House Prices and Credit Constraints:

Making Sense of the U.S. Experience

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Abstract

Most US house price models break down in the early 2000's, apparently due to the omission of exogenous changes in mortgage credit supply (associated with the sub-prime mortgage boom) from house price-to-rent ratio and inverted demand models. Previous models lack data on credit constraints facing first-time home-buyers. Incorporating a measure of credit conditions - the cyclically adjusted loan-to-value ratio for first time buyers – into house price to rent ratio models yields stable long-run relationships, more precisely estimated effects, reasonable speeds of adjustment and improved model fits. We use our model to assess scenarios for US house prices in mid 2009.

JEL Codes: R31, G21, E51, C51, C52.
Key Words: house prices, credit standards, subprime mortgages

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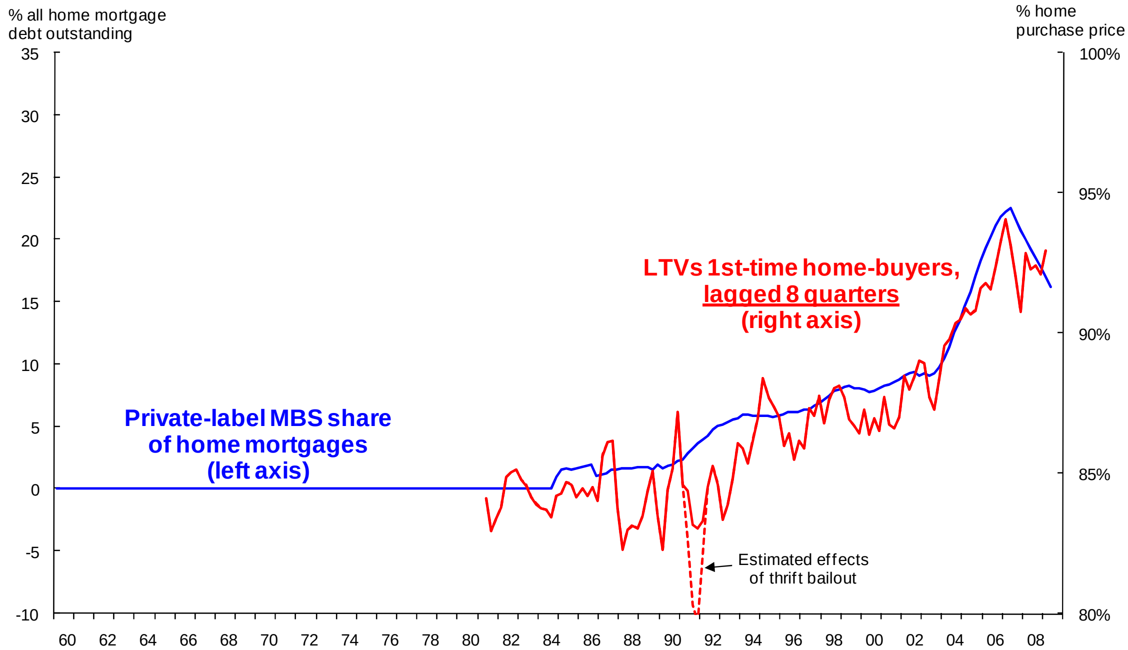
I. Introduction

The recent boom and bust in U.S. housing markets has sparked interest in modeling the links between home prices and credit standards. 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 cost of housing. Kim (2007) shows theoretically that down-payment or loan-to-value (LTV) constraints also help determine the home price-to-rent ratio. Models of U.S. home prices have been hindered by a lack of consistent time series measures of the exogenous changes in the credit constraints facing marginal, first-time home-buyers. This shortcoming suggests that most U.S. home price models suffer from omitted variable bias.

This issue is addressed using Duca, Johnson, and Muellbauer's (2009) data on average LTV ratios over 1979-2007 for first-time home-buyers, the marginal buyers most likely affected by down-payment constraints. Derived from the American Housing Survey, this series implies that down-payment constraints were eased early this decade, in line with Doms and Krainer's (2007) finding that homeownership rates rose among the young. Consistent with a weakening of credit standards during the subprime boom, LTVs for first-time homebuyers 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 usually securitized conforming loans, which met credit standards applied to most mortgages in earlier years. In contrast, nonprime mortgages were mainly funded by being packaged into "private label" MBSs because they did not conform to Fannie Mae or Freddie Mac standards, or were too risky to be held by regulated banks (Credit Suisse, 2007). Because our LTV series reflects originations, it leads the private MBS share of home mortgages by about two years.

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



The rise in LTV ratios from 2000 to 2005 likely reflects two financial innovations: the adoption of credit scoring technology that enabled the sorting and pricing of nonprime mortgages and funding of such loans in the form of collateralized debt obligations (CDOs) or with protection from credit default swaps (CDSs). The later failure of CDOs to protect investors from unanticipated default losses and the soaring cost of using CDSs induced a reversal of the earlier easing of credit standards. Abstracting from the 8-quarter lag, LTVs peak in 2005:q2, and are modestly lower through 2007:q2, before subprime difficulties kicked off the financial crisis that started in August 2007. Reports imply that mortgage standards have tightened further, which will likely be confirmed after we update the series after the 2009 AHS data are released.

Including LTV data on first time home-buyers notably improves house price-to-rent or inverted housing demand house price models by yielding stable long-run relationships, sensible and more precisely estimated income and/or user cost coefficients, reasonable speeds of adjustment, and better model fits. This is true even before LTVs rose in the subprime boom 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 unemployment.

This study is organized as follows. Section 2 presents the models and the data. These, in turn, are estimated using Engle-Granger two-step cointegrating regressions in Section 3 (except that the long-run cointegrating regressions are estimated using the Johansen method in the first step) and more general, autoregressive distributed lag (ADL) models in Section 4. The fifth section assesses whether U.S. home prices are over-valued. The conclusion discusses the links between credit and asset market bubbles. Some inverted housing demand models using our cyclically adjusted LTV measure of exogenous changes in mortgage supply are shown in Appendix 1.

II. House Price Models and Data

(a) The House Price-to-Rent Ratio Approach

Home prices have been modeled using the price-to-rent approach, especially in the U.S., where regional housing stock measures are not readily available and rents are market-determined, in contrast to the UK.[1] This approach assumes that, absent substantial frictions and credit restrictions, arbitrage between owner-occupied and rental housing markets implies the house rent-to-price ratio depends on the real user cost of capital, defined as the nominal user cost of mortgage finance (*NOMUSER*) minus expected appreciation:

(1) $RENT/HP = NOMUSER$ – (expected home price appreciation) = $RUSER$,

where *NOMUSER* is tax-adjusted and can reflect tax effects on rents relative to home prices. The user cost takes into account that durable goods deteriorate, but may appreciate in price and

[1] Other approaches to modeling house prices include the inverted housing demand approach, reduced form models as well as *ad hoc* models which are difficult to theoretically interpret (Cameron, Muellbauer and Murphy, 2006).

incur interest costs. Real user costs are usually approximated by $uc = hp\left(r + \delta + t - \Delta hp^e / hp\right)$, where r is the real after-tax interest rate, δ is the depreciation rate, t is the property tax rate, and $\Delta hp^e / hp$ is the expected real rate of capital appreciation. The variable uc is referred to as the real user cost throughout the paper—note that this terminology differs from that of Jorgenson for whom the real user cost would equal our user cost term uc multiplied by real house prices.

As shown by Kim (2007), this result obtains in an equilibrium model when agency costs make renting housing services more expensive than owning. Inverting and taking logs implies:

(2) $\ln HPRENT = -\ln RUSER$,

where the elasticity equals minus one and the price-to-rent ratio is invariant to the housing stock and deviations of income from trend. However, Kim (2007) theoretically demonstrates that, when rental agency costs are accompanied by binding, maximum LTV ratios on marginal home buyers, the long-run equilibrium log price-to-rent ratio is more complicated:

(3) $\ln HPRENT = f(\ln RUSER, \text{max LTV})$,

with a negative real user cost elasticity smaller than 1 in size, in line with Gallin's (2006) results.

Ex-post user costs can be negative if appreciation rates exceed nominal user costs. An important issue is how to track expectations of house prices. 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 annual rate of appreciation in house prices over the prior 4 years. Given assumptions on transactions costs, *RUSER* is always positive so ln(*RUSER*) is 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 nominal user costs, the market gets into a 'frenzied' state.[2]

(b) 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, I(1) shifts in demographics variables were not found to be statistically or economically significant, 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. To construct the house price-to-rent ratio (*HPRENT*), we seasonally adjust the house price data and divide them by the personal consumption expenditures price 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 home price appreciation over the four prior years adjusted for an assumed 8 percent cost of selling a home. The resulting real rate exceeds zero in the sample, allowing real user costs to enter in logs, an

[2] Hendry (1984) and Muellbauer and Murphy (1997) capture similar effects using a cubic in 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.

appealing aspect stressed by Meen (2001). Some models split the user cost term into nominal user cost (*NOMUSER*) and appreciation (*APP*) terms to assess issues related to speculation.

Exogenous Changes in Mortgage Credit Standards

Mortgage credit standards are tracked by the average LTV for homes bought by first-time home buyers (Duca, Johnson, and Muellbauer, 2009), based on American Housing Survey data since 1979. This series consistently measures LTV ratios on conventional mortgages. This corresponds to the Freddie Mac home price series, which is based on homes bought with conforming, conventional mortgages. The LTV series shifted up slightly, from a range around 85% in the late 1970s and the 1980s, to a range around 87 percent in the 1990s (Figure 1), before jumping significantly after 2002. Although the discontinued series of the Chicago Trust and Title company is from only one month (November) per year, both series move similarly before 2000 (Figure 2).[3]

We adjust the raw quarterly AHS data for two reasons. First, we adjust the data for shifts in average age, seasonality, some unusually small quarterly samples and regional composition. These shifts introduce noise and debt demand factors from which we wish to abstract. Second, we examined the endogenity of the first-time home buyer LTVs by examining its correlation with several cyclical macroeconomic variables over the 1979-2007 period. We found no significant link with income and interest rates. However, the first-time home buyer LTV's are significantly correlated with 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

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This helps explain why the low 1987 reading which followed the October 1987 stock crash seems unrepresentative. The Chicago Trust and Title company data are subject to other comparability problems as the sample of locations covered shifts over time.

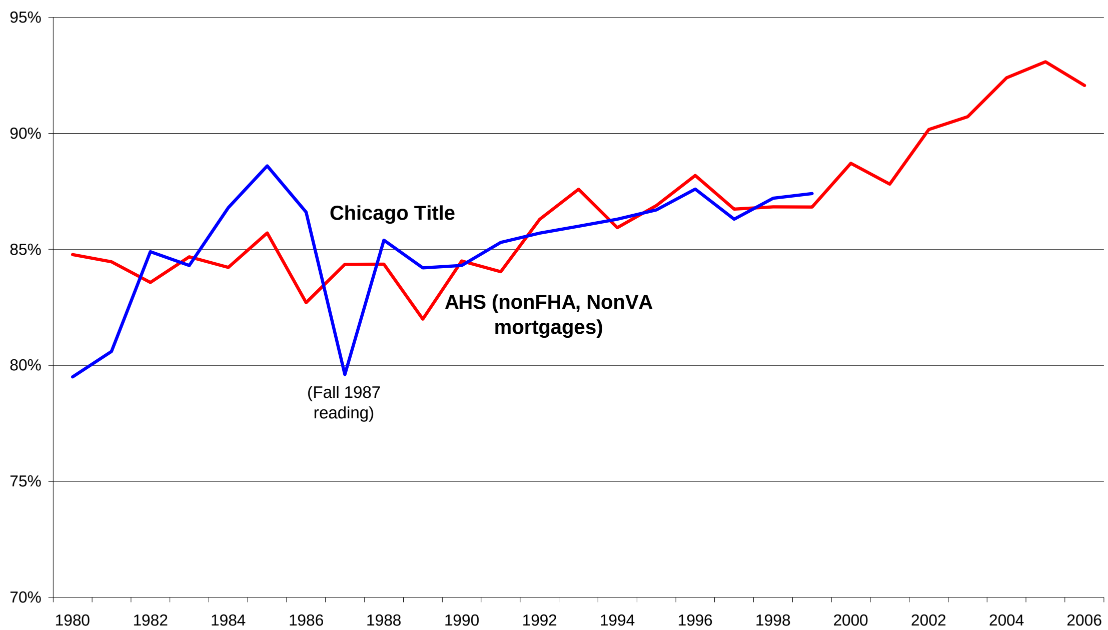
for LTV trends, as well as dummies for two unusual episodes which would otherwise distort the resulting estimates. The latter were the quarter following the September 11, 2001 terrorist attacks (*SEPT11*), which induced a temporary plunge in the LTV ratio, and the two quarters following the passage of thrift bailout legislation in 1989:q3, which temporarily disrupted lending because savings and loan institutions were initially seized before being later closed (*FIRREA*). The resulting LTV regression is:

$$\underset{}{\text{LTV(raw)}} = \underset{(1.37)}{0.082622} - \underset{(-3.02)}{.017889}{*}\Delta U - \underset{(-2.44)}{0.002296}{*}AGE + \underset{(2.67)}{0.074932}{*}WEST - \underset{(-6.20)}{0.061997}{*}SEPT11$$

$$+ \underset{(15.66)}{0.977258}{*}LTVHP - \underset{(-3.70)}{0.047266}{*}FIRREA + \underset{(1.42)}{0.082512}{*}\Delta LTV_{t-1}$$

where t-statistics are in parentheses, $R^2 = 0.866$, standard error = 01145, LM statistics for AR(2) / MA(2) errors = 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*, the western share of first-time buyers per quarter, is 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 negative coefficient on age reflects the fact 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 estimated effects except that of the lagged dependent variable, *FIRREA*, and the H-P filtered LTV. To keep the adjusted LTV near its equilibrium, (1 - 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.

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



The post 2001 rise in LTV ratios likely reflects two financial innovations that fostered the securitized financing of riskier mortgages, as noted above. The adoption of credit scoring technology enabled lenders to sort nonprime borrowers and attempt to price the risk of nonprime mortgages. Since these loans were too risky for banks to hold, they were funded by securities markets, where investor demand for the mortgage-backed securities funding nonprime loans was temporarily boosted by two developments. First, the combination of very low interest rates and expanded credit availability in the early 2000s fueled a rise in house prices that plausibly led investors and analysts to under-estimate the default risk on nonprime mortgages. As DiMartino and Duca (2007) argue, the short history of subprime mortgages over 1998-2006 may have tempted analysts to forecast the incidence of problem loans using labor market conditions, while not having enough data to disentangle the impacts of house prices and interest rates. In addition, the tendency for vintages of Alt A mortgages to have progressively higher proportions of no- or low-documentation of income (Credit Suisse 2007) and to post progressively worsening loan quality (Mayer, Pence, and Sherlund, 2009) suggests that an errors-in-variables problem, from overstatements of borrower income, contributed to the underestimation of nonprime mortgage defaults.

Second, financial innovations that sorted borrowers or funded their loans were accompanied by changes in regulations and public policies leading to noncyclical increases in the demand for the securities funding these mortgages. This included a 2004 SEC decision that doubled the 1935 limits on investment bank leverage from 15:1 to 33:1 and the rise of hedge funds and SIVs that used short-duration debt to fund risky long positions in nonprime mortgages. Also important were large purchases of nonprime MBS by Fannie Mae and Freddie Mac to meet their public policy goals of expanding home ownership (Frame, 2008), even though they did not issue much nonprime MBS. Technological and policy innovations fostered originations of nonprime mortgages which were sold to the GSEs or private 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 defaults and the soaring cost of using CDSs led to a collapse in the funding and availability of nonprime mortgages.

Capital Gains Tax Changes

Although income tax rates are in the user cost of capital variable, capital gains tax changes have notably affected home prices. Before mid-1997, net capital gains on home sales were taxable for households under age 55 if the seller did not purchase a home of equal or greater value. The Tax Reform Act of 1997, passed in the second quarter of 1997, largely eliminated this tax by exempting the first $500,000 ($250,000) of gains for married (single) filers, raising the after-tax value of homes and encouraging turnover (Cunningham and Englehardt, 2009). To control for this, we included a variable (*CAPGAINTAX*) equal to 1 since 1997:q3 and 0 before.[4] The third quarter timing reflects the 1-2 month lag between the signing and actual settlement (when house prices are recorded) of home sale contracts. We use the the t-2 lag of *CAPGAINTAX*, which we find is the most significant lag and yielded cleaner (i.e., white noise like) residuals.

Monetary/Regulatory Variables

We include a number of monetary policy and regulatory controls in our house price–to-rent ratio models in order to obtain better estimates of the long run effects. Our *MONEYTARGET* indicator variable equals 1 (and 0 elsewhere) over the money targeting regime of 1979:q4-1982:q4, which may have reduced the supply of or demand for mortgages by raising interest rate uncertainty. Another control is Δ*REGQ*, the first difference of Duca's (1996) measure of how much Regulation Q ceilings on deposit interest rates were binding until these controls were lifted in the early 1980s. We include the t-1 and t-2 levels of Δ*REGQ* to control for short-run negative short-run disintermediation effects that are not consistently tracked by the user cost of capital (Duca and Wu, 2009). Another regulatory variable (*MMDA*) is a dummy equal to one in 1983:q1 to control for the re-intermediation effects of allowing banks to offer variable interest bearing money market deposit accounts, which boosted deposits according to money demand models (Duca, 2000) and affected the availability of consumer credit (Duca, Muellbauer, and Murphy, 2009). Both *REGQ* and *MMDA* control for the impact of some form of financial liberalization. Note that the timing of *MMDA* is close to the end of the monetary targeting

[4] In other runs, we found that another tax variable to have non-robust effects. This was the time over which rental properties can be depreciated for taxes which may raise the after-tax cost of renting relative to home prices.

regime and it may be difficult to disentangle the two effects using the *MMDA* and monetary targeting variables.

Another variable controls for a large rise in the upfront insurance premium for Federal Housing Administration (FHA) loans in 1983. The FHA provides government guarantees against losses to lenders. Up until 2007, FHA loans had size limits well below those on “conventional” mortgages). A rise in the upfront premium, from 0% to 3.8% of the mortgage principal, was announced to take effect in late 1983:q3, inducing many renters to leave rental housing and purchase “starter” homes in that quarter. This hike in premiums was later partially reduced by small premium cuts, too small to be statistically significant. We include a dummy equal to 1 in 1983:q3 and 0 otherwise ($\Delta FHAFEE_t$) to control for that quarter’s large jump in house prices. Recognizing that that surge likely reflected inter-temporal substitution from later quarters, we include three quarterly lags of this dummy to control for any negative payback effects.

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

The long run variables in our house price to rent ratio models have a unit root, so we present some cointegrating regression results first. We then set out some more general autoregressive, distributed lag (ADL) findings. In both sets of results, we control for tax effects by using income and property tax rates to calculate real user costs, and control for the money targeting regime of 1979-1982 that imparted more interest rate risk to house prices beyond that reflected in user costs. By addressing these important influences, we try to avoid omitted variable bias that can obscure long-run relationships and lead to poorly estimated coefficients.

In the house price-to rent approach, we assess the importance of mortgage availability using our cyclically adjusted LTV ratio for first-time buyers, which we believe captures exogenous shifts in mortgage availability, which are unrelated to income and interest rate. These shifts alter the relative demand for owner-occupied versus rental housing, by raising the effective demand for owner-occupied housing of the credit constrained and lowering their effective demand for rental housing. An example of such an increase is the rise of our LTV series in the early 2000's. This coincided with a jump in subprime mortgage lending and the overall homeownership rate. Of course, 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 supply of structures (Davis and Heathcote, 2005).

Standard house price-to-rent models generally estimate a long-run relationship between mortgage interest rates and the price-to-rent ratio, and often imply that U.S. home prices were over-valued in 2005. Exceptions to the latter are city or regional models that either (1) use a very low real user cost of housing, assuming that unusually high rates of local house price appreciation observed in mid 2000's would persist (e.g., Himmelberg, Mayer, and Sinai, 2006) or (2) argue that rents are higher in high cost locales than implied by official rent data (Smith and Smith, 2006). 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 in our models. 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 omit the LTV ratio.

Long-Run Results

Table 1 reports cointegrating vectors of price-to-rent ratios estimated over the full sample (data from 1979-2007) allowing for deterministic trends in the long-run variables, but not in the cointegrating vector. The long run results in Table 1 are from the Johansen procedure. The short run results in Table 2 are from a second step VAR in first differences, including the error correction term estimated from the first step. The lag lengths were long enough to yield statistically significant unique cointegrating vectors, minimize the AIC statistic, and yield clean (i.e., approximately white noise) residuals. In general, the same procedure was used for both the LTV and non-LTV models. In some of the non-LTV models, there was no unique cointegrating vector so the vector that minimized the SIC statistic was used.

The first two cointegrating vectors (1 and 4) in Table 1 include the capital gains tax, monetary targeting, and Regulation Q terms as extra exogenous variables, and respectively omit and include the LTV ratio. The third and fourth vectors (3 and 6) also include the MMDA and FHA premium short-run variables. The fifth and sixth vectors 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 eigenvalue statistics, highly significant, unique cointegrating vectors were found for all of the LTV models. In the non-LTV models, weaker or no evidence of a unique cointegrating vector was found. Although a unique cointegrating vector for the non-LTV model could be found prior to the subprime boom, a unique vector could not be found in the full-sample, using a full set of monetary policy and regulatory controls.

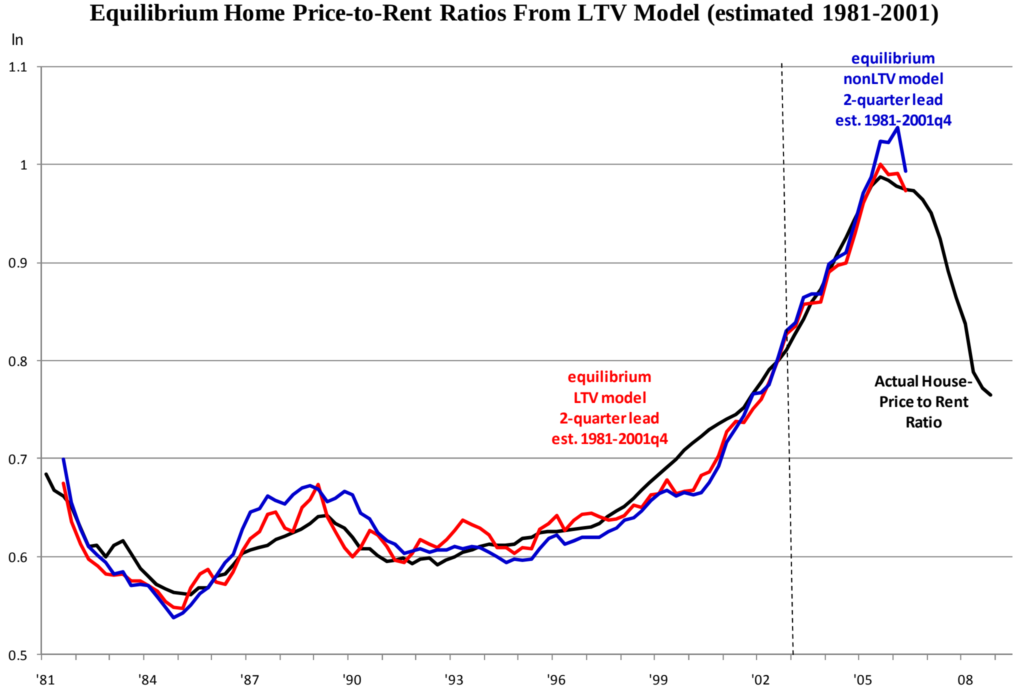
Consistent with priors, the estimated long-run coefficients indicate that the price-to-rent ratio is negatively and significantly related to real user cost of capital, and positively and significantly related to the LTV ratio. In addition, the estimated long-run user cost coefficients are all statistically different from -1, a rejection of a major implication of the perfect capital markets (see Kim, 2008).[5] Furthermore, in vector error correction models, the error-correction term was significant in the price-to-rent equations (t-statistic of 3.47) and was highly

[5] Other reasons for the lower absolute size of the long-run user cost effect could include home buyers being less than fully informed or having other than strictly economic motives, and lumpy transactions costs.

insignificant in the LTV models (t-statistic of -0.24), consistent with the view that LTV ratios are largely exogenous drivers of home prices.

The estimated equilibrium price-to-rent ratios from the LTV models also track the data better than the estimated equilibria in non-LTV models. This can be seen in Figure 3, which plots the two-quarter lead of estimated equilibrium price-to-rent ratios from LTV and non-LTV models (5 and 2, respectively) estimated over the shorter 1980-2001 sample. LTV model equilibrium ratios line up better with actual price-to-rent ratios than equilibrium ratios from the non-LTV. Particularly noteworthy is the LTV model's better ability to track the peak and ebbing of the price-to-rent ratio in 2006-07, consistent with the view that easier mortgage credit standards significantly fueled the home price boom of the mid-2000s.

Figure 3: House Price-to-Rent Ratio Better Tracked Out of Sample By Implied Equilibrium Home Price-to-Rent Ratios From LTV Model (estimated 1981-2001)



Short-Run Results

An easing of mortgage credit standards also has large short-run effects on home prices, as shown in Table 2 which reports the error-correction model results for the change in the home price-to-rent ratio based on the estimated long-run equilibrium relationships in Table 1. In all of the LTV models, the error-correction term is very significant with plausible adjustment speeds of between 11% to 14% per quarter. By contrast, the adjustment speeds in the non-LTV models are very low, ranging between 4% and 6% per quarter, reflecting the lower ability of non-LTV models to track long-run relationships. This is particularly the case in full sample models that include the full set of control variables, where the speed of adjustment is estimated to be 11% percent in the LTV model versus 4% percent in the non-LTV model. Comparing similar LTV and non-LTV models indicates that, including the LTV ratio and its lagged first-difference, improves the R-squares by 5 to 9 percentage points and lowers standard errors by about 15%. There are some short run dynamics - 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 - even though lagged house price appreciation over a longer period is incorporated in log RUSER.

(c) Some ADL Results

The autoregressive distributed lag (ADL) results in Table 3 and vector equilibrium correction model results in Tables 1 and 2 are very similar, both qualitatively and quantitatively. Similar long-run solutions and estimated speeds of adjustment were obtained. Relative to corresponding non-LTV models, all of the LTV models in Table 3 have better fits and faster speeds of adjustment, especially over the full sample.[6] .

(d) Alternative Specifications

We examined two alternative issues / models as a further check on the robustness of our findings. The first issue concerns a short-coming of the repeat sales index - home improvements,

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[6] Because the LTV is a 3-quarter moving average, we include the 3-quarter change in LTV ratios (lagged 2 quarters) to control for short-run dynamics rather than include one-quarter changes that contain similar information. For parsimony, we dropped some insignificant lags of some first difference terms. We also found that lagging the LTV

linked to rising incomes, can cause such indexes to overstate house prices and may lead to over-estimates of the income elasticity of house prices. To address this issue, we construct and analyze a house price index adjusted for home improvements. We first cumulated a quarterly Census series on home structure improvements (which unfortunately ends in 2007), and then adjusted the resulting series for depreciation. The depreciation-adjusted stock of home improvements is then scaled by the Federal Reserve Board Flow of Funds estimates of the replacement cost value of residential home structures. This yields a time series of the relative importance of home improvements as a source of housing stock accumulation. We multiply this series by the Freddie Mac repeat home sales price index to adjust repeat home sales prices for home improvements. This adjusted house price index is used to construct an adjusted price-to-rent ratio (*HPRENTADJ*) and an adjusted real user cost of capital. Some results based on these series are set out in Table 4. Models 1 and 2 in Table 4 correspond to models 3 and 6 in Table 3. They cover the full sample and use all of the exogenous controls. The Table 3 and Table 4 results are similar. Comparing models 1 and 2 in Table 4 with models 3 and 6 from Table 3 reveals, as before, that LTV models yield better fitting models with faster speeds of adjustment.

The second robustness issue has to do with simulating the price-to-rent ratio through 2009:q2, which is outside of our LTV data sample. This entails simulating a path for the LTV ratio, adjusting the user cost for the housing tax credit of 2009, adjusting for major changes in government lending programs and including a dummy variable to gauge the extra impact of the financial crisis. Regarding the LTV path, Sherlund (2008) shows that subprime lending essentially disappeared between 2007:q2 and 2007:q4 and that LTVs for securitized mortgages

by an extra quarter improved model fit, perhaps reflecting the extra time it takes for first-time homebuyers to learn of changes in less visible down-payment constraints fell back to late 1999 levels by the end of 2007. Using this as a benchmark, our assumed LTV path plunges evenly between 2007:q2 and 2007:q4 to its 1999:q4 level, where it remains.

We also model the impact of the 2009 economic stimulus bill, which included an income tax credit of 10% of a home's purchase price up to a cap of $8,000 for couples who were first-time home buyers (technically, those who were not owner-occupiers during the prior three years). The credit covers homes purchased between January 1 and November 30, 2009, but the deadline was later extended to June 30, 2010.[7] We calibrate the tax credit by dividing the $8,000 cap by the average price of homes financed by conforming mortgages between 2008:q4-2009:q2. We adjust the resulting 2.63% figure for the fact that first-time buyers, on average, bought a home that was 20% less expensive than the average price of all homes purchased reported in the 2005 AHS. Applying a 20% downward adjustment to the sales price implies that the tax credit scaling should be 4.11%. This essentially treats the tax credit as having an effect proportional to its impact on real user costs facing the marginal (i.e., first-time) home buyer. The stimulus bill was passed late in 2009:q1, but the first-time home buyer income tax credit provision was non-controversial. The trajectory of most house price series changed dramatically in 2009:q1. To keep things as simple as possible, we adjusted the real user cost *RUSER* by subtracting 4.11 percentage points for the quarters 2008:q4 through 2010:q1. We advance the dating by one quarter because *RUSER* enters the model with at least a one period lag. This defines the variable denoted by *RUCADJ*.

We also took account of the changes in the FHA mortgage program. Prior to the subprime bust, the limits on the size for loans eligible for FHA financing were well below those on conforming mortgages that Freddie Mac and Fannie Mae securitized in their regular MBS

[7] Note there was something called a tax credit in 2008 which was of a similar size but which the borrower had to pay back to the Treasury; this had no discernable effect on home sales in 2008.

pools. In addition, FHA loans also carried a large, upfront premium equal to 1.5% of the loan amount, plus a continuing, non tax-deductible premium of 0.5% added to the mortgage rate for the first 5 to 10 years of the mortgage, depending on the LTV ratio at the time of purchase. These limits and costs made conventional financing preferable for most first-time buyers, who did not need the 96.5 percent LTV cap on FHA loans. Before 2008:q1, FHA loans had a maximum principal ($200,160) that was much lower than that for conventional mortgages ($417,000). Since then, the FHA limit for many areas was raised to $271,050, versus $417,000 for conforming loans. In addition, new mortgage size limits of $729,000 for both FHA and Freddie/Fannie loans were created for high cost areas starting in 2008:q1. With the collapse of subprime lending, the share of mortgage originations insured by FHA soared, while the conventional share plunged. [8] We account for these changes by including the gap (*FHALTVGAP*) between the FHA LTV limit of 96.5 percent and the simulated LTV starting in 2008:q1. Since the latter is flat, this is tantamount to adding a dummy equal to 1 since 2008:q1.

We also tried to control for the plunge in housing demand during the recent financial crisis. In addition to including a dummy (*FINCRISIS*) equal to 1 in 2008:q4 (Lehman failed two weeks before 2008:q4), We also use a continuous variable to control for consumer credit availability in some models. This variable, *DCREXOG*, is the first difference of an index of the share of banks that reported an increasing willingness to make consumer installment loans from a quarter earlier. Following Duca, Muellbauer, and Murphy (2009), this index is adjusted for changes in interest rates, consumer loan delinquency rates, and the economic outlook (using the index of leading economic indicators). Although the index is contemporaneous, the stripping out of interest rate and cyclical factors reduces the scope for simultaneity bias. Positive readings of *CREXOG* likely boost effective housing demand, by making it easier for marginal, first-time

[8] See http://www.huduser.org/periodicals/ushmc/winter08/nat_data.pdf .

home-buyers to indirectly fund mortgage down-payments by using consumer credit to purchase non-housing goods and services. Moreover, the estimated coefficient on this variable was similar for samples ending in 2007:q2 and in 2009:q2, implying that its impact around the financial crisis of late 2008/early 2009 was in line with prior swings in consumer credit availability. Including *DCREXOG* in our cointegrating regressions may help disentangle the effects of general uncertainty during the height of the financial crisis, as captured by the dummy variable *FINCRISIS*, from the increased difficulty first-time buyers faced in meeting LTV constraints.

To assess the relative role of these factors, we estimated four regressions over 1980:q3-2009:q2. The first simulation (model 3 in Table 4) simply substitutes the LTV variable from model 6 in Table 3 with LTVADJ, but makes no allowance for the 2009 tax credit, changes in FHA lending limits, or consumer credit availability. The second simulation (model 4) builds on model 3 by using *RUCADJ* instead of *RUSER* to control for the tax credit. The third simulation (model 5) adds in *DCREXOG* and *FHALTVGAP* to control for changes in consumer credit availability and FHA lending limits. The fourth simulation (model 6) builds on the third simulation by adding in the contemporaneous residual from a rent equation, used to later simulate the house price-to-rent ratio after 2009:q2. This residual picks up changes in rental markets reflecting noncyclical factors. Although this may introduce the possibility of simultaneity bias, this concern is greatly tempered by evidence that changes in house prices have much larger effects on the price-to-rent ratio than on the very smooth rent series. We also made these models more parsimonious than model 6 from Table 3.[9]

[9] We dropped the insignificant t-1 lag on *ΔFHAFEE* and combined the t-2 and t-3 lags of this variable into one dummy variable. In addition, we dropped the insignificant t-1 lag on *Δlog RUCADJ*, the insignificant difference term in the LTV ratio, and the t-2 lag on *ΔREGQ* which became insignificant in the longer sample.

Several patterns emerge across the simulations shown in Figure 4. First, adjusting the real user cost for the tax credit improves model fit, comparing models 3 and 4. Second, across simulation models 4-6, the coefficient on the FHA LTV gap variable is statistically significant, being somewhat smaller in size than the regular LTV variable. This implies that FHA loans have become imperfect, but notable substitutes for private mortgages for middle market homes[10] following the equalization of the size limits on FHA insured loans and mortgages securitized by Fannie Mae and Freddie Mac. Third, the presence of the *DCREXOG* variable indicates that there can be contemporaneous spillover effects from changes in consumer credit availability on real house prices, but that these effects do not affect the estimated effects of LTV ratios on house prices. Fourth, the presence of the *DCREXOG* variable has only a modest effect on the coefficient of the dummy for the financial crisis, consistent with the view that the crisis had an additional effect on housing demand by raising uncertainty. Nevertheless, adding the *DCREXOG* variable helps "clean up" model residuals.[11] Finally, the significance of the rent residual in model 6 suggests that there is nominal inertia in the short run. Nevertheless, although the rent residual's significance may have some general implications for housing demand, its inclusion is not necessary for well-fitting simulations.

Rather, it is the inclusion of adjustments for the tax credit and FHA liberalization that has a decisive role in improving the simulations. This can be seen in Figure 4 by comparing the small improvement from shifting from model 4 to model 5 and then to model 6 compared to the sizable improvement in the simulations by moving from the baseline model 3 to model 4 — which accounts for the tax credit and FHA changes. These results indicate that these policies

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[10] Recall that the house price index are for homes bought with conforming mortgages securitized by Freddie Mac.
[11] Also note that because our assumed LTV path is constant, this leaves the possibility that the dummy for the financial crisis may still pick up the effects of a sudden tightening of mortgage credit standards in late 2008.

helped bolster house prices, with the 2009 gap between model 3 and the others suggesting a sizable impact of the tax credit for first-time home-buyers.

IV. The Overvaluation Question

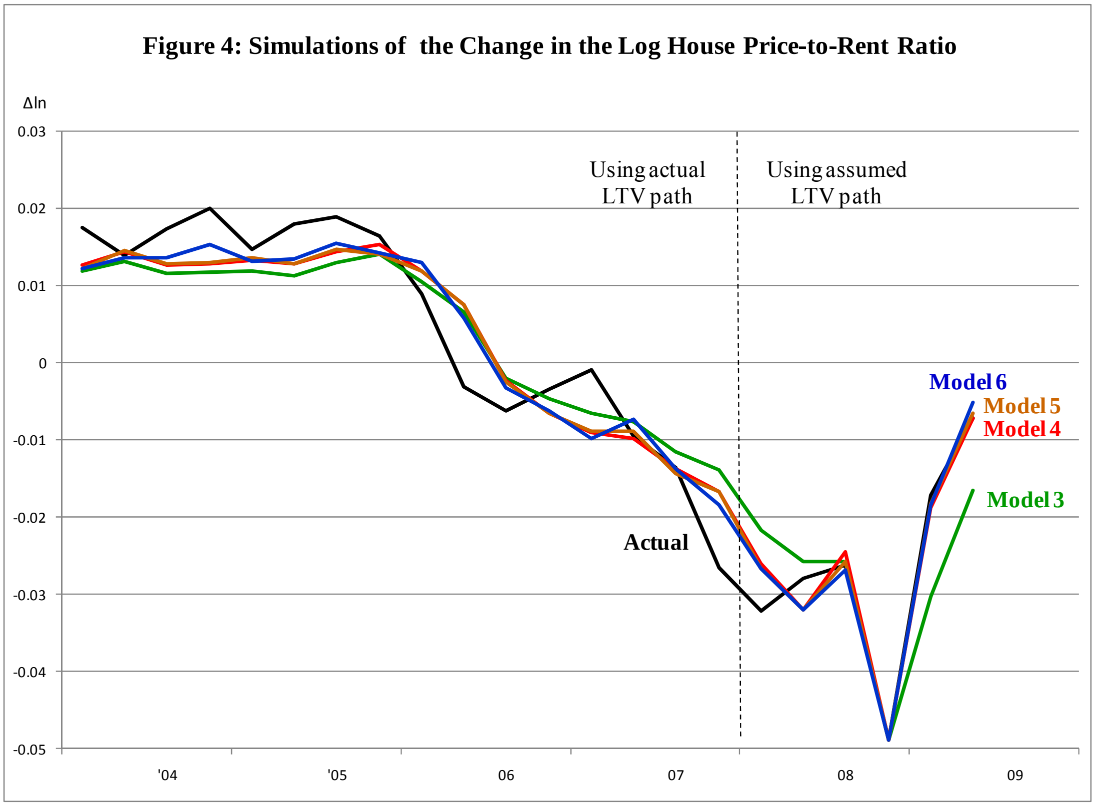
To throw light on how much U.S. home prices were overvalued in the 2007-2009 period, we now examine the implications of our house price-to-rent model incorporating LTV terms for the deviations of prices from their 'equilibrium' or 'long-run' values. As noted in section III, there is more than one concept of equilibrium. The narrow concept is conditional on the observed log real user cost as used in our econometric models. Consider model 6 (Tables 1 and 2) for the home price-to-rent approach as an example.

The long run solution is ln HPRENT = 1.1 - 0.16 ln RUSER + 0.87 ln LTV + fitted effects of persistent terms or step dummies for tax variables and the 1979-82 monetary policy regime. Then, conditional on ln RUSER, the deviation from equilibrium is:

ln HPRENT – 1.1 + 0.16 ln RUSER - 0.82 ln LTV - fitted step function dummies,

which reflects I(0) variables such as lagged changes in ln HPRENT and the residuals.

By this metric, U.S. home prices were over-valued by 9% in 2009:q2 using LTV model 6 versus 7% using non-LTV model 3 in Tables 1 and 2. However, the calculations for the LTV-inclusive models (henceforth, "LTV models") assume that the LTVs of early 2007 were sustainable, an assumption proven incorrect by the subprime bust. In addition, these calculations have the shortcoming that RUSER contains the annual house price appreciation over the prior 16 quarters, which cannot be regarded as permanent and is part of the "bubble builder"' in the model's dynamics, as Abraham and Hendershott (1996) discuss.



A model for rents

To properly address the question of whether house prices were overvalued in mid 2009, we need to examine some house price scenarios. Rents are clearly the key endogenous driving variable in our house price-to-rent models, so requiring a rent equation in order to create these scenarios. Comparing the annual log changes of rents, house prices and consumer prices (the consumer expenditure deflator), house prices are far more volatile than rents or consumer prices. The standard deviations are 0.043 for house prices, 0.023 for consumer prices and 0.021 for rents.

Rents are clearly fairly sticky and often set by annual or even longer duration contracts. Rents often include an allowance for heating and lighting costs, from which estimated energy costs are deducted from contract rents to compute official rents. As a result, sharp changes in energy prices can create sharp changes in official rents, so we include 4-quarter changes in log real energy prices (*Δ4lnRPENERGY*) in our rent models. The arbitrage relationship between house prices and rents, does not specify a rent model. We therefore begin with an eclectic reduced-form, equilibrium correction, rent model and follow standard model selection procedures to find a parsimonious model which explains the data and is consistent with economic priors.

Given lack of money illusion in the long run, a doubling of house prices and of consumer prices is eventually expected to double the rent index. Hence, the log ratio of the overall PCE deflator to nominal rents (ln*PPCE*- ln*RENT*) and that of the home price index to rents (ln*HP*-ln*RENT*) should be key elements of the long run solution. Given that the rent index is adjusted for energy prices, it is possible that dynamics in the ratio of the energy price component of the PCE deflator to the overall PCE deflator might pick up some timing discrepancies in the adjustment. Higher interest rates and property taxes should raise real rents and one would also expect that the user cost term, *RUSER*, which as we have seen, has a strongly negative effect on house prices, to have a positive effect on rents. It is possible that cyclical variables such as the unemployment rate and the rate of growth of non-property income (the four-quarter log change *Δ4*ln*RY* works well) could affect the ratio of rents to consumer prices or to house prices. The population of renters includes a higher proportion of younger and lower income households whose ability to pay is likely to be more sensitive to non-property income growth and the unemployment rate than the population of owner-occupiers.

Apart from property taxes reflected in the user cost, one would expect tax depreciation rules to impact on rents relative to house prices. We define *TAXDEPR* as the number of years over which rental properties can be depreciated for tax purposes. This period has been stable since 1987. However, it shifted greatly in earlier years (Poterba, 1990), with longer depreciation periods raising the after-tax cost of renting. It is also possible that the relaxation of capital gains taxes on owner-occupied homes could have lowered rents relatively to home prices so we test for this effect. (We also check to see if the loan-to-value ratio for first time buyers has the opposite effect on rents than it does on the house price-to-rent ratio.)

To summarize the empirical findings in Table 5, the expected long-run effects on rents of house prices and the PCE deflator are confirmed, with approximately equal weights in the long-run solution, and a speed of adjustment of a little under 10% per quarter. There is evidence of a significant tax depreciation effect, but none of a significant capital gains tax effect on rents. The level of the tax depreciation variable one quarter ago is significant, as well as its four quarter change. The loan-to-value ratio is insignificant, but there is evidence for a positive effect of log real user cost on rents in the long run. Indeed, the log real user cost is most significant as an 8-quarter moving average (ln*RUSERMA8*), at a lag of 2 quarters. The 4 and 8 quarter lagged growth in non property income are also significant and there are traces of effects at similar lags for changes in log real energy prices. The level and quarterly change in the nominal mortgage rate (*NOMMORT*), lagged one quarter are significant. In the dynamics, lagged changes in log rents with lags to four quarters appear, although only the first two lags are significant. The equation also includes impulse dummies for four outliers, in 1977:q1, 1979:q1, 1980:q1 and 1986:q2, which are omitted from the table to conserve space. Table 5 provides details and estimates over different samples, which indicate parameter stability, and show that key coefficients are similar when the tax depreciation terms are omitted. For the house price-to-rent based forecasts, the best fitting model (model 1) was used to forecast rents under various scenarios.

The importance of accurately forecasting rents for forecasting house prices in a house price-to-rent model suggested that we should incorporate the tax depreciation variable more generally in the house price-to-rent model, and not just the rent model. In different models we found that the t-1 and t-3 lags of the TAXDEP variable helped explain the house-price-to-rent model. As shown in table 6, other housing coefficients are similar to those estimated without these two tax law lags, and that coefficients are very stable across different sample periods. Overall, the best fitting model was model 2 from Table 6, which was used with rent model 1 from Table 5 to forecast house prices.

Robustness of Simulations

Dynamic simulations of the pair of house price and rent equations within sample are a useful check on model specification. Out of sample, they can help assess whether home prices in mid-2009 were overvalued or not. To check the robustness of the estimated specifications, a variety of specifications were compared in and out of sample. For the home price/rent equation these included using lags of 1 vs. 2 quarters on *LTV* and *FHALTVGAP*; including or excluding the nominal rent residual, and measuring the lagged annual average home price appreciation over 16 quarters, 14 quarters or relative to the average home price between 3 and 4 years ago. Variations for the rent equation included specifications with and without log log *RUCADJ* to incorporate recent policy shifts. The conclusion of these checks is that the dynamic simulations are remarkably robust in and out of sample. Within sample, the more comprehensive specification of the home price/rent equation including the rent residual and tax depreciation gives marginally better results, as does the rent equation containing log *RUSER*. But modest variations in the lag on LTV and *FHALTVGAP*, and on the span over which annual home price appreciation is measured in the construction of log *RUSER*, make almost no difference. Out of sample, specifications including the 8-quarter moving average of log RUSER in the rent equation and the rent residual in the price-to-rent equation result in a marginally higher home prices over 2011 to 2016, compared to equations omitting these two effects.

Various Scenarios

The economic scenario examined made the following simple assumptions: the mortgage interest rate remains at 5 percent; real per capita non property income grows 2 percent per annum from 2009:q3; average PCE inflation is 1.5 percent in 2010, and 1.8 percent thereafter; the ratio of the PCE energy deflator relative to the total PCE deflator rises by 5 percent in 2009:q4 and no change thereafter; no further changes in LTV, FHA policies (so *FHALTVGAP* is unchanged), and the index of consumer credit availability. For taxation, no changes in capital gains tax or tax deprecation rates are assumed, but most important, it is assumed that the announced withdrawal of the tax credit at the end of 2010:q2 is adhered to. We examine several scenarios which alter key housing variables, but the rent paths are very similar across these scenarios (Figure 5), with the exception of being lower if the first-time home-buyer tax credit became permanent.

Under the baseline assumptions, which are relatively benign on the economic fundamentals, home prices stabilize between 2009:q3 and 2010:q3 (Figure 6). However, in the baseline scenario there is a further dip in 2011, so that nominal home prices reach their trough in 2012:q2, rising thereafter by an average rate of 4 percent per annum to 2015:q2. They end at levels that recapture somewhat more than half of the declines posted during the recent housing bust. Under the alternative assumption that the tax credit remains until 2016, Freddie Mac home prices are essentially flat in 2010 and begin to pick up slowly from the beginning of 2011 and rise at an average annual pace near 4 percent from mid-2011 to mid-2015, reaching nominal levels above the 2006 peak in 2015.

The Freddie Mac home price index lags two to three quarters behind the more volatile Case-Shiller 10 city index, so it is likely that the above scenario would occur two or three quarters earlier in the Case-Shiller index. The evidence in this paper highlights the role of the tax credit in the stabilization and short term rise in home price indices seen in 2009. It is plausible that the belief that the tax credit would be withdrawn at the end of 2009 led to a temporary surge in activity in the second half of 2009. The models suggest that home prices will be vulnerable to the withdrawal of the tax credit and could suffer a further modest nominal decline before beginning a more sustained rise.

The assumption that the LTV is unchanged at 0.866 over the forecast period might be too pessimistic. However, with a coefficient of 0.089 on log LTV and 0.077 on *FHALTVGAP* in the preferred home price/rent model, where *FHALTVGAP* = log (0.965/ *LTV*), and *LTV* assumed to be 0.866 from 2007:q4, the effective composite LTV taking into account the improved access to FHA loans is 0.965 from 2008. This is high relative to the history of the previous 20 years and suggests that the home price stabilization in our main scenario depends on mortgage credit availability. To examine the critical role of credit constraints, the figures plot the baseline scenario along with 2 credit scenarios. In both, FHA reverts back to earlier mortgage size limits starting in 2010:q3, thereby restoring private mortgage credit constraints to their prior role in determining credit for the marginal buyer in the middle-market for U.S. homes. In one alternative scenario, the private LTV ratio is assumed to permanently stay at .866. (Given the two quarter lag on LTV, we set LTV = 0.866 since 2010:q3 in the forecast). In the other credit scenario, the private LTV ratio is assumed to revive to .90 since 2010:q3, which assumes that LTV ratios rebound to about half-way between their pre-subprime boom level of 1999:q4 (.8660) and their 2007:q2 level (.9294), posted just before broader financial markets began noticeably

Figure 5: Rent Simulations

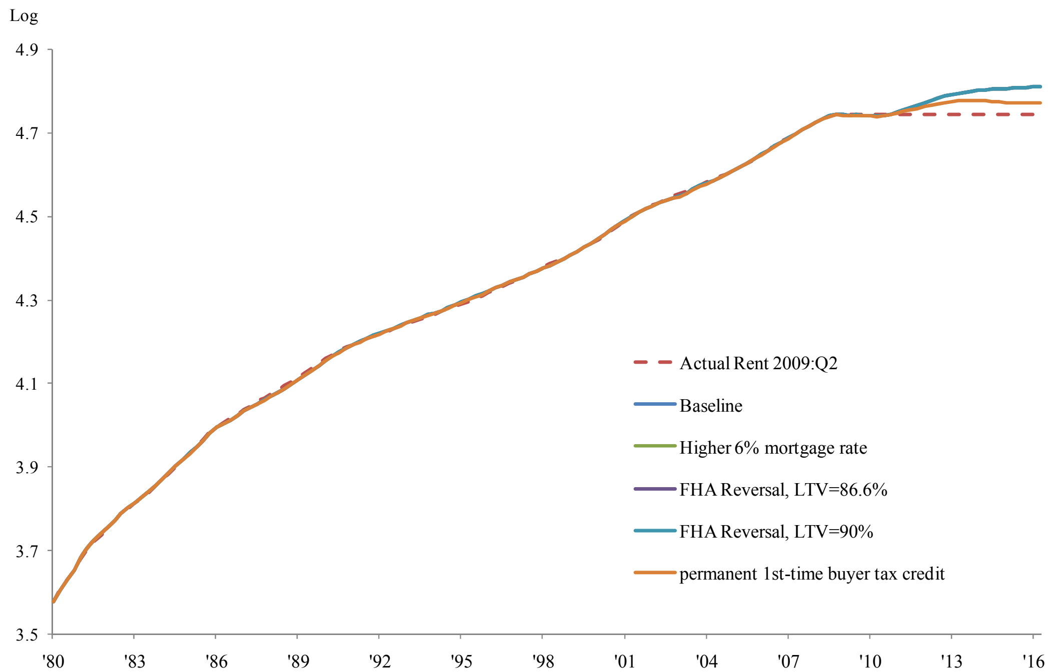
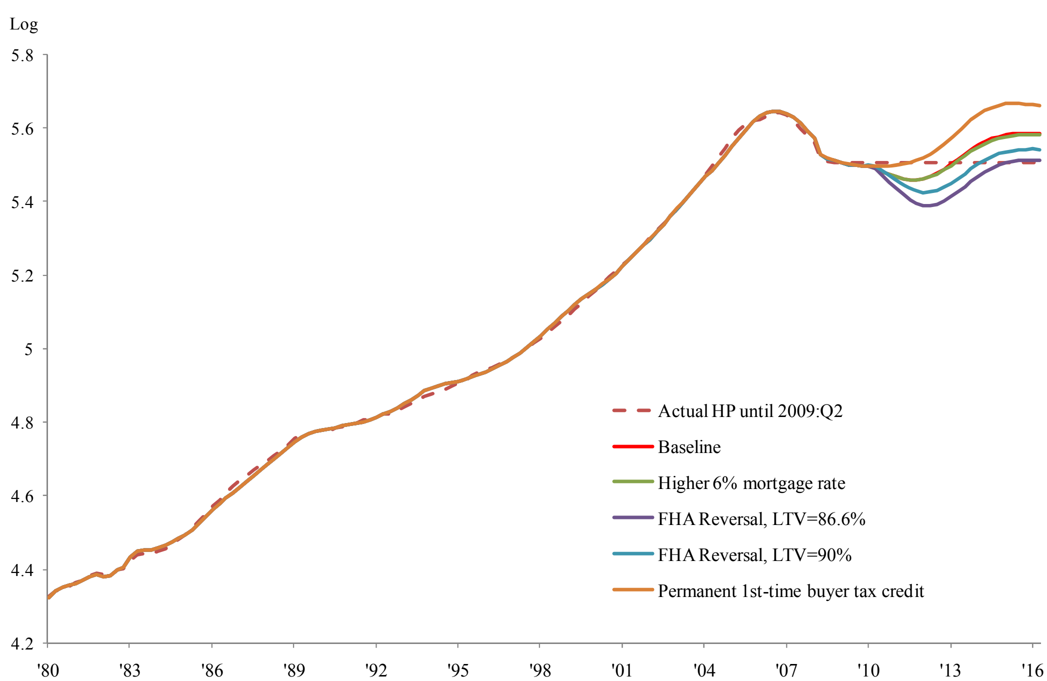


Figure 6. House Price Simulations



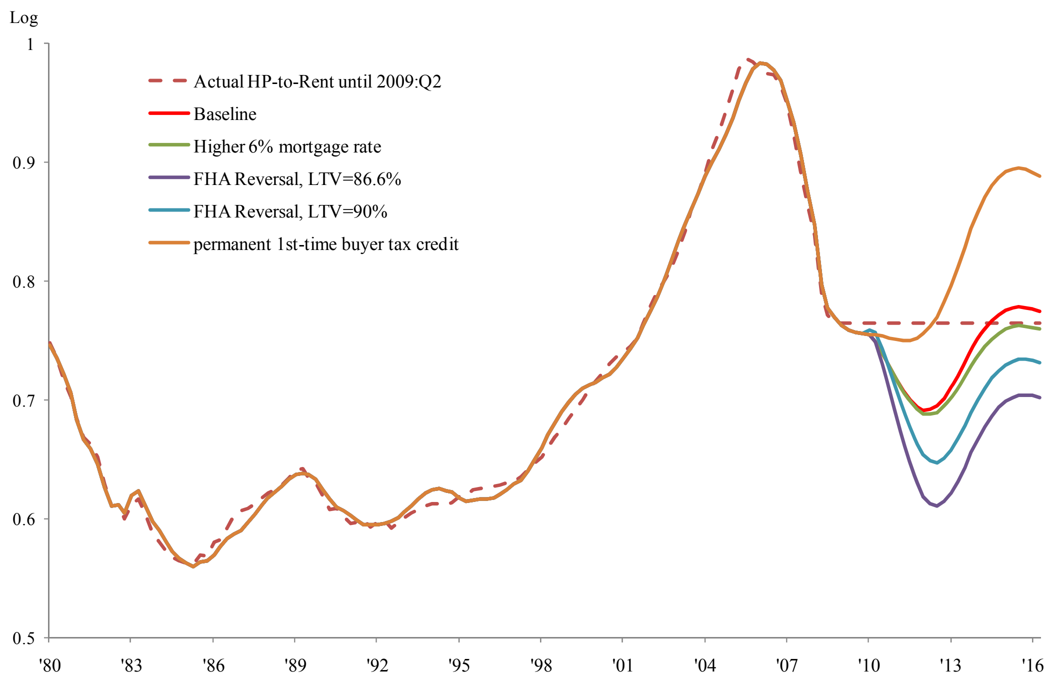
reacting to government interventions into Fannie Mae and Freddie Mac and to the halt in redemptions from some subprime-exposed hedge funds on August 9, 2007.

The implications of changes in down-payment constraints facing first-time buyers are interesting. A reversal of the increases in FHA lending limits coupled with a return of loan-to-value ratios for first time buyers to late 1990s levels, together with the downward momentum of falling home prices since 2006, leads to further falls in house prices. As these declines occur, the growth in rents is dragged down and even reversed, though the higher user cost implied by falling house prices partially offsets the impact of a lower level of house prices. Since rents appear in the long-run solution for house prices, this prolongs the fall in house prices. The impact of a reversal in FHA loan limits is more muted in the less pessimistic scenario in which private mortgage LTVs revert to levels that unwind only half of their jump seen during the subprime boom. We provide these alternative simulations given the uncertainty surrounding the outlook for nonFHA credit standards and the possibility that the FHA policies may be revised.

Lower interest rates are only marginally helpful, according to the two-equation model, since while lower interest rates raise house prices given rents, they also lower rents. To the extent that lower mortgage rates raise income growth and prevent deflation, however, they could positively affect rents and thereby house prices. The limited impact of interest rates is illustrated in a higher interest rate scenario in which nominal mortgage rates rise to 5.2 percent in 2011:q2 then to 5.4 in 2011:q4, to 5.5 in 2012:q1, 5.7 in 2012:q3, and finally 6.0 in 2012:q4. The impact of this scenario is barely visible on the house price-to-rent ratio (Figure 7), and even less so on house prices (Figure 6) where baseline is visually identical to this scenario.

The robustness of these findings to using the inverted housing demand approach remains to be explored. On the face of it, the inverted demand approach may provide more scope for low interest rates to affect house prices and a less pessimistic picture may result. The provisional conclusions drawn above should therefore be treated with considerable caution.

Figure 7. House Price-to-Rent Simulations



V. Conclusion

Our findings provide a theoretically appealing and empirically consistent account of the behavior of U.S. home prices. In the two main theoretical approaches to modeling house prices, the inverted demand and home price-to-rent frameworks, credit standards for first-time home-buyers are important determinants of home prices. Our results, which focus on the price-to-rent approach, also confirmed using the inverted demand approach in Appendix A, indicate that a substantial easing of U.S. mortgage standards, as reflected in the LTV ratios for first-time home-buyers, substantially raised 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, and almost certainly further reversals since the mortgage-related financial market turmoil which started in August 2007 and intensified during the Fall of 2008.

Most empirical models of US home prices lack a measure of mortgage credit standards and thus suffer from a serious 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, 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 stemmed from an easing and subsequent tightening in U.S. mortgage standards affecting potential marginal home-buyers. Our models suggest that loan-to-value ratios for private sector mortgages for first time buyers have returned to 1998 levels, although increased credit availability through changes in FHA lending programs and the tax credit for first-time home-buyers has cushioned much of the impact of tighter private mortgage standards. 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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Appendix A: Model Estimates from Inverting the Demand Function for Housing (Not intended for publication, available upon request from the authors)

For robustness, we assess the importance of our LTV measure in empirical models based on the inverteddemand for housing using error or equilibrium correction models specified in logs(e.g. Cameron, Muellbauer and Murphy, 2006). Perhaps the simplest theory of house price determination treats supply of housing services—assumed proportional to 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*).[12] Let log housing demand be given by

$$\ln HSTOCK = -\alpha \ln HP + \beta \ln Y + Z \qquad (1)$$

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

$$\ln HP = (\beta \ln Y - \ln HSTOCK + Z) / \alpha \qquad (2)$$

Priors for key long run elasticities are the "central estimates" in Meen (2001) and Meen and Andrews (1998), *inter alia*. For example, many estimates imply an income elasticity of demand near 1 to 1.5. Important drivers in the vector *Z* include 'user cost' (defined earlier) and expected or 'permanent' income. Other factors could include nominal as well as real interest rates, credit supply conditions, demography, and proxies for risk, particularly of mortgage default.

Lagged price adjustment is likely given the inefficiency of house prices. The change in and level of per capita housing stock are likely relevant. One interpretation is that seeing much new construction might lower expectations of appreciation. Another is that prices adjust to both stock and flow disequilibria, for which error or equilibrium correction models are well suited. The price-to-rent approach is more grounded in finance, and the inverted demand approach, in consumer demand theory. The empirical advantages of the former are that it is applicable where rental markets are flexible (U.S.), does not require housing stock data, and uses rents that track factors special to housing that may be difficult to control for in the inverted-demand approach. The inverted demand approach[13] is better when housing supply is fairly inelastic and/or when rental markets are highly regulated or small, not ignoring the fact that income drives both rents and home prices. It may also be better at tracking house prices where both home prices and rents may be over-valued or when housing supply shifts. A priori, both approaches are applicable in the US and it is unclear which approach is better.

Additional variables are needed to estimate inverted demand models. As in the FRB-US model, real per capita personal disposable non-property income (*Y*) equals the tax adjusted sum of labor and transfer income, deflated by the overall personal consumption expenditures 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.[14] The real per capita housing stock (*HSTOCK*) is the replacement cost of residential structures of households (Federal Reserve) deflated by the housing construction price index. To control for demographic shifts affecting housing demand, we include the 8 quarter change in the log of the labor force between the ages of 25 and 44, a category containing the vast bulk of first-time home-buyers. Labor force age categories are less distorted by diennial census breaks than population-based categories. Accordingly, this I(1) variable should have a positive coefficient. The t-3 lag of it maximized model fit and is used in the appendix models. Another difference from the price-to-rent model is that the t-2 lag on the first difference of $\Delta REGQ$ was insignificant

[12] Inverse demand functions have a long history, particularly in the analysis of markets for natural resources. Theil (1976) refers to a 1909 Danish study as the first empirical study of inverse demand functions.

[13] Hamilton and Schwab (1985), Case and Shiller (1989, 1990), Poterba (1991) and Meese and Wallace (1994) find house price changes are positively correlated and past information on housing fundamentals forecasts future excess returns. Capozza and Seguin (1996), and Clayton (1997) also find evidence against rational home price expectations.

[14] To address whether the non-property income variable may not reflect changes in expected future income, we added the change in log future income (*EY*) from a small forecasting model, but this variable was insignificant.

and is replaced with the t-4 lag. This lag has a positive effect and helps clean up the model residuals, reflecting the fact that the unwinding of the negative Reg Q effect in time t-1 occurs about three quarters afterward.

We present results from two-step (Johansen / Engle-Granger) cointegration models and one-step autoregressive distributed lag (ADL) models, including and excluding our LTV mortgage credit supply measure. The models are estimated over the full sample and include a full set of controls, corresponding to house price-to-rent models 3 and 6 in Tables 1 and 2. Models 3 and 4 are more parsimonious ADL models corresponding to cointegration models 1 and 2. The latter are estimated over 1980:q3-07:q2, reflecting the number of lagged first difference terms needed to obtain a unique and significant cointegrating vector, clean residuals when possible, and a good fit (in terms of the AIC). We allowed time trends in the endogenous variables. but assumed there was no time trend in the cointegrating vector. The one-stage model samples end in 2007:q4 reflecting the t-2 lag on the LTV ratio and an extra quarter of sample gained when estimating the ADL models.

Although cointegrating vectors are obtained with the expected signs for the non-LTV and all LTV models (models 1 and 2, respectively), the LTV model is better. First, the LTV model fits better, explaining 9 percent more of the variance, with the non-LTV model having a standard error 32 percent larger than that of the LTV model. Second, the speed of adjustment is higher and a more reasonable 11% per quarter in the LTV model. Third, the LTV model yields a more plausible long-run income elasticity of 1.5, versus the less plausible 2.5 value in the non-LTV model.

A natural question is whether the LTV ratio is driven by home prices, which would complicate the interpretation of these findings. Estimating a vector error correction (VEC) system with a lag length of 3 and model 2 from Appendix Table 1, the house price error correction term is insignificant in modeling the LTV ratio (t statistic of 1.63), indicating that the LTV ratio is weakly exogenous to the other variables.

Although *a priori* it is unclear which approach is better, the corresponding inverted demand and price-to-rent models both perform well, and indicate that changes in the LTV ratio for first-time buyers, our proxy for exogenous changes in mortgage credit supply, is an important determinant of US house price booms and busts.

Table 1: Cointegration Results for the U.S. House Price-to-Rent Ratio

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
		Sample: 1981q3-2007q2 (monetary regime, tax, & RegQ variables present)			
1	1	lnHPRENT = 1.069656 - .224500*lnRUSER**	599.0361	0.178126	0.019548
		(-14.00)	(-10.61178)	(23.31833*)	(0.019548)
				(21.18622**)	(3.841466)
4	1	lnHPRENT = 1.099400 - .176790*lnRUSER** + 0.768444*lnLTV**	967.8432	0.301342	0.080892
		(-20.63) (5.02)	(-17.24232)	(47.95519**)	(9.944229)
				(38.01096**)	(8.941237)
		Sample: 1981q1-2007q2 (monetary policy, Reg Q, tax, MMDA, and FHA variables present)			
3	2	lnHPRENT = 1.075951 - .225471*lnRUSER**	604.3817	0.272448	0.080693
		(-17.82)	(-11.43042)	(41.82940**)	(8.750107**)
				(33.07929**)	(8.750107**)
6	1	lnHPRENT = 1.976886 - .159382*lnRUSER** + 0.822818*lnLTV**	1002.442	0.406710	0.108291
		(-21.32) (6.61)	(-17.89513)	(50.04360**)	(10.36789)
				(39.67571**)	(9.184192)
		Sample: 1981q3-2001q4 (monetary policy, Reg Q, tax, MMDA, and FHA variables present)			
2	1	lnHPRENT = 1.05288 - .209881*lnRUSER**	520.4092	0.222987	0.032238
		(-6.78)	(-12.44901)	(23.37552**)	(2.687036)
				(20.68848**)	(2. 687036)
5	1	lnHPRENT = 1.077502- .162795*lnRUSER** + 0.768763*lnLTV**	842.0972	0.311677	0.113602
		(-8.50) (4.81)	(-18.77343)	(41.09687**)	(6.474566)
				(31.00027**)	(10.00886)

	Level (AIC lag in parentheses)	***5% Critical level for lag***	***1% Critical level for lag***	***First Diff. AIC lag in parentheses)***	***5% Critical level for lag***	***1% Critical level for lag***	***Assumptions***
lnHPRENT	-1.611874 (8)	-3.449716	-4.040532	-4.304550** (7)	-3.449716	-4.040532	constant/trend
lnRUSER	-3.117813 (12)	-3.449716	-4.040532	-4.324544** (11)	-3.449716	-4.040532	constant/trend
lnLTV	-2.139151 (3)	-3.451959	-4.045236	-4.906635** (8)	-3.454471	-4.050509	constant/trend

Notes. $^{+}$ (*,**) denotes significant at the 90% (95%, 99%) level. t-statistics in parentheses except when AIC statistic is reported. For vectors numbered 1,2,4-6, lag lengths of (5, 1, 5, 6, and 5), respectively, minimized the AIC, and except for nonLTV models, yielded clean residuals and unique, significant vectors allowing time trends in the variables. Lag lengths in the ADF unit root tests based on the Akaike Information Criterion. Data span 1979-2007:2.

Table 2: Second Stage Error Correction Models of the Change in the U.S. Log Home Price-To-Rent Ratio, ΔlnHPRENT

	No LTV Terms			*LTV Terms*		
	81:1-07:2	81:1-01:4	81:1-07:2	81:1-07:2	81:1-01:4	81:1-07:2
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	0.0006	-0.0001	0.0004	0.0008	-0.0001	-0.0001
	(0.94)	(-0.19)	(0.66)	(1.26)	(-0.22)	(-0.57)
EC_{t-1}	-0.0431^{+}	-0.0620^{**}	-0.0409^{*}	-0.1385^{**}	-0.1072^{*}	-0.1180^{**}
	(-1.92)	(-2.88)	(-2.61)	(-4.21)	(-2.59)	(-3.47)
$MONEYTARGET_{t}$	-0.0093^{*}	-0.0094^{**}	-0.0076^{**}	-0.0131^{**}	-0.0061	-0.0087^{**}
	(-2.42)	(-3.44)	(-3.14)	(-3.50)	(-1.54)	(-2.79)
$\Delta REGQ_{t-1}$	-0.0055^{*}	-0.0041^{*}	-0.0043^{+}	-0.0050^{+}	-0.0020	-0.0043^{*}
	(-2.00)	(-2.04)	(-1.97)	(-1.98)	(-0.69)	(-1.99)
$\Delta REGQ_{t-2}$	-0.0034	-0.0047^{*}	-0.0041^{+}	-0.0041^{+}	-0.0047^{*}	-0.0039^{+}
	(-1.42)	(-2.36)	(-1.90)	(-1.73)	(-1.90)	(-1.93)
$CAPGAINTAX_{t-2}$	0.0053^{**}	0.0053^{**}	0.0034^{*}	0.0068^{**}	0.0057^{**}	0.0055^{**}
	(3.35)	(3.61)	(2.92)	(4.49)	(3.56)	(3.74)
$\Delta FHAFEE_{t}$		0.0166^{**}	0.0177^{**}		0.0188^{**}	0.0198^{**}
		(3.90)	(3.92)		(4.39)	(-4.48)
$\Delta FHAFEE_{t-1}$		0.0045	0.0022		0.0040	0.0004
		(0.98)	(0.47)		(0.76)	(0.08)
$\Delta FHAFEE_{t-2}$		-0.0110^{*}	-0.0126^{**}		-0.0072	-0.0068
		(-2.58)	(2.78)		(-1.37)	(-1.37)
$\Delta FHAFEE_{t-3}$		-0.0094^{*}	-0.0085^{+}		0.0115^{**}	0.0117^{*}
		(-2.19)	(-1.88)		(2.28)	(-2.60)
$MMDA_{t}$		0.0083^{+}	0.0104^{*}		0.0130^{**}	0.0107^{*}
		(1.87)	(2.22)		(2.73)	(2.40)
$\Delta lnHPRENT_{t-1}$	0.3428^{**}	0.3151^{**}	0.4418^{**}	0.3272^{**}	0.2082^{+}	0.3892^{**}
	(3.30)	(3.05)	(4.41)	(3.33)	(1.97)	(3.97)
$\Delta lnHPRENT_{t-2}$	0.0138			-0.0523	0.0640	-0.0291
	(0.12)			(-0.47)	(0.54)	(-0.25)
$\Delta lnHPRENT_{t-3}$	0.0282			0.0921	0.1714	0.2463^{*}
	(0.27)			(0.92)	(1.49)	(2.44)
$\Delta lnRUSER_{t-1}$	0.0001	-0.0141	-0.0160^{*}	-0.0055	-0.0029	-0.0048
	(0.01)	(-1.32)	(-2.11)	(-0.54)	(-0.21)	(-0.55)

$\Delta lnRUSER_{t-2}$	-0.0132			0.0017	-0.0027	0.0060
	(-1.45)			(0.18)	(-0.17)	(0.71)
$\Delta lnRUSER_{t-3}$	-0.0158^{+}			0.0013	0.0038	0.0047
	(-1.84)			(0.15)	(0.29)	(0.58)
$\Delta LLTV_{t-1}$				-0.1545**	-0.1212*	-0.1264**
				(-2.84)	(-2.45)	(-2.64)
$\Delta LLTV_{t-2}$				0.0130	0.0071	0.0293
				(0.24)	(0.15)	(0.61)
$\Delta LLTV_{t-3}$				-0.1348**	0.0309	0.0274
				(-2.64)	(0.67)	(0.72)
R^2	.689	.709	.750	.747	.801	.827
S.E.	.005009	.004026	.004326	.004492	.003385	.003719
VECLM(1)	21.88**	3.60	6.41	8.88	6.17	10.16
VECLM(8)	5.30	3.49	4.97	13.53	9.55	10.19

* (**,$^{+}$) significant at 95% (99%, 90%) level. t-statistics in parentheses. EC terms from VECMs estimating the long and short-run relationships, corresponding to vector numbers from Table 3. Coefficients on lagged changes on lags longer than t-3 are omitted to conserve space.

Table 3: One-Stage Models of the Change in U.S. Log Price-Rent Ratio, 1980-2001 & 1980-2007

	No LTV Terms			*LTV Terms*		
	80:4-07:2	80:4-01:4	80:4-07:2	80:4-07:2	80:4-01:4	80:4-07:2
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	0.0843**	0.0675**	0.0597**	0.1523**	0.1356**	0.1253**
	(4.03)	(2.95)	(3.18)	(5.67)	(5.00)	(4.89)
$\ln HPRENT_{t-1}$	-0.0860**	-0.0893**	-0.0644**	-0.1420**	-0.1386**	-0.1188**
	(-4.07)	(-3.13)	(-3.41)	(-5.72)	(-5.06)	(-5.01)
$\ln RUSER_{t-1}$	-0.0151**	-0.0077^{+}	-0.0097**	-0.0211**	-0.0160**	-0.0160**
	(-3.77)	(-1.96)	(-2.67)	(-5.15)	(-3.81)	(-4.09)
$\ln LTV_{t-2}$				0.1317**	0.1087**	0.1199**
				(3.73)	(3.69)	(3.87)
$MONEYTARGET_{t-1}$	-0.0082**	-0.0043	-0.0047*	-0.0083**	-0.0047^{+}	-0.0052*
	(-3.09)	(-1.56)	(-2.00)	(-3.38)	(-1.89)	(-2.42)
$CAPGAINTAX_{t-2}$	0.0070**	0.0068**	0.0056**	0.0072**	0.0071**	0.0060**
	(3.73)	(3.42)	(3.35)	(4.07)	(4.07)	(3.98)
$\Delta REGQ_{t-1}$	-0.0051*	-0.0041*	-0.0048**	-0.0051*	-0.0048**	-0.0050**
	(-2.49)	(-2.43)	(-2.66)	(-2.56)	(-3.21)	(-3.02)
$\Delta REGQ_{t-2}$	-0.0041^{+}	-0.0038*	- 0.0035^{+}	-0.0049*	-0.0050**	-0.0045**
	(-1.86)	(-2.20)	(-1.88)	(-2.38)	(-3.24)	(-2.64)
$\Delta FHAFEE_{t}$		0.0206**	0.0221**		0.0215**	0.0222**
		(4.85)	(4.80)		(5.75)	(-5.29)
$\Delta FHAFEE_{t-1}$		0.0040	0.0016		0.0073^{+}	0.0050
		(0.94)	(0.35)		(1.89)	(1.16)
$\Delta FHAFEE_{t-2}$		-0.0096*	-0.0094*		-0.0056	-0.0060
		(-2.22)	(2.01)		(-1.41)	(-1.38)
$\Delta FHAFEE_{t-3}$		-0.0155**	-0.0114*		0.0136**	0.0103*
		(-3.66)	(-2.52)		(3.55)	(-2.45)
$MMDA_{t}$		0.0117**	0.0124**		0.0134**	0.0117**
		(2.74)	(2.71)		(2.99)	(2.80)
$\Delta \ln HPRENT_{t-1}$	0.3595**	0.2614*	0.4363**	0.2877**	0.1888*	0.3330**
	(3.74)	(2.63)	(4.51)	(3.15)	(2.13)	(3.61)

$\Delta lnHPRENT_{t-2}$	-0.0814	0.1087	-0.0064	-0.1207	-0.0314	-0.0530
	(-0.76)	(1.00)	(-0.06)	(-1.21)	(-0.32)	(-0.52)
$\Delta lnHPRENT_{t-3}$	0.0978	0.2971**	0.2383*	0.0604	0.2807**	0.2113*
	(1.04)	(3.25)	(2.55)	(0.67)	(3.38)	(2.40)
$\Delta lnRUSER_{t-1}$	-0.0131	0.0015	-0.0066	-0.0096	0.0011	-0.0047
	(-1.40)	(0.13)	(-0.80)	(-1.10)	(0.11)	(-0.63)
$lnLTV_{t-2}-lnLTV_{t-5}$				-0.0314	-0.0144	-0.0189
				(-1.08)	(-0.60)	(-0.76)
R^2	.716	.780	.797	.755	.830	.829
S.E.	.004811	.003663	.004067	.004471	.003224	.003695
LM(2)	1.08	2.12	2.16	1.09	3.83	1.89
Q(24)	21.85	18.30	23.57	25.57	21.25	30.86

* (**,+) significant at 95% (99%, 90%) level. t-statistics in parentheses. Longer lags on first difference price-to-rent and real user cost terms were included in models 1 and 4 to yield models with well-behaved residuals. LM(2) is the Breusch-Godfrey Lagrange Multiplier test for ARMA errors for lags up to 2and Q(24) is the Ljung-Box Q-statistic testing for higher order serial correlation in the autocorrelation and partial autocorrelation functions of the residuals for lags up to 24 quarters.

Table 4: Alternative One-Stage Models for the Change in Log U.S. Price-Rent Ratio (ΔlnHPRENT)

	Home Improvement Adjusted		*Simulations Using an Assumed 2007:q3-09:q2 LTV Path*			
	80:4-07:4	80:4-07:4	80:3-09:2	80:3-09:2	80:3-09:2	80:3-09:2
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	0.0625^{**} (2.87)	0.0037^{**} (3.74)	0.1208^{**} (5.49)	0.1144^{**} (6.66)	0.1126^{**} (6.67)	0.1032^{**} (6.62)
$lnHPRENT_{t-1}$	-0.0734^{**} (-3.06)	-0.1001^{**} (-3.87)	-0.1191^{**} (-5.83)	-0.1127^{**} (-7.06)	-0.1106^{**} (-7.05)	-0.1022^{**} (-7.05)
$lnRUSER_{t-1}$	-0.0108^{*} (-2.52)	-0.0133^{**} (-3.07)	-0.0157^{**} (-4.29)	-0.0144^{**} (-5.03)	-0.0141^{**} (-5.00)	-0.0129^{**} (-4.99)
$lnLTV_{t-2}$			0.0953^{**} (3.66)	0.0959^{**} (4.21)	0.0968^{**} (4.33)	0.0877^{**} (4.26)
$FHALTVGAP_{t-2}$				0.0774^{*} (2.29)	0.0656^{+} (1.95)	0.0732^{*} (2.37)
$MONEYTARGET_{t-1}$	-0.0036 (-1.59)	-0.0029 (-1.33)	-0.0074^{**} (-3.33)	-0.0050^{**} (-2.52)	-0.0056^{**} (-2.82)	-0.0039^{*} (-2.13)
$CAPGAINTAX_{t-2}$	0.0055^{**} (3.28)	0.0051^{**} (3.15)	0.0083^{**} (4.95)	0.0061^{**} (3.77)	0.0060^{**} (4.07)	0.0054^{**} (4.00)
$\Delta REGQ_{t-1}$	-0.0046^{*} (-2.39)	-0.0046^{*} (-2.53)	-0.0062^{**} (-3.39)	-0.0061^{*} (-3.77)	-0.0052^{**} (-3.20)	-0.0050^{**} (-3.33)
$\Delta REGQ_{t-2}$	-0.0030 (-1.51)	-0.0034^{+} (-1.82)				
$\Delta FHAFEE_{t}$	0.0227^{**} (4.67)	0.0233^{**} (5.03)	0.0202^{**} (4.16)	0.0218^{**} (5.01)	0.0229^{**} (5.33)	0.0237^{**} (6.01)
$\Delta FHAFEE_{t-1}$	0.0026 (0.54)	0.0045 (0.94)				
$\Delta FHAFEE_{t-2}$	-0.0056 (-1.13)	-0.0036 (-0.75)				
$\Delta FHAFEE_{t-3}$	-0.0101^{*} (-2.08)	-0.0094^{*} (-2.00)				
$[\Delta FHAFEE_{t-2} + \Delta FHAFEE_{t-3}]$			-0.0166^{*} (-2.36)	-0.0183^{**} (-2.93)	0.0175^{**} (2.84)	0.0125^{*} (-2.18)
$MMDA_{t}$	0.0125^{*} (2.57)	0.0127^{**} (2.72)	0.0107^{**} (2.26)	0.0144^{**} (3.34)	0.0145^{**} (3.44)	0.0153^{**} (3.96)

$\Delta lnHPRENT_{t-1}$	0.4166^{**}	0.3617^{*}	0.3808^{**}	0.4335^{**}	0.4635^{**}	0.4921^{**}
	(4.16)	(3.73)	(5.15)	(6.70)	(7.14)	(8.23)
$\Delta lnHPRENT_{t-2}$	-0.0625	-0.0940	-0.0597	0.0354	-0.0104	-0.0058
	(-0.56)	(-0.87)	(-0.69)	(0.45)	(-0.13)	(-0.08)
$\Delta lnHPRENT_{t-3}$	0.2439^{*}	0.2457^{*}	0.0966	0.1570^{+}	0.1678^{*}	0.2022^{**}
	(2.52)	(2.59)	(1.10)	(1.97)	(2.14)	(2.80)
$\Delta lnRUSER_{t-1}$	-0.0070	-0.0063				
	(-0.88)	(-0.83)				
$FINCRISIS_t$			-0.0227^{**}	-0.0242^{**}	-0.0228^{**}	-0.0232^{**}
			(-4.58)	(-4.78)	(-4.54)	(-5.04)
$DCREXOG_t/100$					0.0062^{*}	0.0076^{**}
					(2.20)	(2.92)
$RENTRESID_t$						-0.7758
						(-4.49)
R^2	.786	.805	.845	.877	.881	.900
S.E.	.004310	.004112	.004513	.004471	.003956	.003624
LM(2)	3.10	5.35^{+}	5.97^{+}	0.61	0.28	1.12
Q(24)	21.60	22.44	42.98^{**}	39.90^{**}	33.24^{+}	32.28

* (**,$^{+}$) significant at 95% (99%, 90%) level. t-statistics in parentheses. Longer lags on first difference price-to-rent and real user cost terms were included in models 1 and 4 to yield models with well-behaved residuals.

Table 5: Models of Nominal Rents for House Price-Rent Forecasts

Variable\Model #:Sample	1:76:3-09:2	2:76:3-01:4	3:76:3-07:2	4:76:3-09:2	4:76:3-09:2
Constant	0.1543**	0.1256**	0.1700**	0.1531**	0.1728**
	(6.82)	(5.96)	(6.04)	(6.68)	(6.90)
$(\ln PPCE - \ln NOMRENT)_{t-2}$	0.0445**	0.0319**	0.0517**	0.0446**	0.0427**
	(7.20)	(6.93)	(5.81)	(6.94)	(6.35)
$(\ln HP - \ln NOMRENT)_{t-3}$	0.0437**	0.0184**	0.0536**	0.0451**	0.0271**
	(4.86)	(6.51)	(3.87)	(4.31)	(3.43)
$NOMMORT_{t-2}$	0.0016**	0.0017**	0.0018**	0.0017**	0.0014**
	(3.85)	(4.11)	(3.59)	(3.88)	(3.10)
$NOMMORT_{t-3}$	-0.0009*	-0.0010*	-0.0009+	-0.0009*	-0.0013**
	(-2.00)	(-2.20)	(-1.78)	(-2.08)	(-2.91)
$\ln RUSER\ MA8_{t-2}$	0.0045**	0.0073*	0.0046*	0.0020	
	(2.95)	(2.32)	(2.58)	(1.52)	
$\Delta 4\ln RPENERGY_{t-2}$	0.0017	0.0035	0.0008	0.0010	0.0035
	(0.73)	(1.50)	(0.02)	(0.42)	(1.43)
$\Delta 4\ln RPENERGY_{t-6}$	0.0039+	0.0051*	0.0042	0.0037	0.0049*
	(1.78)	(2.30)	(1.32)	(1.49)	(2.03)
$\Delta 4\ln Y_{t-2}$	0.0464**	0.0497**	0.0484**	0.0488**	0.0342**
	(4.25)	(4.42)	(3.50)	(4.09)	(2.87)
$\Delta 4\ln Y_{t-6}$	0.0648**	0.0661**	0.0715**	0.0650**	0.0603**
	(5.42)	(5.36)	(4.63)	(5.11)	(4.55)
$TAXDEPR_{t-1}/100$	0.0247**	0.0127*	0.0373*	0.0253**	
	(3.65)	(2.27)	(2.57)	(3.55)	
$\Delta 4TAXDEP_{t-1}/100$	0.0001+	0.0002**	0.0000	0.0001+	
	(1.85)	(3.30)	(0.46)	(1.83)	
$\Delta \ln NOMRENT_{t-1}$	0.3911**	0.3990*	0.3808**	0.3897**	0.4635**
	(5.86)	(5.79)	(4.99)	(5.70)	(7.14)
$\Delta \ln NOMRENT_{t-2}$	-0.2142**	-0.2278**	-0.2031*	-.2111**	-0.0104**
	(-3.18)	(-3.28)	(-2.60)	(3.05)	(-0.13)
$\Delta \ln NOMRENT_{t-3}$	0.0844	0.0460	0.0972	0.0704	0.1678*
	(1.28)	(0.69)	(1.24)	(1.02)	(2.14)
$\Delta \ln NOMRENT_{t-4}$	0.1043+	0.0819	0.1177+	0.1161+	0.1678*
	(1.71)	(1.31)	(1.66)	(1.84)	(2.14)
R^2	.935	.931	.933	.936	.919
S.E.	.001413	.001460	.001530	.001427	.001580
d.h.	-0.72	0.87	-0.82	-0.64	1.13

Table 6: Alternative One-Stage Forecast Models of the Change in the Log U.S. Price-Rent Ratio, ΔlnHPRENT

	Mod 6, Tab. 4	*Models Including Depreciation Variables*		
Model	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Sample	80:q3-09:q2	80:q3-09:q2	80:q3-07:q2	80:q3-01:q4
Constant	0.1032**	0.1171**	0.1090**	0.1160**
	(6.62)	(7.13)	(5.27)	(4.85)
$lnHPRENT_{t-1}$	-0.1022**	-0.1109**	-0.1019**	-0.1138**
	(-7.05	(-7.60)	(-5.45)	(-4.57)
$lnRUSER_{t-1}$	-0.0129*	-0.0149**	-0.0133**	-0.0137**
	(-4.99)	(-5.62)	(-4.07)	(-3.66)
$lnLTV_{t-2}$	0.0877**	0.0890**	0.0949**	0.0872**
	(4.26)	(4.40)	(4.52)	(4.12)
$FHALTVGAP_{t-2}$	0.0732*	0.0766**		
	(2.29)	(2.53)		
$MONEYTARGET_{t-1}$	-0.0039*	-0.0057**	-0.0057**	-0.0058*
	(-2.13)	(-2.84)	(-2.71)	(-2.25)
$CAPGAINTAX_{t-2}$	0.0054**	0.0056**	0.0054**	0.0056**
	(4.00)	(4.23)	(3.86)	(3.33)
$TAXDEPR_{t-1}/100$		-0.0423*	-0.0381**	-0.0472*
		(-2.40)	(-2.11)	(-2.55)
$TAXDEPR_{t-3}/100$		0.0261	0.0234	0.0324*
		(1.56)	(1.41)	(2.05)
$\Delta REGQ_{t-1}$	-0.0050**	-0.0042**	-0.0042**	-0.0040*
	(-3.33)	(-2.79)	(-2.85)	(-2.90)
$\Delta FHAFEE_t$	0.0237**	0.0220**	0.0219**	0.0212**
	(6.01)	(5.57)	(5.51)	(5.68)
$[\Delta FHAFEE_{t-2}$	0.0125*	0.0165**	-0.0173**	-0.0205**
$+ \Delta FHAFEE_{t-3}]$	(-2.18)	(-2.79)	(-2.88)	(-3.58)
$MMDA_t$	0.0153*	0.0136**	0.0132**	0.0130**
	(3.96)	(3.50)	(3.39)	(3.48)
$\Delta lnHPRENT_{t-1}$	0.4921**	0.4568*	0.4317**	0.3374**
	(8.23)	(7.58)	(5.82)	(4.38)
$\Delta lnHPRENT_{t-2}$	-0.0058	0.0083	0.0066	0.0699
	(-0.08)	(0.11)	(0.08)	(0.88)

$\Delta \ln HPRENT_{t-3}$	0.2022^{**}	0.2129^{**}	0.2186^{**}	0.2567^{**}
	(2.80)	(3.01)	(3.09)	(3.73)
$FINCRISIS_t$	-0.0232^{**}	-0.0218^{**}		
	(-5.04)	(-4.82)		
$DCREXOG_t/100$	0.0076^{**}	0.0082^{**}	0.0078^{**}	0.0071^{**}
	(2.92)	(3.15)	(2.94)	(2.81)
$RENTRESID_t$	-0.7758^{**}	-0.6516^{**}	-0.6192^{**}	-0.4400^{*}
	(-4.49)	(-3.68)	(-3.52)	(-2.55)
Adjusted R^2	. 900	.905	.851	.837
S.E.	.003624	.003542	.003466	.003174
LM(2)	1.12	1.79	0.61	2.27
Q(24)	32.28	22.44	42.98^{**}	39.90^{**}

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

Appendix Table 1: Inverted Demand Models of Real House Prices, 1980-2007

	Cointegration		*Partial Adjustment Models*	
(inverted coint. vector, mod. 1-2)	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Constant	0.1605	4.7018	n.a.	n.a.
$lnHP_{t-1}$	n.a.	n.a.	-0.0920^{**}	-0.1142^{**}
			(-3.49)	(-5.32)
lnY_{t-1}	2.1563^{**}	1.5858^{**}	0.1711^{**}	0.1579^{**}
	(4.92)	(6.84)	(4.13)	(6.82)
$lnHSTOCK_{t-1}$	-0.8314^{+}	-1.0618^{**}	-0.0584	-0.1132^{**}
	(-1.87)	(-4.41)	(-1.62)	(-3.76)
$lnRUSER_{t-1}$	-0.0527^{+}	-0.1171^{**}	-0.0080^{**}	-0.0108^{**}
	(-1.67)	(-7.65)	(-2.27)	(-3.75)
$lnLTV_{t-1}$		1.4856^{**}		0.1579^{**}
		(7.22)		(6.82)
L-run Price Elasticity	-1.20	-0.94	-1.57	-1.01
L-run Income Elasticity	2.59	1.49	2.93	1.81
L-run LTV Elasticity		1.40		1.39
EC_{t-1}	-0.0697^{**}	-0.1155^{**}		
	(-4.73)	(-7.88)		
Constant	-0.0007	0.0039^{**}	0.1964^{*}	0.4338^{**}
	(-0.42)	(3.14)	(2.35)	(5.73)
$\Delta_8 POP2544_{t-1}$	0.1474^{**}	0.0691^{**}	0.1763	0.1487^{+}
	(3.46)	(2.72)	(1.55)	(1.62)
$MONEYTARGET_t$	0.0037	-0.0112^{**}	0.0021	-0.0033
	(1.54)	(-5.02)	(0.47)	(-0.92)
$\Delta REGQ_{t-1}$	-0.0044^{*}	-0.0048^{**}	-0.0051^{**}	-0.0056^{**}
	(-2.23)	(-3.25)	(-3.13)	(-4.24)
$\Delta REGQ_{t-4}$	0.0033^{+}	0.0339^{*}	0.0020	0.0026^{*}
	(1.86)	(2.59)	(1.23)	(1.99)
$\Delta FHAFEE_t$	0.0237^{**}	0.0189^{**}	0.0238^{*}	0.0233^{*}
	(4.80)	(5.14)	(4.43)	(5.58)
$\Delta FHAFEE_{t-1}$	0.0055	0.0009		
	(1.15)	(0.25)		
$\Delta FHAFEE_{t-2}$	-0.0043	-0.0075^{*}	-0.0008	-0.0334

	(-0.92)	(-2.16)	(-0.17)	(-0.88)
$\Delta FHAFEE_{t-3}$	-0.0021	-0.0131**	-0.0029	-0.0085*
	(-0.46)	(-3.66)	(-0.62)	(-2.19)
$CAPGAINTAX_t$	0.0063**	0.0074**	0.0055**	0.0063**
	(3.24)	(4.69)	(2.86)	(4.04)
$MMDA_t$	0.0187**	0.0094*	0.0216**	0.0148**
	(3.84)	(2.59)	(4.07)	(3.36)
$\Delta lnHP_{t-1}$	0.4619**	0.6444**	0.5089**	0.4608**
	(4.77)	(6.40)	(5.70)	(5.39)
$\Delta lnHP_{t-2}$	-0.0777	-0.1571	-0.1428	-0.1296
	(-0.72)	(0.61)	(-1.57)	(-1.60)
$\Delta lnRUSER_{t-1}$	0.0090	0.0143*	0.0150**	0.0146*
	(1.21)	(2.50)	(1.99)	(2.41)
$\Delta lnRUSER_{t-2}$	0.0031	0.0127^{+}		
	(0.37)	(1.93)		
ΔlnY_{t-1}	-0.2732**	-0.2059**	-0.2486**	-0.2160**
	(-3.99)	(-4.05)	(-3.86)	(-4.15)
ΔlnY_{t-2}	-0.1379^{+}	-0.0864	-0.1158^{+}	-0.0879^{+}
	(-1.88)	(-1.56)	(-1.82)	(-1.71)
$\Delta lnLTV_{t-1}$		-0.1606**		
		(-5.12)		
$\Delta lnLTV_{t-2}$		0.0334		
		(1.05)		
$\Delta lnHSTOCK_{t-1}$	-0.2764	-0.8970**	-0.3061	-0.6834^{+}
	(-0.64)	(-2.63)	(-0.68)	(-1.86)
$\Delta lnHSTOCK_{t-2}$	0.7257	0.0262	-1.0448*	0.5260
	(1.28)	(0.06)	(-2.07)	(1.27)
R^2	.794	.882	.810	.877
S.E.	0.004012	0.003042	0.003889	0.003132
VECLM(2)/LM(2)	16.41	21.45	0.34	3.12
VECLM(8)/Q(8)	11.40	16.89	2.18	5.96

* (**,$^{+}$) significant at 95% (99%, 90%) level. t-statistics in parentheses. Estimates of lags longer than t-2 omitted to conserve space.

Coint. Stats.	Model 1, 1 Vector	Model 1, 2 Vectors	Model 2, 1 Vector	Model 2, 2 Vectors
Eigenvalue	0.294	0.127	0.524	0.206
Trace Statistic	62.029**	29.797	126.098**	45.994
Max-Eigen Statistic	37.607**	14.658	80.104**	24.951
(# vectors, lags, AIC)	(1, 3, -29.244)		(1, 3, -36.209)	