Reserve Bank of Australia

RESEARCH DISCUSSION PAPER

More Potent Monetary Policy? Insights from a Threshold Model

Jarkko Jääskelä

RDP 2007-07

MORE POTENT MONETARY POLICY? INSIGHTS FROM A THRESHOLD MODEL

Jarkko Jääskelä

Research Discussion Paper
2007-07

July 2007

Economic Research Department
Reserve Bank of Australia

I would like to thank Christopher Kent, Marion Kohler, Mariano Kulish, Philip Liu, Kristoffer Nimark, Anthony Richards and Tim Robinson for comments. The views expressed in this paper are those of the author and do not necessarily reflect those of the Reserve Bank of Australia. Any errors are my own.

Author: jaaskelaj at domain rba.gov.au

Economic Publications: ecpubs@rba.gov.au

Abstract

It has been argued that the effect of a change in the monetary policy interest rate on aggregate demand may be larger at higher levels of indebtedness through its impact on cash flows. However, the extent of credit constraints may be at least as important, if not more so. In particular, monetary policy could have a larger impact on aggregate demand when credit constraints are pervasive (which could be the case at low or high levels of indebtedness, or both). This paper examines the extent to which the strength of credit growth, which can be seen as a proxy for credit constraints, may affect the transmission of monetary policy in a way that cannot be captured in linear models. The results reveal that GDP growth is more responsive to interest rate shocks when credit growth is low. Separate models for household and business credit growth confirm this finding: consumption and business investment are more responsive to interest rate shocks when credit is growing slowly for the household and business sectors, respectively.

JEL Classification Numbers: C51, C52, E37, E52
Keywords: monetary policy, business-cycle asymmetries, threshold models

Table of Contents

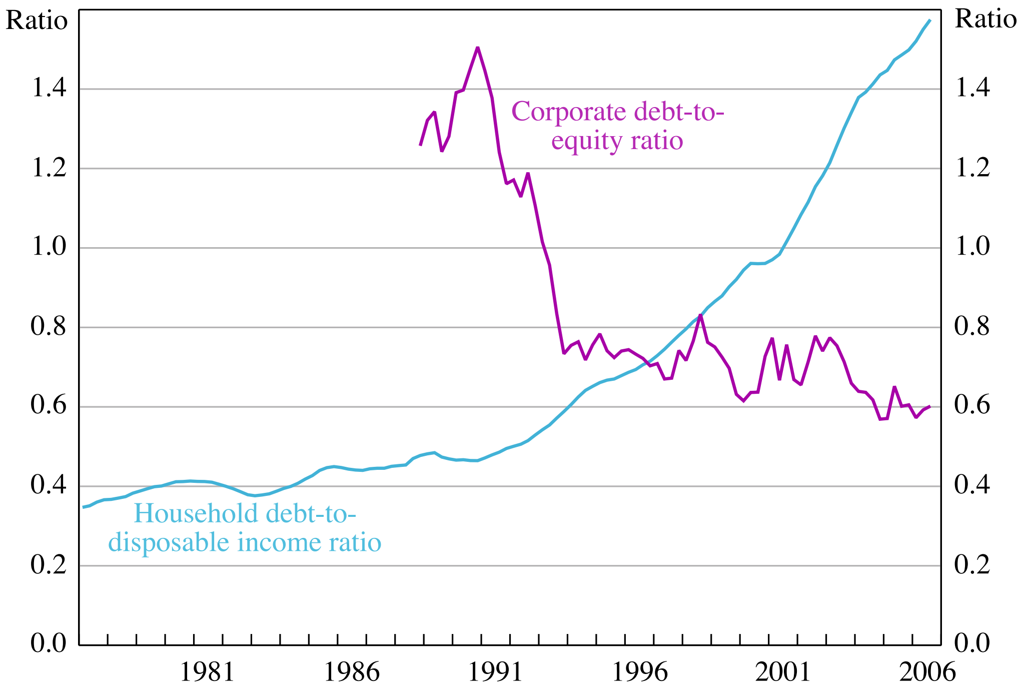
MORE POTENT MONETARY POLICY? INSIGHTS FROM A THRESHOLD MODEL

Jarkko Jääskelä

1. Introduction

The household sector's balance sheet has transformed substantially over the past two decades. The ratio of household debt to disposable income in Australia has risen rapidly from an average of about 40 per cent in the late 1980s to around 160 per cent in 2006 (Figure 1). It has been argued that higher levels of household debt may make the economy more sensitive to a given change in interest rates through its impact on cash flows. However, this effect may have been offset somewhat by the trend decline in business-sector leverage over a similar period, so that the net effect on the interest rate sensitivity of aggregate demand is unclear.

Figure 1: Household and Corporate Debt Indicators



Sources: ABS; RBA

In regard to the cash-flow channel of the transmission mechanism, the impact of monetary policy on aggregate demand may depend on more than just the level of indebtedness.[1] Of potentially greater relevance is the existence of credit-constrained borrowers. If borrowers are severely credit-constrained – that is, they have exhausted all available borrowing opportunities – they will tend to adjust spending substantially in response to even a temporary change in disposable income, including via a change in interest rates. In contrast, unconstrained borrowers (who base their consumption decisions on their expected permanent income) need to adjust their behaviour much less in response to temporary changes in disposable income, since these can be accommodated via an adjustment in saving (that is, via a change in net borrowing). It is easy to see that monetary policy could be more potent in cases where credit constraints are more pervasive. For example, higher interest rates raise the cost of servicing household debt, thereby transferring resources from borrowers (who have a high marginal propensity to consume, particularly if they face credit constraints) to lenders who are likely to have a lower marginal propensity to consume. Aggregate consumption is therefore likely to fall by more than if borrowing constraints were modest. Analogously, a similar story could be told about business investment. Bearing this in mind, this paper asks whether there is evidence that the interest rate sensitivity of the Australian economy depends on credit conditions.

The paper attempts to examine the sensitivity of economic activity to monetary policy by estimating the impact of interest rate shocks on output, conditional on the growth rate of credit. Credit growth provides a simple and readily available indicator of credit conditions. It is used in preference to a measure of indebtedness,[2] since credit constraints could be just as likely to be binding when

---

1 There are, of course, a number of other ways in which interest rates affect the economy besides the cash-flow channel. For instance, interest rates affect the price of financial assets, such as bonds and shares, and the exchange rate, which affect households and businesses in a variety of ways.

2 Indicators of indebtedness will tend to split the sample into two parts given that these have typically trended up for household and down for business sectors over the past two decades.

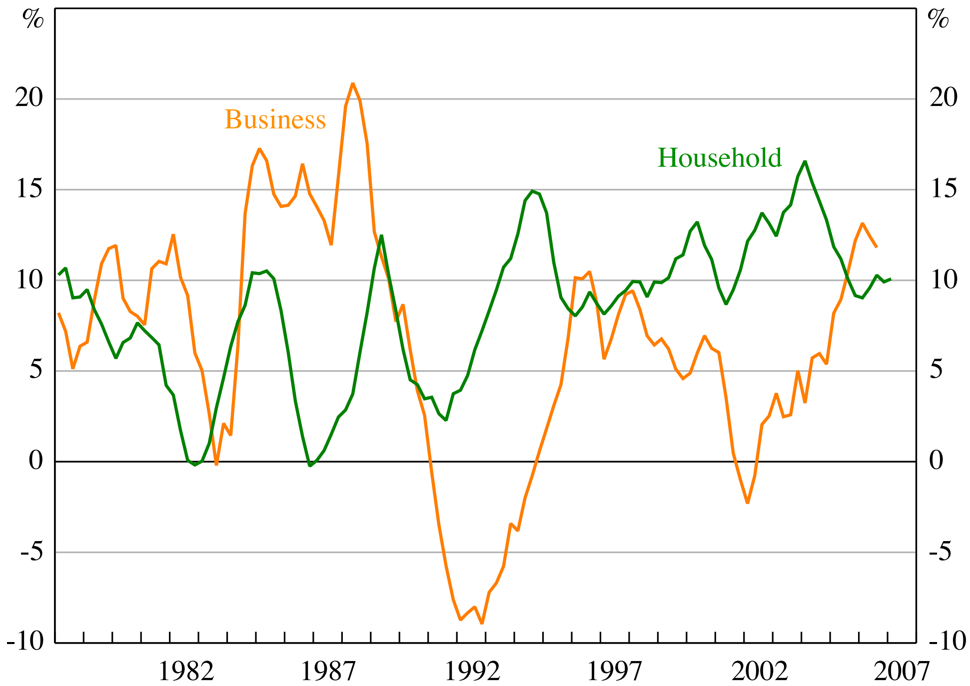
indebtedness is high or when it is low.[3] Of course, credit growth will depend on the strength of both demand and supply, which means that some caution is needed when interpreting the results.

One way to do this is to identify various episodes when supply considerations were clear drivers of credit growth. One obvious example is financial deregulation, which affected both financial institutions and borrowers. First, there was a removal of interest rate controls in the 1980s. Second, overseas borrowing controls were relaxed and restrictions prohibiting Australian financial institutions from borrowing overseas and restrictions on foreign banks entry were removed. These reforms enhanced Australian households' and firms' ability to access credit by spurring competition as banks sought to expand their lending operations to maintain or expand market share (see, for example, Edey and Gray 1996). As indicated in Figure 2, household and business sector credit growth have moved in slightly different phases over time. Following deregulation in the second half of the 1980s, business credit growth rose significantly, boosted also by sharp increases in prices of commercial property, which was an important source of collateral at the time (Gizycki and Lowe 2000). Business credit fell during the recession in the early 1990s, but here too, supply constraints played a role. Heavy losses on commercial loans by the banks, coupled with a large and prolonged decline in commercial property prices, led to tight credit conditions for businesses extending beyond the recessionary period (Tallman and Bharucha 2000). Moreover, this period coincides with financial institutions reducing their appetite for risk; some even announced explicit goals of reducing their exposure to business lending. For the household sector, credit conditions remained relatively tight for most of the 1980s. It was not until after the 1990s recession that these constraints eased substantially and household credit growth was maintained at a high rate for an extended period. This easing in constraints was associated with increased

3 A number of other alternatives have been used in the literature. Balke (2000) identifies 'tight' credit regimes as periods when the spread between commercial paper (four to six months) and 6-month Treasury bill rates is abnormally high. He also analyses alternative credit condition proxies such as the mix of bank loans and commercial paper in total external finance, and the difference between the growth rates in the short-term debt of small and large manufacturing firms. Atanasova (2003) considers the 10-year corporate bond spread. The idea being that a high spread on these rates is indicative of periods where firms' financing costs are high. These indicators are less useful for the analysis of both business and household credit conducted in this paper.

competitive pressures in the market and a persistent decline in inflation (see Edey and Gray 1996). As well as examining a model with aggregate credit growth and GDP, this paper separately analyses business and household sectors to take advantage of their different experiences in credit conditions over time.

Figure 2: Real Household and Business Credit Yearly Growth Rate



Sources: ABS; RBA

Credit constraints nowadays feature prominently in economic analyses of short-term business-cycle fluctuations. There is considerable macroeconomic literature suggesting that business cycles and credit interact (see Blinder 1987, Bernanke and Gertler 1989, Kiyotaki and Moore 1997 and Azariadis and Smith 1998). Although the theories presented in these studies differ in various dimensions, they all imply that the responsiveness of the economy to shocks might depend on prevailing credit conditions.

There is some indirect empirical evidence supporting the idea that recessions are likely to be periods when borrowers' balance sheets are weak and the availability of credit is tight. The result, that monetary policy shocks have a greater effect on output during recessions than during expansions, appears to hold across a number of countries for a number of different time periods: see for instance, Peersman and Smets (2001) for the euro area; Sensier, Osborn and Öcal (2002) for the United Kingdom; and Garcia and Schaller (2002) and Lo and Piger (2005) for the United States. Moreover, Garcia, Lusardi and Ng (1997) estimate the relationship between consumption and income for households in the US that are identified as credit-constrained and those that can borrow more freely, and find asymmetries in consumption behaviour. Cover (1992) provides a related finding that an expansionary monetary policy has less effect on output than a contractionary policy of the same order of magnitude.

In this paper I test for the presence of asymmetries by employing a threshold model.[4] This nonlinear model endogenously divides the sample into high and low credit-growth regimes and allows for different dynamic responses in each regime. The two regimes are delineated according to whether the moving average of the rate of growth of real credit is above or below an estimated critical threshold; values below the estimated threshold are assumed to represent periods of relatively tight credit and vice versa. The approach is closest in spirit to recent studies by Balke (2000), Atanasova (2003) and Calza and Sousa (2006). Balke concludes that there is evidence of threshold effects in the relationship between measures of credit conditions and economic activity in the US. Atanasova finds similar threshold effects in UK data, as do Calza and Sousa for the euro area. These studies, however, focus only on aggregate credit indicators, whereas this paper also distinguishes between household and business credit indicators.

To preview the findings, it appears that GDP growth in Australia is more responsive to interest rate shocks in the low credit-growth regime. This result is confirmed in separate models for household and business credit growth: consumption is more responsive to interest rate shocks when household credit is growing slowly, and real investment responds similarly in the low business credit-growth regime.

The remainder of the paper is organised as follows. Section 2 describes the econometric methodology. Section 3 presents the empirical specification, explains the test for threshold effects, and generates nonlinear impulse responses functions from the estimated model to examine whether there are any asymmetries. Section 4 concludes.

---

4 Previous studies using Australian data (with some measure of credit) have had a somewhat different focus, aiming to match linear models to the data; see, for instance, Suzuki (2004) and Berkelmans (2005).

2. Methodology

The starting point is to estimate a model to capture relationships between key macroeconomic variables in which nonlinearities can arise by conditioning on the credit regime. In particular, I consider the following two-regime model:

$$X_t = A_1(L)X_{t-1}I[q_{t-d} \leq \widehat{q}] + A_2(L)X_{t-1}I[q_{t-d} > \widehat{q}] + \varepsilon_t \quad (1)$$

where: X is a vector of endogenous variables; q_{t-d} is the threshold variable determining the prevailing regime of the system; and ε_t is the vector of disturbances. The indicator function $I[.]$ identifies two separate regimes on the basis of the value of the threshold variable. The delay lag d and critical threshold value $\widehat{q}$ are unknown parameters, which have to be estimated along with the parameters A_1 and A_2. The nonlinearity is introduced by allowing the linear structure – given by A_1 and A_2 – to vary across regimes.

I use a set of macro variables, X, that provides a minimal statistical summary of the evolution of the economy:

$$X_t \equiv [\Delta y_t, \pi_t, i_t, \Delta credit_t] \quad (2)$$

where: Δy is real GDP growth; π is CPI inflation; i is the nominal cash rate; and $\Delta credit$ is real credit growth. Further details regarding the data and sources are provided in Appendix A.[5,6]

The threshold variable (q) is specified as a moving average of quarterly credit growth. The smoothing is applied to avoid an implausible frequency of regime-switching. The order of the moving average is allowed to vary across different

5 This specification ignores open-economy considerations for the benefit of parsimony. In a nonlinear model such as used here, each additional variable implies (at least) two extra parameters, adversely affecting the size and power of the linearity tests. I nevertheless checked the robustness of the results to alternative model specifications with open-economy variables. For instance, including US GDP growth to represent world economic activity (as in Dungey and Pagan 2000) did not change the results qualitatively.

6 Dickey-Fuller tests indicated that inflation and the interest rate series are integrated series. Therefore I also considered a model with these two variables in first differences. The general qualitative features of impulse responses were retained. The impulse response functions, however, tend to revert to zero slightly more rapidly when the analysis is conducted in the first differences. Lanne and Saikkonen (2002) point out that the existence of a unit root may indicate factors not accounted for by linear testing procedures.

specifications from two to four quarters.[7] Because the threshold variable is constructed as a function of one of the variables in X, it means that shocks to any variable in X can (through an impact on the variable underlying q) induce a shift to a different regime.

The key test of the threshold model given in Equation (1) is whether $A_1 \neq A_2$. One complication is that the threshold is not identified under the null of a linear model, but must be estimated under the alternative. In order to test for threshold behaviour, the model is estimated (by ordinary least squares) for values of q over a wide range (with the restriction that at least 10 per cent of the observations fall in each regime, allowing for a reliable test of whether $A_1 = A_2$). For each possible value of q, a test statistic of no difference between regimes ($A_1 = A_2$) is calculated (as suggested by Hansen 1996, 1997). Because the distributions of the test statistic are non-standard, the p-values are calculated by bootstrap simulations. If formal tests reject the linear model, the estimated threshold value $\widehat{q}$ is the one that minimises the log-determinant of the variance-covariance matrix of residuals.

It is generally difficult to easily interpret nonlinear time-series models by considering only the estimated parameter values of the model (van Dijk, Franses and Boswijk 2007). Perhaps the easiest way to do this is to analyse the effects of different shocks using nonlinear impulse response functions. These should not be confused with the 'traditional' (linear) impulse response function. Gallant, Rossi and Tauchen (1993) and Koop, Pesaran and Potter (1996) point out that in nonlinear models: (i) the effects of a shock depend on the entire history of the system up to the point when the shock occurs; and (ii) the effect of the shock does not need to be proportional to its size. This contrasts with the traditional linear impulse response function, which is conveniently: (i) symmetric (a negative shock of a given magnitude has exactly the opposite effect as a positive shock of the same magnitude); (ii) linear in the sense that the response of the system is proportional to the size of the shock; and (iii) independent of history. The features of nonlinear impulse responses allow the model to change regimes during the simulation period. In order to allow for such switching behaviour, we examine the effects of shocks using the Generalised Impulse Response Function (GIRF).

---

7 The credit variable itself, however, enters the system of equations (X) directly in its original (non-moving-average) form.

The GIRF for a specific shock ξ_t (for example, an interest rate shock) and history Ω_{t-1} (defined over X's from periods $t-1$ and earlier) is

$$GIRF = E[X_{t+k} \mid \xi_t, \Omega_{t-1}] - E[X_{t+k} \mid \Omega_{t-1}], \quad \text{for} \quad k = 0, 1, .. \tag{3}$$

The GIRF is the difference between two conditional expectations of X (which are themselves random variables). For the first term the expectation is conditioned on the particular history and the shock, while for the second term it is conditioned just on the history. The difference between the two yields the dynamic response of the variables in the system at a given horizon, k. The details of the computation of GIRFs are provided in Appendix B.

3. Estimation and Results

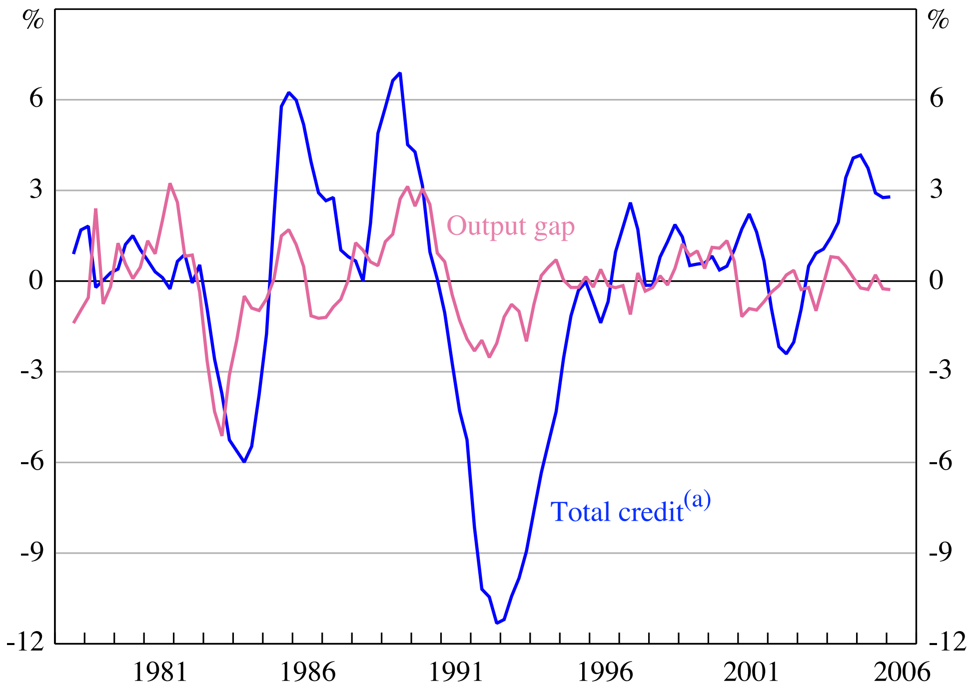
The benchmark model is estimated using quarterly Australian data on real GDP growth, CPI inflation, real credit growth and the cash rate over the sample period 1978:Q4 to 2006:Q1.

The length of the moving average (MA) component applied to the credit-growth threshold is allowed to vary from two to four quarters and is determined jointly with its lag length of d (from one to four quarters), and the lag length of the whole system (from one to four quarters). The optimal lag lengths are determined by means of the Schwarz and Akaike information criteria (see Table C1 in Appendix C). The Akaike criterion suggests a two-quarter lag for the whole system (that is, a VAR(2)). The threshold variable is based on a four-quarter moving average of the quarterly growth in real credit (q) with a lag of three quarters. The Schwarz criterion suggested a more parsimonious specification of a one-quarter lag for the system; the choice of q_{t-d} is, however, in line with the Akaike criterion. I set the number of lags to two according to the Akaike criterion, which also encompasses the lag length of the Schwarz criterion.

The bootstrapped p-value of the sup F test for a threshold model against the baseline alternative of the linear specification is 0.002. Therefore, the hypothesis of linearity in favour of the hypothesis of threshold effects is strongly rejected. Using a linear model in this context may induce misleading conclusions about the general dynamic behaviour of the series, the pattern of the impulse responses and the persistence of the shocks.[8] The estimated critical value for the threshold variable (based on the MA4, $d = 3$ quarters specification) is quarterly growth of real credit of 7.7 per cent on an annualised basis; growth rates below this value are assumed to imply less readily available credit. The sample is distributed reasonably evenly between the credit-growth regimes: there are 43 and 68 observations in the low and high regimes, respectively.

Figure 3 plots the deviations of this credit-growth threshold variable from its estimated critical value, and also shows a simple measure of the output gap for comparison (the percentage difference between actual GDP and trend GDP, based on the Hodrick-Prescott filter). Clearly the high-growth regime has been dominant in recent years. Credit growth appears to be broadly pro-cyclical (periods of slower output growth are associated with a negative deviation of the threshold variable from its critical value). So it is not immediately obvious that the threshold variable is doing much more than identifying periods of strong and weak economic activity.

Figure 3: The Output Gap and Deviations of the Threshold Variable from its Estimated Critical Value



Note: (a) Quarterly growth annualised

8 The choice of the model is supported by a likelihood ratio test which finds that the residuals are consistent with white noise. The *Q*-statistics are not significant for residuals (nor squared residuals), indicating that there is no serial correlation in the residuals. In addition, the residual normality test indicates that the residuals are normal (not reported for brevity).

Close inspection of Figure 3 suggests that there have been a number of occasions when the threshold variable based on credit growth has not lined up exactly with the business cycle. In particular, credit growth remained relatively low for a time after recoveries in economic activity following the recessions in the early 1980s and early 1990s. Also, credit growth was especially high during the second half of the 1980s and from 2003 to 2006. It makes sense, therefore, to re-examine the model using GDP growth as the basis for the threshold variable.[9] Figure 4 shows how the sample is divided into high and low GDP-growth regimes based on a threshold value, $\widehat{q}$, of 3.4 per cent on an annualised basis.[10] There are some marked differences between the two alternative threshold variables. Perhaps most importantly, compared with the credit threshold variable, the GDP threshold variable switches between regimes with an implausibly high frequency. The GDP threshold variable implies 34 instances of switching compared to only 12 instances for the credit threshold variable.[11]

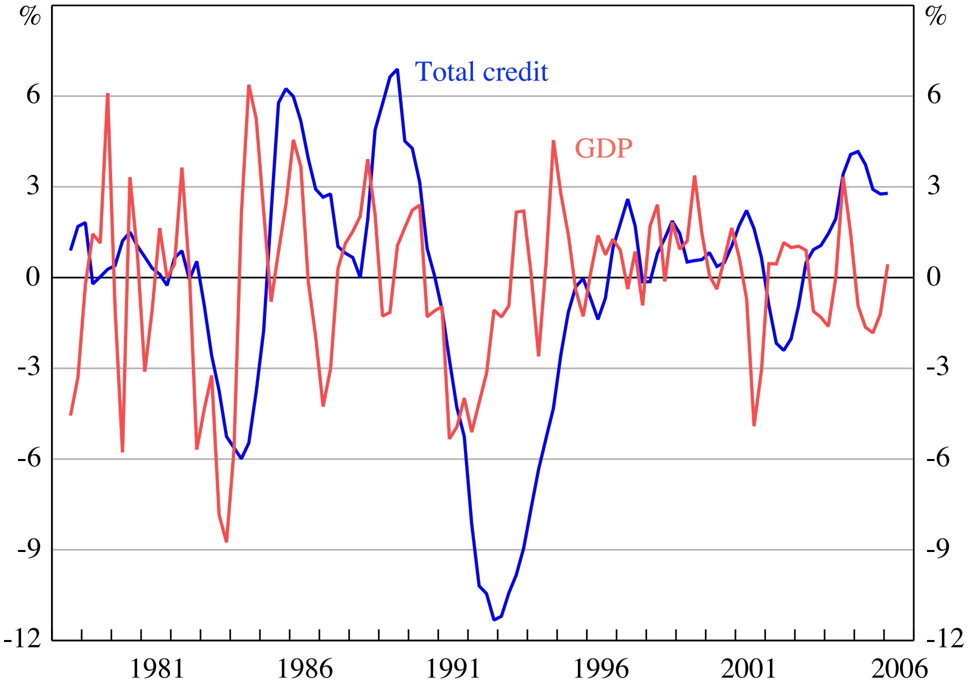
---

9 The information criteria for this model suggest a specification with a lag length of three quarters and a two-quarter moving average of the quarterly GDP growth with a lag of three quarters for the threshold variable. Again, the linearity test strongly rejects the null hypothesis of linearity with a *p*-value of 0.000. Values for the Akaike and Schwarz information criteria are smaller for the specification based on the credit-growth threshold variable. The R^2 measures are, however, somewhat higher for the alternative specification using GDP growth as the basis for the threshold, but may reflect overfitting of the model given excessive switching between regimes. Diagnostic tests indicate that the residuals contain no autocorrelation, but there appears to be a problem with excess kurtosis. This leads to rejection of the Jarque-Bera test for normality.

10 The GDP-growth threshold variable is based on the MA2, d = 3 quarters specification.

11 Instead of MA smoothing of the growth rate of GDP, one possibility would be to extract the trend using a filter. I repeated the exercise using an output gap measure (obtained with the Hodrick-Prescott filter) in place of GDP growth in Equation (2). As above, two different types of threshold variables were used: the rate of growth in real credit (smoothed with moving average terms) and the output gap (in this case no further smoothing was applied). Using the output gap as the threshold variable, the Akaike criterion suggests a three-quarter lag for the whole system with the threshold variable based on a lag of one quarter. The output gap threshold variable is much less volatile than the GDP growth variable; there are 25 instances of regime-switching instead of 34 with GDP growth. There are 22 switches when credit growth is used as the threshold variable (this system contains a four-quarter lag for the whole system, and the threshold variable is based on the MA2, d = 3 quarters specification). Statistical comparison across two specifications suggests that the credit threshold model is preferred both in terms of the R^2 measures and the information criteria.

Figure 4: Deviations from Estimated Critical Values – Total Credit Versus GDP



Note: Quarterly growth annualised

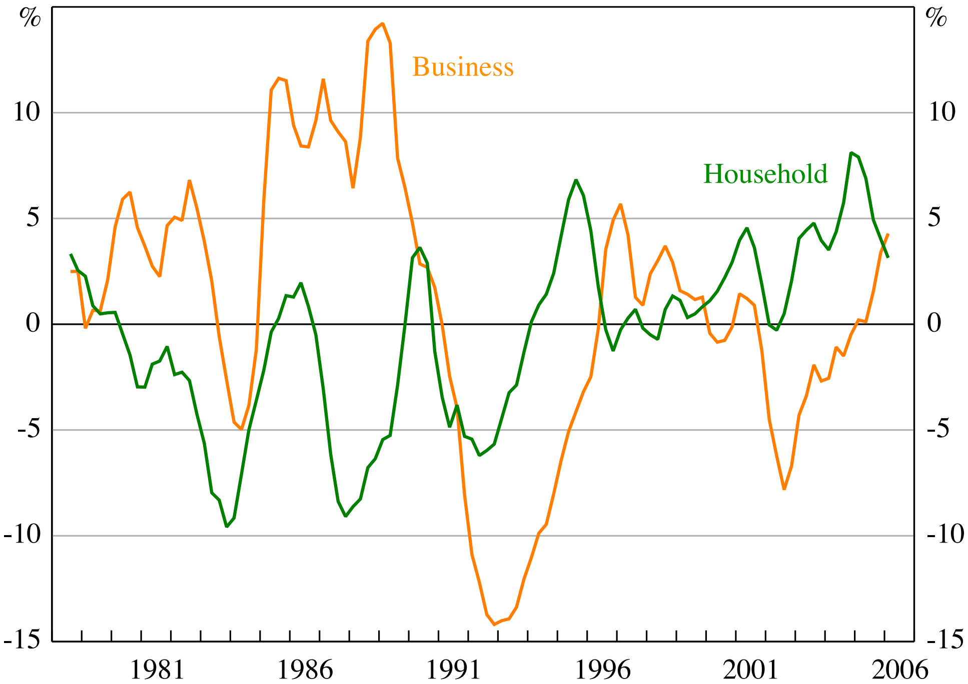
3.1 Household and Business Sector Credit

Given the difficulties in determining whether the asymmetries relate to the credit cycle or the business cycle, it may be helpful to repeat the earlier exercise using a separate model for business and household sectors, which have had quite divergent credit cycles. Greater access to credit may help households to smooth consumption, and businesses to take advantage of profitable investment opportunities. So, real household consumption growth is substituted for GDP growth in Equation (2) when analysing household credit, and real business investment is used in the analysis of business credit.[12]

Figure 5 shows the deviations of the household and business real credit-growth threshold variables from their estimated critical values. The critical thresholds for quarterly household and business credit growth are 8.8 per cent and 5.5 per cent,

[12] Another possibility is to analyse consumption and residential investment jointly in the household credit model. This specification yields qualitatively similar results with the household credit model based solely on consumption.

Figure 5: Real Business and Household Credit – Deviations from Their Estimated Critical Values



Note: Quarterly growth annualised

respectively (on an annualised basis). The linearity hypothesis is rejected in both cases.[13] When credit grows more slowly than these threshold values, credit constraints are likely to be more pervasive than when credit growth is above these values. It can be seen that up to the mid 1990s, except for a few brief instances, household credit growth was below its critical threshold value. However, since then household credit growth has remained, more or less consistently, above the threshold value (there are 55 observations in the low credit-growth regime and 56 in the high credit-growth regime).[14] Business credit growth shows more volatility,

13 Information criteria suggest the consumption-household credit model fits better than the total credit model given in Equation (2), but the fit of the investment-business credit model is worse than that of the total credit model. The diagnostic tests for both alternatives are generally satisfactory, although there is evidence of non-normality of the residuals.

14 There are 16 observations above the threshold before 1994, and 8 observations below it after 1994. If, instead of breaking the sample into two parts according to this threshold variable, it is arbitrarily split into pre- and post-1994 periods, model diagnostics indicate that this specification is inadequate. So it appears that the threshold model is able to capture some important features of data that could have been overlooked when grouping data arbitrarily and non-statistically.

though it crosses its critical threshold less frequently than household credit growth (there are 47 observations below the threshold value and 65 above it). Clearly, the broad changes in credit regimes depicted in Figure 5 are consistent with the discussion above about the timing of apparent credit constraints across the two sectors.

3.2 Impulse Responses across Regimes

Having found evidence of threshold effects, the next step is to calculate the response of GDP to interest rate shocks in each regime, in order to examine the precise nature of the asymmetries. The impulse responses are based on a Cholesky decomposition with the following ordering of variables: GDP growth; inflation; the interest rate; and real credit growth (much of the VAR literature is based on a similar ordering, see, for instance, Leeper, Sims and Zha 1996). Hence, real credit is assumed to react contemporaneously to unanticipated changes in all the other variables in the system, but shocks to credit affect all the other variables with a delay of at least one quarter. The results presented are robust to the alternative ordering of GDP growth, inflation, real credit growth and the interest rate. Although the model is nonlinear, this does not guarantee that the response of the variables to interest rate shocks varies across the two regimes. Figure 6 reports impulse responses for GDP growth following an interest rate shock, conditional on the economy initially being in either the high or the low credit-growth regime.[15]

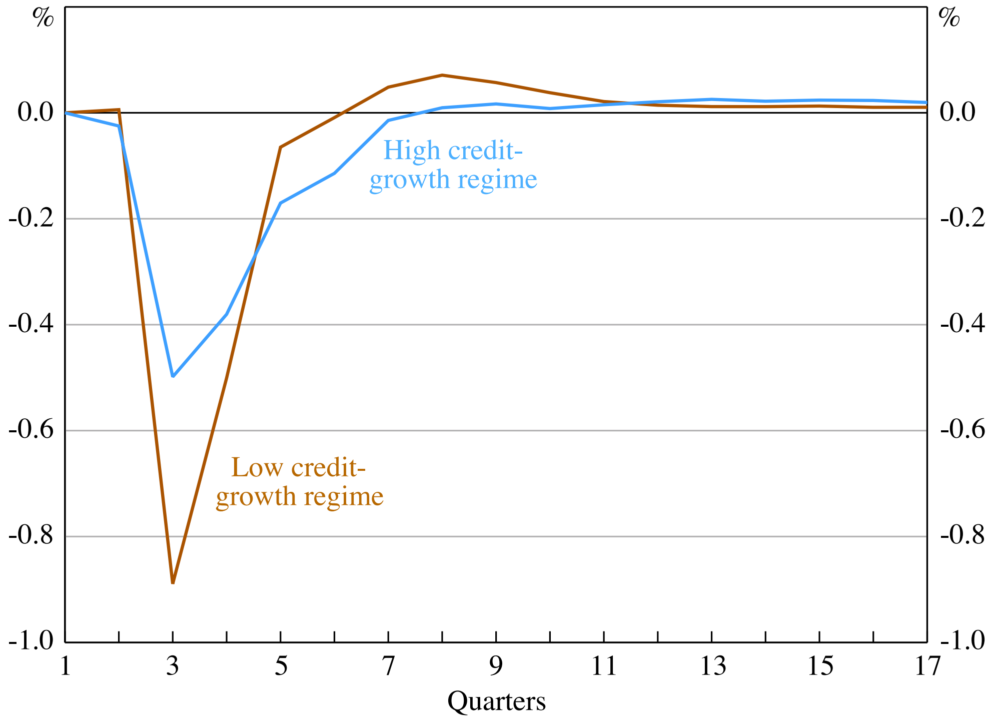
There is clearly evidence of asymmetry across the regimes. The response of GDP growth is considerably larger when the economy is initially in the low credit-growth regime.[16] The observed pattern of the impulse response for GDP growth is consistent with the predictions of the credit channel model of Bernanke, Gertler

---

[15] Note that confidence intervals around the simulated responses are not shown. It is not clear how to compute confidence intervals accurately in nonlinear models that allow for switching regimes (see, for example, Kilian 1998). However, given that the hypothesis of linearity was strongly rejected, this should mean that the two impulse responses shown are likely to be significantly different from each other as well.

[16] Berkelmans (2005) also includes a credit variable in his model. He estimates (linear) impulse responses which show somewhat more persistency than the ones presented here. One obvious reason for this is that he estimates a model with GDP in levels, whereas I consider the growth of GDP.

Figure 6: Response of GDP Growth to a Positive One Standard Deviation Interest Rate Shock



and Gilchrist (1999), in which households and business are more affected by a contractionary interest rate shock when they are credit-constrained.[17,18]

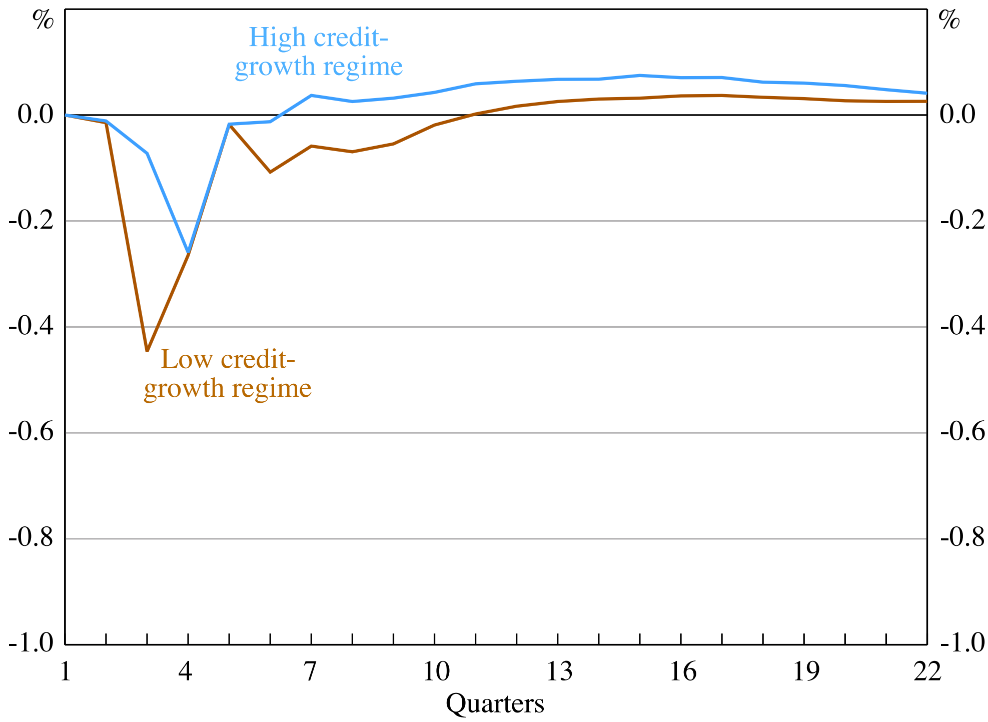
It is worth noting that there is no evidence of asymmetric responses within the regimes: negative and positive interest rate shocks of similar absolute magnitudes have an equal size impact on GDP growth in the opposite direction (results not shown). Moreover, the persistence of positive and negative shocks appears to be roughly the same.

17 The robustness of this empirical finding was tested by replacing credit growth with a measure of household gearing (the growth rate in the ratio of debt to disposable income, shown in Figure 1). Following a positive interest rate shock, GDP growth decreases in both regimes, but by much more in the low-gearing regime.

18 Over the past few years gross national expenditure (GNE) has been growing at a faster rate than GDP. Using GNE instead of GDP in Equation (2) does not alter the result shown in Figure 6: the effect of monetary policy is still stronger during periods when credit growth is low.

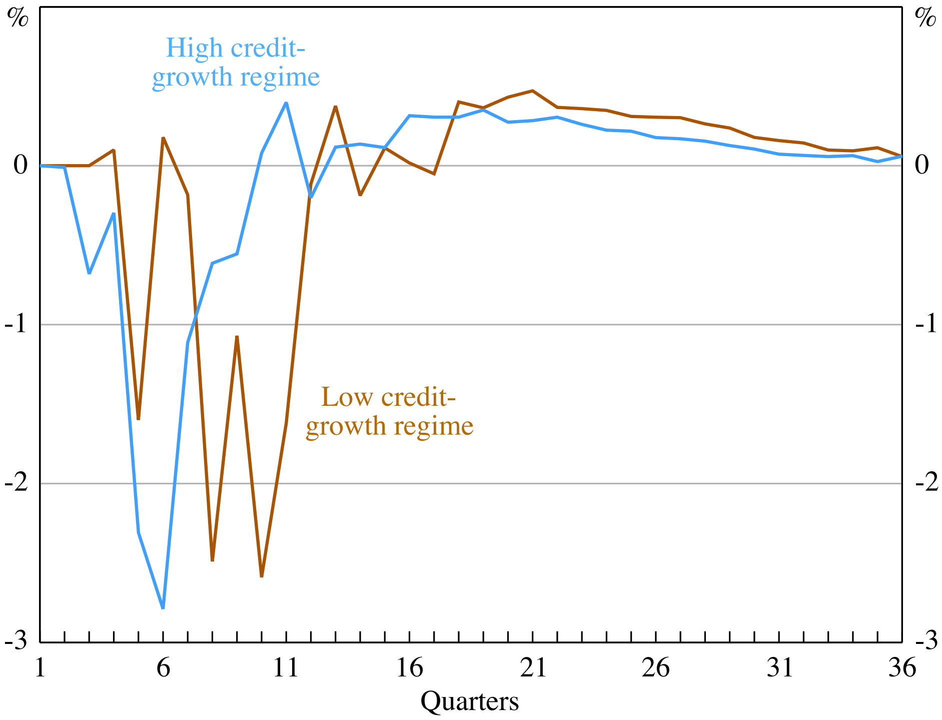
We obtain broadly similar results when the exercise is repeated with alternative model specifications based on either household or business credit. When the growth rate of credit is below the critical threshold value, interest rate movements are more potent. In particular, Figure 7 shows that consumption is more responsive to interest rate shocks when household credit growth is relatively weak, in line with the notion that, at these times, households are less able to smooth consumption in response to temporary shocks.[19] Also, real business investment shows some signs of being more responsive in the low credit-growth regime (Figure 8). The response of real business investment growth highlights a well-known challenge for modelling short-run movements in investment: investment is especially volatile at a quarterly frequency (Cockerell and Pennings forthcoming). The cumulative effect of a positive interest rate shock on real business investment is, however, negative – and even more so in the low credit-growth regime.

Figure 7: Response of Household Consumption Growth to a Positive One Standard Deviation Interest Rate Shock



[19] The robustness of this finding was tested by estimating a specification based on the sum of consumption and residential investment growth. Following a positive interest rate shock, the sum of consumption and residential investment decreases in both regimes, but by more in the low-gearing regime.

Figure 8: Response of Investment Growth to a Positive One Standard Deviation Interest Rate Shock



In contrast to the findings based on the credit growth threshold, it is interesting to note that if the (smoothed) growth rate of GDP is used as a threshold variable (see Figure 4), interest rate shocks in the low GDP-growth regime have a somewhat *smaller* impact than those in the high GDP-growth regime.[20] The degree of asymmetry between the regimes is, however, negligible and much less pronounced than it is in Figures 6 and 7. This is hardly surprising given the implied frequency of switches between the high and low growth regimes based on GDP growth. This finding can also be taken as evidence that the presence of asymmetry in impulse responses is related to changing credit conditions rather than to the business cycle.

4. Conclusions

The behaviour of the economy to a range of shocks may depend on conditions in the market for credit. This paper has presented indirect evidence for the proposition that credit constraints could lead to asymmetric responses to changes in monetary policy using a threshold model to capture nonlinear relationships in

---

[20] This result is in line with Weise (1999) who finds a larger response in the high output regime for the US.

the data. There is evidence of regimes switching, whereby interest rate changes appear to have a larger effect on economic activity in the regime with low credit growth, which is likely to characterise periods when credit constraints are more pervasive.

This may appear to be at odds with the notion that increasing household indebtedness – following a period of relatively rapid credit growth – would, by itself, suggest that household cash flows may be more responsive to interest rate changes. However, two other factors could be at work. First, the business sector is less indebted than it had been in the late 1980s and early 1990s. Second, relatively strong credit growth in recent years is consistent with the notion that households appear able to smooth consumption in the face of temporary shocks to disposable income. Nevertheless, it is conceivable that a long period of rapid credit growth and rising indebtedness could at some point lead to more constrained credit conditions in the future.

Appendix A: Data Description and Sources

Australian gross domestic product (*y*): The logarithm of seasonally adjusted quarterly GDP (Australian Bureau of Statistics (ABS) Cat No 5206.0).

CPI inflation (π): Quarterly, based on the weighted median consumer price index excluding taxes and interest (Reserve Bank of Australia (RBA)).

Cash rate (*i*): Overnight cash rate, averaged over the quarter (RBA).

Real credit (*credit*): The logarithm of seasonally adjusted break-adjusted (total, household and business) credit deflated by the consumer price index, excluding taxes and interest, averaged over the quarter (RBA).

Investment (*inv*): The logarithm of seasonally adjusted quarterly private business investment (ABS Cat No 5206.0).

Consumption (*c*): The logarithm of seasonally adjusted quarterly household final consumption expenditure (ABS Cat No 5206.0).

Corporate debt to equity ratio: Market value of debt (net of derivatives and other accounts payable) divided by market value of listed and unlisted equity (ABS Cat No 5232.0).

Household debt to disposable income ratio: Total household debt (including securitisation) divided by household gross disposable income before interest rate payments (excluding unincorporated enterprises) (ABS; RBA).

Appendix B: Computation of the Generalised Impulse Response Function

The method for computing generalised impulse response function follows Koop *et al* (1996). The GIRF is defined as follows:

$$GIRF = E[X_{t+k} \mid \xi_t, \Omega_{t-1}] - E[X_{t+k} \mid \Omega_{t-1}], \quad \text{for} \quad k = 0, 1, ... \tag{B1}$$

The two components of the RHS are conditional expectations of X. The first term is conditional on the shock to the i^{th} variable and the initial values (the history) of the variables in the model. The second term is conditional only on the history. The GIRF is calculated as follows:

1. Pick a history Ω^r_{t-1}, where $r = 1, 2, 3 \ldots R$. The history is the actual value of the lagged endogenous variables at a particular date r (there are as many histories as there are observations in the regime for which the impulse response is computed).

2. Generate residuals (u) by taking bootstrap samples from the estimated residuals (ε) of the model.

3. Using u, Ω^r_{t-1} and the estimated model parameters A_1 and A_2, simulate the evolution of the threshold model X over k periods. This yields $X_{t+k}(u_t, \Omega_{t-1})$.

4. To obtain the first term in the RHS, the previous step has to be modified by adding a shock (ξ) to the i^{th} variable of the residual of the system. Again, simulate the evolution of the threshold model X over k periods. This gives $X_{t+k}(\xi_t, u_t, \Omega_{t-1})$.

5. Repeat steps 2 to 4 B (= 1 000) times to get B estimates of $X_{t+k}(u, \Omega_{t-1})$ and $X_{t+k}(\xi, u, \Omega_{t-1})$. The average over the difference of these estimates gives an estimate of the expectation X for a given history Ω^r_{t-1}.

6. Repeat steps 1 to 5 R times, that is, repeat the steps for all possible histories the impulse response has to be conditioned on (all the observations in each regime). For R histories this yields R estimates of $\frac{1}{B}\sum X_{t+k}(\xi, u, \Omega^r_{t-1})$ and $\frac{1}{B}\sum X_{t+k}(u, \Omega^r_{t-1})$. Averaging these over all the histories, that is, $\frac{1}{R}\sum \frac{1}{B}\sum X_{t+k}(\xi, u, \Omega^r_{t-1})$ and $\frac{1}{R}\sum \frac{1}{B}\sum X_{t+k}(u, \Omega^r_{t-1})$ provides estimates of $E[X_{t+k} \mid \xi_t, \Omega_{t-1}] - E[X_{t+k} \mid \Omega_{t-1}]$, that is, the generalised impulse response function for a given regime.

Appendix C: Model Selection

Akaike (*AIC*) and Schwarz (*SIC*) information criteria for a VAR with four variables and p lags (in regime i) are given by:

$$AIC = [ln(\det(\sum)) + 2(4(4p+1))/T^i]$$

and

$$SIC = [ln(\det(\sum)) + 4(4p+1)\ln(T^i)]/T^i$$

where $ln(\det(\sum))$ denotes the log-determinant of the estimated variance-covariance matrix of residuals and T^i is the number of observations.

Table C1: Akaike and Schwarz Information Criteria for Model Selection

	Moving-average terms for threshold variable		
	2	3	4
L = 1			
d = 1	11.36	10.34	10.77
	12.32	11.30	11.74
d = 2	10.73	11.07	11.50
	11.69	12.04	12.47
d = 3	11.34	11.05	11.23
	12.31	12.02	12.21
d = 4	10.49	11.51	11.68
	11.46	12.48	12.66
L = 2			
d = 1	11.44	10.36	10.55
	13.16	12.09	12.28
d = 2	10.86	10.94	11.24
	12.59	12.67	12.99
d = 3	11.02	10.81	9.88
	12.76	12.56	11.64
d = 4	10.50	10.23	11.07
	12.23	11.98	12.84
L = 3			
d = 1	11.26	10.24	10.38
	13.74	12.74	12.89
d = 2	10.78	11.07	11.46
	13.27	13.59	13.99
d = 3	11.02	11.43	11.39
	13.53	13.95	13.93
d = 4	10.57	11.50	11.08
	13.09	14.04	13.63
L = 4			
d = 1	11.05	10.48	10.86
	14.30	13.74	14.14
d = 2	10.30	11.06	11.80
	13.56	14.34	15.10
d = 3	11.30	11.46	11.30
	14.58	14.76	14.58
d = 4	10.11	11.02	11.23
	13.41	14.34	14.57

Appendix D: Estimated Models

Table D1: Total Credit – Low Credit-growth Regime

	Δy	π	i	$\Delta credit$
Δy (–1)	0.300	0.160	–0.096	0.134
	(0.15)	(0.06)	(0.09)	(0.11)
Δy(–2)	–0.126	–0.138	0.122	0.283
	(0.17)	(0.05)	(0.11)	(0.14)
π(–1)	–0.832	0.649	0.553	0.504
	(0.44)	(0.07)	(0.20)	(0.25)
π(–2)	0.702	0.026	–0.237	–0.269
	(0.44)	(0.11)	(0.21)	(0.29)
i(–1)	–0.993	0.251	0.721	–0.173
	(0.37)	(0.07)	(0.16)	(0.24)
i(–2)	0.232	–0.125	–0.107	–0.021
	(0.09)	(0.11)	(0.09)	(0.13)
$\Delta credit$(–1)	0.232	–0.038	0.126	0.952
	(0.09)	(0.05)	(0.09)	(0.13)
$\Delta credit$(–2)	–0.184	0.098	–0.149	–0.265
	(0.07)	(0.04)	(0.09)	(0.10)
Constant	4.175	–0.029	0.687	0.557
	(1.76)	(0.56)	(0.98)	(0.354)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

Table D2: Total Credit – High Credit-growth Regime

	Δy	π	i	$\Delta credit$
Δy (–1)	–0.047	–0.030	–0.063	0.106
	(0.11)	(0.04)	(0.05)	(0.12)
Δy(–2)	0.076	0.027	0.093	–0.012
	(0.11)	(0.04)	(0.04)	(0.08)
π(–1)	0.005	0.424	0.310	–0.301
	(0.66)	(0.08)	(0.20)	(0.48)
π(–2)	0.149	0.559	–0.117	0.451
	(0.67)	(0.10)	(0.21)	(0.20)
i(–1)	–0.181	0.140	0.665	–0.636
	(0.44)	(0.09)	(0.17)	(0.35)
i(–2)	–0.202	–0.181	0.142	0.338
	(0.09)	(0.11)	(0.09)	(0.13)
$\Delta credit$(–1)	–0.043	0.058	0.076	0.493
	(0.02)	(0.04)	(0.07)	(0.13)
$\Delta credit$(–2)	–0.100	0.035	0.041	0.061
	(0.21)	(0.04)	(0.02)	(0.04)
Constant	5.610	–0.613	–1.131	4.307
	(1.72)	(0.52)	(0.76)	(1.42)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

Table D3: Business Credit Model – Low Credit-growth Regime

	Δinv	π	i	$\Delta credit$
Δinv (–1)	–0.264	0.007	0.007	–0.005
	(0.15)	(0.01)	(0.01)	(0.04)
Δinv(–2)	–0.025	0.018	0.003	0.026
	(0.16)	(0.01)	(0.01)	(0.02)
π(–1)	0.741	0.310	0.112	0.989
	(1.17)	(0.15)	(0.10)	(0.69)
π(–2)	2.636	0.370	0.423	0.300
	(1.13)	(0.17)	(0.21)	(0.57)
i(–1)	–3.807	0.264	0.631	0.970
	(1.17)	(0.14)	(0.15)	(0.94)
i(–2)	–0.516	–0.184	0.114	–1.389
	(1.39)	(0.15)	(0.14)	(0.72)
$\Delta credit$(–1)	1.110	–0.03	0.065	0.940
	(0.38)	(0.03)	(0.04)	(0.11)
$\Delta credit$(–2)	–0.898	0.017	–0.059	–0.362
	(0.24)	(0.04)	(0.03)	(0.19)
Constant	30.310	0.102	0.045	0.143
	(8.02)	(0.42)	(0.44)	(2.71)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

Table D4: Business Credit Model – High Credit-growth Regime

	Δinv	π	i	$\Delta credit$
Δinv (–1)	–0.105	0.001	0.032	0.073
	(0.11)	(0.01)	(0.01)	(0.03)
Δinv(–2)	–0.031	0.014	0.001	0.064
	(0.15)	(0.01)	(0.01)	(0.04)
π(–1)	1.275	0.447	–0.018	0.393
	(1.21)	(0.12)	(0.16)	(0.49)
π(–2)	–0.895	0.486	0.256	0.110
	(1.75)	(0.10)	(0.17)	(0.50)
i(–1)	–0.107	0.158	1.050	–0.708
	(1.72)	(0.14)	(0.14)	(0.42)
i(–2)	–1.179	–0.174	–0.215	0.639
	(1.62)	(0.13)	(0.13)	(0.72)
$\Delta credit$(–1)	0.989	0.055	0.077	0.466
	(0.54)	(0.02)	(0.03)	(0.09)
$\Delta credit$(–2)	–0.185	–0.004	–0.029	–0.001
	(0.45)	(0.03)	(0.04)	(0.12)
Constant	9.513	0.102	–0.200	2.288
	(4.79)	(0.42)	(0.33)	(1.68)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

Table D5: Household Credit Model – Low Credit-growth Regime

	Δc	π	i	$\Delta credit$
Δc (–1)	–0.079	0.126	0.130	–0.153
	(0.09)	(0.06)	(0.07)	(0.12)
Δc(–2)	–0.044	–0.139	–0.105	–0.216
	(0.18)	(0.07)	(0.08)	(0.12)
π(–1)	0.108	0.555	0.192	0.335
	(0.36)	(0.11)	(0.14)	(0.29)
π(–2)	0.506	0.371	0.373	0.121
	(0.49)	(0.09)	(0.21)	(0.29)
i(–1)	–0.579	0.262	0.795	–0.675
	(0.35)	(0.12)	(0.13)	(0.35)
i(–2)	0.400	–0.214	–0.083	0.164
	(0.46)	(0.15)	(0.11)	(0.36)
$\Delta credit$(–1)	0.336	0.041	0.127	0.650
	(0.19)	(0.07)	(0.09)	(0.19)
$\Delta credit$(–2)	0.109	0.041	0.103	0.136
	(0.14)	(0.05)	(0.11)	(0.026)
Constant	–1.243	–0.734	–1.601	5.678
	(2.15)	(1.05)	(0.87)	(2.11)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

Table D6: Household Credit Model – High Credit-growth Regime

	Δc	π	i	$\Delta credit$
Δc (–1)	–0.226	0.164	0.290	–0.305
	(0.14)	(0.06)	(0.12)	(0.16)
Δc(–2)	–0.68e–5	0.040	0.114	–0.151
	(0.01)	(0.05)	(0.13)	(0.19)
π(–1)	0.005	0.534	0.719	0.187
	(0.25)	(0.15)	(0.39)	(0.53)
π(–2)	–0.349	0.668	0.040	–0.670
	(0.27)	(0.12)	(0.19)	(0.32)
i(–1)	0.300	–0.023	0.602	–0.147
	(0.17)	(0.09)	(0.22)	(0.32)
i(–2)	–0.155	–0.161	0.013	0.170
	(0.15)	(0.05)	(0.09)	(0.14)
$\Delta credit$(–1)	0.442	–0.063	0.07	0.908
	(0.15)	(0.05)	(0.09)	(0.15)
$\Delta credit$(–2)	–0.288	0.039	–0.066	–0.265
	(0.13)	(0.06)	(0.10)	(0.19)
Constant	2.808	0.014	–1.467	6.676
	(2.36)	(0.68)	(1.02)	(2.14)

Note: Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses.

References

Atanasova C (2003), 'Credit Market Imperfections and Business Cycle Dynamics: A Nonlinear Approach', *Studies in Nonlinear Dynamics and Econometrics*, 7(4), pp 516–536.

Azariadis C and B Smith (1998), 'Financial Intermediation and Regime Switching in Business Cycles', *American Economic Review*, 88(3), pp 516–536.

Balke NS (2000), 'Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks', *Review of Economics and Statistics*, 82(2), pp 344–349.

Berkelmans L (2005), 'Credit and Monetary Policy: An Australian SVAR', RBA Research Discussion Paper No 2005-06.

Bernanke BS and M Gertler (1989), 'Agency Costs, Net Worth, and Business Fluctuations', *American Economic Review*, 79(1), pp 14–31.

Bernanke BS, M Gertler and S Gilchrist (1999), 'The Financial Accelerator in a Quantitative Business Cycle Framework', in JB Taylor and M Woodford (eds), *Handbook of Macroeconomics*, Volume 1C, Elsevier, Amsterdam, pp 1341–1393.

Blinder AS (1987), 'Credit Rationing and Effective Supply Failures', *Economic Journal*, 97(386), pp 327–352.

Calza A and J Sousa (2006), 'Output and Inflation Responses to Credit Shocks: Are There Threshold Effects in the Euro Area?', *Studies in Nonlinear Dynamics and Econometrics*, 10(2), pp 1–19.

Cockerell L and S Pennings (forthcoming), 'Private Businesss Investment in Australia', RBA Research Discussion Paper.

Cover JP (1992), 'Asymmetric Effects of Positive and Negative Money-Supply Shocks', *Quarterly Journal of Economics*, 107(4), pp 1261–1282.

Dungey M and A Pagan (2000), 'A Structural VAR Model of the Australian Economy', *Economic Record*, 76(235), pp 321–342.

Edey M and B Gray (1996), 'The Evolving Structure of the Australian Financial System', in M Edey (ed), *The Future of the Financial System*, Proceedings of a Conference, Reserve Bank of Australia, Sydney, pp 6–44.

Gallant AR, PE Rossi and G Tauchen (1993), 'Nonlinear Dynamic Structures', *Econometrica*, 61(4), pp 871–907.

Garcia R, A Lusardi and S Ng (1997), 'Excess Sensitivity and Asymmetries in Consumption', *Journal of Money, Credit and Banking*, 29(2), pp 154–176.

Garcia R and H Schaller (2002), 'Are the Effects of Interest Rate Changes Asymmetric?', *Economic Inquiry*, 40, pp 102–119.

Gizycki M and P Lowe (2000), 'The Australian Financial System in the 1990s', in D Gruen and S Shrestha (eds), *The Australian Economy in the 1990s*, Proceedings of a Conference, Reserve Bank of Australia, Sydney, pp 180–215.

Hansen BE (1996), 'Inference When a Nuisance Parameter Is Not Identified under the Null Hypothesis', *Econometrica*, 64(2), pp 413–430.

Hansen BE (1997), 'Inference in TAR Models', *Studies in Nonlinear Dynamics and Econometrics*, 2(1), pp 1–14.

Kilian L (1998), 'Small-Sample Confidence Intervals for Impulse Response Functions', *Review of Economics and Statistics*, 80(2), pp 218–230.

Kiyotaki N and J Moore (1997), 'Credit Cycles', *Journal of Political Economy*, 105(2), pp 211–248.

Koop GM, H Pesaran and SM Potter (1996), 'Impulse Response Analysis in Nonlinear Multivariate Models', *Journal of Econometrics*, 74(1), pp 119–147.

Lanne M and P Saikkonen (2002), 'Threshold Autoregressions for Strongly Autocorrelated Time Series', *Journal of Business and Economic Statistics*, 20(2), pp 282–289.

Leeper EM, CA Sims and T Zha (1996), 'What Does Monetary Policy Do?', *Brookings Papers on Economic Activity*, 2, pp 1–63.

Lo M and J Piger (2005), 'Is the Response of Output to Monetary Policy Asymmetric? Evidence from a Regime-Switching Coefficients Model', *Journal of Money, Credit and Banking*, 37(5), pp 865–886.

Peersman G and F Smets (2001), 'Are the Effects of Monetary Policy in the Euro Area Greater in Recessions than in Booms?', European Central Bank Working Paper No 52.

Sensier M, DR Osborn and N Öcal (2002), 'Asymmetric Interest Rate Effects for the UK Real Economy', *Oxford Bulletin of Economics and Statistics*, 64(4), pp 315–339.

Suzuki T (2004), 'Is the Lending Channel of Monetary Policy Dominant in Australia?', *Economic Record*, 80(249), pp 145–156.

Tallman EW and N Bharucha (2000), 'Credit Crunch or What? Australian Banks during the 1986–93 Credit Cycle', *Economic Review*, 85(3), pp 13–33.

van Dijk D, PH Franses and HP Boswijk (2007), 'Absorption of Shocks in Nonlinear Autoregressive Models', *Computational Statistics and Data Analysis*, 51(9), pp 4206–4226.

Weise CL (1999), 'The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach', *Journal of Money, Credit and Banking*, 31(1), pp 85–108.