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ABSTRACT

Credit Conditions and the Real Economy: The Elephant in the Room*

Changes in credit market architecture are an important but unobservable structural influence on economic activity. For Australian data, we model non-price credit supply conditions within equilibrium correction models of consumption, house prices, mortgage credit and housing equity withdrawal. Our "latent interactive variable equation system" (LIVES) employs a single latent variable to capture evolutionary shifts (in credit conditions) that affect not only the intercept of each equation, but also interact with key economic variables. We show that credit conditions impact on consumption by: (i) lowering the mortgage downpayment constraint facing young households; (ii) introducing a housing collateral channel from house prices to real activity; and (iii) facilitating intertemporal consumption smoothing.

JEL Classification: E02, E21, E44, G21 and R31
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1 Introduction

We explore crucial but unobserved influences on the real economy due to structural shifts in non-price credit supply conditions. As the global financial crisis (GFC) of 2007-09 demonstrated, shifts in credit conditions really are the "elephant in the room" for economies with liberalised financial markets: large and ignored at one's peril. Flow of funds and household balance sheet data are rich with information about the drivers of consumption, house prices, mortgage debt and housing equity withdrawal (HEW). Consumption is around 70 percent of GDP for most OECD countries while household debt levels, of which mortgages account for 70-80 percent, have become a matter of great policy concern. House prices play an increasingly important role in business cycle dynamics through their potential effects on residential construction, consumer spending and, if major house price falls lead to loan defaults, on financial stability.

Australia is an interesting case study because it experienced one of the most rapid increases in household balance sheets and house prices in the world. Over 1980 to 2008, household debt relative to disposable income quadrupled while gearing ratios (housing debt to gross housing assets) and debt servicing ratios (nominal interest payments to household disposable income) on housing approximately tripled. Established house prices doubled as a proportion of income but owner-occupation rates remained broadly unchanged. Household consumption rose as a proportion of non-property income by around 15 percentage points. While gross housing investment to income remained fairly steady (though cyclical), mortgage credit growth increased over the 1990s and became much more volatile. Owner-occupier mortgage refinancing approvals as a share of total monthly mortgage finance approvals quadrupled over 1991 to 2008. Australian households, though traditionally net mortgage equity injectors, made positive equity withdrawals after 2000 like their UK and US counterparts. It is difficult to account for these phenomena except through a transformation of the credit market architecture.

The literatures on consumption, house prices and credit suggest that credit conditions may operate on the real economy through several channels. First, financial liberalisation and innovation (FLIB) enhances the ability of all households to smooth housing and non-housing consumption across periods. Second, FLIB relaxes the mortgage downpayment constraint on young, first-time home buying households. Third, FLIB introduces a collateral channel from housing capital gains to real activity. Households with existing housing wealth can extract capital gains for other purposes through mortgage refinancing or home equity withdrawal products. However, rising house prices not only boost collateral for existing home-owners but also raise the mortgage deposit requirement. The balance of these two effects on the economy depends on the state of credit conditions and, to a lesser extent, the age distribution of the population. When credit conditions are easy, the positive collateral benefit of higher house prices to existing homeowners outweighs the negative effect on non-home owning households who must now save for a larger deposit. Under these conditions, rising house prices raise consumption, mortgage debt and HEW.

We have chosen the acronym, "latent interactive variable equation system" (LIVES), to describe our method. A common unobserved factor - a credit conditions index - determines intercept and parameter shifts in equations for consumption, house price, mortgage credit and HEW. This methodology provides a powerful technique for handling evolving and far-reaching structural change in an economy - a serious problem for econometric modellers. Our system is based on single equation modelling for Australia in Williams (2009, 2010), consumption models for the UK, US and Japan in Aron et al. (2010), and multi-equation work using UK credit data in Fernandez-Corugedo and Muellbauer (2006). Strong priors about the institutional environment and rich controls for other economic and demographic variables allow interpretation of the latent variable as credit conditions shifts due to FLIB. We represent this as a spline function consisting of smoothed step dummies. Credit conditions enter each equation as a common intercept term and through their interaction with interest rates, income growth expectations, housing collateral and so on. The estimated credit conditions index, CCI, is plotted at Chart 1.

The structure of the paper is as follows. Section 2 reviews the changes in Australia's credit market architecture. Section 3 explains the estimation methodology, identification strategy, general-to-specific model reduction strategy and cointegration approach. Section 4 provides thumbnail sketches of the theory, literature and models for house prices, consumption, mortgage demand and HEW. Section 5 presents the results. Figures, charts and tables are at Appendix 1. Data sources, variable construction, descriptive statistics and unit root tests are available on-line in Williams (2010).

2 Institutional background

Non-price credit conditions in Australia: eased from the late 1970s until about 1992 (financial sector deregulation) and mid-1990s to 2006 (see below); and tightened during the early 1990s (banking sector distress) and after 2007 (the GFC). The Australian financial system of the 1970s comprised a banking sector subject to strict capital controls and a largely unregulated, rapidly growing non-bank sector. Over the 1980s, the government progressively relaxed financial sector regulations including the floating of the Australian dollar, removal of interest rate ceilings and other banking restrictions, permitting foreign bank entry, and deregulating the stock exchange. However, the early 1990s witnessed a period of consolidation in the banking sector. Several state-level financial institutions failed and major banks' return on equity collapsed due to excessive corporate lending during the 1980s.

From the mid-1990s, the credit market featured: (i) new entrants; (ii) vigorous debt product competition and innovation (see RBA (2002)); (iii) widespread use of securisation, especially in the 2000s (see Debelle (2008, 2009)); and (iv) a relaxation of bank lending standards (see Laker (2007), Yates (2010)). Sharp improvements in computing and communication technologies also reduced mortgage origination costs. Home equity loans were first introduced by St George Building Society in the late 1980s, followed soon after by the Commonwealth Bank in October 1990. They were heavily promoted by the mortgage managers in the mid-1990s. However, credit conditions most likely tightened after 2007. The GFC saw the withdrawal of many household debt products and a severe downturn in the mortgage-backed securities market.

To illustrate, Figure 1 depicts the credit market incorporating the effects of asymmetric information on credit supply. The pre-FLIB loan offer curve results in loans L_1. Equilibrium mortgage rationing due to asymmetric information is $L_e - L_1$, where L_e is the full information credit market equilibrium. The supply curve now shifts to the right following FLIB: the removal of lending controls, access to foreign capital markets; or the entry of new lenders, proliferation of new debt products, lower cost of capital due to securisation and relaxed lending standards. This results in higher loans (L_2) and less equilibrium credit rationing ($L_e - L_2 < L_e - L_1$) for a given level of credit demand.

Figure 2 shows the effect on household utility. The household would like to borrow at point A corresponding the full information equilibrium L_e in Figure 1. However due to asymmetric information, banks impose non-price screening on households to weed out bad borrowers. Households face some combination of a downpayment constraint and a debt servicing constraint which limit borrowing to point

B (corresponding to L_1 in Figure 1). FLIB relaxes these non-price borrowing constraints (as lending expands to L_2 in Figure 1) allowing the household to reach point C on a higher indifference curve.

3 Methodology

Shifts in the credit supply schedule (Figure 1) are not directly observable. Indirect measures (such as credit to GDP or income, acceleration of log credit, interest spreads and so on) suffer from obvious endogeneity with other economic and demographic variables. An alternative strategy is a common factor or latent variable approach. Stock and Watson's (1988) seminal reference suggests that some time series may be cointegrated by possessing the same stochastic trend. Hendry (1997) discusses a variation, co-breaking, where a common unobserved regime change affects the mean of several economic variables. Maravall (1995) reviews the unobserved components analysis literature, including economic applications such as the business cycle, natural unemployment rate, credibility of the monetary authority, persistence of economic shocks and so on.

Our LIVES method is more general. A single latent variable (a credit conditions index) captures an evolutionary structural shift that affects not only the intercept of each equation, but also interacts with some of the other variables. We do not rely on "black box" type statistical methods (linear or ad hoc filters to decompose the aggregate data) because economic theory provides exploitable prior information for a more disciplined approach. This includes information about the direction of the change in the latent credit conditions index and its impact. For example, credit liberalisation should raise the marginal propensity to consume (MPC) out of (previously highly illiquid) housing wealth.

We represent credit conditions (CCI) as a linear combination of smoothed step dummies ($SDMMAs$) that form a spline function. A step dummy (SD) is defined as 0 until t-1 and 1 from time t. A four quarter moving average ($SDMA$) is taken of the step dummy and then a five quarter moving average ($SDMMA$) is taken of $SDMA$. $SDMMA$ therefore rises from 0 to 1 over eight quarters with an "S-shape". A linear combination of $SDMMAs$ every two years (or more frequently) forms a smooth non-linear curve.

An important set of priors are those for the slope coefficients in the spline function since, in principle, this function could be very general. These priors rely on knowledge of the institutional environment (Section 2). They suggest: non-negative coefficients on the $SDMMA$ terms from 1982 to 1990; non-positive for around 1992 to 1994; non-negative until 2006; and non-positive from 2007 due to the GFC. The method also requires strict priors about the sign and magnitude of other economic and demographic influences in the specification and their interaction with the latent variable. These are guided by economic theory and previous empirical work for Australia and overseas.[1] Eleven parameters are needed to fit CCI subject to these priors and the priors on the coefficients for the economic variables.

[1] Shifts in credit conditions were proxied in Williams (2009, 2010) as a linear combination of several smoothed split trend dummies. These trends rise 1, 2, 3 etc beginning in 1979(1), 1992(1), 1998(1) and 2007(3), corresponding to the turning points of a stochastic trend identified in a state space model of house prices (with extensive controls for other influences). The credit conditions index takes the form:

$$CCIH = \varphi_1 split79(ma4) - \varphi_2 split92(1)(ma4) + \varphi_3(split98(1)(ma4) - \varphi_4 split07(3)) \tag{1}$$

$CCIH$ then enters as an intercept term and through its interaction with key variables in models of house prices (Williams (2009)) and consumption (Williams (2010)). As in Fernandez-Corugedo and Muellbauer (2006), our multi-equation setting now permits a more sophisticated and flexible representation of credit conditions. However, that study did not condition on consumption, house prices or HEW data in its set of jointly modelled credit indicators.

The system consists of equilibrium correction models (ECMs) for house prices, consumption, mortgage credit and HEW:

$$\begin{aligned} \Delta y^*_{it} &= \phi_i(\alpha_{i0} + \zeta_i CCI_t + \alpha_i Z_t - y^*_{it-1}) + \beta_i \Delta X_t + \varepsilon_{it} \quad (2) \\ for\ i &\in [1,4] \\ CCI_t &= \sum_{s=1} a_s SDMMA_{st} \quad (3) \end{aligned}$$

y^*_i is the dependent variable when correctly measured, ϕ_i is the equilibrium speed of adjustment for equation i, ζ_i is the intercept effect of credit conditions (CCI_t) in equation i, Z_t is a vector of long run explanatory variables (including interaction effects with CCI) and ΔX_t is a vector of I(0) short run dynamic terms. Several key explanatory variables such as interest rates, income growth expectations and so on in each equation are interacted with the credit conditions in the form: $CCI_t \times (x_{jt-1} - \bar{x}_j)$, where x_j is the explanatory variable and $\bar{x}$ is the post-1979 arithmetic mean. The speeds of adjustment (ϕ_i), the long run coefficients (α_i) and short run coefficients (β_i) are uniquely identified in Equation (2). Identification of the coefficients in Equation 3 requires that one of the ζ_i is normalised to one. This is done for the house price equation.

We argue below that the mortgage stock before 1990 and house prices before 1986 are subject to measurement biases. If y_i are the observed data, and y^*_i are data measured without bias, then:

$$y_i = y^*_i + w_i \quad (4)$$

Here, w is the bias and is a function either of a split time trend or some dummies. This measurement equation can then be substituted into Equation 2 to translate it into observable data. Note that the lagged mortgage stock enters the Z vector in the house price, consumption and HEW, and is part of the dependent variable in the HEW equation. In each of the equations, the appropriate measurement bias term is therefore included. The same applies to the measurement bias term for house prices which also enters the Z or X vector in some equations in addition to the house price equation.[2]

The steady state and dynamic solutions are jointly estimated for each equation i. Direct estimation provides a more efficient estimation of the long run parameters where economic theory suggests a unique cointegrating vector (Banerjee et al. (1986) and Kremers et al. (1992)). The cointegrating relationship is conditioned on information contained in both the structural and equilibrium correction dynamics. Strong significance of the long run parameters and speeds of adjustment implies and is implied by cointegration. In Equation **2**, cointegration occurs between the long run variables in parentheses (which are I(1) in most cases or at least strongly persistent). The I(0) variables outside the parentheses reinforce or offset equilibrium adjustment in the short run. Johansen's (1989, 1991) generalised cointegration test serves as a robustness check (see Section 6).

A general to specific model reduction strategy, in spirit of Doornik (2009) and Hendry and Krolzig (2005), is used to omit variables that are insignificant or contradict the sign priors. Parameters are set to zero starting with the variable, if any, that most strongly contradicts the sign prior. Impulse dummies are initially added to each equation for large outliers in the residuals (greater than two and half standard

[2] Where a non-linear transformation of y enters an equation, the appropriate Taylor approximation is used to linearise the bias term. For example, the mortgage stock equation is log-linear while the mortgage stock enters the consumption function as part of the ratio of liquid assets minus debt to income.

errors). The system is then re-estimated and the reduction process repeated. The lag structures are empirically determined as much as possible. For example in the long run equations, we check whether current or lagged terms can be expressed as four or eight quarter moving averages. In the dynamics, we check for quarterly lags up to four as well as simplifications as four and eight quarter changes. The order of reduction from general to specific can affect the final parsimonious model chosen. We therefore check alternative reduction paths by varying the order of the foregoing steps and re-estimating the system, as well as repeatedly checking the restrictions imposed at earlier stages.

4 Model derivations

4.1 Consumption

The consumption to income ratio in Australia has risen substantially since the late 1970s (Charts 2 and 3). Standard life cycle models of the Ando and Modigliani (1963) kind suggest that part of the explanation lies in wealth effects. Widely-used consumption functions of this type, for example the FRB-US consumption function (Brayton and Tinsley (1996)), employ net worth - that is, total assets including housing wealth, minus debt - as the wealth measure. The natural log linearisation of the simple life cycle model with habits suggest the following model, where A is net worth, see Aron et al. (2010):

$$\Delta \log c_t = \phi(\alpha_0 + \gamma A_{t-1}/y_t + \psi \log(y^p/y)_t + \log y_t - \log c_{t-1}) + \varepsilon_t \tag{5}$$

The model implies partial adjustment of log consumption to a long run target defined by the first four terms in the parentheses of Equation 5. y^p is permanent real per capita non-property income and the log ratio to current income (y) is:[3]

$$\log(y^p/y)_t = (E_t \sum_{s=1}^{k} (1-\eta)^{s-1} \log y_{t+s}) / \sum_{s=1}^{k} (1-\eta)^{s-1} - \log y_t \tag{6}$$

Thus, $\log y^p$ is the annualised discounted future value of log income. While not exactly the same as the log of the discounted future value of the level of income, it is a very good approximation. The strict version of the hypothesis implies that the weight on $\log(y_p/y)_t$ should be equal to one minus the risk-adjusted real interest rate ($\psi = 1 - \eta$), using the discount rate used to construct $\log y^p$. This is a useful restriction later as it suggests an upper bound on the estimated value of ψ.

$\log y^p$ could be constructed either by taking the fitted value from a forecasting model or by taking the perfect foresight view and using actual future data. To apply either approach, one needs a discount rate to weight future incomes. This rate could be larger than a "safe" market real interest rate, since standard models of behaviour under uncertainty suggest adding a risk premium to the market interest rate, see Kimball (1990), Muellbauer and Lattimore (1995). Indeed, Friedman (1957, 1963) suggested that a discount rate as high as 30 percent per annum, with an effective horizon of only around 3 years, was appropriate. Other authors support substantial discount rates. Carroll (2001) has put forward buffer stock models of consumption with calibrated income processes which justify such high discount rates. Hayashi (1982) finds US evidence suggesting a discount rate of around 12 percent per annum (though the

[3] Blinder and Deaton (1985) show non-property household disposable income as the appropriate metric for consumption modelling. Williams (2009) develops an Australian measure.

standard error around his estimate is substantial). In this paper, we assume that households discount future income at roughly 20 percent per annum ($\eta = 0.05$) with a ten year horizon ($k = 40$). Note the scaling of log permanent income in Equation 6 means that the equation is equivalent to a larger horizon model in which growth in these 40 quarters is expected to be representative of longer term growth.

One must then decide what knowledge to impute to households in forming expectations about $\log(y^p/y)_t$ (that is, moving beyond the perfect foresight view). Williams (2010) canvassed several alternatives. A "naive" information set includes a trend, the current income level and income growth rates over the previous 5 years. A "basic" information set additionally consists of levels and four quarter changes in asset prices and long and short term interest rates. Finally, a "sophisticated" set draws on a wide range of lagged economic information additionally including levels and changes in the log real exchange rate, log terms of trade, log bilateral USD exchange rate, log real US GDP (representing foreign demand), the annual trade balance to GDP ratio, the annual budget balance to GDP ratio, real and nominal log oil prices. In our estimations below, we experimented with "sophisticated" and "basic" sets of information and found only small differences in the results, so report the former case in Section 5.

The concept of net worth used in the Ando-Modigliani model and in the FRB-US consumption model aggregates all assets minus debt into a single figure. Net worth includes housing wealth, so that this imputes the same wealth effect to liquid assets and to housing as to all other types of wealth. However, as King (1990) correctly remarked, the wealth effect from housing implied by the life-cycle theory is suspect and hence, so must be the theory's net worth concept. If there is a credit channel, systematic rises in consumption can result from increases in the collateral values of houses (Muellbauer and Murphy (1990), Miles (1992)). The presence of mortgage downpayment constraints faced by first time buyers introduces another link between house prices and consumption (Aron and Muellbauer (2000)). Shifts in credit accessibility will affect the size of these linkages and the balance of house price effects on consumption. When access to credit is restricted, a rise in house prices, given the downpayment constraint, can actually result in a fall in aggregate consumption, particularly if home equity loans are hard to access. There is evidence for such a fall for Italy (Boone et al. (2001) and Slacalek (2009)), and for Japan (Muellbauer and Murata (2009)).

There is also a liquidity argument for not aggregating liquid with illiquid financial assets, formalised in a calibrated transactions cost model by Otsuka (2006). The buffer stock role of liquid assets gives them a higher MPC than for illiquid assets. Similarly, but contingent on the availability of home equity loans and cheap refinancing, housing equity can play a buffer stock role against unanticipated income fluctuations (Miles (1992), Parkinson et al. (2009)). Thus the combination of the collateral and liquidity arguments suggest a three-fold disaggregation of wealth into liquid assets minus debt, illiquid financial assets, and housing wealth interacted with an index of credit liberality.

The original consumption function of Ando and Modigliani (1963) took no explicit account of income uncertainty, the precautionary motive for saving, or of time varying interest rates. A more comprehensive model needs to take these factors into account, as emphasised by Zeldes (1989), Caballero (1990) and Miles (1997). One simple proxy for income uncertainty is the change in the unemployment rate but its role could diminish as credit conditions ease. Real interest rates affect consumers because they influence intertemporal substitution choices and the user cost effects for goods with some durability. However, changes in nominal rates may also have cash flow effects on households with floating rate debt. About three quarters of the Australian mortgage stock is at variable rates. However, the incidence of such constraints may shift with credit availability and with the size of debt relative to income. This suggests the possibility of an interaction effect between a CCI and the change in nominal borrowing rates weighted by the debt to income ratio.

Finally, Pagano (1990) noted another potential credit interaction effect in the following passage: "financial liberalisation would be not a cause but a mere precondition for revised expectations to translate fully into consumption changes". As credit access improves, so the role of income growth expectations should increase because households can then borrow to consume ahead of the expected income rise.

The above considerations and the three potential credit interaction effects have been combined in an empirical model for UK, US and Japan in Aron et al. (2010):

$$\begin{aligned}\Delta \log c_t &= \phi(\alpha_{0t} + \alpha_{1t} r_{t-1} + \alpha_{2t}\theta_t + \gamma_{1t} HA_{t-1}/4y_t + \gamma_2 IFA_{t-1}/4y_t \\ &\quad + \gamma_3 NLA_{t-1}/4y_t + \psi_t \log(y^p/y)_t + \log y_t - \log c_{t-1}) \\ &\quad + \beta_{1t}\Delta \log y_t + \beta_{2t}\Delta_4 \log i_{t-1} \times (CR_{t-1}/4y_t) + \varepsilon_t \qquad (7)\end{aligned}$$

The speed of adjustment is ϕ; r is the real interest rate; θ is uncertainty; $HA_{-1}/4y$ is the ratio of housing wealth to annualised non-property income, $IFA_{-1}/4y$ is the ratio of illiquid financial assets to income, $NLA_{-1}/4y$ is the ratio of liquid assets minus debt to income; $\Delta_4 \log i_{-1} \times (CR_{-1}/4y)$ measures the cash flow impact on borrowers of changes in nominal mortgage rates (i) scaled by the household debt to income ratio. The parameters, γ_i, measure the marginal propensities to consume (MPCs) for each of the three asset types. The log income growth term can be rationalised by aggregating over credit constrained and unconstrained households, (Muellbauer and Lattimore (1995), pp279-280). Equation (7) reduces to Equation (5) with an appropriate set of testable restrictions:

$$\alpha_{1t} = \alpha_{2t} = 0; \gamma_{1t} = \gamma_2 = \gamma_3; \beta_{1t} = \beta_{2t} = 0; \psi_t = \psi \qquad (8)$$

There is time variation in some of the parameters of Equation (7) induced by shifts in credit availability. The credit channel enters the consumption function through the different MPCs for net liquid assets and for housing; through the cash flow effect for borrowers; and by allowing for possible parameter shifts. As noted above, credit market liberalisation should raise the intercept α_0, implying a higher level of $\log(c/y)$; shift the real interest rate coefficient α_1 in a negative direction; raise α_3 by increasing the impact of expected income growth; and increase the MPC for housing collateral, γ_1. It could also lower the current income growth effect, β_1, and the cash flow impact of the change in the nominal rate, β_2.

Aron et al. (2010) handle these parameter shifts by writing each of these time-varying parameters as a linear function of a UK CCI. The CCI enters the model both as an intercept shift and through interaction with several economic variables. For example, $\alpha_{0t} = \alpha_0 + \zeta_i CCI_t$. Williams (2010) estimates a consumption function of this type for Australia. The empirical work reported below also checks for demographic effects. Finally, in Equation 7, housing assets combine prices and volume. However, the operation of the downpayment constraint discussed above more properly depends on house prices relative to average income. We therefore test, in addition, for a time-varying effect of $\log(p^h/y)_{t-1}$.

4.2 House prices

The canonical housing demand function takes the following log-linear form:

$$\log h = \tau \log y - \lambda \log r^h + \log D \tag{9}$$

h is per capita demand for housing services, y is per capita real disposable non-property income, r^h is real housing rent or the user cost adjusted real house price and D represents other demand factors. τ and λ are the income and price elasticities respectively. In equilibrium, $r^h = p^h ucc$, where p^h is the real house price and ucc is the real after-tax housing user cost of capital.[4]

The housing demand function is inverted so that real house prices for existing (or established) houses are determined by real income per existing house (assuming the income elasticity, τ, is unity), the user cost of capital and other demand factors:

$$\log p^h = \frac{1}{\lambda} \log(y/h) - \log ucc + \frac{1}{\lambda} \log D \tag{10}$$

The inverse price elasticity ($1/\lambda$) is typically estimated at around two (Muellbauer and Murphy (1997), Meen and Andrew (1998) and Cameron et al. (2006)). It is helpful to initially impose constraints on τ and λ before relaxing them in a parsimonious model. Factors that structurally shift D may include credit conditions, government housing subsidies and tax changes, demographics and economic uncertainty. The model conditions on the lagged net dwelling capital stock enabling observed changes in established house prices to be interpreted as shifts in the demand curve rather than movements along it.

Inverse housing demand functions are estimated by Buckley and Ermisch (1982), Hendry (1984), Meen (1990*b*), Muellbauer and Murphy (1997) and Miles and Pillonca (2008) for the UK; Poterba (1984, 1991) and Mankiw and Weil (1989) for the US; and Abelson et al. (2005) and Williams (2009) for Australia. We condition on a wide range of controls, including: credit conditions and interaction effects; non-property income per house; household income growth expectations; real and nominal interest rates; the introduction of a first home owners' subsidy (FHOS)[5] in 2000; changes in economic uncertainty; net financial wealth; population growth and age structure effects; and "frenzy" behaviour.

We estimate an empirical house price model as follows:

$$\begin{aligned} \Delta \log(p^h p)_t \quad = \quad & \phi_h(\alpha_{h0} + \zeta_h CCI_t + \kappa(\log y_{t-1} - (1/\tau) \log h_{t-1}) + \alpha_h Z_t - \log p^h_{t-1}) \\ & + \beta_h \Delta X_t + \varepsilon_{ht} \end{aligned} \tag{11}$$

Here, $\log p^h$ is the log real established house price index (national), p is the household consumption deflator, $\kappa = \tau/\lambda$, Z is a vector of steady state variables (inclusive of ucc and D) and ΔX is a vector of I(0) dynamic terms. Preliminary results for a model of log real house prices suggested a negative unity coefficient on current inflation, so the dependent variable is reparameterised in nominal terms.

[4] See Cramer (1957), Jorgenson (1963) and Dougherty and Van Order (1982)). The user cost of capital can be negative so in empirical work the level of ucc is sometimes used rather than $\log ucc$. We tried both methods and found little difference in the results, so report only the latter.

[5] The FHOS was introduced in July 2000 and provides a \$7,000 grant for first time owner-occupying home buyers purchasing new and established dwellings. The FHOS was extended in March 2001 to provide an additional \$7,000 for all first time buyers (including investors) of newly constructed dwellings. The additional component was reduced to \$3,000 from January 2002 until June 2002, and ceased thereafter. Williams (2009) constructed a $FHOS$ step dummy as the (four quarter moving average of the) nominal value of the grant scaled by the national nominal house price, starting from 2000(3).

The short run structural dynamics, ΔX, are particularly interesting. Our model helps explain short run overshooting in house prices, leading to booms and busts, through a "frenzy" effect measured as a cubic of lagged house price changes (Hendry (1984)). House prices generally correct to the steady state path (determined by the variables in parentheses in Equation 11) at about 20 percent per quarter as determined by the equilibrium speed of adjustment. The cubic in the short run offsets or augments the equilibrium correction dynamics depending on the recent history of house price changes. When recent house price growth has been high, households extrapolatively form positive expectations about near-term future capital gains, thus giving house prices temporary "momentum" or persistence.

There are multiple interpretations for "frenzy". Non-linear price adjustment is suggested by the housing demand function above through the expectations term within the log user cost component. As ucc approaches zero, $\log ucc$ approaches minus infinity in the limit causing house prices to rise precipitously. Such an event might occur if households form expectations by extrapolating from recent house price growth during housing booms. However, since we find a highly significant frenzy effect even in a model that includes the log user cost, the latter cannot entirely explain non-linear price adjustment.

Frenzy behaviour might also be due to transaction costs, information costs, indivisibility and other frictions in the housing market that deter households from continually optimising their housing choices each quarter. When house prices are booming, these trading costs might be lower so that house prices adjust more quickly. For example, real estate agents have higher volumes through which to match buyer/seller preferences. Alternatively, frenzy might be interpreted as the tendency of households to overreact to noisy public information - while discounting their own private information - purporting to convey information about "true" housing asset values.[6] There are therefore several reasons to incorporate extrapolative expectations, momentum trading or frenzy effects in the short run dynamics.

4.3 Mortgage stock

Consumption theory is mostly silent on the drivers of household credit demand. The rational expectations permanent income hypothesis (REPIH) contains a single, homogenous asset used for consumption smoothing whereas there are multiple motivations for holding debt: financing "lumpy" consumer purchases, especially housing, housing renovations and consumer durables; portfolio investment in other assets; to offset suboptimal compulsory superannuation rules; human capital investment in education or training; or as a buffer against unanticipated income fluctuations.

Brueckner's (1994) mortgage demand model demonstrates that households may borrow up to their mortgage credit limit where the mortgage interest rate is less than the rate of return on alternative assets, as has typically been the case in Australia, and where households are impatient. Miles (1992) emphasises the housing collateral channel. A representative household maximises lifetime housing consumption, non-housing consumption and terminal net wealth (a bequest) subject to an intertemporal budget constraint. A binding mortgage constraint (loan to valuation limit) raises the user cost of housing for credit con-

[6] Morris and Shin's (2002) strategic interaction model shows households with two competing objectives. They seek to match their actions with the true value of housing (based on steady state fundamentals), but also to minimise the distance between their actions and the actions of other households. This is akin to "herd" behaviour or Keynes's beauty contest analogy. Because they care about the second objective, households tend to overreact to public information (which purports to give information about other households' valuations) at the expense of private information (giving information about the true value of housing assets). Public information is noisy and tends to increase during periods of high housing market activity (increased media and political commentary, housing "infotainment" programmes on television and radio), which exacerbates price volatility and causes "frenzy" in the housing market.

strained households, resulting in lower bequests and housing consumption (house sizes). After the loan to valuation constraint is relaxed, the model predicts: (i) an increase in house prices, given inelastic housing supply, and higher average housing consumption (house size); (ii) an increase in the mortgage stock and housing equity withdrawal; (iii) a permanent increase in the consumption to income ratio (decrease in financial savings); (iv) an increase in the trade deficit; (v) a redistribution of home ownership towards households previously credit constrained and with lower preferences for bequests. These predictions are all consistent with the Australian experience.

The time series debt literature is somewhat limited and dated.[7] Meen (1990*a*) reviews several UK studies and estimates a structural (switching) model of UK mortgage demand and supply. Mortgage rationing ceases from mid-1980, the market having previously been in a state of excess demand. This finding is instructive for Australia since the major deregulatory changes lagged the UK by about three years. Blundell-Wignall and Gizycki's (1994) structural model of Australian business credit bears this out showing evidence of credit rationing only until 1983. More recently, Fernandez-Corugedo and Muellbauer (2006) treat credit conditions as a common factor within a ten equation model of UK debt markets.

Our mortgage demand model takes the form:

$$\Delta \log m_t = \phi_m(\alpha_{m0} + \zeta_m CCI_t + \alpha_m Z_t - \log(m/p)_{t-1}) + \beta_m \Delta X_t + \varepsilon_{mt} \tag{12}$$

$\log m$ is the log nominal mortgage stock per capita and Z is a vector of other steady state variables incorporating many of the controls suggested by Fernandez-Corugedo and Muellbauer (2006). These include real non-property income per capita, credit conditions, income growth expectations, household wealth (as collateral), real and nominal interest rates, risk variables, age demographics and dummies for government policy changes. FLIB implies a positive intercept effect from the relaxation of the downpayment constraint and a series of interaction effects discussed below.

4.4 Housing equity withdrawal

HEW data provides additional information about credit conditions. Housing investment to income has been relatively stable (though cyclical) whereas mortgage flows have become larger and more volatile since the mid-1990s. Life cycle motivations for HEW cannot be the complete story. The RBA produces an unpublished HEW time series defined as the change in residentially secured household debt (ΔD^h, including mortgages and some personal debt), plus housing-related government grants (G^h, notably the FHOS from 2000), less gross investment including dwelling ownership transfer costs (I^h):[8]

$$hew = \Delta D^h + G^h - I^h \tag{13}$$

In tightly regulated credit markets, housing equity is inaccessible so (with positive population growth) households tend to be net housing equity injectors. Without a housing collateral channel, higher house prices necessitate equity injection by raising the mortgage deposit requirement. As predicted by Miles

[7] For cross-sectional work using household survey data, see La Cava and Simon (2005) and Worthington (2006) for Australia, Leece (2000) for the UK and Ling and McGill (1998) and Dunsky and Follain (2000) for the US. However, these studies tend to measure "financial distress" - the inability to pay household bills and so on - rather than credit conditions.

[8] The Bank of England's HEW measure includes private sector land purchases (from the government sector) as part of gross housing investment. No such adjustment is made for Australia due to a lack of data. However, we are not aware of any major transfers of public housing into private ownership. See Schwartz et al. (2008) on measurement issues.

(1992), post-FLIB debt product innovations (especially home equity loans) and cheap mortgage refinancing introduce a link, via residentially-secured mortgage borrowing, from housing equity to real activity. FLIB enables HEW to be used for: portfolio management (rebalancing asset portfolios, debt consolidation); immediate consumption (non-housing durables, windfall consumption); and precautionary savings (housing assets as a buffer against unanticipated income shocks, see Skinner (1996)). These usages hinge on the state of credit conditions.

Our equilibrium correction model for HEW takes the form:

$$z_{t-1}[\Delta(hew/y)_t = z_{t-1}[\phi_w(\alpha_{w0} + \zeta_w CCI_t + \alpha_w Z_t - (hew/y)_{t-1}) + \beta_w \Delta X_t + \varepsilon_{wt}] \tag{14}$$

Here, hew/y is nominal HEW to non-property income, ϕ_w is the speed of adjustment, Z is a vector of steady state variables and ΔX is a vector of structural dynamic terms. The equation is pre-multiplied by the inverse housing wealth to income ratio, $z = (1/HA_{-1}/y)$, which overcomes heteroskedasticity induced by growth in the credit growth data as gearing ratios rise. As extra equations in the system, the mortgage credit and HEW equations are helpful by informing on the latent influence of credit conditions.

5 Empirical results

5.1 Overview

We estimate the system using quarterly data for 1978(1) to 2008(2). In each equation, the credit conditions index (CCI) interacts with (de-meaned) key variables as determined by economic theory and after general-to-specific model selection with strict sign priors. The intercept effect is scaled by ζ_i (and $\zeta = 1$ for the house price equation). Imposing our sign priors, we insist on: non-negative coefficients (a_s in Equation 3) from 1982 to 1990 (financial deregulation); non-positive coefficients during the early 1990s (banking sector distress); non-negative coefficients from the mid-1990s to 2006 (new entrants, debt product competition and innovation, securitisation and relaxed lending standards); and negative coefficients from 2007 (the GFC). Where coefficients contradict the sign priors (or are insignificant at the end of the testing down process), we set them to zero. That is, we revert to the assumption that credit conditions are temporarily unchanged. CCI is reported in Table 5 and plotted at Chart 1.

5.2 Consumption model results

Table 1, Column 1, presents the parsimonious results for the consumption model. The long run aggregate consumption to non-property income ratio is determined by: credit conditions shifts; household income growth expectations; a three-fold disaggregation of household net worth; variable real interest rates; the change in the proportion of the population of working age (15-64 years) and of first home buying age (22-34 years). These demographic variables, in change form, are I(1) since their underlying levels are I(2). They are expected to have negative coefficients since the working age population save for retirement and the young save to invest in housing. The long run coefficients on housing collateral, income growth expectations and real interest rates are all time-varying depending on the degree of credit liberality.

The consumption equation's standard error is 0.00408 and R^2 is 0.64.[9] The model satisfies diagnostic

[9] We also tested for a range of other long run variables that were not significant, including: changes in the income

tests for autocorrelation, normality and heteroskedasticity. The equilibrium speed of adjustment here is 28.6 percent per quarter, with a strong t-statistic of 8.8. It takes about 7 quarters to remove 90 percent of the effects of a shock to the steady state consumption to income ratio. The long run solution explains the 14.4 percentage point rise in the consumption to non-property income ratio across 1978-2008 in the following partial equilibrium terms (in each case holding other variables constant).

Shifts in the mortgage downpayment constraint are important in several dimensions. First, the intercept effect of CCI captures the structural relaxation of the downpayment constraint due to FLIB. This reduces the saving requirement facing young households prior to household formation and first home purchase. Holding other variables constant, $\zeta_c CCI$ contributes about 14.2 percentage points to the long run rise in the consumption to income ratio.[10] Second, lower growth in the proportion of the population that are of working age (high savers), $\Delta_4 WAPOP$, contributes about 2 percentage points to the 1978-2008 rise in the consumption to income ratio. Lower growth in the proportion of the population that are of first home buyers age, $\Delta_4 DEMFTB$, contributes a further 4 percentage points. Third, a higher level of house prices (relative to income) reduces consumption (relative to income) by raising the amount of saving required for a deposit, though we allow for this effect to decline as CCI rises.[11] However, higher house prices also increase the potential for HEW by older households with existing wealth. The balance of these two effects on aggregate consumption at any given time depends on the state of credit conditions.

Housing collateral is inaccessible prior to FLIB so housing wealth has no consumption impact: there is no "classical" housing wealth effect. After FLIB, housing wealth (de-meaned $HA_{-1}/4y$ interacted with CCI) is "unlocked" and contributes about 13 percentage points to the 1978-2008 rise in the consumption to income ratio. The rise in the illiquid financial asset ratio ($IFA_{-1}/4y$) contributes an additional 5 percentage points. However the greater indebtedness of households, through net liquid assets ($NLA_{-1}/4y$), subtracts an offsetting 18 percentage points. The estimated long run wealth MPCs are 0.0488 for housing assets (at the peak of credit liberality, dropping to 0.0452 in 2008(2)), 0.022 for illiquid financial assets and 0.159 for net liquid assets.[12]

Credit liberalisation also facilitates intertemporal consumption smoothing. Parameter shifts are captured by interacting (de-meaned) income growth expectations and real interest rates with CCI. Real interest rates are naturally higher following financial liberalisation since credit allocation becomes based on the price mechanism rather than on quantitative restrictions (Cameron et al. (2006)). The (positive-only) real interest rate increases by 5.6 percentage points over 1978 to 2008, which subtracts about 4 percentage points from the long run consumption to income ratio.

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distribution; alternative demographic effects; the proportion of investor mortgage approvals; the FHOS; and measures of industrial disputation. The standard error here is a substantial reduction (of about 15-17 percent) compared to Williams (2010). That paper relied on a simpler CCI measure ($CCIH$, a linear combination of smoothed split trends).

[10] Note, if the demeaned interaction effects are replaced by non-demeaned ones, the intercept effect of CCI is -0.07 with a t-ratio of -0.9. We can therefore accept the hypothesis that $\zeta_c = 0$. This means that the downpayment constraint aspect of CCI becomes almost entirely absorbed by $\log(p^h/y)$ and its interaction effect, so that CCI elsewhere in the equation has a simple liquidity interpretation. This reparameterisation slightly tightens the economic interpretation and reduces the dimension of the long run solution by one.

[11] This is done through the composite term $[1 - \varpi CCI_t\ ][\log(p^h/y)_{t-1} - mean - HPbias\ correction]$. Using the peak value of CCI, we calibrate ϖ at 1.2 so that the effect of the downpayment constraint almost vanishes at the CCI peak. This is plausible since 100 per cent mortgages do not appear to have been available in Australia, even in 2006. The $\varpi = 1.2$ restriction is easily statistically acceptable and the composite effect has a t-ratio in excess of three. The composite house price to income term contributes 1.3 percentage points to the 1978-2008 rise in the consumption to income ratio.

[12] The wealth variables here are defined as real assets (at time t-1) to real income (at time t). If instead the ratios of nominal assets (at time t-1) to nominal income (at time t) are used, the log likelihood ratio of the system scarcely changes (it rises to 2268.24, from 2268.23) and the MPC on net liquid assets rises by just 0.002. This particular asset measurement issue is therefore a trivial one.

We assume households employ a sophisticated information set to forecast future income (see Section 4.1).[13] We impose the weight on permanent income (ψ_t in Equation 7) to rise from 0.20 in 1978 (when $CCI = 0$) to a maximum of 0.95 at the peak of credit liberality. The former restriction is difficult to estimate since there are very few observations when $CCI = 0$. For a range of different models, estimated values between 0 to 0.4 were found. We calibrate the 1978 coefficient at 0.2, a statistically acceptable restriction. The restriction on the maximum weight on permanent income is justified as a strict application of the consumption theory of Section 4.1. Freely estimated, the maximum effect would exceed 0.95, which violates the constraint. It is helpful to impose both restrictions on a general specification. After model reduction, the restrictions are still required to help pin down the effects of credit conditions, our principal focus, in what is a highly parameterised system with many trending variables. With those caveats, the model suggests household's rising sanguinity about future income contributes about 5 percentage points to the 1978-2008 rise in the ratio of consumption to income.

In the short run, the model includes the change in the log unemployment rate (economic uncertainty), the lagged four quarter log change in consumption, risk aversion to negative housing returns and some outlier dummies. An increase in the unemployment rate from 5 percent to 6 percent over the previous two years ($\Delta_8 \log ue_{t-1}$) decreases consumption growth by 0.2 percent. However, we calibrate an interaction effect so that the overall effect roughly disappears by the peak of credit liberality. The data accept the implied restriction. The interpretation is that economic uncertainty becomes less important as credit conditions ease. Lagged annual consumption growth, $\Delta_4 \log c_{t-1}$, captures some negative autocorrelation perhaps attributable to durable goods consumption. That is, if aggregate consumption increased by 1 percent over the past year then, because the consumers' stock of durable goods has increased, consumption growth next quarter will be about 0.11 percent lower. This variable might disappear if the model were estimated using consumption data excluding durables. A one standard deviation in negative housing returns ($DSRISK_{t-1}$) depresses quarterly consumption growth by 0.3 percent.[14]

Charts 2 and 3 plot the partial equilibrium long run influences on the log consumption to non-property income ratio. During the 1980s, the major positive influences on consumption are easing credit conditions, low house prices relative to income, rising illiquid financial wealth and age demographic effects. The latter broadly reflect the ageing of the post-WWII "baby-boomer" generation. The easing of the downpayment constraint through CCI contributes about 0.10 to the log consumption to income ratio across 1978-1992, subtracts about 0.02 during the early 1990s, and contributes another 0.06 from 1998 until the GFC in 2007. The significant role for the downpayment constraint in the 1980s (both through CCI and the log house price to income term) confirms a similar finding for Australia by Lattimore (1994).

The relaxation of the housing collateral constraint, effected through the interaction between housing wealth (to annualised income) and CCI, contributes a further 0.09 contribution to the log consumption to income ratio between 1998-2007. Rising optimism about future income begins to play a positive role from the early 1990s, offset by higher real interest rates and rising household indebtedness (negative net liquid assets to annualised income). The exception is during the period 2000-2004 when low real interest rates contributed positively to consumption. This was perhaps an unnecessary policy setting given the easy state of credit conditions.

[13] Results (available on request) are similar if we assume households rely on a "basic" information set.

[14] Unlike UK estimates reported by Aron et al. (2010), there is no hint of a negative short run effect on consumption from the change in nominal interest rates, even though most household debt is at floating rates. A partial explanation could be that the effect is already strongly captured by fitted income growth expectations. Another could be that the policy rule of the RBA is well understood by consumers who have already adjusted their behaviour in anticipation of a rise in rates.

5.3 House price model results

Table 2 reports the parsimonious results for the house price model. Long run real house prices are determined by: real non-property income and the housing stock; credit conditions; the log user cost of housing; income growth expectations and real interest rates (but only after credit liberalisation); net financial wealth; population growth; the change in the proportion of first home buying aged persons in the total population; and the FHOS. We impose an income elasticity of demand for housing of 1.1 in the long run solution, an easily acceptable restriction.

The house price model shows a standard error of 0.00839, R^2 of 0.84, and satisfies standard residuals tests. The equilibrium speed of adjustment is 24.4 percent (with a t-statistic of 8.7) implying that, following a shock to steady state house prices, it takes a little over 2 years for 90 percent of the disturbance to dissipate. The additional short run dynamics include current income growth, downside risk (aversion to negative housing returns), restrictions on investor tax deductions across 1985-1987 and "frenzy" effects. All explanatory variables are significant at the 5 percent level.

The long run variables explain the 104 percent rise in national real house prices over 1978-2008 in the following partial equilibrium terms. For the combination of real non-property income and the real net dwelling capital stock, $\kappa(\log y_{t-1} - (1/\tau)\log h_{t-1})$, we initially impose κ at two (see Section 4.2). We relax the constraint after model reduction and find a freely estimated coefficient of 1.988, with a standard error of 0.284. Real non-property income per house across 1978-2008 subtracts around 65 percentage points from long run house prices.[15]

The intercept effect of CCI here captures the relaxation of the downpayment constraint facing first time buyers and also the enhanced value of housing wealth as loan collateral. The partial equilibrium intercept effect of CCI contributes about 75 percentage points to the long run rise in real house prices, and as much as 81 percentage points at the CCI peak in 2007. Credit conditions also play an important role through their interaction with real interest rates and household income growth expectations. Neither have a significant effect on house prices prior to FLIB. CCI captures the parameter shifts in the coefficients on real interest rates (negatively) and income growth expectations (positively) as intertemporal housing consumption smoothing becomes possible. Real interest rates are necessarily higher in a deregulated financial market that relies on the price mechanism, rather than on regulated quantity controls, to clear the credit market (Cameron et al. (2006)). The (positive-only) real mortgage rate (r) rises by 5.6 percentage points across 1978-2008 and subtracts about 12 percentage points from long run real house prices. Rising optimism about income growth, $\log(y^p/y)_t$ weighted by CCI_t, contributes 7 percentage points. According to our model, there is also a 15 percent reduction in the real user cost of housing ($\log ucc$) across the sample, which contributes about 2 percentage points. The log user cost of housing is defined in Table 2a.

The ratio of net financial wealth (financial assets less household debt) to annualised non-property income ($\log NFA_{-1}/4y$) increases by around 67 percent across 1978-2008 and contributes about 30 percentage points to long run house prices. The FHOS contributes about 8 percentage points. Finally, demographic influences are likely to be important determinants of long run house prices, but it is less clear

[15] The decline occurs mostly occurs before 1993. This is due to: near-zero real labour earnings growth associated with the wage accords between the government and trade unions; rising incorporation by small businesses (also contributing to the decline in the household share of factor income); strong property income growth, excluded by this income metric; and modest housing supply growth.

how they should be characterised.[16] We settle on representing demographic effects in two dimensions. First, a declining proportion of young, first time home buyer households (23-35 years, $\Delta_4 DEMFTB_{t-4}$) subtracts about 8 percentage points. Second, higher population growth ($\Delta_4 \log pop$), including the impact of higher immigration, contributes an offsetting 4 percentage points.

Finally, the national, median, established, detached house price series we use splices pre-1986 Real Estate Institute of Australia (REIA) data with post-1986 Australian Bureau of Statistics (ABS) data. The former is not mix-adjusted so we expect some measurement bias, represented here by a linear trend from 1978(1) until 1986(1) ($HPMEAS$).[17] The estimated pre-1986 bias to house prices is in the order of 5 percent per annum.

In the short run dynamics we test for restrictions on negative gearing by investors between 17 July 1985 and 15 September 1987 (using an impulse dummy set to 1 for this period and 0 otherwise). Losses in relation to rental properties could only be deducted against rental income (not ordinary income). The model suggests that such restrictions depressed quarterly house price growth by 2.9 percent over 1985-87.

The model allows for the possibility that households are risk averse to negative housing returns, but neutral to positive returns (Muellbauer and Murphy (1997)). Such attitudes reflect households being able to increase saving, but not borrowing, in response to fluctuations in housing returns. The nominal rate of return on housing is $ROR_t = \Delta_4 \log(p^h p)_{t-1} + 0.02 - i_t/100$, where 0.02 is an estimate of rental returns net of maintenance and depreciation and i_t is the nominal interest rate. $DSRISK$ is then defined by $DSRISK_t = 0$ if $ROR_t > 0$ and $DSRISK_t = 0$ if $ROR \leq 0$. A one standard deviation increase in downside risk ($DSRISK_{t-1}(ma8)$) reduces quarterly house price growth by about 1.1 percent.

"Frenzy" dynamics may arise from: the log user cost component (housing demand theory); housing market frictions; and strategic interactions between households (see Section 4.2). Previous applications include Hendry (1984) and Muellbauer and Murphy (1997) for the UK and Williams (2009) for Australia. The frenzy effect (a cubic of lagged real house price changes) is parameterised to remove its correlation with $\Delta \log p^h_{t-1}$ and has a t-ratio of 10.7 even after controlling for (potentially non-linear) log user cost effects in the long run solution.[18] The significant positive coefficient on $\Delta \log p^h_{t-1}$ suggests that households expect last quarter's house price changes to continue, while the negative coefficient on $\Delta_4 \log p^h_{t-1}$ effectively lags the equilibrium correction dynamics to allow some adjustment from the previous year. The combined effect of the three autoregressive terms is that when house price growth is low, there is a small short run impulse to quarter-ahead price growth in the same direction as equilibrium correction. For example, if real house prices grow at their mean quarterly rate of 0.85 per cent, the net autoregressive impulse is -0.3 per cent. However, when house price growth exceeds a threshold of about 4-4.5 per cent, $frenzy$ dominates. The autoregressive dynamics then push short run house price growth in the opposite direction to equilibrium correction. If real house price growth is 8.1 per cent, as it was in 1988(4), the net impulse to quarter-ahead house prices jumps to +8.6 per cent. These non-linear dynamics help explain

[16] Age demography data must be interpolated from annual data. These trending variables (we treat them as either I(1) or I(2)) may confound identification of the also trend-like CCI. We mitigate these pitfalls by imposing strict priors on CCI and other aspects of the long run solution.

[17] Evidence for some bias comes from a comparison of the Reserve Bank estimates of real housing wealth with the constant price net capital stock multiplied by the house price index. The former rises around 25 percent less than the latter over 1978-1986 whereas for other periods the two series are more similar

[18] Because $(\Delta \log p^h_t)^3$ is collinear with $\Delta \log p^h_{t-1}$, the cubic is parameterised as the residual of the following regression: $(\Delta \log p^h_t)^3 = \alpha + \beta \Delta \log p^h_t + \varepsilon_t$. That is, $frenzy_t = (\Delta \log p^h_t)^3 - \hat{\alpha} - \hat{\beta} \Delta \log p^h_t$. This parameterisation ensures orthogonality between $frenzy_{t-1}$ (with zero mean) and $\Delta \log p^h_{t-1}$. To simulate the effect of $\Delta \log p^h_{t-1}$ on $\Delta \log(p^h p)_t$, the lagged quarterly and annual real house price changes are treated as equivalent.

momentum and overshooting dynamics in house prices.[19]

Charts 4 and 5 plot the long run influences on log real house prices. In the 1980s, rising real house prices are mostly attributable to easing credit conditions, rising net financial wealth and measurement bias, offset by falling real non-property income per house. Measurement bias is clearly an issue in the early part of the sample and perhaps could be calibrated to have a lesser impact. Across the 1990s, rising real house prices are mainly attributable to easing credit conditions (from 1998-2006), the decline in the user cost of housing and rising net financial wealth. From 2000, there are also small contributions from higher real income per house and the introduction of the FHOS.

5.4 Mortgage stock model results

Table 3 presents the mortgage stock model results. The real per capita mortgage stock is determined by non-property income, real and nominal interest rates, credit conditions, housing assets, the FHOS and the proportion of the population of first home buying age. The short run dynamics include lagged growth in the mortgage stock, incomes, nominal interest rates, the eight quarter change in the log unemployment rate (proxying uncertainty), negative quarters of house price growth and two outlier dummies.

The equation's standard error is 0.00420, R^2 is 0.79, and diagnostic tests are satisfied. The adjustment speed, at 4.5 percent per quarter with a t-statistic of 7.6, is roughly similar to UK estimates in Fernandez-Corugedo and Muellbauer (2006). The dependent variable is a stock, so shocks to the steady state path unwind slowly. It takes about twelve years to remove 90 percent of a shock to the mortgage stock.[20]

The steady state variables explain the 231 percent increase in the real per capita mortgage stock over 1978-2008 in the following partial equilibrium terms. As expected, the intercept effect of CCI has its largest impact in the mortgage stock equation. $\zeta_m = 1.70$ with a t-statistic of 10.5 meaning that CCI's effect on the mortgage stock is around 1.7 times the impact on house prices. The relaxation of credit constraints thus directly contributes more than half of the total rise in the real mortgage stock per capita (about 127 percentage points). The reason is that the relaxation of the collateral constraint could be even more important than that of the downpayment constraint.

The intertemporal consumption smoothing channel suggests interacting CCI with interest rates and income growth expectations. Real interest rates (r) have no effect at the start of the sample but higher post-FLIB real interest rates subtract about 22 percentage points from the mortgage stock across 1978-2008. Nominal interest rates ($\log i$), by affecting immediate cash flows, negatively affect credit constrained households but this effect diminishes as credit conditions ease. The elasticity of the mortgage stock with respect to nominal interest rates falls from -1.28 at the start of the sample to -0.17 by 2008. The net result is that lower nominal interest rates contribute about 2 percentage points. Also, more optimistic expectations about future income, $\log(y^p/y)$, raise the mortgage stock by about 10 percentage points.

Non-property income per capita rises by 43 percent over 1978-2008, contributing 60 percentage points to the rise in the dependent variable. The weight on (lagged) income is 1.39 (with a t-ratio of 3.50),

[19] Alternative approaches include Abelson et al.'s (2005) asymmetric equilibrium correction model which shows an equilibrium adjustment speed some 50 per cent higher during house price booms. Bourassa and Hendershott (1995) and Bodman and Crosby (2003) apply the so-called "bubbles" estimation approach (Abraham and Hendershott (1993)) where short run house price dynamics are determined by the interplay of bubble builder and bubble burster terms.

[20] We checked interaction effects with CCI to see if the speed of equilibrium adjustment is affected by the degree of credit liberalisation. The interaction effect was not significant over the full sample. However, over a shorter sample using 1986-2008 data, the interaction effect has a t-statistic of -1.9. This might constitute some mild evidence that the mortgage stock has become more flexible due to FLIB.

similar to UK estimates in Fernandez-Corugedo and Muellbauer (2006). The ratio of housing assets to income ($\log HA_{-1}/4y$) increases by 76 percent across 1978-2008. As loan collateral, this contributes 27 percentage points. The $FHOS$ from 2000 contributes a further 4 percentage points. The reduction in the proportion of the population that are of first home-buying age subtracts 40 percentage points.

The mortgage stock data are affected by a legion of reporting changes and structural breaks, especially in the 1980s, as non-bank financial institutions (NBFIs) became banks. The Reserve Bank attempts to correct these as much as possible but we include some step dummies during the 1980s to capture any residual discrepancies. The alternative approach would see these unobserved data discrepancies captured in CCI, which is unsatisfactory. We posit that the level of the mortgage stock is slightly under-reported prior to 1990. Our measurement error correction explains another 8 percentage points of the rise in the real mortgage stock across 1978-2008. The function specifying the mortgage stock measurement bias, $MSMEAS$, is defined as:

$$MSMEAS = b_{88}(1 - SDMMA_{1988})$$

The b_j coefficients take on negative values; while $(1 - SDMMA_{1988})$ is 1 before 1988 and falls to zero in 1989(4). With b_{88} estimated at -0.083, this imputes a proportionate downward bias to the 1987(4) measure of the log real mortgage stock (that is, the stock was underestimated by 8.3 percent), falling to zero by 1989(4) as the coverage of the mortgage stock data improved (see Table 6 and Chart 7). We also checked for effects around 1984 and 1986 (not significant).

In the short run dynamics, an increase in the unemployment rate from, say, 5 percent to 6 percent over the previous eight quarters has an insignificant impact on mortgage demand when credit conditions are tight, but reduces nominal growth in the mortgage stock by -0.4 percent at the 2008 level of CCI. The interpretation is that when very conservative rules for granting mortgage credit are followed by banks, unemployment is almost irrelevant. However, as these rules are relaxed, households facing greater unemployment risk are given mortgages, and with higher debt to income ratios for most households, unemployment becomes more relevant for mortgage growth.

Charts 6 and 7 plot the long run influences on the log real mortgage stock per capita. During the moderate expansion of the mortgage stock in the 1980s, the main positive influences are credit conditions and a high proportion of young persons in the population, offset by rising nominal interest rates. The main drivers during the 1990s are falling nominal interest rates from 1990 to 1998, easing credit conditions from 1990 to 1992 and from 1998 to 2006, rising non-property incomes and the introduction of the FHOS (after 2000). Lower real interest rates made a positive contribution to the mortgage stock during the years from mid-2000 to mid-2004.

5.5 Housing equity withdrawal model results

Table 4 presents the estimation results for the HEW model. The long run level of housing equity withdrawal to household non-property income (hew/y) is determined by credit conditions, real interest rates, the proportion of the population of working age and the mortgage stock to income. The short run dynamics include the eight quarter change in the log unemployment rate and the change in nominal interest rates (weighted by the household credit to income ratio) and outlier dummies.

The model's standard error is 0.000599 and R^2 is 0.54, where the former reflects the scaling of the equation to avoid heteroskedasticity. The model satisfies residuals tests for autocorrelation, normality and heteroskedasticity. Since *hew* is the balance of two flows - mortgage stock growth and gross housing investment - equilibrium correction is fast at 78.6 percent per quarter (with a t-statistic of 14.2). It takes barely two quarters to remove 90 percent of a disturbance to the steady state level of hew/y.

Housing equity withdrawal to income (hew/y) rises from -5.6 percent in 1978 to -1.6 percent in 2008, peaking at +8.3 percent in 2003(4). The long run solution explains the rise in the following partial equilibrium terms. The intercept effect of CCI (the deposit constraint) raises *hew* by 29 percent of income over 1978-2008. However, the ratio of the mortgage stock to income rises from 0.2 in 1978 to 1.5 in 2008, and subtracts 13 percent of income from the rise in *hew*. Higher real interest rates subtract a further 7 percent by raising the relative price of current consumption and deterring intertemporal substitution. Finally, the rising proportion of population of working age persons ($WAPOP$) subtracts about 13 percent.

In the short run, increases in nominal interest rates encourage housing equity injection, especially as household debt increases. As in the mortgage stock equation, the change in the unemployment rate enters only through interaction with CCI, so that a rise in unemployment has a negative effect on equity withdrawal when access to credit is easy. A surprising finding is that neither the housing wealth to income ratio nor its interaction with CCI have an effect on equity withdrawal relative to income. It appears that the strong CCI intercept effect on hew/y is sufficient.

Chart 8 plots the long run influences on the HEW to income ratio. There are steady downward influences from demographics and the rising stock of outstanding mortgage debt, but these are more than offset by credit liberalisation and especially so between 1998 to 2007. Note there is a positive effect on HEW from lower real interest rates for 2000-2004.

6 Alternative system specifications

We apply a series of robustness checks. First, we estimate CCI using only a three equation system of house prices, mortgage credit and HEW (denoted as CCI_{3EQ} in the tables and plotted at Chart 1). We then estimate the consumption equation separately and conditional on CCI_{3EQ}. The results are presented in Column 2 of Table 1 (results for the other three equations are available on request). Aside from a marginally higher equation standard error, to be expected, the differences with the results in Column 1 are very slight. All coefficients are within one standard error of their corresponding (four equation estimated) values in Column 1. CCI_{3EQ}, estimated without use of the consumption equation is virtually identical (Chart 1). Our CCI is therefore robust to the omission of the consumption data.

Second, in the estimations we have relied upon the fitted values of a separate regression for $\log(y^p/y)_t$ reported in Williams (2010) (estimated on a 1972-2008 sample). These regression results are re-stated as Column 1 in Table 7. We now include this parsimonious income forecasting equation (sophisticated information set) as a fifth equation in the system. Joint estimation nullifies any potential generated regressors efficiency or inference problem (Pagan (1984)). The results for the jointly estimated income forecasting equation are reported in Column 2 of Table 7. The results for the consumption equation are reported in Column 3 of Table 1. The real interest rate effects are somewhat weaker in both the consumption and income forecasting equations. This is probably due to the shorter sample length now being used for the latter equation (without negative values of the real interest rate). Overall, this exercise suggests there is scope to improve the income forecasting equation, for example by incorporating regime shifts or some learning capability on the part of households (and especially between 1970s and later periods). The dividend of such work could be to allow the restrictions on ψ_t in the consumption equation to be relaxed. Nonetheless, because we have imposed such tight restrictions on the weight of permanent income in the consumption equation, these issues are relatively minor. Chart 1 shows negligible impact on our estimate of CCI.

Third, we estimated the system over two shorter samples to check on parameter stability. We estimate the system for 1986(1)-2008(2), omitting pre-1986 outliers and fixing early sample parameters such as a_{78}, a_{80} and a_{82} to their full sample values. This is a normalisation without consequences for goodness of fit. We also constrain the long run income parameter in the mortgage stock equation to 1.39 (an easily acceptable restriction that helps pin down the rest of the parameters). Most of the key long run parameters throughout the system are similar and within one standard error of their full sample value. The quarterly speeds of adjustment rise in both the consumption and mortgage stock equations (to 37.7 percent and 5.9 percent respectively). We tested an interaction effect between ϕ_m and CCI and estimated the system over 1986-2008. That is, we redefined the speed of adjustment in Equation 12 as $(\phi_{m0} + \phi_{m1}CCI)$. ϕ_{m0} had a coefficient of around 0.039, while ϕ_{m1} had a coefficient of about 0.025 (with a t-statistic of 1.9). These findings suggest that, at least since the mid-1980s, the mortgage stock and consumption have become a little more flexible with FLIB. We also estimated the system over 1978(1)-2000(4). These findings are very close to the full sample results.

Fourth, the log ratio of property income to non-property income ($\log(yprop/y)$) was included in the long run solution of each equation to test whether non-property income alone drives consumption, house prices, the mortgage stock and equity withdrawal. The former effect, measured as a four quarter moving average of the log ratio, is positive in the first three equations, but all the t-ratios are below 2. The point estimates suggest that replacing log non-property income in the system by a weighted average with weights around 0.9 and 0.1 on log non-property income and log property income respectively would produce a slight improvement in the system log likelihood. The main changes to system estimates are a small reduction in the estimated measurement bias for house prices, a reduction in the MPC out of net liquid assets from 0.16 to 0.12, and a small increase in the maximum value of CCI. Otherwise, little else changes. However, not too much weight should be placed on these results. The measurement of property income is likely to have been distorted by inflation, since a component of property income as measured in the national accounts consists of nominal interest payments divided by the consumer prices index. Future research might examine property income, more properly measured, to see if it has an independent role in addition to the portfolio effects already present in these models.

Finally, we conducted a Johansen (1988, 1991) cointegration test on the consumption equation (results available on request). All variables were first weighted by their estimated coefficients listed in Table 1, Column 1. The I(1) endogenous variables (with one lag) in the vector order regression (VAR) were consumption, permanent income growth, a composite wealth term and the composite house price to income term. Treated as weakly exogenous were the persistent variables CCI and a composite demographic variable; the I(0) variables downside risk, current income growth and the composite unemployment rate variable; plus three outlier dummies. We checked weak exogeneity by finding the lagged residual from the long equation as insignificant in equations for the three I(0) variables.[21] A trace test on the VAR

[21] The lagged equilibrium correction term was marginally significant in the equation for the log change in the unemployment rate . However, since the latter enters the consumption equation with a lag it seems reasonable to treat $\Delta_8 \log ue_{t-1}$ as weakly exogenous.

rank cannot reject the null of a unique cointegrating vector between the endogenous variables. In a reduced rank regression, the speed of adjustment (alpha) is around 0.21 while the long run coefficients (betas) are all close to one, which confirm our earlier estimates. Our results are therefore robust to a more generalised treatment of cointegration.

7 Conclusion

Unobserved shifts in credit conditions help explain many of the stylised facts about the Australian economy over the last three decades. These include: sustained increases in consumption and house prices relative to income; an unprecedented expansion in household balance sheets; increased mortgage refinancing activity; and an increase in the level and volatility of housing equity withdrawal (HEW). Australia was high on the OECD's (2005) list of countries with greatly overvalued house prices, but there are few signs of the kinds of distress suffered by the US after 2007. Among the reasons are better financial regulation and hence the absence of poor quality sub-prime lending (see Debelle (2008, 2009), better monetary policy which in part headed off excessive house price euphoria, the absence of a speculative house building boom, and Australia's good economic fortune in riding the commodities boom fuelled by China and other emerging markets.

We show that credit conditions operate on the real economy through several channels. First, the relaxation by lenders of the mortgage downpayment requirement facing young, first time home buyers raises long run mortgage demand, house prices and consumption. Second, debt product innovation introduces a collateral channel from house prices to real activity. Older households with existing wealth benefit from cheap mortgage refinancing and home equity loans (popular since about the mid-1990s). Through HEW, housing capital gains can be accessed and redirected towards immediate consumption, asset portfolio rebalancing or debt consolidation. However, for young households without collateral, higher house prices require saving for a larger deposit. The balance of house price effects on consumption and mortgage demand thus hinges on the state of credit conditions. Third, easing credit conditions make intertemporal consumption smoothing possible. This raises the importance of real interest rates and income growth expectations in household decisions, and diminishes the importance of economic uncertainty. With liberal credit conditions, mortgage credit and housing equity are increasingly used to smooth fluctuations in economic conditions.

The latent interactive variable equation system (LIVES) estimated in this paper presents a solution to the difficult macro-econometric challenge of handling large, unobserved structural changes. The method relies on institutional knowledge, economic theory, and consistency in logic and empirical findings across the equations (with common roles played by the latent credit conditions index (CCI), income growth expectations and other variables). Our system is only a subset of larger potential econometric model that could trace the consequences of shifts in banking regulation, housing tax policies or land-use policies on house prices, consumption and output.

Overall, together with the income forecasting equation, our system throws a good deal of light on the underlying shocks driving the economy and on the workings of the monetary policy transmission mechanism. Evidence of non-linearities and shifts in marginal responses with the CCI imply that the underlying impulse response functions are far from constant. These findings have obvious application for policy-makers since existing models without credit conditions effects are mis-specified and are likely to lead to policy errors.

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Appendix 1: Figures, charts and tables

Figure 1 : Loan offer curve and FLIB

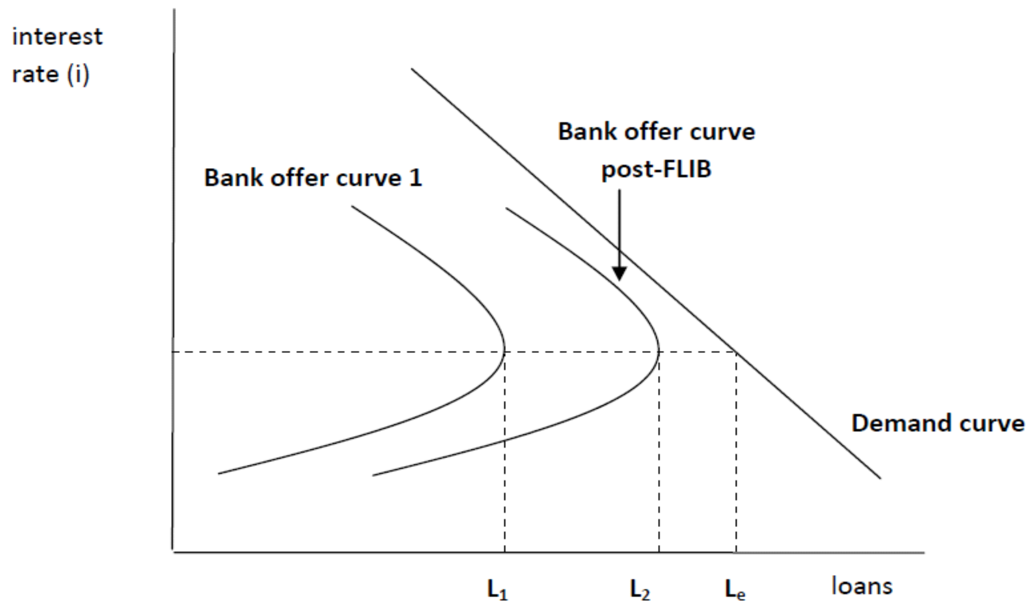


Figure 2 : Lender′s best offer curve

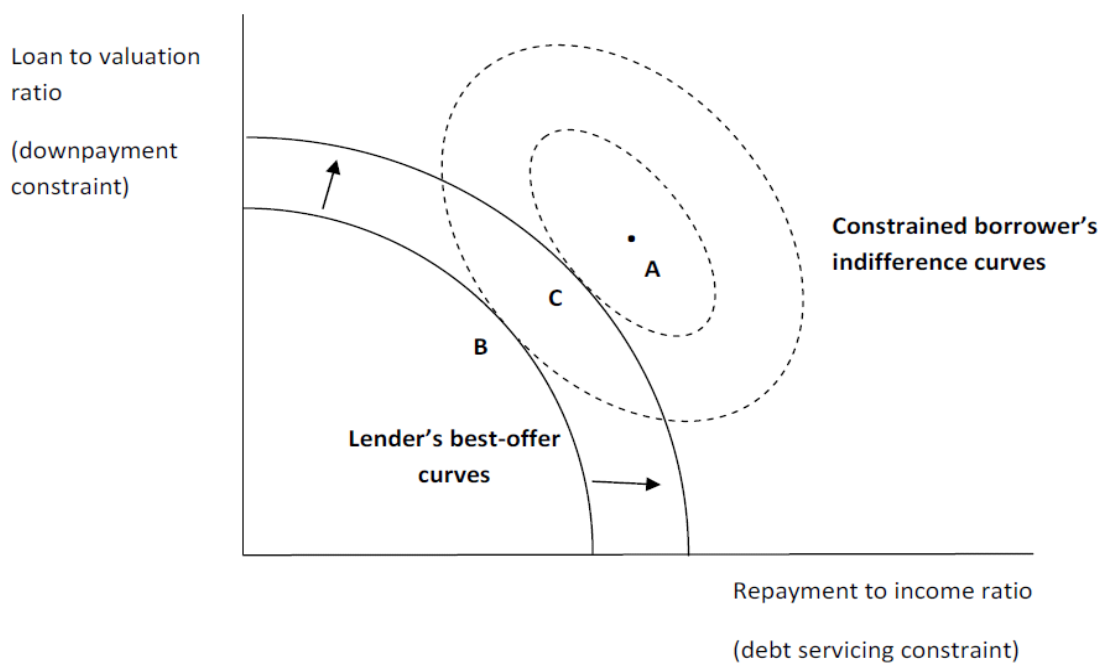


Chart 1 : **Estimated credit conditions index** (CCI)

(expressed in terms of long run impact on log real house prices)

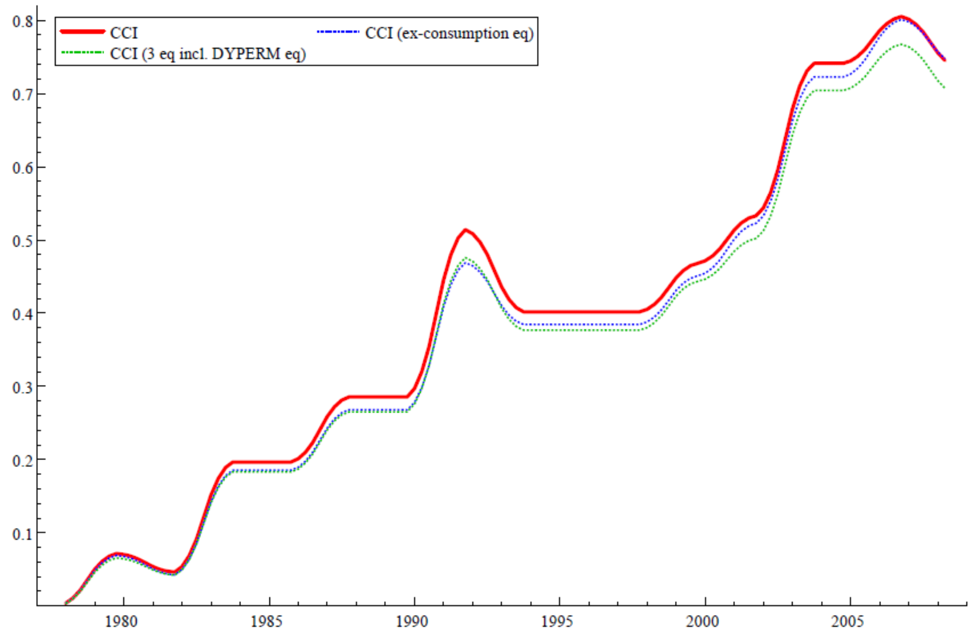
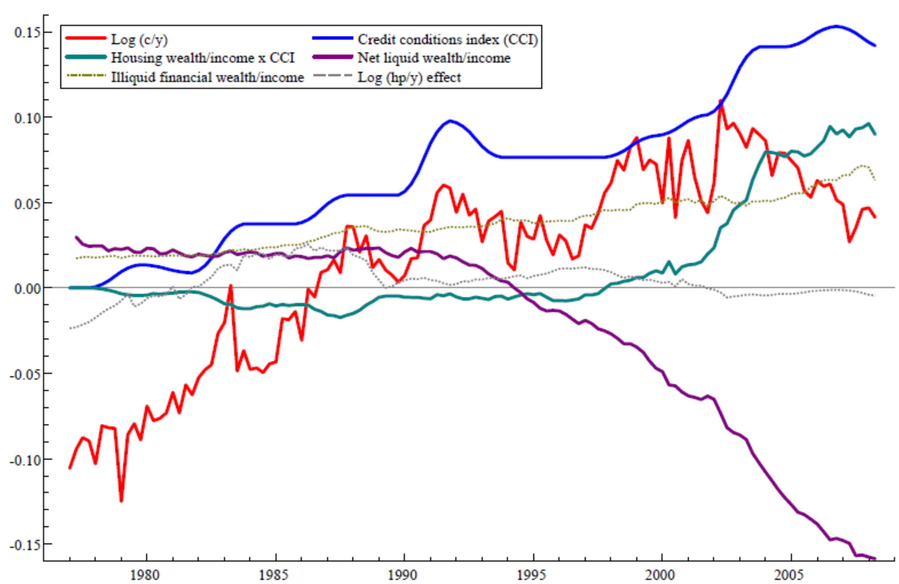


Chart 2 : **Australian household consumption I**[22]



[22] Charts 2 to 8 show the de-meaned contributions from the interaction terms (and net of their intercept effect, if any). The interaction effect is constructed as: $\alpha_{ij}(x_{ij} - mean(x_j)) \times CCI_t$ where α_{ij} is the long run coefficient on variable x_j (for example $\log(y^p/y)$) in equation i. The plotted demographic variable for the consumption model combines the effects of $\Delta_4 DEMFTB$ and $\Delta_4 DEMWA$.

Chart 3 : Australian household consumption II[23]

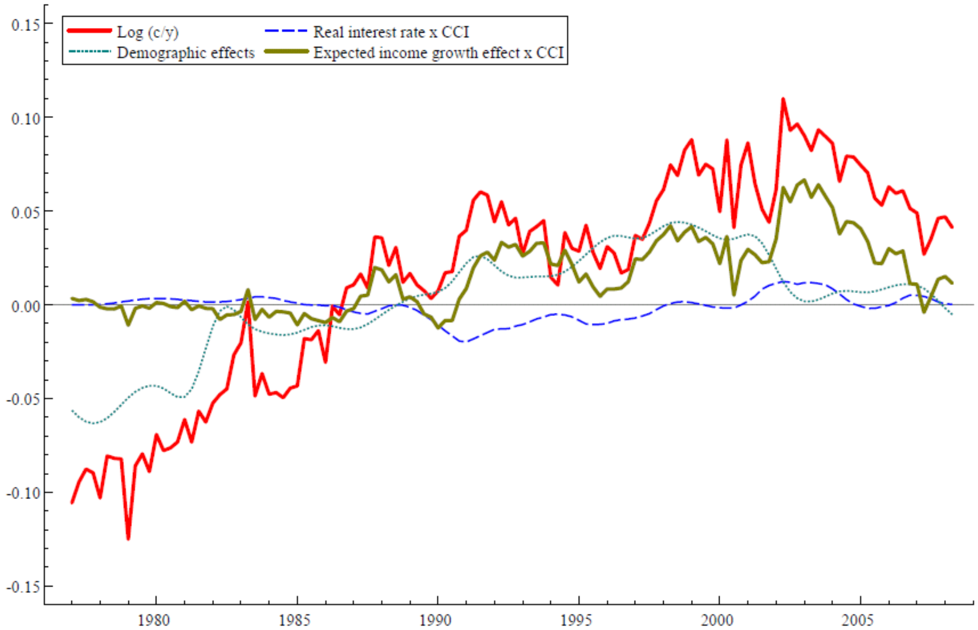
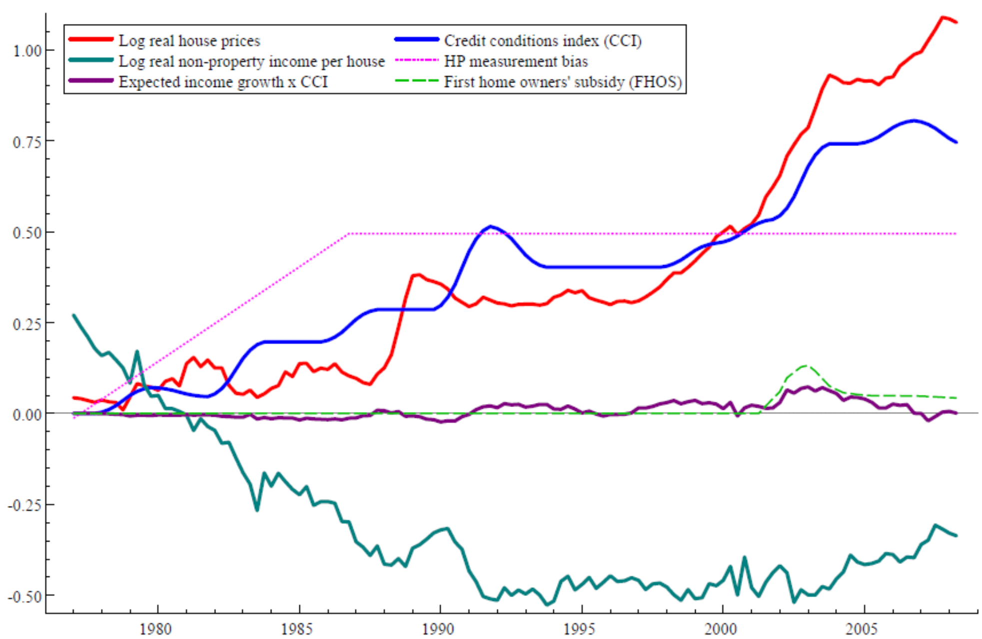


Chart 4 : Australian real house prices I



[23] Charts 2 to 8 show the de-meaned contributions from the interaction terms (and net of their intercept effect, if any). For the house price charts, the plotted demographic variable combines the effects of $\Delta_4 DEMFTB$ and $\Delta_4 \log pop$. Log real house prices ($\log p^h - 0.5$) and log real non-property income per house ($\log(y_{t-1}/h_{t-4}) + 4.5$) are re-scaled for ease of comparison.

Chart 5 : Australian real house prices II[24]

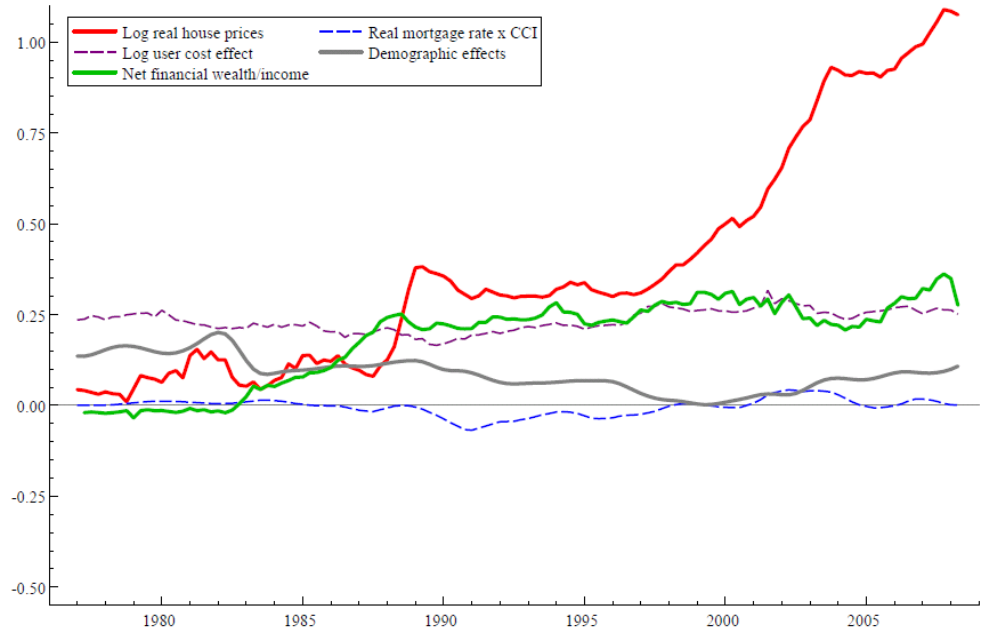
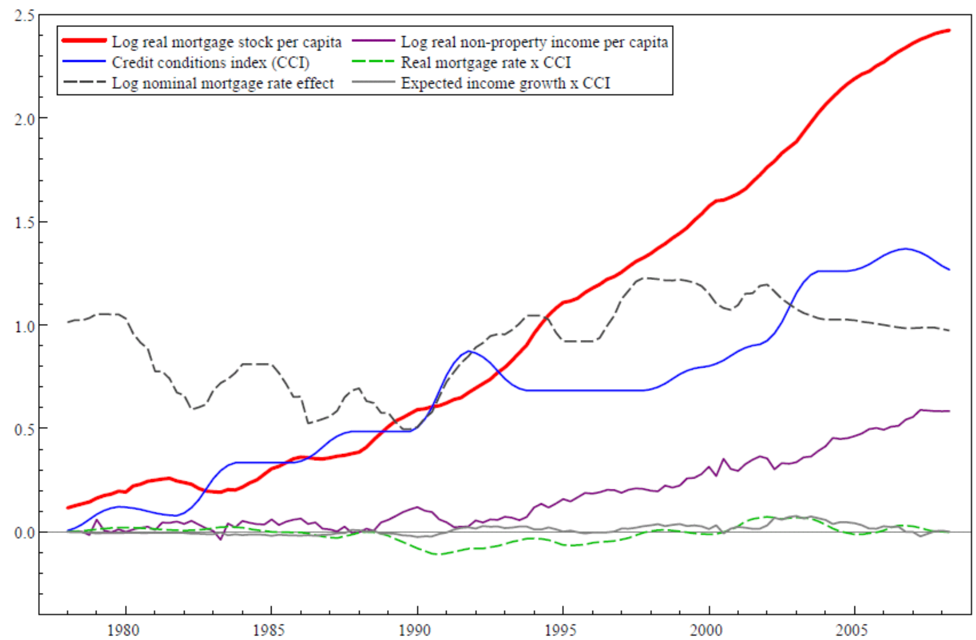


Chart 6 : Australian real mortgage stock I



[24] Charts 2 to 8 show the de-meaned contributions from the interaction terms (and net of their intercept effect, if any). For the mortgage stock charts, the plotted demographic variable combines the effects of $DEMFTB$ and $\Delta_4 DEMFTB$.

Chart 7 : Australian real mortgage stock II[25]

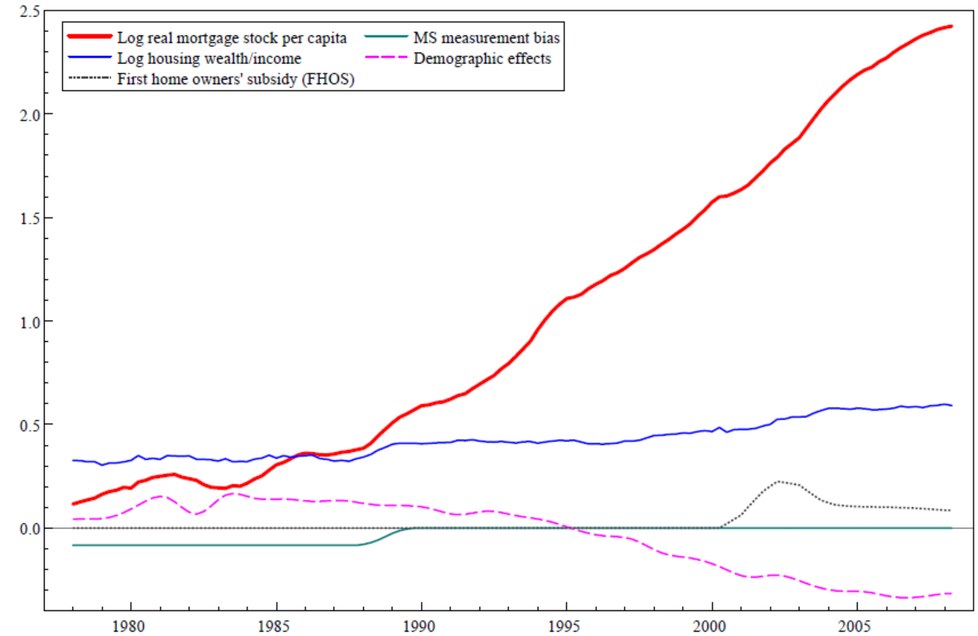
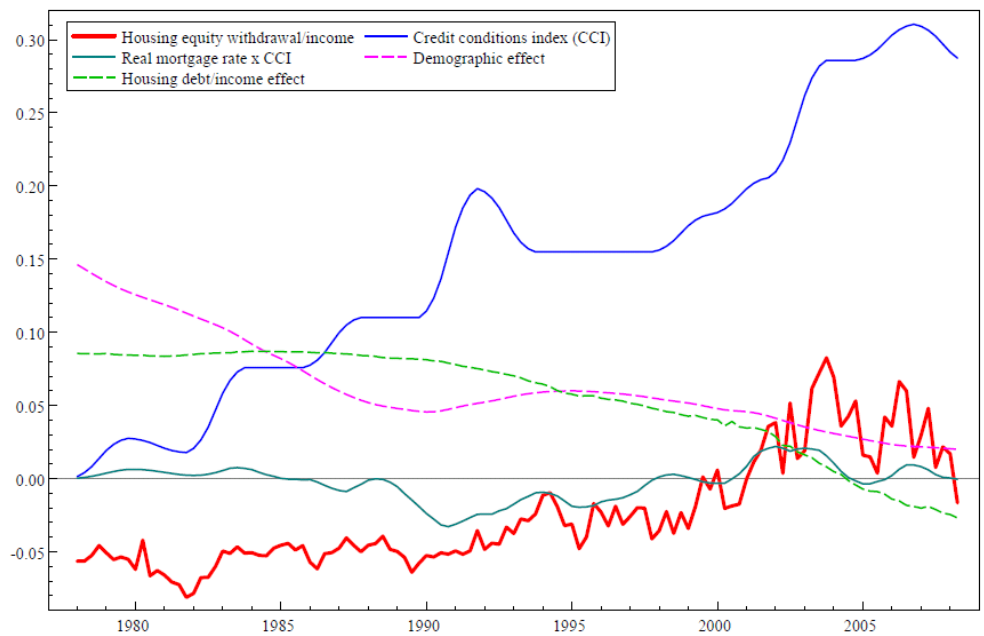


Chart 8 : Australian housing equity withdrawal



[25] Charts 2 to 8 show the de-meaned contributions from the interaction terms (and net of their intercept effect, if any).

Table 1 : Consumption model[26]

Dependent variable $= \Delta \log c_t$

$1978(1) - 2008(2)$

		(1)	(2)	(3)
		4 eq system	cond. on CCI_{3EQ}	5 eq system
Variable	Param.	Coeff. (Std error)	Coeff. (Std error)	Coeff. (Std error)
speed of adj.: $\log(y_t/c_{t-1})$	ϕ_c	0.2858*** (0.0325)	0.2754*** (0.0348)	0.2902*** (0.0324)
constant	α_{c0}	-0.1048*** (0.0209)	-0.0930*** (0.0230)	-0.1074*** (0.0202)
CCI_t	ζ_c	0.1902*** (0.0370)	0.1875*** (0.0429)	0.2012*** (0.0383)
$r_{t-1}(ma4) \times CCI_t$	α_{c1}	-0.8711** (0.4305)	-0.9544** (0.4620)	-1.0579** (0.4939)
$HA_{t-1}/4y_t \times CCI_t$	γ_1	0.0606*** (0.0189)	0.0646*** (0.0206)	0.0669*** (0.0201)
$IFA_{t-1}/4y_t$	γ_2	0.0219** (0.0108)	0.0194* (0.0116)	0.0263** (0.0107)
$NLA_{t-1}/4y_t$	γ_3	0.1588*** (0.0303)	0.1683*** (0.0325)	0.1754*** (0.0308)
$\log(y^p/y)_t$	ψ_0	0.20	0.20	0.20
$\log(y^p/y)_t \times CCI_t$	ψ_1	0.93	0.93	0.975
$\Delta_4 DEMFTB_t$	α_{c2}	-0.1375*** (0.0244)	-0.1522*** (0.0276)	-0.1314** (0.0242)
$\Delta_4 WAPOP_{t-1}$	α_{c3}	-0.0692** (0.0330)	-0.0586 (0.0373)	-0.0726** (0.0333)
$\log(p^h/y)_{t-1}(1\text{-}1.2CCI_t)$	α_{c4}	-0.1298*** (0.0427)	-0.1050** (0.0426)	-0.1133*** (0.0375)
$DSRISK_{t-1}(ma8)$	β_{c1}	0.0503*** (0.0176)	0.0432** (0.0190)	0.0564*** (0.0172)
$\Delta_8 \log ue_{t-1}(1\text{-}1.2CCI_t)$	β_{c2}	-0.0208*** (0.0043)	-0.0202*** (0.0046)	-0.0199*** (0.0042)
$\Delta_4 \log c_{t-1}$	β_{c3}	-0.1098*** (0.0406)	-0.0916** (0.0441)	-0.1360*** (0.0404)
$D1978(2)$	β_{c4}	0.0231*** (0.0044)	0.0231*** (0.0049)	0.0236*** (0.0043)
$D1982(3)$	β_{c5}	-0.0175*** (0.0043)	-0.0172*** (0.0048)	-0.0169*** (0.0043)
$D1986(1)$	β_{c6}	-0.0138*** (0.0043)	-0.0133*** (0.0048)	-0.0147*** (0.0043)
$\zeta_c CCI_{2008(2)}$		0.1418	0.1401	0.1423
Standard error		0.00408789	0.00445521	0.00436801
R^2		0.636730	0.627522	0.596392
DW		1.933960	1.95196	1.68727
Diagnostics (p-values)				
B-G LM: AR/MA1		0.730	0.919	0.099
B-G LM: AR/MA5		0.146	0.167	0.372
Ljung-Box Q-statistic2		0.728	0.750	0.215
LM hetero. test		0.114	0.074	0.248
J-B normality test		0.225	0.320	0.423

[26] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.

Table 2 : House price model[27]

Dependent variable $= \Delta \log(p^h p)_t$

1978(1) − 2008(2)

(estimated within 4 equation system)

Variable	Parameter	Coefficient	Standard error
speed of adj.: $-\log p^h_{t-1}$	ϕ_h	0.2437***	(0.0280)
constant	α_{h0}	4.4694***	(0.6256)
CCI_t	ζ_h	1.0	
$\log y_{t-1} - 0.9 \log h_{t-4}$	κ	1.9883***	(0.2841)
$r_{t-1}(ma4) \times CCI_t$	α_{h1}	-2.9966**	(1.4516)
$\log ucc_{t-1}$	α_{h2}	-0.1088***	(0.0338)
$\log NFA_{t-1}/4y_t$	α_{h3}	0.4426***	(0.0866)
$\log(y^p/y)_t \times CCI_t$	α_{h4}	1.6082**	(0.8166)
$\Delta_4 DEMFTB_{t-4}$	α_{h5}	0.2453***	(0.0697)
$\Delta_4 \log pop_{t-1}$	α_{h6}	7.8715***	(2.7207)
$FHOS_{t-4}(ma4)$	α_{h7}	0.0256***	(0.0074)
$HPMEAS_{t-1}$	α_{h8}	0.0130***	(0.0023)
NG_t	β_{h1}	-0.0294***	(0.0044)
$DSRISK_{t-1}(ma8)$	β_{h2}	0.1783***	(0.0375)
$\Delta \log y$	β_{h3}	0.2476***	(0.0769)
$\Delta_4 \log p^h_{t-1}$	β_{h4}	-0.0453*	(0.0270)
$\Delta \log p^h_{t-1}$	β_{h5}	0.2174***	(0.0562)
$frenzy_{t-1}$	β_{h6}	215.221***	(20.171)
$seasonal_{t-1}$	β_{h7}	0.0068***	(0.0017)
$D1981(1)$	β_{h8}	0.0701***	(0.0086)
$D1981(4)$	β_{h9}	0.0343***	(0.0091)
$D1988(3)$	β_{h9}	0.0479***	(0.0094)
$D1991(3)$	β_{h10}	0.0435***	(0.0090)
$\zeta_h CCI_{2008(2)}$		0.74533	
Standard error		0.00838957	
Adj R^2		0.846279	
DW		2.27162	
Diagnostics (p-values):			
Breusch/Godfrey LM: AR/MA1		0.134	
Breusch/Godfrey LM: AR/MA5		0.079	
Ljung-Box Q-statistic2		0.315	
LM hetero. test		0.841	
Jarque-Bera normality test		0.662	

[27] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.

Table 2a : Log user cost of housing[28]

$$\log ucc_t = \log(0.04 + \frac{i_{t-1}}{100} - \Delta_4 \log \hat{p}^h_{t+4})$$

where

$$\textit{Dependent variable} = \Delta_4 \log(p^h p)_{t+4}$$

$$1978(1) - 2007(2)$$

Variable	Coefficient	Standard error
constant	1.4145***	(0.2638)
$\log p^h_{t-1}$	-0.0791***	(0.0195)
$\log y^h_{t-4}$	0.2532***	(0.0468)
$\Delta \log(p^h p)_{t-1}$	0.1790**	(0.0835)
$\Delta \log p_t$	0.5617*	(0.3326)
$\Delta \log p_{t-1}$	0.4718	(0.3190)
$\Delta \log i_{t-1}$	-0.1236***	(0.0456)
Standard error	0.018333	
Adj R^2	0.294973	
DW	1.39633	

[28] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.

Table 3 : Mortgage stock model[29]

Dependent variable $= \Delta \log m_t$

1978(1) − 2008(2)

(estimated within 4 equation system)

Variable	Parameter	Coefficient	Standard error
speed of adj.: $-\log(m/p)_{t-1}$	ϕ_m	0.0451***	(0.0059)
constant	α_{m0}	-10.6890***	(2.3162)
CCI_t	ζ_m	1.6999***	(0.1624)
$MSMEAS_t$		1.0	
$\log y_{t-1}$	α_{m1}	1.3896***	(0.3973)
$r_{t-1}(ma4) \times CCI_t$	α_{m2}	-5.3279**	(2.2730)
$\log i_{t-1}$	α_{m3}	-1.2778***	(0.1350)
$\log i_{t-1} \times CCI_t$	α_{m4}	1.4822***	(0.2391)
$\log(y^p/y)_t$	α_{m5}	1.6944	(1.0840)
$\log HA_{t-1}/4y_t$	α_{m6}	0.3470**	(0.1400)
$DEMFTB_{t-4}$	α_{m7}	0.1460***	(0.0341)
$\Delta_4 DEMFTB_t$	α_{m8}	0.3495***	(0.0938)
$\Delta_4 DEMFTB_{t-4}$	α_{m9}	-0.2653***	(0.0733)
$FHOS_t(ma8)$	α_{m10}	0.0134***	(0.0028)
$\Delta \log m_{t-1}$	β_{m1}	0.2999***	(0.0531)
$\Delta_4 \log i_t$	β_{m2}	-0.0138***	(0.0052)
$\Delta_4 \log i_{t-1}$	β_{m3}	0.0090**	(0.0042)
$\Delta \log y_t$	β_{m4}	0.0543***	(0.0172)
$\Delta_8 \log ue_{t-1} \times CCI_t$	β_{m5}	-0.0686***	(0.0107)
$\text{neg}(\Delta \log p^h_{t-1})$	β_{m6}	0.0828***	(0.0212)
$D1980(2)$	β_{m7}	0.0057***	(0.0017)
$D1986(1)$	β_{m8}	-0.0074***	(0.0016)
$D1986(2)$	β_{m9}	-0.0055***	(0.0016)
$D1988(3)$	β_{m10}	0.0087***	(0.0016)
$\zeta_m CCI_{2008(2)}$		1.2670	
Standard error		0.00419838	
Adj R^2		0.791781	
DW		2.0231	
Diagnostics (p-values)			
Breusch/Godfrey LM: AR/MA1		0.861	
Breusch/Godfrey LM: AR/MA5		0.271	
Ljung-Box Q-statistic2		0.951	
LM hetero. test		0.198	
Jarque-Bera normality test		0.756	

[29] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.

Table 4 : Housing equity withdrawal model[30]

Dependent variable $= z_t \Delta \log(hew/y)_t$

$1978(1) - 2008(2)$

(estimated within 4 equation system)

Variable	Parameter	Coefficient	Standard error
speed of adj.: $-\log(hew/y)_{t-1}$	ϕ_w	0.7859***	(0.0553)
constant	α_{w0}	2.8052***	(0.3050)
CCI_t	ζ_w	0.3856***	(0.0415)
$r_{t-1}(ma4) \times CCI_t$	α_{w1}	-1.603***	(0.3034)
$\log HC_{t-1}/4y_t$	α_{w2}	-0.0442***	(0.0047)
$WAPOP_{t-1}$	α_{w3}	-0.1002***	(0.0230)
$\Delta \log i_{t-1}(CR_{t-1}/4y_t)$	β_{w1}	-0.0598***	(0.0110)
$\Delta_8 \log ue_{t-1} \times CCI_t$	β_{w2}	-0.1512***	(0.0232)
$D2002(3)$	β_{w3}	0.0150***	(0.0043)
$D2006(4)$	β_{w4}	-0.0131***	(0.0050)
$\zeta_w CCI_{2008(2)}$		0.2874	
Standard error		0.000598731	
Adj R^2		0.543558	
DW		2.00395	
Diagnostics (p-values)			
Breusch/Godfrey LM: AR/MA1		0.937	
Breusch/Godfrey LM: AR/MA5		0.308	
Ljung-Box Q-statistic2		0.995	
LM hetero. test		0.119	
Jarque-Bera normality test		0.584	

[30] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.

Table 5 : Parameter estimates for CCI

1978(1) – 2008(2)

(est. within 4 eq. system, expressed in terms of
long run contribution to log real house prices)

Variable	Parameter	Coefficient	Standard error
$SDMMA_{1978}$	a_{78}	0.0715***	(0.0107)
$SDMMA_{1980}$	a_{80}	-0.0253***	(0.0094)
$SDMMA_{1982}$	a_{82}	0.1505***	(0.0143)
$SDMMA_{1986}$	a_{86}	0.0889***	(0.0128)
$SDMMA_{1990}$	a_{90}	0.2284***	(0.0259)
$SDMMA_{1992}$	a_{92}	-0.1121***	(0.0241)
$SDMMA_{1998}$	a_{98}	0.0664***	(0.0120)
$SDMMA_{2000}$	a_{100}	0.0648***	(0.0164)
$SDMMA_{2002}$	a_{102}	0.2083***	(0.0172)
$SDMMA_{2005}$	a_{105}	0.0638***	(0.0177)
$SDMMA_{2007}$	a_{107}	-0.0704***	(0.0255)
$CCI_{\max}$		0.8052	
$CCI_{2008(2)}$		0.7453	

Table 6 : Parameter estimates for mortgage stock measurement bias (MSMEAS)

1978(1) – 2008(2)

(est. within 4 eq. system, expressed in terms of
long run contribution to log real mortgage stock per capita)

Variable	Parameter	Coefficient	Standard error
$SDMMA_{1988}$	b_{88}	-0.0830***	(0.0110)

Table 7 : Income growth expectations equation[31]

Dependent variable $= \Delta \log(y^p/y)_t$

	(1) (as est. in Williams (2010)) 1972(3) – 2008(2)		(2) (as est. in 5 eq system) 1978(1) – 2008(2)	
Variable	Coefficient	Std error	Coefficient	Std error
constant	-4.7484***	(0.0683)	-4.2977***	(0.1007)
$\log y_t$	-0.8259***	(0.0683)	-0.7703***	(0.0174)
trend	0.0021***	(0.0002)	0.0025***	(0.0058)
real mortgage rate$_t$	-1.6021***	(0.2191)	-1.0444***	(0.0301)
real 10yr T-bond rate$_t(ma4)$	0.8004***	(0.2259)	0.1882***	(0.0256)
log real house prices$_{t-1}(ma4)$	0.1797***	(0.0263)	0.1213***	(0.0058)
log real share prices$_{t-1}(ma4)$	0.0342**	(0.0144)	0.0114***	(0.0031)
$\Delta_4$log real share prices$_{t-1}$	0.0183**	(0.0074)	0.0081***	(0.0022)
$\Delta_4$log nom. mortgage rates$_{t-1}$	-0.0398***	(0.0140)	-0.0188***	(0.0033)
$\Delta_4$log real US GDP$_{t-1}$	0.1705*	(0.0906)	0.1652***	(0.0223)
log real oil prices$_{t-1}(ma4)$	-0.0271***	(0.0053)	-0.0130***	(0.0016)
ann. (budget surplus/GDP)$_{t-1}$	0.1317	(0.1002)	0.0750***	(0.0272)
Standard error	0.0105141		0.00380397	
R^2	0.930353		0.989615	

Notes:

$\log(y^p/y)_t = (\sum_{s=1}^{k}(1-\eta)^{s-1}E_t \log y_{t+s})/(\sum_{s=1}^{k}(1-\eta)^{s-1}) - \log y_t$

y is real non-property household disposable income per capita; $k = 40$; $\eta = 0.05$

[31] ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively.