	80:3-07:2 <u>Model 6</u>
Constant	0.0037 ⁺ (1.73)	0.0242 (0.61)	0.0174 (0.44)	0.0084 ^{**} (2.61)	0.0074 (0.19)	-0.0195 (-0.57)
ECM _{t-1}	0.0197 (-0.78)	-0.2144 ^{**} (-3.85)	-0.1291 ^{**} (-2.62)	-0.2162 ^{**} (-4.83)	-0.2054 ^{**} (-4.56)	-0.1740 ^{**} (-6.25)
MONEYTARGET _{t-1}	-0.0051 (-1.16)	-0.0148 ^{**} (-2.62)	-0.0133 ^{**} (-2.36)	-0.0223 ^{**} (-4.19)	-0.0194 ^{**} (-3.60)	-0.0203 ^{**} (-5.73)
CAPGAIN _t		0.0068 ^{**} (3.21)	0.0015 (0.56)		0.0068 ^{**} (3.41)	0.0046 ^{**} (2.82)
TAXDEP _t		-0.0007 ^{**} (-4.28)	-0.0007 ^{**} (-3.53)		-0.0004 ^{**} (-2.65)	-0.0005 ^{**} (-3.94)
BUYPROSPER _t		0.0008 ^{**} (3.22)	0.0006 ^{**} (2.81)		0.0008 ^{**} (3.79)	0.0002 (1.50)
LCONFLABOR _t		0.0045 (0.05)	0.0018 (0.21)		0.0028 (0.34)	0.0089 (1.19)
ΔLHP _{t-1}	0.5330 ^{**} (5.09)	0.4835 ^{**} (4.57)	0.5129 ^{**} (4.41)	0.5117 ^{**} (4.89)	0.4533 ^{**} (4.47)	0.3868 ^{**} (4.37)
ΔLHP _{t-2}	-0.0675 (-0.57)	0.0425 (0.27)	-0.0918 (-0.67)	0.2400 ⁺ (1.87)	0.0741 (0.50)	0.0983 (0.92)
ΔLHP _{t-3}	0.3574 ^{**} (3.11)	0.5073 ^{**} (3.85)	0.5089 ^{**} (3.87)	0.4927 ^{**} (4.17)	0.5249 ^{**} (4.25)	0.6327 ^{**} (6.17)
ΔLHP _{t-4}		-0.1441 (-1.09)	-0.2446 ⁺ (-1.97)	-0.1271 (-1.09)	-0.0953 (-0.76)	
ΔLRUSER _{t-1}	-0.0022 (-0.19)	0.0199 (1.23)	0.0157 (1.09)	0.0345 ^{**} (3.04)	0.0271 ⁺ (1.79)	0.0259 [*] (2.61)
ΔLRUSER _{t-2}	-0.0016 (-0.12)	0.0118 (0.74)	0.0112 (0.87)	0.0180 (1.37)	0.0195 (1.28)	0.0268 ^{**} (2.83)
ΔLRUSER _{t-3}	0.0013 (0.11)	-0.0081 (-0.55)	-0.0040 (-0.37)	0.0245 [*] (2.21)	-0.0010 (-0.01)	0.0097 (1.30)
ΔLRUSER _{t-4}		-0.0115 (-1.08)	-0.0072 (-0.67)	0.0066 (0.57)	-0.0094 (-0.95)	
ΔLY _{t-1}	-0.0583 (-0.75)	-0.2966 ^{**} (-2.92)	-0.2210 ^{**} (-2.64)	-0.1150 (-1.59)	-0.3231 ^{**} (-3.40)	-0.2620 ^{**} (-3.95)

ΔLY_{t-2}	0.0289 (0.35)	-0.2783 ^{**} (-2.67)	-0.1300 (-1.53)	0.0052 (0.08)	-0.2782 ^{**} (-2.90)	-0.1836 [*] (-2.60)
ΔLY_{t-3}	0.0355 (0.08)	-0.1540 ⁺ (-1.70)	-0.0564 (-0.72)	-0.0230 (-0.34)	-0.1806 [*] (-2.11)	-0.0901 (-1.49)
ΔLY_{t-4}		-0.0922 (-1.15)	-0.0140 (-0.19)	0.0331 (0.52)	-0.0910 (-1.22)	
$\Delta LHSTOCK_{t-1}$	-0.5320 (-0.86)	-2.1244 ^{**} (-3.06)	-1.3524 ^{**} (-2.13)	-1.4239 [*] (-2.57)	-2.5352 ^{**} (-3.85)	-1.519 ^{**} (-3.05)
$\Delta LHSTOCK_{t-2}$	1.1404 (1.43)	1.7491 [*] (2.21)	1.0708 (1.57)	0.5329 (0.79)	1.7290 [*] (2.37)	0.5262 (0.91)
$\Delta LHSTOCK_{t-3}$	-1.0645 ⁺ (-1.95)	-1.2978 [*] (-2.21)	-1.0169 (-1.54)	-0.7898 (-1.17)	-1.3303 ⁺ (-1.87)	-0.6121 (-1.49)
$\Delta LHSTOCK_{t-4}$		0.1036 (0.19)	0.3899 (0.58)	0.1984 (0.30)	0.0253 (0.05)	
$\Delta LLTV_{t-1}$				-0.2907 ^{**} (-4.69)	-0.1891 ^{**} (-3.48)	-0.1471 (-3.53)
$\Delta LLTV_{t-2}$				-0.0341 (-0.53)	0.0185 (0.40)	0.0420 (1.01)
$\Delta LLTV_{t-3}$				-0.0749 (-1.30)	-0.0262 (-0.58)	-0.011 (-0.26)
$\Delta LLTV_{t-4}$				-0.1874 ^{**} (-2.86)	-0.1152 ^{**} (-2.14)	
R^2	.582	.706	.714	.796	.755	.778
S.E.	0.005417	0.004458	0.004707	0.003779	0.004065	0.004146
VECLM(2)	19.50	30.48 [*]	24.75 ⁺	31.54	40.03 [*]	21.71
VECLM(10)	22.25	30.81 [*]	12.80	28.71	43.75 [*]	17.30

(^{**}, ⁺) significant at 95% (99%, 90%) level. t-statistics in parentheses. EC terms from VECMs estimating the long and short-run relationships. EC terms in the numbered models are derived from the corresponding numbered vector in Table 1. Δ lags later than t-4 omitted to conserve space.

Table 3: Cointegration Results for the U.S. Home Price-to-Rent Ratio, 1981 -2007:q2

Model # &Vec.	# Sign. Vectors	Cointegrating Equilibrium Relationship (assumption: no trend in vector or in variables)	Log Likelihood (AIC)	Eigenvalue (Trace Statistic, Max-Eigen Statistic)	
				0 vectors	1 vector
<i>Sample: 1981q4-2007q2 (only monetary policy regime variable added)</i>					
1	1	$\ln(\text{HPRENT}) = 1.007087 - .2275729 * \ln(\text{RUSER})^{**}$ (-9.61)	599.2679 (-10.89506)	0.124167 (13.68116 ⁺) (13.65573 ⁺)	0.0000418 (0.025421) (0.025421)
4	1	$\ln(\text{HPRENT}) = 1.0093959 - .189656 * \ln(\text{RUSER})^{**} + 1.093959 * \ln(\text{LTV})^{**}$ (-14.48) (5.29)	960.5231 (-17.07812)	0.215564 (31.69837 [*]) (25.00739 [*])	0.060842 (6.690977) (6.690977)
<i>Sample: 1981q3-2007q2 (all tax and monetary policy regime variables present)</i>					
3	1	$\ln(\text{HPRENT}) = 0.991350 - .267297 * \ln(\text{RUSER})^{**}$ (-11.22)	597.7456 (-10.99511)	0.152725 (19.75999 [*]) (17.23597 [*])	0.023977 (2.524025) (2.524025)
6	1	$\ln(\text{HPRENT}) = 0.933061 - .169823 * \ln(\text{RUSER})^{**} + 0.808590 * \ln(\text{LTV})^{**}$ (-21.97) (6.19)	969.8769 (-17.26686)	0.264799 (46.64308 ^{**}) (31.99156 ^{**})	0.121906 (14.65153) (13.52016)
<i>Sample: 1981q3-2001q4 (all tax and monetary policy regime variables present)</i>					
2	1	$\ln(\text{HPRENT}) = 0.842831 - .186376 * \ln(\text{RUSER})^{*}$ (-4.19)	497.9771 (-11.70676)	0.122390 (12.93122) (10.70534)	0.017273 (2.225883) (2.225883)
5	1	$\ln(\text{HPRENT}) = 1.000351 - .195132 * \ln(\text{RUSER})^{**} + 0.887307 * \ln(\text{LTV})^{**}$ (-7.95) (4.71)	803.1959 (-17.83405)	0.276905 (34.41995 [*]) (26.58559 ^{**})	0.086260 (7.834362) (7.397135)

	<i>Level (AIC lag in parentheses)</i>	<i>5% Critical level for lag</i>	<i>1% Critical level for lag</i>	<i>First Diff. AIC lag in parentheses)</i>	<i>5% Critical level for lag</i>	<i>1% Critical level for lag</i>	<i>Assumptions</i>
ln(HPRENT)	-2.105505 (1)	-3.450436	-4.042042	-5.198989 ^{**} (0)	-3.451959	-4.045236	constant/trend
ln(RUSER)	-2.389194 (2)	-3.449716	-4.040532	-4.124070 ^{**} (1)	-3.449716	-4.040532	constant/trend
ln(LTV)	-2.060300 (3)	-3.451959	-4.045236	-10.78284 ^{**} (3)	-3.451959	-4.045236	constant/trend

Notes. + (*, **) denotes significant at the 90% (95%, 99%) level. t-statistics in parentheses except when AIC statistic is reported. For vectors numbered 1-6, lag lengths of (8, 3, 5, 8, 7, and 7), respectively, minimized the AIC and yielded significant and unique vectors allowing time trends in the variables. Lag lengths in the ADF unit root tests based on the Schwartz Information Criterion. Data used span 1979-2007:2.

Table 4: 2nd-Stage EC Models of the Percent Change in the U.S. Home Price-To-Rent Ratio, 1981-2007q2

Variable	<i>No LTV Terms</i>			<i>LTV Terms</i>		
	81:4-07:2 <u>Model 1</u>	81:3-01:4 <u>Model 2</u>	81:3-07:2 <u>Model 3</u>	81:4-07:2 <u>Model 4</u>	81:3-01:4 <u>Model 5</u>	81:3-07:2 <u>Model 6</u>
Constant	0.0013 ⁺ (1.96)	0.0034 (0.85)	-0.0022 ⁺ (-0.58)	0.0019* (2.58)	0.0085 (1.31)	0.0080* (2.23)
EC _{t-1}	-0.0212 (-1.16)	-0.0816* (-2.32)	-0.0304 ⁺ (-1.67)	-0.0884* (-2.54)	-0.1802** (-3.11)	-0.1985** (-4.31)
MONEYTARGET _t	-0.0028 (-0.66)	-0.0094* (-2.34)	-0.0043 (-1.04)	-0.0060 (-1.46)	-0.0147** (-2.44)	-0.0139** (-3.22)
CAPGAIN TAX _t		0.0064* (3.02)	0.0044** (2.94)		0.0057** (3.11)	0.0069** (4.31)
TAXDEP _t		-0.0005 (-0.29)	0.00001 (0.80)		-0.0003 (-1.30)	-0.0003 (-1.54)
Δln(HPRENT) _{t-1}	0.4402** (3.96)	0.2500* (2.23)	0.3388** (3.24)	0.4392** (3.78)	0.2687* (2.18)	0.3872** (3.77)
Δln(HPRENT) _{t-2}	0.0205 (0.16)	-0.0459 (-0.35)	-0.0968 (-0.81)	0.0434 (0.33)	0.0647 (0.48)	0.0554 (0.50)
Δln(HPRENT) _{t-3}	0.0755 (0.62)	0.1366 (1.18)	0.1089 (0.96)	0.0366 (0.30)	0.1189 (0.95)	0.0882 (0.83)
Δln(RUSER) _{t-1}	-0.0203 ⁺ (-1.70)	-0.0208 (-1.25)	-0.0236* (-2.18)	-0.0123 (-1.04)	-0.0044 (-0.26)	0.0003 (0.03)
Δln(RUSER) _{t-2}	-0.0066 (-0.55)	0.0125 (0.72)	-0.0020 (-0.17)	-0.0035 (-0.29)	0.0123 (0.57)	0.0087 (0.77)
Δln(RUSER) _{t-3}	-0.0038 (-0.32)	0.0068 (0.43)	-0.0079 (-0.71)	0.0070 (0.59)	0.0143 (0.79)	0.0161 (1.47)
R ²	.635	.541	.662	.673	.639	.748
S.E.	.00506	.00505	.00500	.00479	.00447	.00432
VECLM(2)	2.13	1.61	5.27	11.15	7.31	3.79
VECLM(10)	2.78	4.52	3.46	5.11	7.26	4.91

* (**, +) significant at 95% (99%, 90%) level. t-statistics in parentheses. EC terms from VECMs estimating the long and short-run relationships, where the EC terms in the numbered models in Table 4 are derived from the corresponding vector numbers from Table 3. Coefficients on lagged changes in LTV ratios are omitted to conserve space.

Table 5: One-Stage Models of the Percent Change in Real U.S. Home Prices, 1980-2001 & 1980-2007

Variable	<i>No LTV Terms</i>			<i>LTV Terms</i>		
	80:1-07:3 Model 1	80:1-01:4 Model 2	80:1-07:3 Model 3	80:1-07:3 Model 4	80:1-01:4 Model 5	80:1-07:3 Model 6
Constant	0.2368* (2.19)	0.8913** (5.24)	0.5376** (4.77)	0.4604** (4.21)	0.8295** (4.92)	0.6119** (5.59)
LHP _{t-1}	-0.0726** (-2.68)	-0.2825** (-5.35)	-0.1851** (-5.85)	-0.1071** (-4.18)	-0.2393** (-4.32)	-0.1773** (-5.88)
LY _{t-1}	0.1475** (2.75)	0.3913** (4.80)	0.3033** (4.87)	0.2047** (4.08)	0.3517** (4.31)	0.3035** (5.13)
LHSTOCK _{t-1}	-0.0098+ (-1.86)	-0.1711** (-3.30)	-0.1346** (-2.96)	-0.1354** (-3.65)	-0.1796** (-3.54)	-0.1657** (-3.75)
LRUSER _{t-1}	-0.0802* (-2.07)	-0.0369** (-4.79)	-0.0292** (-5.12)	-0.0140** (-2.89)	-0.0320** (-4.07)	-0.0267** (-3.18)
LLTV _{t-1}				0.1495** (4.66)	0.0769* (2.12)	0.1025** (3.27)
MONEYTARGET _{t-1}	-0.0091+ (-1.96)	-0.0141** (-3.00)	-0.0128** (-3.06)	-0.0135** (-3.14)	-0.0167** (-3.52)	-0.0154** (-3.80)
CAPGAIN TAX _t		0.0061+ (1.89)	0.0028 (1.01)		0.0061+ (1.96)	0.0042 (1.60)
TAXDEP _t		-0.0009** (-3.55)	-0.0010** (-5.53)		-0.0007* (-2.59)	-0.0007** (-3.86)
LCONFLABOR _t		0.0203* (2.08)	0.0156+ (1.97)		0.0155 (1.59)	0.0131+ (1.74)
BUYPROSPER _t		0.0003 (0.97)	0.0003 (1.00)		0.0004 (1.08)	0.0003 (1.06)
ΔLHP _{t-1}	0.5480** (5.23)	0.3861** (3.86)	0.3783** (3.99)	0.5067* (5.31)	0.3544* (3.59)	0.3598** (3.99)
ΔLHP _{t-2}	0.0897 (0.70)	0.1503 (1.28)	0.0371 (0.34)	0.1808 (1.53)	0.1772 (1.53)	0.0989 (0.92)
ΔLHP _{t-3}	0.4605** (4.14)	0.5474** (5.36)	0.4624** (4.82)	0.5700** (5.51)	0.5731** (5.71)	0.5164** (5.58)

$\Delta LRUSER_{t-1}$	0.0151 (1.51)	0.0299** (3.01)	0.0248** (2.84)	0.0214* (2.33)	0.0289** (2.98)	0.0255* (3.07)
$\Delta LRUSER_{t-2}$	0.0167+ (1.86)	0.0215* (2.52)	0.0196* (2.56)	0.0246** (2.97)	0.0249** (2.94)	0.0236** (3.20)
$\Delta LHSTOCK_{t-1}$	-0.8821+ (-1.84)	-1.5403** (-3.19)	-0.9173* (-2.14)	-1.3061** (-2.95)	-1.5914** (-3.37)	-1.1291** (-2.74)
ΔLY_{t-1}	-0.1592+ (-1.94)	-0.4244** (-4.65)	-0.3545** (-4.59)	-0.1570** (-3.95)	-0.3744** (-4.06)	-0.3279** (-4.44)
ΔLY_{t-2}	-0.0610 (-0.73)	-0.3406** (-3.63)	-0.2573** (-3.27)	-0.0820 (-1.08)	-0.3056** (-3.28)	-0.2527** (-3.38)
ΔLY_{t-3}	-0.470 (-0.56)	-0.2312* (-2.56)	-0.1947* (-2.54)	-0.0871 (-1.14)	-0.2242* (-2.55)	-0.2136** (-2.92)
ΔLY_{t-4}	-0.0507 (-0.65)	-0.1641* (-2.04)	-0.1467* (-2.14)	-0.0893 (-1.26)	-0.1700* (-2.17)	-0.1710* (-2.60)
R^2	.638	.709	.746	.702	.723	.770
S.E.	0.0045	0.00449	0.00455	0.00420	0.00438	0.00433
LM(2)	18.82**	3.81	5.50+	2.57	2.38	3.38
Q(24)	23.77	20.20	15.77	14.00	17.07	13.01

* (**,+) significant at 95% (99%, 90%) level. t-statistics in parentheses

Table 6: One-Stage Models of the Percent Change in U.S. Price-Rent Ratio, 1980-2001 & 1980-2007

Variable	<i>No LTV Terms</i>			<i>LTV Terms</i>		
	80:2-07:3 Model 1	80:2-01:4 Model 2	80:2-07:3 Model 3	80:2-05:4 Model 4	80:2-01:4 Model 5	80:2-05:4 Model 6
Constant	0.0233 (1.27)	0.0429 (0.66)	0.0636 (1.10)	0.0759** (3.32)	0.0638 (1.00)	0.0816 (1.50)
LHPRENT _{t-1}	-0.0204 (-1.00)	-0.0878* (-2.31)	-0.0889** (-2.84)	-0.0716** (-2.95)	-0.1281** (-3.13)	-0.1490** (-4.50)
LRUSER _{t-1}	-0.0063 (-1.43)	-0.0146* (-2.04)	-0.0201** (-3.10)	-0.0124** (-2.73)	-0.0199** (-2.71)	-0.0256** (-4.12)
LLTV _{t-1}				0.1055** (3.51)	0.0835* (2.34)	0.1227** (3.94)
CAPGAIN TAX _t		0.0052* (2.02)	0.0052* (2.48)		0.0062* (2.44)	0.0063** (3.20)
TAXDEP _t		0.0001 (0.51)	-0.0001 (-0.54)		0.00008 (0.30)	-0.00009 (-0.50)
MONEYTARGET _{t-1}	-0.0063+ (-1.91)	-0.0080 (-1.66)	-0.0108** (-2.89)	-0.0072* (-2.30)	-0.0092+ (-1.95)	-0.0108** (-3.12)
LCONFLABOR _{t-1}		0.0047 (0.47)	0.0041 (0.46)		0.0099 (1.00)	0.0131 (1.52)
BUYPROSPER _t		0.0005* (2.00)	0.0004+ (1.81)		0.0003 (0.94)	0.0001 (0.47)
ΔREGQ _{t-1}	-0.0050* (-2.13)	-0.0060* (-2.12)	-0.0051+ (-1.87)	-0.0057* (-2.54)	-0.0067* (-2.40)	-0.0065* (-2.52)
ΔREGQ _{t-2}	-0.0036 (-1.48)	-0.0059* (-2.43)	-0.0048* (-2.01)	-0.0043+ (-4.18)	-0.0066** (-2.77)	-0.0057* (-2.57)
ΔREGQ _{t-3}	0.0049** (2.20)	0.0029 (1.21)	0.0039+ (1.83)	0.0037+ (1.71)	0.0019 (0.82)	0.0022 (1.09)
ΔLHRENT _{t-1}	0.4321** (4.20)	0.1822 (1.66)	0.3495** (3.46)	0.3657** (3.68)	0.1682 (1.58)	0.2960** (3.12)
ΔLHRENT _{t-2}	-0.0046 (-0.04)	-0.0649 (-0.53)	-0.0610 (-0.52)	-0.0254 (-0.23)	-0.0744 (-0.61)	-0.0720 (-0.65)

$\Delta LHRENT_{t-3}$	0.0664 (0.60)	0.0255 (0.23)	0.0285 (0.26)	0.0738 (0.71)	-0.0118 (-1.08)	0.0552 (0.54)
$\Delta LHRENT_{t-4}$	-0.0844 (-0.81)	-0.1845 ⁺ (-1.76)	-0.1522 (-1.47)	-0.0826 (-0.83)	-0.1545 (-1.51)	-0.1055 (-1.09)
$\Delta LRUSER_{t-1}$	0.0167 ⁺ (1.77)	-0.0072 (-0.59)	-0.0099 (-0.98)	-0.0117 (-1.29)	-0.0017 (-0.14)	-0.0018 (-0.18)
$\Delta LRUSER_{t-2}$	-0.0175 ⁺ (-1.92)	-0.0205 ⁺ (-1.79)	0.0127 (1.28)	-0.0151 ⁺ (-1.72)	-0.0173 (-1.54)	-0.0093 (-0.99)
$\Delta LRUSER_{t-3}$	-0.0112 (-1.22)	-0.0136 (-1.22)	-0.0088 (-0.91)	-0.0086 (-0.98)	-0.0118 (-1.08)	-0.0057 (-0.63)
$\Delta LRUSER_{t-4}$	0.0095 (1.24)	0.012 (1.20)	0.0136 ⁺ (1.84)	0.0102 (1.40)	-0.1545 (-1.51)	-0.0151* (-2.17)
$\Delta LLTV_{t-1}$				-0.0823 ⁺ (-1.81)	-0.0938* (-2.02)	-0.0990* (-2.28)
R^2	.691	.654	.724	.722	.677	.761
S.E.	.00502	.00460	.00474	.00477	.00471	.00442
LM(2)	0.36	2.92	0.04	2.43	2.49	0.25
Q(24)	20.60	25.17	20.93	18.31	21.74	27.87

* (**,+) significant at 95% (99%, 90%) level. t-statistics in parentheses.

