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Stress Testing the Australian Household Sector Using the HILDA Survey

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Enquiries:

Phone: +61 2 9551 9830
Facsimile: +61 2 9551 8033
Email: rbainfo@rba.gov.au
Website: http://www.rba.gov.au

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Tom Bilston*, Robert Johnson* and Matthew Read**

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*Financial Stability Department
**Economic Research Department
Reserve Bank of Australia

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Author: readm at domain rba.gov.au

Media Office: rbainfo@rba.gov.au

Abstract

In Australia, the banking sector's substantial exposure to the household sector gives reason to continuously assess the financial resilience of households. In this paper, we further explore the simulation-based household stress-testing model presented in Bilston and Rodgers (2013). This model uses data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey to quantify the household sector's financial resilience to macroeconomic shocks.

The model suggests that through the 2000s the household sector remained resilient to scenarios involving asset price, interest rate and unemployment rate shocks, and the associated increases in household loan losses under these scenarios were limited. Indeed, the results suggest that, despite rising levels of household indebtedness in aggregate, the distribution of household debt has remained concentrated among households that are well placed to service it. In turn, this suggests that aggregate measures of household indebtedness may be misleading indicators of the household sector's financial fragility. The results also highlight the potential for expansionary monetary policy to offset the effects of increases in unemployment and decreases in asset prices on household loan losses.

JEL Classification Numbers: C15, D31

Keywords: stress test, household surveys

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1. Introduction

The Australian banking sector's lending to households accounts for a sizeable share of its total lending exposures and this share has increased over recent decades. Furthermore, recent international experience has emphasised the risks that the household sector can pose to financial stability and, consequently, to the broader macroeconomy. Therefore, it is prudent to continuously assess the household sector's financial resilience. Aggregate data – such as the household debt-to-income ratio – can only partially assist in this type of assessment; even if aggregate household indebtedness has increased, the household sector could still be highly resilient to macroeconomic shocks if debt is owed by households that are well placed to service it. Household surveys provide an insight into this, as they contain information on the distributions of household debt, assets and income.

In this paper, we use a simple stress-testing model based on data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. This allows us to: (1) quantify household financial resilience and exposure to shocks; (2) estimate the banking system's exposure to households that are more likely to default; and (3) assess how these measures have changed over the 2000s.

The remainder of this paper is set out as follows. Section 2 reviews the literature on stress testing and micro-simulation. Section 3 presents some descriptive statistics. Section 4 describes our stress-testing model, while Section 5 presents the results. Section 6 discusses some limitations of, and potential improvements to, the model. Finally, Section 7 concludes.

2. Literature Review

Stress testing typically attempts to quantify the impact of adverse scenarios, such as recessions and serious financial shocks, on financial institutions.[1] Private financial institutions use stress tests as part of their internal risk management. Prudential supervisors and other authorities also use stress tests to assess vulnerabilities facing individual financial institutions or financial systems as a whole.

The prominence of system-wide stress testing has increased since the onset of the global financial crisis, partly because authorities have wanted to make assessments of financial system resilience more forward-looking. The most common risk assessed in these stress tests is credit risk – the risk that borrowers will not repay their debts – given its central role in past episodes of financial instability. Stress tests are also increasingly used to assess other risks, such as liquidity risk.

Simulations based on cross-sections of household-level data (household micro-simulations) have become increasingly popular tools for stress testing household credit risk. One method for performing these is the 'financial margin' approach, where each household is assigned a financial margin, which is usually the difference between each household's income and estimated minimum expenses.[2] Under this approach, households with negative financial margins are assumed to default on their debts. An alternative method is the 'threshold' approach, where each household is assumed to default when a certain financial threshold is breached (for example, when total debt-servicing costs exceed 40 per cent of income).[3] Information on household balance sheets can be used to estimate loss

1 See Bilston and Rodgers (2013) for more detail on central banks' stress-testing frameworks. See APRA (2010) for more information on regulatory stress-testing practices in general.

2 Financial margin-type approaches are also known as the household budget constraint method, financial surplus method or the residual income approach. For some examples of these approaches, see Johansson and Persson (2007) and Sveriges Riksbank (2009) for Sweden, Holló and Papp (2007) for Hungary, Herrala and Kauko (2007) for Finland, Andersen *et al* (2008) for Norway, Albacete and Fessler (2010) for Austria, and Sugawara and Zaluendo (2011) for Croatia.

3 Threshold-type approaches have been used for the household sectors of Canada (Faruqui, Liu and Roberts 2012), Chile (Fuenzalida and Ruiz-Tagle 2009) and Korea (Karasulu 2008), among others.

given default and, when combined with information on which households are assumed to default, can be used to estimate 'debt at risk' (or expected loan losses).

Under either approach, shocks to macroeconomic variables – including asset prices, exchange rates, interest rates and the unemployment rate – can be applied. The impacts of these shocks can be estimated by comparing pre- and post-shock default rates and loan losses. Shocks are typically applied in a single-period framework, where defaults and loan losses occur instantaneously.

Both approaches have advantages and disadvantages. Financial margin-based approaches more closely match the processes lenders typically use to determine loan serviceability. Threshold-based approaches require fewer assumptions, but these assumptions may be overly simplistic; specifically, the assumption that all households with debt-servicing costs above a certain threshold will default may be unrealistic. Indeed, higher-income households should be better able to bear higher debt-servicing ratios than lower-income households.

Either approach can be modified to allow households to draw down on their assets or borrow against suitable collateral to avoid default. For example, Herrala and Kauko (2007) and Karasulu (2008) include a measure of assets directly into each household's financial margin. This approach reduces the number of wealthy households that are expected to default. The Bank of Canada (Djoudad 2012; Faruqui *et al* 2012) employs a multi-period model, where households default if they are unable to service their debts for a period of at least three consecutive months. In this model, households are able to draw down on their liquid asset holdings to help service their debts following an unexpected spell of unemployment. The model also allows unemployed households to return to employment in later periods.

As far as we are aware, there have been no published studies using household micro-simulations to stress test the Australian household sector. The model in this paper is based on a financial margin approach and shares many features with Albacete and Fessler's (2010) model for the Austrian household sector.

3. Descriptive Statistics

Lower nominal interest rates and financial deregulation have driven an increase in the Australian household sector's aggregate level of indebtedness from around 40 per cent in the 1980s to around 150 per cent by the mid 2000s; a similar trend has also been observed in other countries. However, this does not necessarily imply that the financial fragility of the household sector has increased. Higher levels of household indebtedness are an endogenous – and expected – response to permanently lower nominal interest rates (Ellis 2005). Additionally, higher household indebtedness can facilitate consumption smoothing, consistent with life-cycle (Modigliani 1986) or permanent-income (Friedman 1957) hypotheses. Furthermore, to the extent that higher household indebtedness increases entrepreneurship and access to further education, it may raise living standards and long-run economic growth. Nevertheless, higher household indebtedness can also amplify the effects of economic and financial shocks on households (Debelle 2004).

Despite the increase in aggregate household indebtedness over the 2000s, the distribution of household debt was little changed. The share of households with some debt rose slightly over the 2000s, to be around 70 per cent in 2010. Higher-income households (those in the top 40 per cent of the income distribution) owed around three-quarters of household debt (Table 1); these households generally have the lowest debt-to-income and debt-servicing ratios. Similarly, the most asset-rich 40 per cent of households owed around three-quarters of household debt.

Households where the head was prime working age (35 to 54 years) owed about 60 per cent of household debt. However, the share of household debt owed by older households rose slightly over the decade. This probably reflected a decrease in the rate of property downsizing, increased life expectancies and a trend toward geared property investment. Even so, because older households tended to be among the wealthiest households, their increased indebtedness did not necessarily reflect a rise in the household sector's overall financial vulnerability.

Table 1: Distribution of Household Debt

Share of total household debt by household type

	2002	2006	2010
Tenancy			
Mortgagor owner-occupiers	65	71	71
Other owner-occupiers	24	18	19
Rental or other arrangement	11	11	10
Income quintiles			
1st	4	4	3
2nd	9	8	8
3rd	15	17	16
4th	29	26	27
5th	43	46	46
Asset quintiles			
1st	2	2	2
2nd	8	7	8
3rd	18	17	18
4th	25	25	24
5th	47	49	50
Age of household head (years)			
15–34	26	26	24
35–44	35	32	30
45–54	26	28	29
55+	12	14	17

Sources: Authors' calculations; HILDA Release 12.0

Household debt generally appears to have been well collateralised during the 2000s. The share of household debt secured by property rose slightly over the decade, to be nearly 90 per cent in 2010 (Table 2). About half of household debt was for the purchase of owner-occupier property ('primary mortgages'). However, the rise in the share of household debt secured by housing was due to an increase in 'other' housing loans, such as second mortgages secured against owner-occupier property (e.g. home equity loans) and loans for the purchase of investment property. The value of credit card and other personal loans as a share of household debt both fell slightly over the decade.

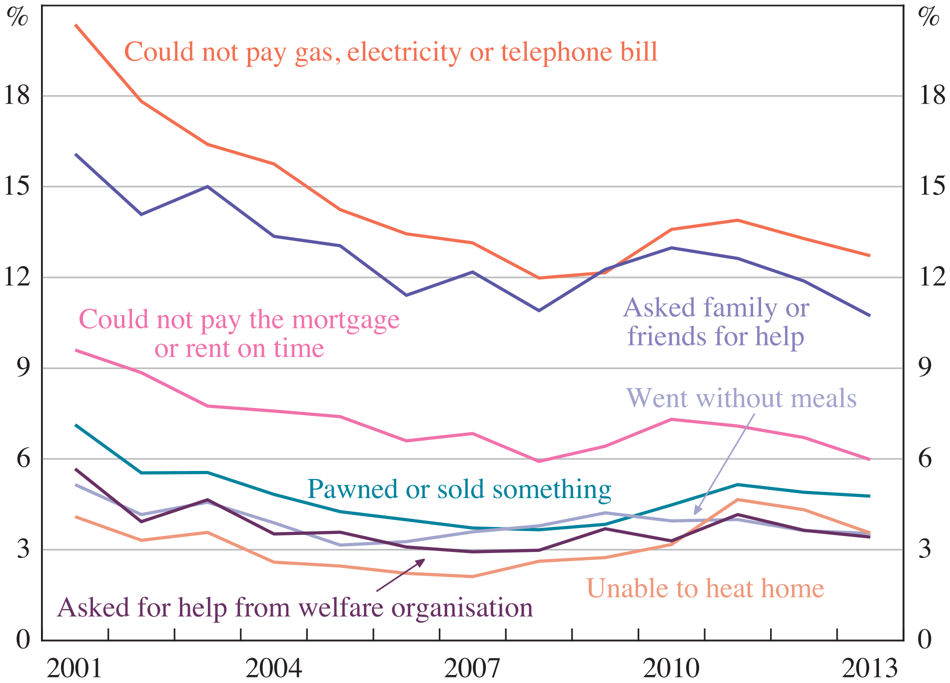
Table 2: Household Debt by Product Type
Share of total household debt

	2002	2006	2010
Housing – primary mortgage	50.8	50.9	50.7
Other housing	34.8	35.0	36.5
Total housing	**85.6**	**85.9**	**87.2**
Credit card	1.8	1.4	1.3
Other personal	12.6	12.7	11.5
Total personal	**14.4**	**14.1**	**12.8**

Sources: Authors' calculations; HILDA Release 12.0

Survey measures based on a broader set of households (i.e. including unindebted households) also imply that the financial health of the household sector improved over the 2000s. A number of self-reported indicators of financial stress declined, such as the share of households unable to make a bill, rental or mortgage payment on time (Figure 1).

Figure 1: Financial Stress Indicators
Share of households



Sources: Authors' calculations; HILDA Release 13.0

So, on the whole, the household sector did not appear to become less financially resilient over the 2000s. However, the economic environment was relatively benign during this period. In the following sections, we use a model to simulate the effects of large macroeconomic shocks on the household sector, with the aim of further investigating how the financial resilience of the Australian household sector has evolved over the 2000s.

4. Method

4.1 Data

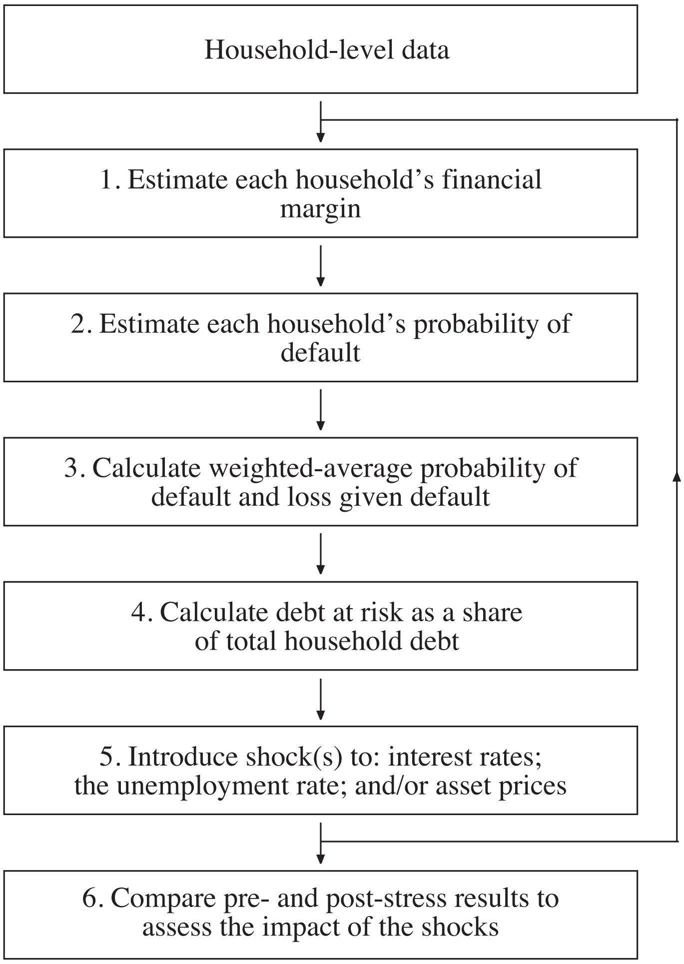
The stress-testing model uses data from the HILDA Survey, which is a nationally representative household-based longitudinal study collected annually since 2001. The survey asks questions about household and individual characteristics, financial conditions, employment and wellbeing. Modules providing additional information on household wealth ('wealth modules') are available every four years (2002, 2006 and 2010).

In this paper, we heavily rely on information from the HILDA Survey's wealth modules, so the years where these data were collected form the basis of our sample. Imputed responses are used where possible to minimise the number of missing responses and thus to increase the sample size. The total sample size for each year is around 6 500 households. Individual respondent data are used to estimate probabilities of unemployment; this part of the model is based on a sample of around 9 000 individuals each year.

4.2 Model

The model in this paper is comparable to the financial margin approach used in Albacete and Fessler (2010). Figure 2 provides an overview of the model.

Figure 2: Model Overview



Initially, a pre-stress baseline is established. The first step in calculating this is to estimate a financial margin (*FM*) for each household (where *i* subscripts for households):

$$FM_i = Y_i - DS_i - MC_i - R_i, \tag{1}$$

where *Y* is household disposable income, *DS* is minimum debt-servicing costs (if any), *MC* is minimum consumption expenditure and *R* is rental payments (if any). All measures are supplied on an annual basis or annualised before inclusion. Disposable income and rental payments are reported in the HILDA Survey. While actual consumption is reported in the survey, minimum consumption is not. However, in a scenario of financial stress, minimum consumption is of greater relevance than actual consumption, as households can reduce discretionary spending to meet their debt obligations. We estimate minimum consumption by mapping values from the Henderson Poverty Line (HPL) to each household based on their characteristics.[4] Under the HPL, minimum consumption depends on family structure and increases linearly with the number of dependent children.

Minimum debt-servicing costs are estimated as:

$$DS_i = PM_i + SM_i + P_i + C_i, \tag{2}$$

where *PM* is the estimated minimum primary mortgage payment, *SM* is the reported usual payment on second mortgages,[5] and *P* and *C* are the estimated interest payments on personal and credit card debt, respectively.

The HILDA Survey contains information on ‘usual’ primary mortgage payments; however, this is probably an overestimate of minimum payments, because around half of Australian households pay more principal than required. Instead, minimum primary mortgage payments are estimated using a credit-foncier model, which is a standard financial formula used to calculate mortgage payments on amortising loans. The scheduled loan balance (*V*) for each household is calculated as:

$$V_i = V_{0i} \prod_{t=1}^{n} \left[1 + r_{t-1} - \frac{r_{t-1}}{1 - \left(1 + r_{t-1}\right)^{-(n-t)}} \right], \tag{3}$$

where t is age of the loan in months, V_0 is the household’s original loan balance, r is the discounted standard variable interest rate, and n is the initial loan term (which is assumed to be 25 years) in months.[6] The scheduled balance is used as an

4 The HPL estimates the minimum income level required to avoid a situation of poverty for a range of family sizes and circumstances. Some lenders use this measure of household living expenses in their assessments of loan serviceability for new borrowers. In recent years, many lenders have moved away from the HPL toward the Household Expenditure Measure (HEM), which was designed to be a more accurate estimate of living expenses. Overall, although the results can be heavily influenced by the assumptions about minimum consumption, the difference between the HPL and the HEM is small enough to have only a minor effect.

5 The survey contains insufficient information to calculate minimum secondary mortgage repayments. Hence, reported usual repayments are used.

6 The month in which a loan is taken out is not available in the dataset, so we assume that all loans were taken out in September.

input to estimate the minimum monthly primary mortgage payment (w) for each year:

$$w_i = \frac{V_i r}{1-(1+r)^{-(n-1)}}. \tag{4}$$

If minimum primary mortgage payments cannot be estimated (due to missing data on key variables), the household's reported usual mortgage payments are used. The estimated minimum annual primary mortgage payment for each year, PM, is obtained by annualising w. Personal and credit card payments are estimated as the product of the reported outstanding balance and average annualised interest rates from that period. This assumes the household does not repay any principal.[7]

The second step uses the financial margin to calculate each household's probability of default (PD):

$$PD_i = \begin{cases} 1 \text{ if } FM_i < 0 \\ 0 \text{ if } FM_i \geq 0 \end{cases}. \tag{5}$$

For the purposes of this model, households with a PD of one are assumed to default with certainty. This is a simplification because at least some of these households could draw down on liquid assets or sell property to avoid default. Departures from this assumption are discussed in Section 6.

The third step combines each household's PD with information on debt and assets to calculate the household sector's weighted-average probability of default and loss given default. The weighted-average probability of default (WPD) is:

$$WPD = \frac{\Sigma_i^N PD_i D_i}{\Sigma_i^N D_i}, \tag{6}$$

where D is each household's debt and N is the total number of households.

7 The HILDA Survey includes personal loan payment data in the 2002 and 2006 surveys, but not in 2010. For consistency, these data have not been used.

The weighted-average loss given default as a percentage of household debt in default (LGD) is the amount that lenders are unable to recover on defaulted loans:

$$LGD = \frac{\Sigma_i^N PD_i M_i}{\Sigma_i^N PD_i D_i} \times 100, \tag{7}$$

where $M_i = \max(D_i - A_i, 0)$ is the dollar value that is lost as a result of a household defaulting, and A is the value of a household's 'eligible' collateral – that is, the collateral that lenders would be able to make a claim on in the event of default. Housing loans in Australia are typically full recourse. Hence, in the event of default, lenders have the option of making claims on assets other than the mortgaged property. In practice, however, lenders do not always exercise this option. Throughout this paper, we assume that eligible collateral consists of housing assets only; assuming a broader definition of eligible collateral would result in a lower LGD. Losses are assumed to be borne in order of credit cards, other personal loans and mortgages; this puts downward pressure on LGDs for housing loans and upward pressure for credit card and other personal loans.

In step four, the WPD and LGD are combined to estimate the weighted-average debt at risk as a share of total household debt (DAR); that is, expected household loan losses flowing through to lenders:

$$DAR = WPD \times LGD = \frac{\Sigma_i^N PD_i M_i}{\Sigma_i^N D_i} \times 100. \tag{8}$$

Once the baseline (or pre-stress) results are established, macroeconomic shocks are applied individually or in combination to obtain post-stress results. The difference between the pre- and post-stress results quantifies the impact of the shock in the model. The process is repeated for the three years.

The simulation in this paper in effect assumes that shocks occur instantaneously. As a result, the shocks within the model are difficult to directly compare to real-world shocks, such as a prolonged downturn that involves a long period of high unemployment. In addition, only the first-round effects of the shocks are analysed. The effect of the shocks may be larger or smaller in a multi-period framework. They would also probably be larger if second-round or contagion effects were taken into account.

5. Results

5.1 Pre-stress Results

Prior to applying shocks, we review the pre-stress results to: (1) quantify household financial resilience; (2) estimate the financial system's exposure to households with negative financial margins; and (3) assess changes in these measures through the 2000s. This exercise also allows us to compare our results against those of other studies.

5.1.1 Financial margins

According to the model, the share of households with negative financial margins was 12 per cent in 2002, 10 per cent in 2006 and 8 per cent in 2010. These estimates compare reasonably with other literature. For example, using the ABS 2007–08 Survey of Income and Housing and a different definition of basic consumption, Burke, Stone and Ralston (2011) estimate that at least 14 per cent of Australian households had negative financial margins. Albacete and Fessler (2010), whose approach is comparable to our own, estimate that 5.6–9.2 per cent of Austrian households had negative financial margins.[8]

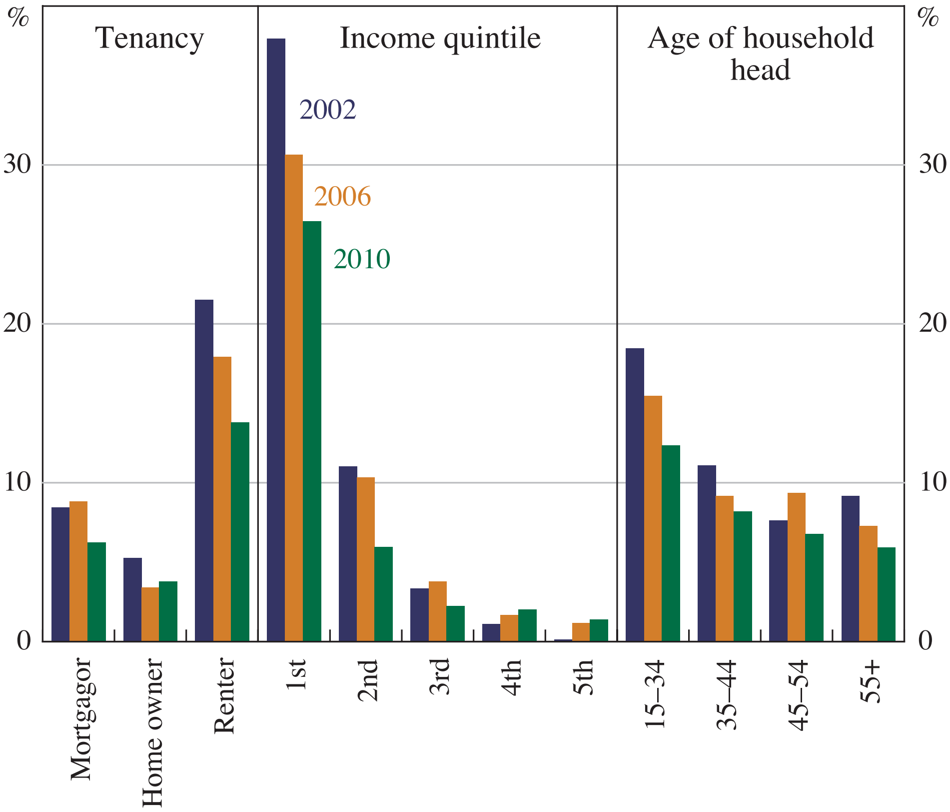
Renters were more likely to have negative financial margins than owner-occupiers, and lower-income households were more likely to have negative financial margins than higher-income households (Figure 3). Renters and lower-income households were also the main source of the decline in the share of households with negative financial margins over the decade. In contrast, the share of higher-income households with negative financial margins rose slightly in each year. Households with younger heads were more likely to have negative financial margins than households with older heads; this is broadly consistent with consumption-

8 Other models that are less comparable to our own also find reasonably similar results. Sveriges Riksbank (2009) estimate 6.3 per cent for Sweden, Herrala and Kauko (2007) estimate 13–19 per cent for Finland, and Andersen *el al* (2008) estimate 19 per cent for Norway.

smoothing theories, where younger households borrow against future income to maintain relatively smooth consumption over their life cycle.

Figure 3: Pre-stress – Households with Negative Financial Margins

Share of households by characteristic

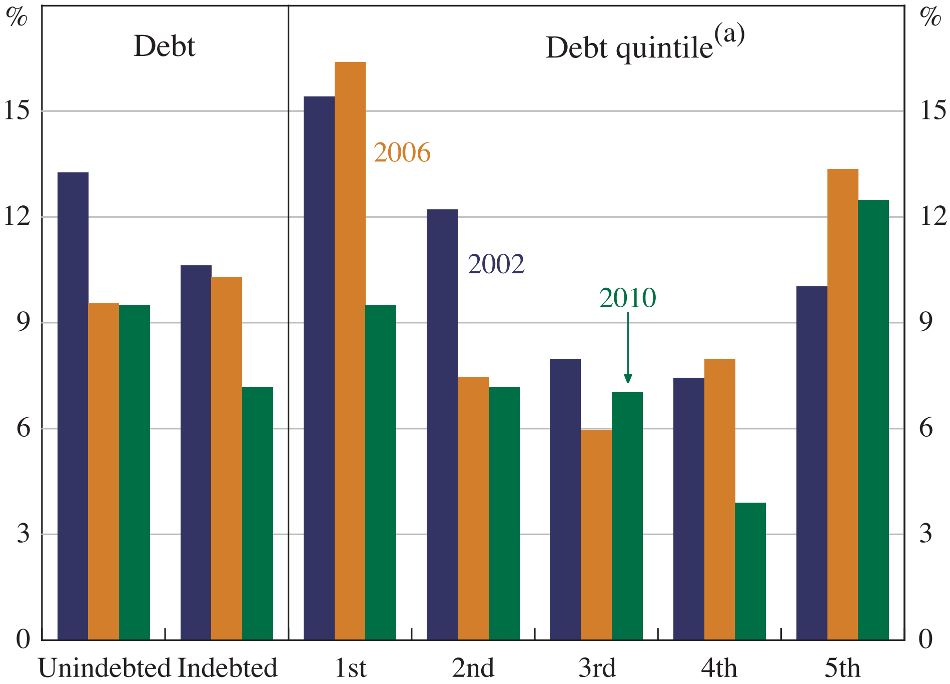


Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

Interestingly, indebted households were not necessarily more likely to have negative financial margins than unindebted households (Figure 4). In addition, the share of households with a negative financial margin tends to decrease as debt increases, although it increases for the highest debt quintile. These findings are consistent with Worthington (2006), who finds that indebtedness is only weakly correlated with financial stress. Furthermore, this result could be interpreted as evidence that the screening lenders carry out in assessing loan applications is broadly effective. That is, before granting a loan, lenders are able to effectively predict whether potential borrowers will be able to comfortably service the loan given their income and other expenses.

Figure 4: Pre-stress – Households with Negative Financial Margins

Share of households by characteristic



Note: (a) Indebted households only

Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

It is important to note that most of the households with negative financial margins in the model will not actually default in reality.[9] One reason for this is that households often have assets that they can draw on, so they may actually be in a sound financial position despite having a negative financial margin. We estimate that, in all three years, at least one-third of households with negative financial margins had enough liquid assets – defined here as deposits, equities and trusts – to avoid default for at least one year. If households were able to sell less-liquid assets (such as property), then over three-quarters of households with negative financial margins may have been able to avoid default for over one year.

5.1.2 Debt at risk

As discussed above, LGD (and thus DAR) depends on the collateral that is assumed to be recoverable by the lender in the event of default; assuming that this collateral consists of housing assets only, pre-stress DAR was 0.8 per cent in 2002,

9 As a reference point, personal bankruptcies and other administrations as a share of the adult population averaged only 0.2 per cent per year in the 2000s.

1.2 per cent in 2006 and 1.5 per cent in 2010.[10] The increase in DAR means that even though the share of households with negative financial margins fell over the period, on average these households owed a larger share of debt and/or held less valuable collateral relative to their debt. Overall, however, lenders' exposure to households with negative financial margins appeared fairly limited throughout the 2000s.

By product type, the rise in DAR was mostly driven by credit card and other personal lending (which are generally unsecured). Indeed, the LGD on credit cards and other personal loans averaged around 50 per cent and 25 per cent in each year, respectively (although these loan types only account for about 10 per cent of household debt). DAR on primary mortgages and other property loans remained close to zero in all years, predominantly because Australian housing loans tend to be well-collateralised; each year, less than 5 per cent of owner-occupier mortgagors said that the value of their home was less than their outstanding mortgage. In contrast, DAR on other housing loans, such as second mortgages and investor housing loans, was around 1 per cent. To some extent, the assumption in the model that households default on other debt before housing loans drives these results by driving down LGDs on housing loans and pushing up LGDs on other loans.

The rise in DAR over time is also broadly consistent with actual outcomes; the impairment rate on banks' household loans rose through most of the 2000s and peaked at about 0.2 per cent in June 2011. Moreover, the *relative* levels of DAR by product type in 2010 compare reasonably with the relative levels of actual portfolio losses experienced by three of Australia's four largest banks over the same period; annualised net write-offs reported by the three banks averaged 3 per cent between 2010 and 2012 for both credit card and other personal lending, while the write-off rate on housing lending was much lower, at 0.04 per cent.[11]

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10 DAR is roughly ½ percentage point lower when collateral is defined more broadly as total household assets less non-retirees' superannuation and life insurance assets (both of which are generally protected from creditors in bankruptcy proceedings).

11 These data only became available from 2008. One of Australia's largest banks does not publish comparable data. The modelled *levels* of portfolio losses are not comparable with actual (annual) outcomes because of the instantaneous nature of the model.

5.2 Macroeconomic Shocks

The effects of shocks to interest rates, the unemployment rate and asset prices are assessed individually. Applying each macroeconomic shock in isolation gives a sense of its effect on household credit risk in the model, even though the shocks would not typically occur in this manner in a real-world scenario. Additionally, this section explains how each of these shocks operates in the model.

5.2.1 Interest rates

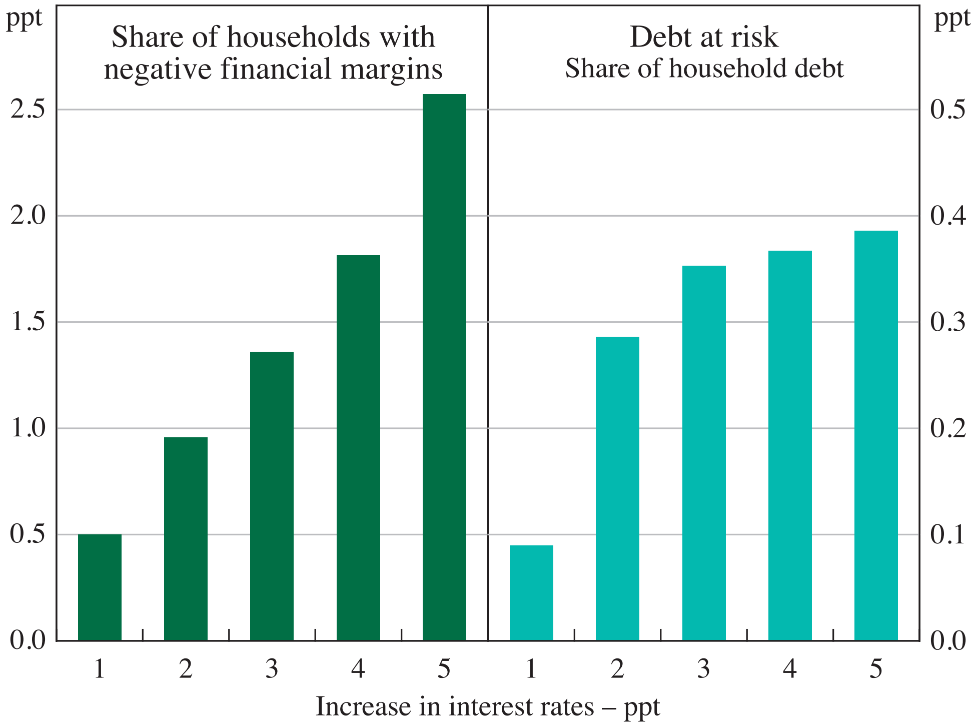
An increase in interest rates leads to an increase in debt-servicing costs for indebted households, lowering their financial margins. Therefore, interest rate rises tend to increase the share of households with negative financial margins, and thus the share of households assumed to default. Interest rate shocks are assumed to pass through in equal measure to all household loans.[12]

A 1 percentage point rise in interest rates causes the share of households with negative financial margins to increase by 0.5 percentage points and DAR to rise by 0.1 percentage points (Figure 5). The impact on DAR is limited because the households whose financial margins are reduced below zero by the rise in interest rates tend to have debt that is well collateralised. Indeed, on average, the households whose financial margins fall below zero due to the shock have debt that is better collateralised than that of the households that already had negative financial margins (i.e. LGD falls after the interest rate shock). For larger increases in interest rates, the share of households with negative financial margins increases approximately linearly. In contrast, the effect of interest rate increases on DAR is nonlinear.

12 All loans are assumed to be variable rate. Data from the Australian Bureau of Statistics indicate that variable-rate loans accounted for about 90 per cent of owner-occupier housing loan approvals on average over the 2000s.

Figure 5: Effect of Increase in Interest Rates

Change relative to pre-stress results, 2010



Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

5.2.2 Unemployment rate

A rise in the unemployment rate causes the income of those individuals becoming unemployed to fall to an estimate of the unemployment benefits that they would qualify for, lowering the financial margins of the affected households.[13]

Methods for simulating unemployment rate shocks differ throughout the literature. Albacete and Fessler (2010) set whole *households* to enter unemployment, where the probability that each household becomes unemployed is estimated using a logit model. Fuenzalida and Ruiz-Tagle (2009) allow *individuals* to become unemployed, with unemployment probabilities estimated using survival analysis. Holló and Papp (2007) and Sveriges Riksbank (2009) assume that each individual has an equal probability of becoming unemployed.

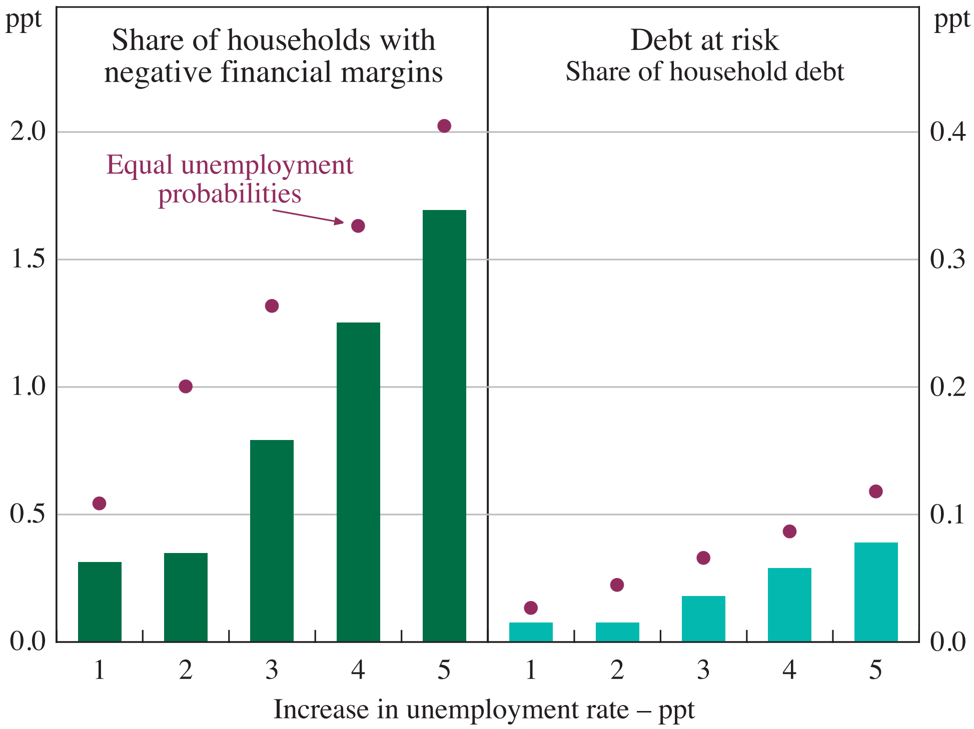
13 In more complicated models, an unemployment shock could be part of a more general income shock. For example, wages could be made to fall.

Our approach uses a logit model to estimate the probability of individuals becoming unemployed. This means that unemployment shocks in the model will tend to affect individuals with characteristics that have historically been associated with a greater likelihood of being unemployed. The unemployment probabilities are perturbed to yield unemployment rate shocks. Post-stress results are presented as the average of 1 000 Monte Carlo simulations using these probabilities. For details on how the unemployment probabilities are generated, see Appendix A.

A 1 percentage point increase in the unemployment rate raises the share of households with negative financial margins by 0.3 percentage points (Figure 6). A 5 percentage point rise in the unemployment rate causes this share to rise by 1.7 percentage points. Despite the rise in the share of households with negative financial margins, the unemployment rate shock has little impact on DAR in each year. This result largely reflects the limited debt and good collateral position of the households most likely to become unemployed. Assigning equal probabilities of unemployment to all individuals increases the effect of the unemployment rate shock on both the share of households with negative financial margins and DAR.

Figure 6: Effect of Increase in Unemployment Rate

Change relative to pre-stress results, 2010



Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

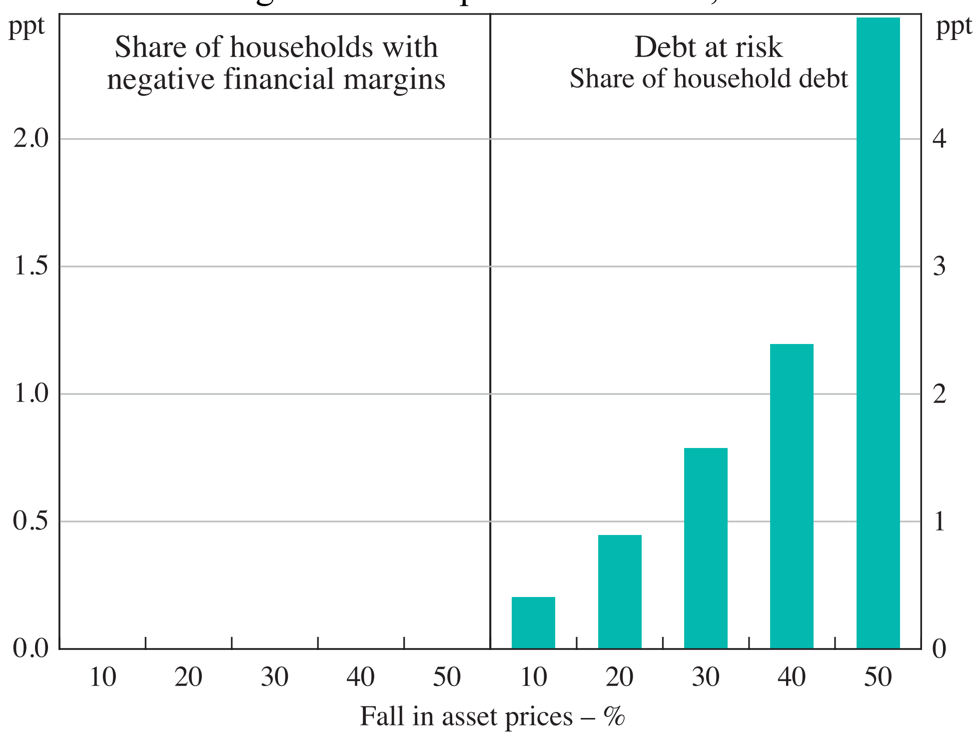
5.2.3 Asset prices

Falling asset prices increase LGD but have no effect on the share of households with negative financial margins. We assume that a given asset price shock applies equally to all households.

A 10 per cent fall in all asset prices causes DAR to rise by 0.4 percentage points (Figure 7). A 50 per cent fall in all asset prices causes DAR to rise by 5 percentage points. Mortgagors are the most affected by this shock, particularly younger mortgagors, because they tend to have paid down relatively little of their loans and have experienced limited cumulative growth in dwelling prices.

Figure 7: Effect of Fall in Asset Prices

Change relative to pre-stress results, 2010



Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

5.3 Stress-testing Scenarios

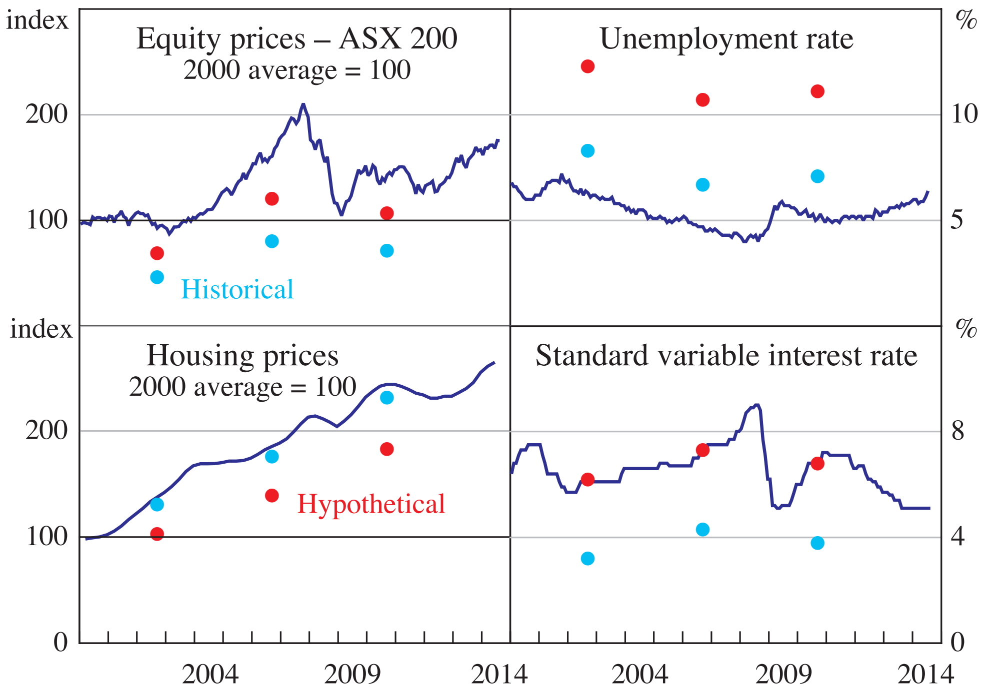
The following simulations apply the above shocks in combination to examine household resilience under two scenarios, labelled 'historical' and 'hypothetical' (as described below). The magnitudes of the shocks under each of these scenarios are shown in Table 3, while Figure 8 overlays the shocks against aggregate data.

Table 3: Scenarios

	Historical	Hypothetical
Change in assets prices (per cent):		
Housing	–5	–25
Equities	–50	–25
Retirees' superannuation and trust funds	–30	–25
Other[(a)]	0	–25
Change in unemployment rate (ppt)	2	6
Change in cash rate (ppt)	–3	0

Note: (a) Includes collectible and vehicle assets

Figure 8: Macroeconomic Factors and Scenarios



Sources: ABS; Bloomberg; RBA; RP Data-Rismark

The 'historical' scenario is designed to roughly replicate the change in macroeconomic conditions that occurred in Australia during the global financial crisis. This includes a sharp fall in equity prices, a moderate fall in housing prices, a slight rise in the unemployment rate and an offsetting large fall in interest rates.

The 'hypothetical' scenario is calibrated similarly to the stress-test scenario in APRA (2010), in which a global deterioration in economic conditions causes a downturn in Australia that is significantly worse than that experienced in the early

1990s. Compared to the historical scenario, the fall in equity prices is smaller, the decline in housing prices and the rise in the unemployment rate are larger, and there is no offsetting change in interest rates.

The results from the scenarios should be interpreted as indicating the effects of stress on household financial resilience and how these effects have changed over the 2000s. However, it is important to keep in mind the assumptions underlying the model, and its limitations. Some of these limitations are outlined in Section 6.

5.3.1 Historical scenario

Under the historical scenario, the share of households with negative financial margins *falls* in all years by around 1 percentage point relative to the pre-stress baseline (Figure 9). This is due to the fall in interest rates, which more than offsets the rise in unemployment. This result illustrates the potential for expansionary monetary policy to offset the effects of increases in unemployment on household loan losses; by reducing debt-servicing costs, the interest rate reduction increases financial margins and thus makes borrowers less likely to default.[14] The decline in the share of households with negative financial margins is largest for the most indebted households, which are typically mortgagors (Figure 10). The share of households with negative financial margins rises for renters and those with little or no debt. Relative to the pre-stress scenario, LGD rises in each year due to the fall in asset prices. However, the decrease in the share of households with negative financial margins means that DAR declines (Figure 9).

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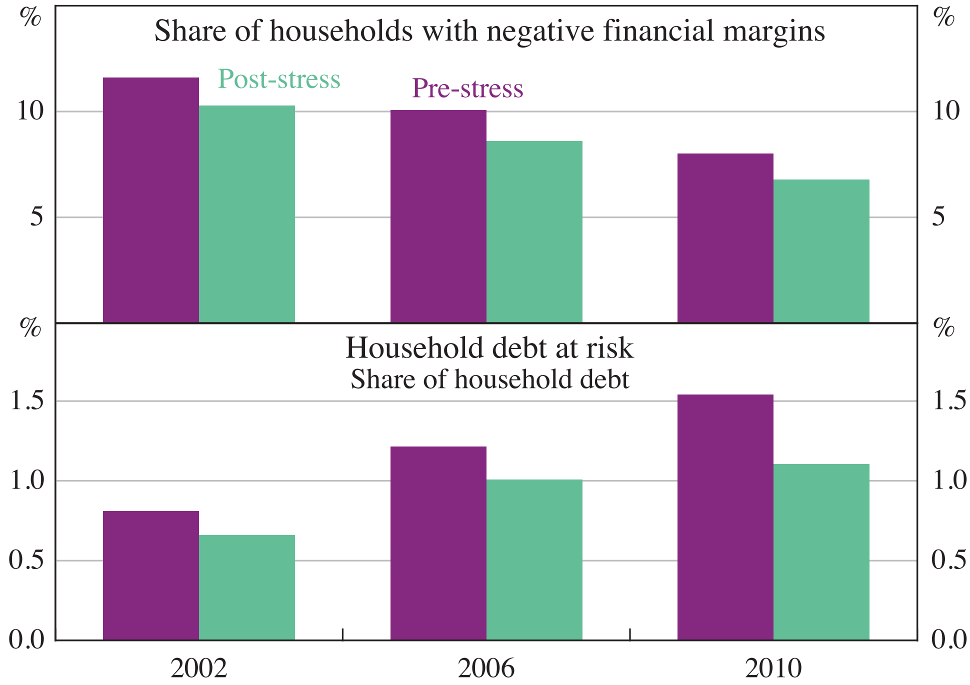
14 This effect relies on reductions in the cash rate being passed on in full and instantaneously to borrowers. Excluding the fall in interest rates, the share of households with negative financial margins increases by around ¾ percentage points relative to the pre-stress baseline in each survey and DAR rises by around 0.2 percentage points. Additionally, the assumption that interest rates on credit cards change one-for-one with the cash rate is unrealistic given the relative stickiness of credit card interest rates. However, even under the assumption that credit card interest rates are unchanged, the share of households with negative financial margins and DAR both fall by a similar amount as under the historical scenario.

Figure 9: Historical Scenario

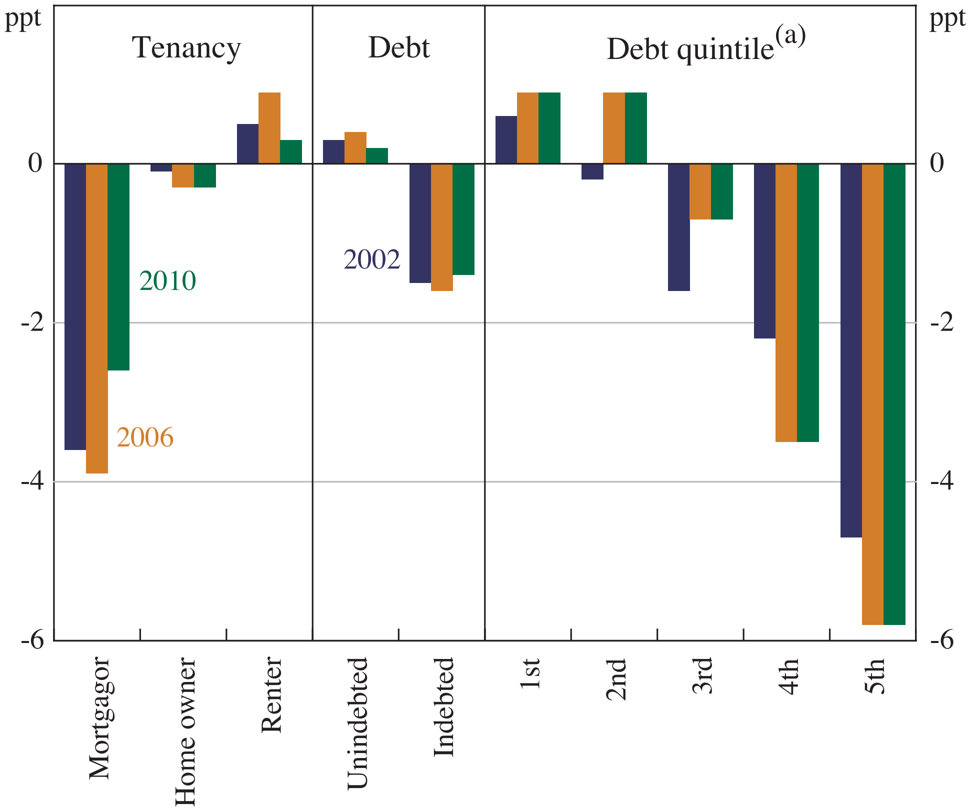


Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

As noted, the results from the historical scenario are driven by the strong offsetting effects of lower interest rates in the model. While this may partially reflect the simple nature of the model, Australia's experience during the global financial crisis suggests that it is not implausible; with the assistance of accommodative monetary policy, the Australian economy was able to absorb a shock of similar magnitude during the crisis with limited aggregate impact on household loan performance.

Figure 10: Historical Scenario – Households with Negative Financial Margins

Change relative to pre-stress



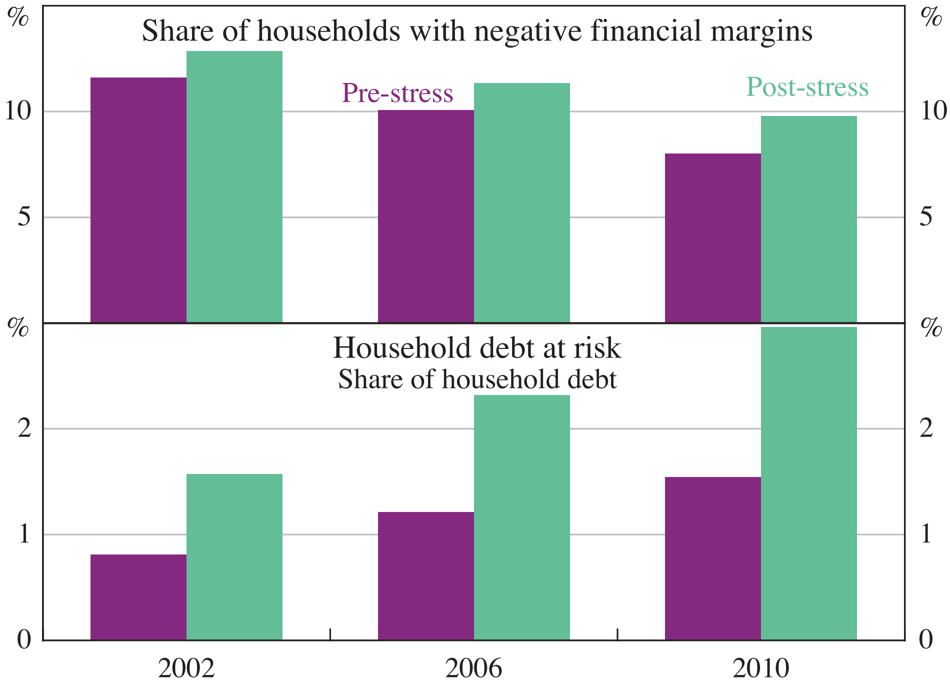
Note: (a) Indebted households only

Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

5.3.2 Hypothetical scenario

The hypothetical scenario is much more severe, along most dimensions, than the historical scenario. Accordingly, under this scenario, the share of households with negative financial margins increases by around 2 percentage points in each year, to a total of 13 per cent in 2002, 11 per cent in 2006 and 10 per cent in 2010 (Figure 11).

Figure 11: Hypothetical Scenario



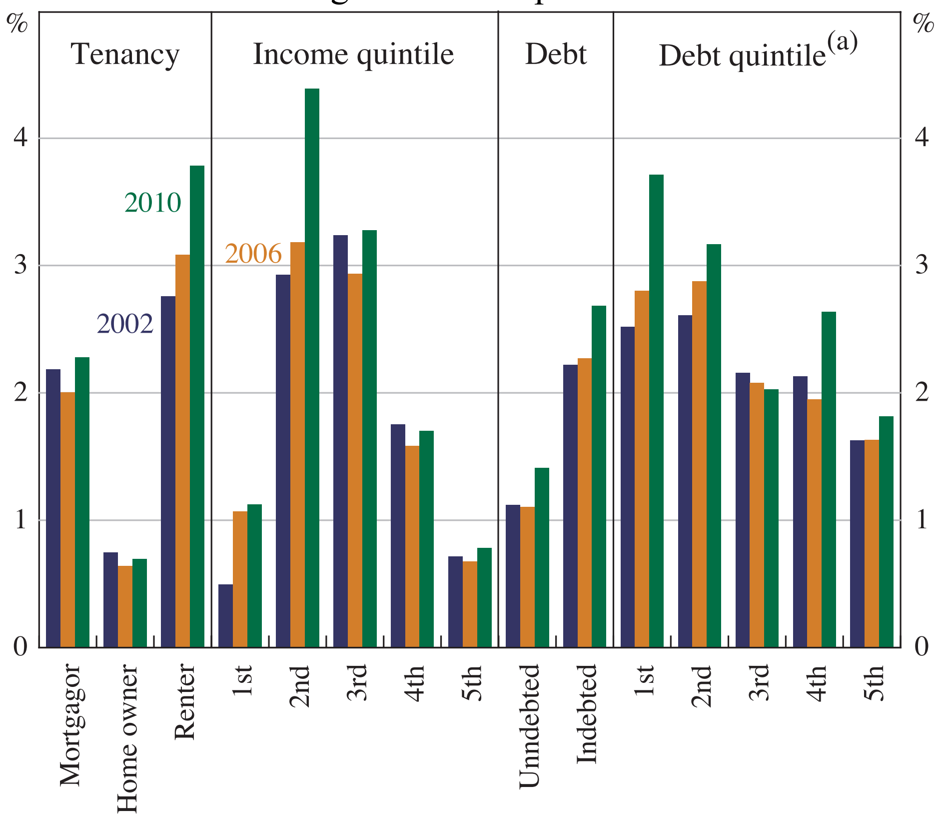
Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

Under this scenario, households in the middle of the income distribution and renters are the most affected (Figure 12). Households with younger heads are also affected, while household with older heads are not especially affected in any year, suggesting that the increase in indebtedness among these households through the 2000s did not significantly expose the household sector to additional risks. Households with debt are more likely to be impacted by the scenario than those without debt. However, of those households with debt, the impact of the scenario is greatest on those with relatively little debt.

Under the hypothetical scenario, post-stress DAR increases relative to pre-stress DAR in each year (Figure 11). This result is largely because of the fall in asset prices, which causes the LGD to rise (but has no effect on the frequency of default). The magnitude of the difference between pre- and post-stress DAR (i.e. the effect of the shock on DAR) increases over time, to peak at about 1.5 percentage points in 2010.

Figure 12: Hypothetical Scenario – Households with Negative Financial Margins

Change relative to pre-stress



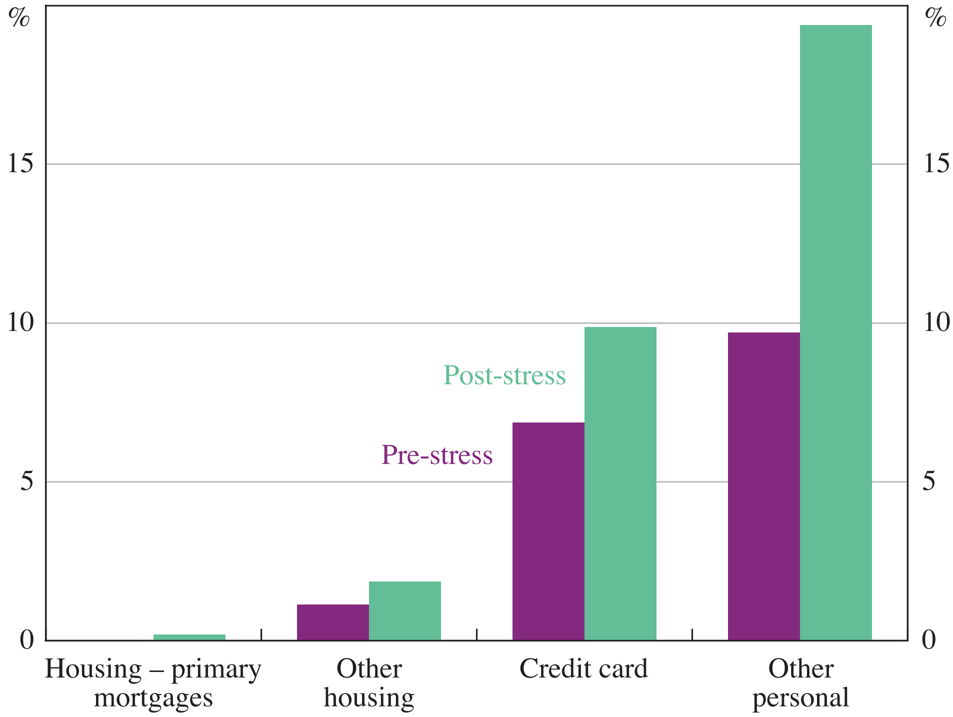
Note: (a) Indebted households only

Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

The increase in expected losses on credit card and other personal debt drives the rise in household DAR; DAR on other personal loans doubles to nearly 20 per cent (Figure 13). By comparison, the rise in DAR on primary housing loans is small, largely because of the strong collateralisation of housing loans in Australia (and the assumptions around loss precedence). Regardless, given that housing loans make up the vast bulk of household lending, small changes in DAR on housing loans result in large changes in total household DAR.

Figure 13: Hypothetical Scenario – Household Debt at Risk by Product Type

Share of household debt by product type, 2010



Sources: Authors' calculations; HILDA Release 12.0; Melbourne Institute; RBA

The results from the hypothetical scenario suggest that the household sector would have remained fairly resilient to macroeconomic shocks during the 2000s, and that the households that held the bulk of debt tended to be well placed to service it, even during macroeconomic shocks. However, based on this scenario, the effect of macroeconomic shocks on DAR appears to have increased over the 2000s. This suggests that household vulnerability to shocks may have risen a little. This might be because some households were in a less sound financial position following the global financial crisis (for instance, because the labour market had weakened and the prices of some assets had declined). As a consequence, shocks of a magnitude that previously would have left these households with a positive financial margin and/or sufficient collateral so as not to generate loan losses for lenders may, following the crisis, have been large enough to push these households into having a negative financial margin and/or insufficient collateral.

5.3.3 Comparison with bank capital

The stress-testing model in this paper is used to examine household financial resilience over the 2000s. In contrast, stress-testing frameworks that are developed for practical prudential purposes are used to assess the resiliency of the banking sector. Our model design means that we can only make very simple comparisons regarding the size of expected losses under the scenarios relative to bank capital. Nonetheless, this still provides some context for the results by giving a broad indication of the magnitude of the direct flow-on effects to the banking sector from household loan losses (i.e. DAR) generated by the model. Using data from the Australian Prudential Regulation Authority (APRA), we compare the results from the hypothetical scenario to banks' total capital. We assume that pre-stress losses have already been properly provisioned for and that loss rates are equal across lenders (i.e. banks, other authorised deposit-taking institutions (ADIs) and non-ADI lenders, such as mortgage originators).

The DAR results imply that expected losses (under the scenario outlined) on banks' household loans were equivalent to a little less than 10 per cent of total bank capital (on a licensed ADI basis), assuming that eligible collateral consists of housing assets only. As mentioned previously, this result assumes that banks have already provisioned for pre-stress losses, but this may not always be the case, as the deterioration in asset quality may surprise some institutions or may take place before *objective evidence of impairment* has been obtained. Assuming pre-stress losses are not provisioned for, potential losses as a share of total bank capital roughly double. It is important to reiterate that these estimates are simplistic and could differ to actual losses incurred in reality under this scenario by a large margin. For example, some of these loan losses may be absorbed by lenders mortgage insurance.[15]

6. Limitations and Future Work

As with all stress-testing models, the model described in this paper has some limitations that are critical to its interpretation. In addition to the limitations already discussed above, some other notable limitations are:

- The one-period nature of the model means that the impact on ADIs cannot be compared with that predicted by APRA in its stress tests using scenarios with a

15 Lenders mortgage insurance is often taken out by lenders on loans with loan-to-valuation ratios above 80 per cent, which have made up about one-third of loan approvals in recent years.

time dimension. For example, a 5 percentage point increase in the unemployment rate in the model means that 5 per cent of individuals in the labour force (on top of those already unemployed) instantly become unemployed. Within this extra 5 per cent, any household whose financial margin falls below zero is assumed to default instantly. By contrast, in a real-world downturn involving a multi-year period of high unemployment, a certain proportion of the individuals that become unemployed would find jobs prior to defaulting. Additionally, loan losses would be spread over time rather than occurring instantaneously.

- Household surveys may not adequately identify households with negative financial margins (for instance, because households tend to understate their debt and income).[16] In addition, although efforts are made to ensure that the HILDA Survey sample is representative, households with precarious finances often do not disclose their financial position, while higher-income households are less likely to remain in the survey over time. Furthermore, household surveys such as this are generally only available around 12 to 15 months after fieldwork has been completed, reducing their usefulness as a real-time stress-testing tool.

- The predictive ability of household micro-simulations is relatively untested. While these models have been established in a number of countries, none of these countries have had recent crises that emanated from the household sector. The US household sector could be a useful case study to test this. Household surveys, such as the Federal Reserve's Survey of Consumer Finances, contain many of the required variables to run such an experiment.

A number of adjustments could be made to potentially improve the model:

- *Asset price variability*: asset prices are currently assumed to fall by a set percentage for all households. However, it might be more realistic for asset prices to fall by differing amounts for each household; for example, housing prices could fall based on characteristics such as the property's location. Shocks to asset prices could also be geographically correlated with unemployment shocks. Preliminary exercises indicate that allowing for variability in asset price

16 For example, Watson and Wooden (2004) demonstrate that the population-weighted sum of debt reported in the 2002 HILDA Survey was about 20 per cent below aggregate measures.

changes – so that some households experience very large price falls – can substantially affect loan losses.

- *Property possession costs*: the baseline model assumes that there are no costs involved in selling the collateral securing a defaulted loan. However, the default process may be costly, including costs such as property depreciation while the property is unoccupied, lost interest income, fees paid to sales intermediaries, legal fees and increased labour costs in collections departments. Preliminary investigation suggests that including estimates of these other costs has a relatively small (but non-trivial) effect.

- *Multiple periods*: the model assumes that households 'jump to default' in a single period. However, households with negative financial margins could gradually draw down on liquid assets, possibly sell less-liquid assets, such as property, and unemployed households could return to employment. Including multiple periods and other dynamics could potentially increase or decrease losses.

  Preliminary analysis suggests that including liquid assets directly in households' financial margins does not affect the DAR results. For instance, assuming that unemployed households can draw down on their assets for three months to avoid default reduces the pre-stress share of households with negative financial margins in 2010 to about 1¾ per cent (down from 8 per cent) and in the hypothetical scenario to about 2¼ per cent (down from 10 per cent). However, there is a negligible change in DAR, since households with negative financial margins have less assets (having drawn down on them) and thus higher LGD.

7. Conclusion

In this paper, we have analysed the resilience of the Australian household sector through the 2000s using data from the HILDA Survey and a simulation-based household stress-testing model. The results suggest that the share of households whose incomes are estimated to be less than minimum expenses (i.e. with negative financial margins) fell from around 12 per cent in 2002 to 8 per cent in 2010. These households tend to have lower incomes, be younger and live in rental accommodation; however, these groups tend to hold a relatively low proportion of total household debt. Households that were more indebted did not necessarily appear to be more likely to have negative financial margins than households that were less indebted. This could be interpreted as evidence that the screening lenders carry out in assessing loan applications is effective.

Lenders' exposure to households with negative financial margins appears to have remained limited, with expected loan losses (based on the assumptions underlying our model and in the absence of any adverse shocks) increasing over the 2000s, but remaining fairly low. This increase occurred despite the share of households with negative financial margins falling over this period, implying that these households owed an increasing share of debt and/or held less valuable collateral relative to this debt. The limited increase in expected loan losses is despite a substantial increase in aggregate household indebtedness, as well as the impact of the global financial crisis on the labour market and asset prices. This suggests that aggregate measures of household indebtedness may be a misleading indicator of the household sector's financial fragility.

Although the stress-testing model used in this paper is relatively simple and relies on a number of assumptions, it generates plausible results in response to shocks to interest rates, the unemployment rate and asset prices. The results from the two stress scenarios considered – both of which incorporate a substantial increase in the unemployment rate and a substantial decline in asset prices – imply a high level of household financial resilience and limited expected loan losses for lenders. That said, the effect on expected household loan losses of a relatively severe stress scenario, under which unemployment rises, asset prices fall and interest rates are unchanged, increased over the 2000s, suggesting that the household sector's vulnerability to macroeconomic shocks may have increased a little. However, expected loan losses are actually lower under the less severe of the two scenarios, which has rising unemployment and falling asset prices comparable to Australia's experience during the financial crisis. This is due to the offsetting effect of lower interest rates, highlighting the potential for expansionary monetary policy to offset the effect of negative macroeconomic shocks on household loan losses.

Appendix A: Unemployment Probabilities

We generate an unemployment shock using a Monte Carlo simulation, where each individual's probability of becoming unemployed is estimated using a separate logit model for each year. The probability that individual i is unemployed is:

$$\Pr\left(U_i = 1 \middle| \mathbf{x}_i \boldsymbol{\beta}\right) = \frac{\exp\left(\mathbf{x}_i \boldsymbol{\beta}\right)}{1 + \exp\left(\mathbf{x}_i \boldsymbol{\beta}\right)}, \tag{A1}$$

where U is an indicator variable equal to one if individual i is unemployed and equal to zero otherwise, $\mathbf{x}$ is a vector of regressors and $\boldsymbol{\beta}$ is a vector of coefficients. To select the regressors, we use a general-to-specific modelling approach for 2010, removing insignificant variables to arrive at a parsimonious model (Table A1).[17] All remaining variables are significant, or for categorical variables jointly significant, at the 5 per cent level. The same regression is replicated for 2002 and 2006.

The signs of each marginal effect are generally as expected, although there is some variability across surveys. Previous spells of unemployment, less education, not being born in an English-speaking country, not being married, being a single parent, being Aboriginal or Torres Strait Islander, not earning rental income or being in poor health increase the probability of being unemployed. Up to a point, ageing makes individuals less likely to be unemployed.

Examining the size of each marginal effect gives us an idea of which variables have the greatest effect on our predictor of unemployment. Using a base case, where all categorical and dummy variables are set to the sample mode and continuous variables to the sample mean, demonstrates that many variables in our regression have sizeable effects on unemployment; for example, relative to the base case, being unemployed for at least one year prior to the survey increases the base case individual's probability of being unemployed by between 16 and 40 percentage points in each year. Conversely, a university education reduces the probability of being unemployed by 3–5 percentage points.

17 The variables in the initial regression were similar to those in Buddelmeyer, Lee and Wooden (2009).

Table A1: Logit Model – Unemployment

Individuals in labour force

Variable	**Marginal effects (ppt)**		
	2002	2006	2010
Aboriginal or Torres Strait Islander	9.7	11.8***	27.9***
Age (quadratic term included)	–0.2***	–0.2***	–0.3***
Born in English-speaking country	–4.1***	–2.4***	–3.6***
Earns rental income	–4.8***	–1.8	–2.9**
Educational attainment			
Completed year 12	–4.2***	–2.5***	–4.0***
Diploma	–3.4***	–2.0***	–3.8***
University	–5.2***	–3.2***	–4.5***
Family structure			
Couple with dependent children	–1.9	–0.1	1.3
Couple without dependent children	–2.8	0.1	–0.1
Single with dependent children	7.5***	5.7***	5.7***
Long-term health condition	10.7***	7.2***	5.8***
Married	–1.0	–1.4	–2.9**
Previously unemployed for at least one year	39.5***	16.2***	21.1***
Pseudo-R^2	0.19	0.17	0.17
Number of observations	8 604	8 789	9 179

Notes: Base case sets categorical variables to their mode and continuous variables to their mean; *, **, *** denote significance at the 10, 5 and 1 per cent levels, respectively, for the test of the underlying coefficient being zero; marginal effects calculated for categorical variables as a discrete change from the base case and for continuous variables as a one-unit change

Sources: Authors' calculations; HILDA Release 12.0

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