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A Model of Australian Household Leverage

In a recent *Viewpoint*, we looked at the potential implications of rising household debt in Australia for both monetary policy and real activity. Economic theory tells us that unanticipated increases in household wealth lead to increased consumption, known as the "wealth effect". Increases in asset prices can be caused by factors such as higher wage expectations, profits or rental yields, or alternatively, irrational exuberance. So, the key questions are: In which category do recent Australian house price increases belong? Is there a housing bubble in Australia, and how would households react to a potential decline in wealth? By many measures, like the rent-to-price ratio, Australian homes look expensive. Will Australian households deleverage as prices go down as they levered up when the going was good?

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While econometric models will not provide a definitive answer to these questions, the U.S. experience – both leading into the financial crisis of 2008 and the deleveraging since then – is a good laboratory. Following the global financial crisis of 2008, household deleveraging acted as a significant headwind to the U.S. economic recovery. This deleveraging happened despite zero policy rates and has compelled many researchers to focus on what drives consumer debt ratios (Eggertsson and Krugman, 2012; Guerrieri and Lorenzoni, 2011). For example, the European Central Bank (Albuquerque, Baumann and Krustev, 2014) modelled the U.S. household equilibrium debt-to-income ratio in a panel-error correction framework and identified deleveraging as a "significant headwind to consumption and activity in recent years".

Even before the 2008 financial crisis, U.S. household leverage was of interest to policymakers and researchers. Many analysts were questioning whether higher debt levels had increased the sensitivity of consumer spending to asset price shocks. In their 2007 Federal Reserve Board discussion paper, "The Rise in U.S. Household Indebtedness: Causes and Consequences", Karen E. Dynan and Donald L. Kohn identified rising U.S. house prices as a primary source of the continued increase in the debt-to-income ratio. They flagged the possibility of large and negative consequences for the macro economy given unexpected shocks to asset prices in a highly levered environment.

Given the impact household de-leveraging had on the U.S. economy during and after the global financial crisis, it is important to also consider what drives the Australian debt-to-income ratio. We modelled both U.S. and Australian leverage (the household debt-to-income ratio) and found that the correlations between wealth and increases in aggregate leverage in the two countries are remarkably similar. If anything, mortgage finance in Australia has even fewer frictions than in the U.S. Thus, Australian households respond faster to increases in wealth, and the sensitivity of leverage to interest rates is higher.

Method, model and data

We fit a vector autoregressive model with exogenous variables (VARX) to understand the time series dynamics in the debt-to-income ratio. We modelled the U.S. and Australian debt-to-income ratio with:

$$y(t) = \alpha + \sum_{j=0}^{r} \beta_j z(t-j) + \nu(t); \qquad t = 1,\dots,T$$

$$E[\nu(t)] = 0, \quad E[\nu(t)\nu(t)'] = \Omega$$

$y(t)$ and $z(t)$ are zero-mean, wide-sense stationary time series of dimension n and q, respectively, where $y(t) = \{y_1(t), y_2(t),\dots,y_n(t)\}'$ are nx1 observations on the endogenous variables at time t and the $z(t)$ are qx1 observations on the exogenous variables at time t. $\nu(t)$ is an nx1 stationary vector process.

$\beta_\tau, \tau = 1,2,\dots,r$ denote nxq coefficient matrices, respectively, $b_\tau^{i,j}$ is the $(i,j)^{th}$ entry of β_τ, and $k=1+rq$ is the number of parameters per equation.

We employed a model-fitting technique known as subset autoregression with exogenous variables to model the debt-to-income ratio. Full order VARX models are modified to arrive at subset VARX (SARX). A SARX is a special form of the more basic autoregression model that allows us to capture the dynamic behavior present in the data. This approach of first identifying the full model in the VARX avoids over-identifying restrictions and accidentally excluding important variables especially given the lack of strong economic theory on how restrictions should be imposed. We take a more data-driven approach given our limited a priori knowledge of what restrictions should be imposed. When using SARX models, the data drive the model while identifying both the short-run and long-run influences of variables on each other.

To account for model uncertainty, we used an information-theoretic approach based on AIC (Akaike Information Criterion) likelihood estimates and identified the most likely models given the data set. The model likelihoods provide a measure of relative importance that allows us to rank models and variables and calculate average coefficients across models. AIC likelihoods indicate the probability that the model is the best among the whole set of candidate models. For instance, an Akaike likelihood of 0.90 for a single model tells us that it has a 90% chance of being the best one among the candidate models.

Using standard definitions of AIC, we define AIC differences δ_i as:

$$\delta_i = AIC_i - AIC\min$$

Where $AIC\min$ is the model with the smallest AIC among the set of models considered and AIC_i is the AIC for model i. We used the following rules of thumb:

$\delta_i = AIC_i - AIC\ min$	Support for Model i
0-3	Substantial
4-7	Considerably less
>10	Essentially none

Source: PIMCO

In the analysis to follow we restricted the set of models to be used as part of our model to those with $\delta_i \leq 3$. We then calculated the relative likelihood of a model given the data and the set of R restricted models with $\delta_i \leq 3$ as:

$$\omega_i = \frac{\exp(-\frac{1}{2}\delta_i)}{\sum_{r=1}^{R}\exp(-\frac{1}{2}\delta_r)}$$

The ω_i's are known as AIC likelihoods and sum to 1 over the set of R candidate models. AIC likelihoods indicate the probability that the model is the best among the whole set of candidate models.

Predictor importance

We estimated the relative importance of predictors by summing the AIC likelihoods across all the models that include the predictor of interest. The higher the sum, the more relative importance the predictor has compared with the other predictors considered.

Full model averaged coefficient estimates are calculated as:

$$\overline{\hat{\beta}} = \sum_{r=1}^{R} \omega_r I_i(g_r)\hat{\beta}_{i,r}$$

Where $I_i(g_r)$ is 1 if the predictor is in the model g_r and zero otherwise.

The data

The variables modelled are shown in Tables 1 and 2. The sample period covers December 1988 to September 2014 for Australia and June 1971 to June 2014 for the U.S. To ensure stationarity, all data series are modelled as quarterly percentage changes.

To understand which predictors may be important drivers of Australian household leverage, we first examined the predictors that have been important drivers of U.S. household leverage. Predictors have been identified as possible candidates based on extant literature where debt/assets, debt/income or consumption for U.S. households is modelled (Eggertsson and Krugman, 2012; Guerrieri and Lorenzoni, 2011; Albuquerque, Baumann and Krustev, 2014; Dynan and Kohn, 2007). We list the candidate predictor variables for both the U.S. and Australia in Tables 1 and 2.

We first tested the significance of each predictor for each country using a simple linear regression. If the predictor was significant, then it was a candidate for the full AR model. We used a very low hurdle of 20% for the significance level initially so as to not accidentally exclude important predictors. These regressions also indicated the sign the coefficients should take in the full model. Please see the results section for these univariate regressions.

TABLE 1: U.S. VARIABLES MODELLED[1]

Variable	Description	Proxy	Source
$y(t)$	Quarterly percentage change in household leverage	Quarterly percentage change in ratio of household debt to income	Bloomberg
$z_1(t)$	Quarterly percentage change in wealth/income expectations	Quarterly percentage change in wages and salaries	FRED
$z_2(t)$	Quarterly percentage change in income expectations and uncertainty	Quarterly percentage change in the unemployment rate	Bloomberg
$z_3(t)$	Quarterly percentage change in wealth	Quarterly percentage change in housing assets	Bloomberg
$z_4(t)$	Quarterly percentage change in the cost and availability of credit	Quarterly percentage change in mortgage rate	FRED

Source: PIMCO

[1]**Ratio of household debt to income** is calculated from the Federal Reserve's financial accounts data set and is the ratio of U.S. household debt outstanding to household income. **Wages and salaries** are sourced from the FRED database and measured in billions of dollars – (Code A576RC1Q027SBEA Compensation of employees: Wages and salaries). **Unemployment rate** is sourced from the Bureau of Labor Statistics (Series ID LNS14000000). **Housing Assets** is the FOF Federal Reserve U.S. Household Real Estate Asset series. **Mortgage Rate** is sourced from the FRED database and is the 30-year conventional mortgage rate as a percentage.

TABLE 2: AUSTRALIAN VARIABLES MODELLED[2]

Variable	Description	Proxy	Source
$y(t)$	Quarterly percentage change in measure of household leverage	Quarterly percentage change in ratio of household debt to income	RBA
$z_1(t)$	Quarterly percentage change in wealth/ income expectations	Quarterly percentage change in wages and salaries	Bloomberg
$z_2(t)$	Quarterly percentage change in wealth/ income expectations	Quarterly percentage change in real net disposable income	Bloomberg
$z_3(t)$	Quarterly percentage change in income expectations and uncertainty	Quarterly percentage change in unemployment rate	RBA
$z_4(t)$	Quarterly percentage change in wealth	Quarterly percentage change in net worth	RBA
$z_5(t)$	Quarterly percentage change in income expectations and uncertainty	Quarterly percentage change in Westpac-Melbourne Institute consumer confidence	Bloomberg
$z_6(t)$	Quarterly percentage change in wealth	Quarterly percentage change in housing asset values	RBA
$z_7(t)$	Quarterly percentage change in the cost and availability of credit	Quarterly percentage change in mortgage rate	RBA
$z_8(t)$	Quarterly percentage change in the cost and availability of credit	Quarterly percentage change in ratio of interest payments on housing debt to household disposable income	RBA

Source: PIMCO

[2]**Ratio of household debt to income** is sourced from the RBA (Series ID BHFDDIT) and is the ratio of household debt to annualised household disposable income. **Wages and Salaries** is the Australian Bureau of statistics total wages and salaries and is measured in millions. **Real net disposable income** is sourced from the Australian Bureau of statistics and measures Australia's real net national disposable income per capita. **Unemployment Rate** is the number of unemployed persons as a percentage of the labour force and sourced from the RBA. **Net Worth** is sourced from the RBA (series ID BSPNSHUNW) and calculated as total assets less total liabilities and is measured in billions. **Westpac-Melbourne Institute Consumer Confidence** is an average of five component indexes which reflect consumers' evaluations of their household financial situation over the past year and the coming year, anticipated economic conditions over the coming year and the next five years, and buying conditions for major household items. **Asset Values** is sourced from the RBA and measures household real estate assets. **Mortgage Rate** is sourced from the RBA (series ID FILRHLBVS) and represents banks' variable standard rate. **Ratio of interest payments on housing debt to quarterly household disposable income is sourced from the RBA (series ID BHFIPDH).**

The results

Table 3 shows the diagnostics for the univariate fits of the U.S. debt-to-income ratio against each of the predictors at the various lags as listed in Table 1. We only show the predictors with a p-value of 20% or less. These predictors form the set of candidate predictors for our full model.

Household wealth, as measured by the value of housing assets, is significant at lags of three, four and five quarters. We also note that the R-square for assets lagged four quarters is the highest, suggesting that this predictor describes the most variation in the debt-to-income ratio when compared with the other predictors modelled.

The other candidate predictors for the U.S. model are unemployment at lags two and five, wages also at lags two and five, and the mortgage rate at lag four.

TABLE 3: U.S. PREDICTOR SIGNIFICANCE

Predictor	Coefficient	T-Stat	P-Value	R-Square
Assets lag 4	0.26	5.31	0.00	0.15
Assets lag 3	0.25	5.23	0.00	0.14
Assets lag 5	0.23	4.63	0.00	0.12
Unemployment lag 2	-0.05	-3.33	0.00	0.06
Unemployment lag 5	-0.05	-3.11	0.00	0.06
Wages lag 2	0.26	2.70	0.01	0.04
Wages lag 5	0.21	2.16	0.03	0.03
Mortgage rate lag 4	-0.04	-2.08	0.04	0.03

Source: PIMCO

TABLE 4: AUSTRALIAN PREDICTOR SIGNIFICANCE

Predictor	Coefficient	T-Stat	P-Value	R-Square
Assets	0.27	5.00	0.00	0.25
Assets lag 1	0.24	4.35	0.00	0.20
Assets lag 2	0.25	4.45	0.00	0.21
Net worth lag 1	0.25	3.76	0.00	0.16
Net worth lag 2	0.24	3.65	0.00	0.15
Mortgage rate lag 3	-0.08	-3.64	0.00	0.15
Net worth	0.20	3.01	0.00	0.11
Mortgage rate lag 4	-0.07	-3.00	0.00	0.11
Unemployment	-0.13	-2.95	0.00	0.10
Mortgage rate lag 2	-0.06	-2.31	0.02	0.07
Interest to income lag 2	-0.07	-1.90	0.06	0.05
Interest to income lag 3	-0.06	-1.85	0.07	0.04
Sentiment lag 2	0.04	1.84	0.07	0.04
Real net disposable income	0.25	1.74	0.09	0.04

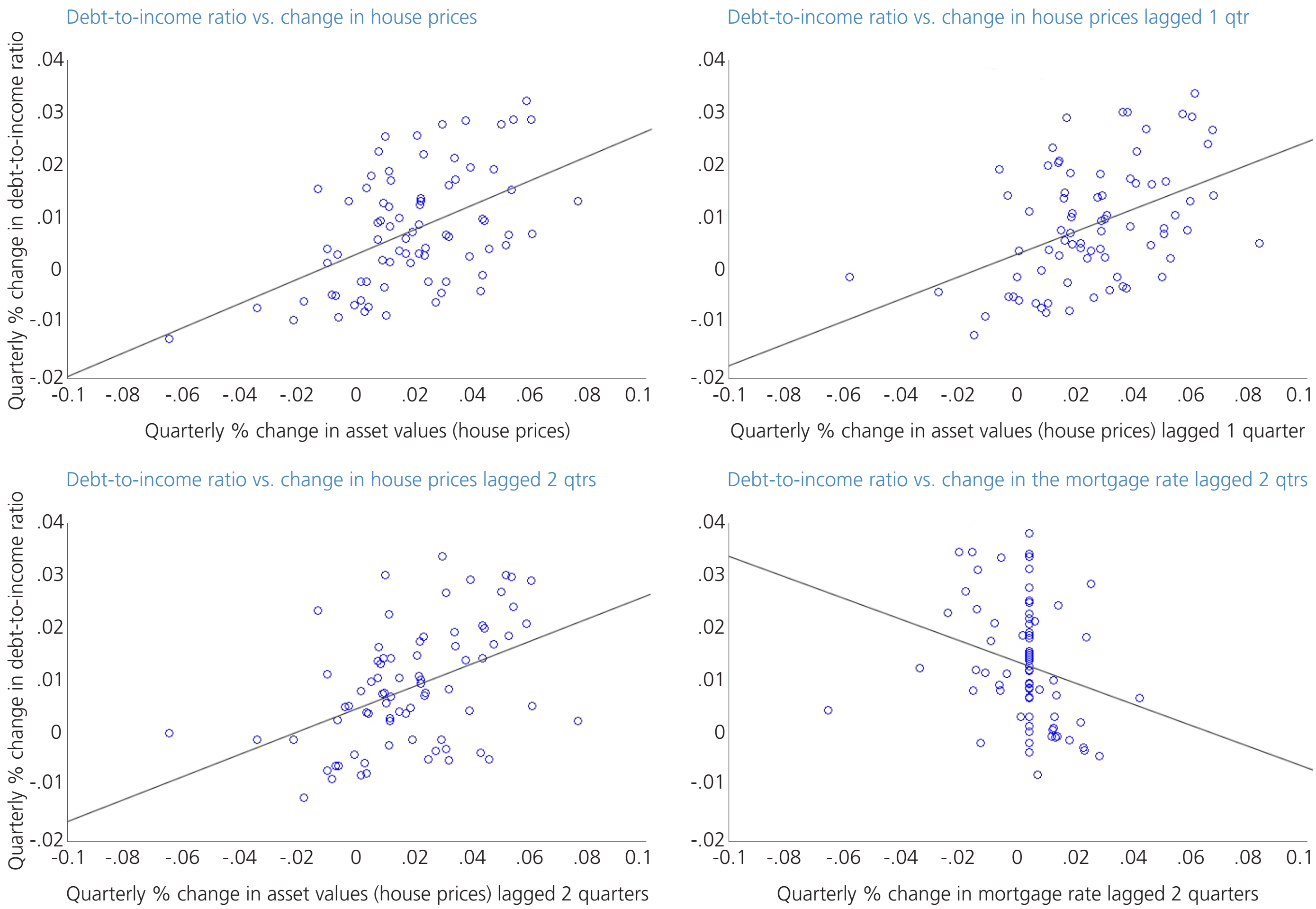
Source: PIMCO

Table 4 lists the candidate predictors for the Australian model. Similar to the U.S., household wealth (as measured by housing asset values) describes most of the variation in the Australian consumer debt-to-income ratio when compared with the other candidate predictors, but appears to have a stronger linear relationship given the R-squares. We also modelled total assets and got almost identical results in the full model. We chose to use the full model with housing assets as the model diagnostics were superior and wanted to try to avoid the problems that including superannuation assets may have on the interpretation given superannuation is compulsory in Australia and not in the U.S. As expected, net worth (assets – liabilities) also has a high R-square given it is a function of asset values. The cost and availability of credit as measured by the mortgage rate (with lags at two, three and four quarters) appears to have a stronger linear relationship with the debt-to-income ratio for Australian consumers when compared with U.S. consumers.

Other candidate predictors include contemporaneous unemployment, interest to income at lags two and three, sentiment at lag two and real net disposable income (contemporaneous).

Figure 1 below presents the univariate plots of the Australian debt-to-income ratio against a selection of predictors (assets, assets lagged one quarter, assets lagged two quarters and the mortgage rate at lag two).

FIGURE 1: RELATIONSHIP BETWEEN THE AUSTRALIAN DEBT-TO-INCOME RATIO AND A SELECTION OF PREDICTORS (DECEMBER 1988 – SEPTEMBER 2014)



Source: PIMCO

Table 5 shows the top six most likely models of the U.S. consumer debt-to-income ratio given the data. We can see that the model that ranked the most likely, with a model likelihood of 0.38, includes assets at lag four, the mortgage rate at lag four and the unemployment rate at lag five.

Also shown in Table 5 is the model-averaged coefficient and the relative likelihood of each predictor. For example, asset values lagged four quarters have a model averaged coefficient of 0.22 and a likelihood of 0.89. The higher the likelihood, the greater the importance placed on this predictor compared with the other predictors considered. Note that the likelihoods are relative and should not be interpreted in an absolute sense. The likelihood of 0.89 tells us this predictor is more important than unemployment at lag five with a likelihood of 0.52, but not as important as the mortgage rate at lag four.

The signs of the predictors are correct given the univariate fit of the debt-to-income ratio against each of the variables, except for wages at lag three. This suggests that the predictor is correlated with the other predictors in the model. It also has a low predictor likelihood, indicating that after the other candidate predictors are included in the model, wages do not describe any additional variation in the debt-to-income ratio for U.S. consumers. Overall, in terms of predictor importance, assets at lag four and the mortgage rate at lag four are on an almost equal footing, and can be interpreted as the most important predictors.

We interpret the positive slopes for assets at lags three and four to mean that U.S. consumers choose to lever up when they perceive their wealth to have increased. The coefficient for the cost-of-credit predictor (the mortgage rate lagged four quarters) indicates that as the cost of credit increases the debt-to-income ratio decreases, an expected result given a tightening of the availability of credit. The negative slope for the change in unemployment can be interpreted as consumers deleveraging as income expectations and employment certainty are declining.

Table 6 shows the top two models for the Australian consumer debt-to-income ratio. We can see the model ranked highest has a likelihood of 0.85 and includes asset values and the mortgage rate, a similar result to the U.S. model. However, the predictor likelihoods for asset values lagged two quarters, and the mortgage rate lagged two quarters, imply these variables are more important for the Australian consumer debt-to-income ratio (based on the predictor likelihoods). These two predictors appear in both of the top models. Additionally, only two models are identified, suggesting there is less uncertainty about which predictors are important for the Australian debt-to-income ratio. The signs of the predictors are correct given the univariate fits. Furthermore, changes in asset values and the mortgage rate in Australia flow through to the debt-to-income ratio faster than they do in the U.S. (i.e., it takes only two lags for a change in the mortgage rate to impact leverage as compared with four lags in the U.S.). Therefore,

TABLE 5: TOP SIX MODELS FOR THE U.S.

Model	Assets lag 3	Assets lag 4	Mortgage rate lag 4	Unemployment lag 2	Unemployment lag 5	Wages lag 3	Model likelihood
1		0.28	-0.05		-0.03		0.38
2		0.25	-0.05		-0.03		0.14
3		0.26	-0.04	-0.03			0.14
4	0.12	0.18	-0.05				0.14
5	0.27		-0.04				0.11
6		0.26		-0.05		-0.18	0.09
Model avg. coeff.	0.05	0.22	-0.04	-0.01	-0.02	-0.02	
Predictor likelihood	0.25	0.89	0.91	0.23	0.52	0.09	

Source: PIMCO

TABLE 6: TOP TWO MODELS FOR AUSTRALIA

Model	Assets	Assets lag 1	Assets lag 2	Mortgage rate lag 2	Model likelihood
1	0.16		0.25	-0.06	0.85
2		0.12	0.24	-0.08	0.15
Model avg. coeff.	0.13	0.02	0.25	-0.06	
Predictor likelihood	0.85	0.15	1.00	1.00	

Source: PIMCO

Australian investors are more sensitive to changes in wealth and the mortgage rate. The unemployment rate, consumer confidence and wages are less influential than both the mortgage rate and asset values and don't explain any variation in the debt-to-income ratio once these variables have been included in the model.

There are a number of possible reasons for this result. Unlike in the U.S. and U.K., the majority of Australian borrowers have their loan costs (indirectly) determined by the overnight cash rate. This makes Australian households extremely sensitive to monetary policy movements given housing assets are the largest component of Australian household total assets.

Further, Australian households are extremely sensitive to the "wealth effect" due to a number of other characteristics particular to the Australian market. Equity withdrawal facilities on home loans mean homeowners can essentially treat their home as a facility to access cash at low rates easily (often likened to an ATM). Furthermore, the tax environment encourages speculation (negative gearing). The impact on an investor's tax position of owning a negatively geared property is a net rental loss. An investor can claim a deduction for the full amount of rental expenses against their rental and other income. The 2014 Australian Commonwealth Financial System Inquiry states: "The tax treatment of investor housing, in particular, tends to encourage leveraged and speculative investment".

Scenario analysis

Next, we performed a series of sensitivity tests showing how the debt-to-income ratio reacts in the model (dynamically through the autoregressive model) for various combinations of the mortgage rate and changes to house prices for the two years from 1 July 2015.

TABLE 7: FOUR SCENARIOS REFLECTING VARIOUS COMBINATIONS OF CHANGES IN THE MORTGAGE RATE AND HOUSE PRICES OVER THE TWO YEARS 1 JULY 2015 TO 1 JULY 2017

	Bullish	Modest normalisation
Mortgage rates Housing prices	+100 bps + 10%	+100 bps - 10%
Change in debt/income ratio	5.20%	-2.80%
	Bearish	**Slow grind**
Mortgage rates Housing prices	-100 bps - 20%	-100 bps + 10%
Change in debt/income ratio	-3.90%	8.04%

Source: PIMCO

The "bullish" scenario tells us that even when the mortgage rate increases by 1 percentage point over two years, if house prices continue growing in the vicinity of 5% (or more) per year, then households will continue to lever up, providing more evidence for the wealth effect in Australia. If there is a small correction, for example, the "modest normalization" scenario, we see that the combination of declining house prices and increasing mortgage rates will see households choose to de-lever. A more "bearish" scenario, where house prices fall 20%, sees an even further decline in leverage. Similar to the current environment, a 1-percentage-point decline in mortgage rates and 10% appreciation in house prices (under the "slow grind" scenario) will see households increase the debt-to-income ratio. These results, of course, could be an understatement given that Australia has not experienced a prolonged deleveraging environment. It may be that there will be asymmetry in the response during such an event.

Conclusion

Our modeling shows asset valuations (as measured by house prices) and the mortgage rate are the most important variables for explaining the change in household leverage in both the U.S. and Australia. Other variables such as the unemployment rate, consumer confidence and wages are less influential than both the mortgage rate and asset values. Consumers choose to lever up when they perceive their wealth to have increased. A declining cost of credit is also positively correlated with household leverage. We find Australian consumers react more swiftly to changes in asset values and the mortgage rate than U.S. consumers. Given the size of the model coefficients, and the predictor importance for these two predictor variables, they will dominate any potentially offsetting influence by other macroeconomic variables.

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Biography

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