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New models for South African consumption, house prices, and mortgage and non-mortgage debt

Insights for financial stability and monetary transmission

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Abstract: Aggregate consumption typically exceeds 60 per cent of GDP and should be pivotal in central bank policy models. Most use semi-structural macro-models, yet consumption is usually inadequately specified. We use a systems approach to estimate new equations for South African consumption, house prices, mortgage and non-mortgage debt, and income forecasting. A credit-augmented consumption function approach introduces a greater role for uncertainty and a key role for credit conditions, and varies the spendability of different wealth components. This provides new insights into the multiple monetary transmission mechanisms, from policy interest rates and credit conditions to aggregate demand, including via non-homogeneous household balance sheet items on consumption. Credit conditions for mortgages and for other debt move quite differently from each other, with implications for consumer spending. Non-mortgage debt covers a larger fraction of total household debt than in advanced market economies, affecting household financial vulnerability. Housing market participants tend to extrapolate recent house price changes when forming expectations of capital gains, so positive shocks to housing demand can feed back onto house prices and consumption and extend boom conditions. House prices and debt can overshoot relative to their fundamentals, affecting financial stability. These findings should benefit future policy modelling in South Africa.

Key words: aggregate consumption, house prices, credit conditions, household debt, housing collateral, monetary transmission, equation system

JEL classification: C32, E21, E51, E58

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Contents

1 Introduction and motivation

Consumption typically accounts for 60 per cent or more of GDP in advanced economies, so that the aggregate consumption function has a pivotal role in central bank policy models. These models must capture the key determinants of consumption. Moreover, central bank models that lack a well-articulated credit channel and clear links between the financial sector and the real economy may misrepresent the timing and profile of monetary policy transmission and the risks to financial stability. Thus, modelling consumption, taking proper account of a country's credit architecture and other institutional features relating to housing markets and credit markets, has important implications for monetary transmission, stabilization policy, and financial stability.

Until relatively recently, the dominant models of consumption were representative-agent, rational-expectations New Keynesian dynamic stochastic general equilibrium (DSGE) models. These incorporate the simple textbook permanent income model of consumption. In these models monetary transmission works mainly through the real interest rate and the inter-temporal substitution channel, where a higher real interest rate reduces current consumption by raising planned future consumption. Credit constraints faced by households, and household wealth, play no role whatsoever in influencing consumption. Credit flows and asset prices (e.g. prices of equities and real estate) are effectively 'memo items', merely proxying expectations of future growth but absent from the system dynamics or for consumption in the long run.

In recent years, the New Keynesian 'science of monetary policy' (see Gertler et al. 1999) has been increasingly challenged. Accumulating evidence, both macro and especially micro, has undermined key elements of the framework (for example, see the 2018 special issue of the *Journal of Economic Perspectives*). In particular, Hendry and Muellbauer (2018) criticize the representative agent New Keynesian DSGE models as insufficiently 'stochastic', as they trivialize the role of uncertainty and heterogeneity; insufficiently 'dynamic', because they miss key lags in relationships; insufficiently 'general equilibrium', as important feedback loops are ignored (seen for example in the global financial crisis, GFC); and insufficiently 'Keynesian', as co-ordination failures in labour and financial markets are completely absent.

Blanchard (2018: 49) has argued that in contrast to the DSGE model approach, 'Partial equilibrium modelling and estimation are essential to understanding the particular mechanisms of relevance to macroeconomics'. At most central banks, the more flexible semi-structural econometric policy models, which give scope to learn from data, are now preferred to the New Keynesian DSGE models. This is a step forward. Despite this, and despite the importance of consumption in GDP, the majority of central banks still retain an inadequate specification of the consumption function in their econometric policy models, based on the simple textbook permanent income form. A comparative, critical exemplification of central bank policy models, focused on European central banks and the European Central Bank (ECB), is given in Muellbauer (2022).

The three key problems with this highly restricted specification of the consumption function can each be addressed by taking a different approach. First, an unrealistic assumption is made that the relevant concept of wealth in the consumption function for households is 'net worth'. Net worth is measured as the sum of liquid and illiquid financial assets and housing wealth, minus debt. However, using aggregate net worth as a regressor rather than including the individual components of wealth themselves restricts their effects to being identical (i.e. to the coefficients being the same). In practice, these separate effects differ considerably. For example, the marginal propensity to consume (MPC) is higher for liquid than for illiquid wealth. There are large distributional effects too, since liquid assets are held by the majority of the population whereas illiquid assets are held mainly by affluent households. These factors have an impact on spending and they need to be empirically estimated. Debt, for example, *ceteris paribus*, often has a far more negative effect on consumption than when it is restricted by the net worth assumption. Housing wealth potentially has a collateral effect,[1] as well as a wealth effect like that of financial wealth. The effect, then, is often underestimated, and the time-varying nature of the effect is missing.

A second problem is that the restricted specification of the consumption function assumes away the borrowing or liquidity constraints faced by households. Yet access to credit for households to fund consumption, especially consumption of durables, using mortgages or non-mortgage loans (e.g. credit card or hire purchase loans), has varied greatly over time. Credit quality and availability influence the numbers and volumes of mortgages extended and hence affect house prices. They affect the ability to fund expenditure. Banks with high volumes of non-performing loans may be more restrictive and cautious in lending. Interestingly, the time profiles of consumer credit and of mortgage debt tend to be different, suggesting that each has different drivers (e.g. for France, see Chauvin and Muellbauer 2018).

A third problem is that the simple textbook model of consumption assumes that income uncertainty has little relevance for households. Historically, many post-war consumption models have focused on permanent income rather than *current* income, but the extent to which either drives consumption should be tested empirically. Hence, a model is needed to represent the expectations of private agents about future income growth, with discounting that reflects the high degree of income uncertainty faced by many households.

An empirical reformulation of the consumption model that generalizes the textbook permanent income model to a 'credit-augmented consumption function' explicitly addresses the above three problems (Aron et al. 2012; Duca and Muellbauer 2014; Muellbauer 2020, 2022). The reformulation incorporates qualitative insights from the literature on buffer stock saving by heterogeneous agents facing liquidity constraints (including distinguishing renters and owner-occupiers), and also from the literature on the cash flow channel of monetary transmission. The credit channel is explicitly recognized in this reformulation by including credit conditions indices for both non-mortgage (unsecured and secured) and mortgage credit. Easier lending conditions will promote *aggregate* consumer spending, depending on the levels and distributions of household income and wealth portfolios. But easier lending conditions also change the levels and distributions of household portfolios, for example through raising debt levels and asset prices, hence feeding in to future spending decisions. A second feature is that rather than using the net worth concept, household balance sheets are split into liquid assets and debt, illiquid financial assets, and housing wealth. This allows the measurement of the *different* propensities to consume from the various components of wealth. Finally, a higher discount rate is applied to future income streams than in the textbook model, to capture income uncertainty.[2] Short-term roles for income insecurity are added, proxied by the change in the employment rate; and changes in interest rates are introduced to capture cash flow effects on indebted households in floating interest rate environments.

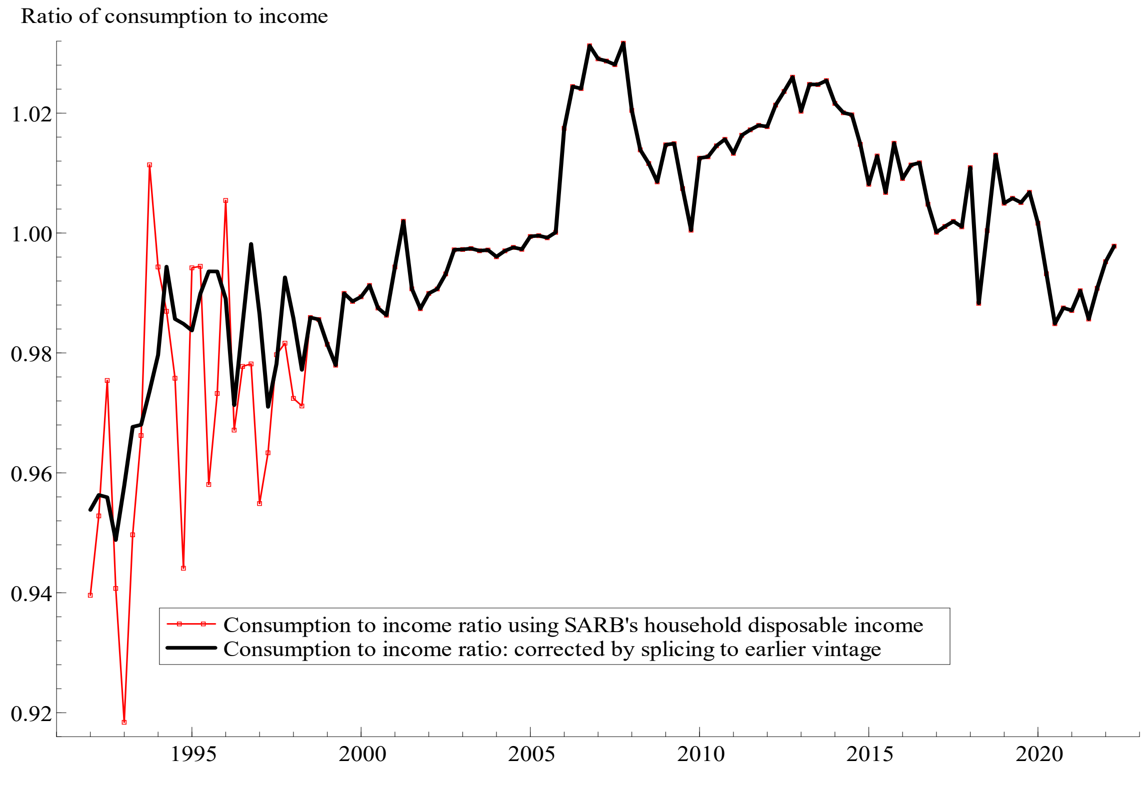
Econometric work of this kind on South Africa is particularly challenging, given the structural changes since 1990, the year Nelson Mandela was released from prison, and during the run-up to

[1] The collateral interpretation is that a higher level of housing wealth increases consumption by allowing more borrowing through higher collateral and equity withdrawal from housing wealth; see Aron et al. (2012).

[2] This approach does not claim that all households discount cash flows identically but argues that it is better to control for an average effect than to ignore such effects altogether.

the democratic transition in 1994 and beyond. Figure 1 shows that the ratio of total consumer spending to household disposable income (HDI) in South Africa has gone through a significant transition since 1985. A striking feature is that prior to 2005, this ratio was mostly below 1, reflecting a household saving rate that was positive, even if small. European countries in this period had substantially higher saving ratios, especially in those countries with more restricted credit access (e.g. Italy). After 2005, there was household dissaving in South Africa, as shown in the figure by the implied negative household saving ratio. During the pandemic, there was a substantial fall in South Africa's consumption-to-income ratio, with a sharp contraction in household income. The other feature shown by Figure 1 is the remarkable volatility of the consumption-to-income ratio before 1998, based on recent National Accounts data, partly reflecting the volatile politics of the time but also indicating noisier and perhaps incorrect data. After extensive investigation (see Appendix 1) we have concluded that in the process of rebalancing the National Accounts in later years, distortions have been introduced in the measurement of HDI for this earlier period. We therefore chose to correct this error by splicing the HDI data in 1998 Q3 to an earlier data vintage from 2006, used in Aron and Muellbauer (2013). As Figure 1 shows, the consumption-to-income ratio before 1998 is far less noisy using the spliced HDI series.

Figure 1: Ratio of household consumption to household disposable income



Source: authors' illustration based on data from Table 1.

In South Africa, consumption is strongly affected by the housing market, credit standards, interest rates, and income. This was demonstrated in an earlier analysis of consumption and total household debt for 1971–2005 by Aron and Muellbauer (2013), using the 'credit-augmented consumption function'.[3] The 2013 study used the balance sheet estimates of disaggregated wealth data developed by Aron and Muellbauer (2006) and Aron et al. (2006, 2008), which work was later adopted and adapted for ongoing publication and use in models by the SARB.[4] Liquid assets were found to be far more 'spendable' than illiquid assets (i.e. with a higher MPC) and debt had far more negative effects on consumption than the restrictive net worth formulation would have implied. Debt, itself driven by interest rates, non-price credit conditions (i.e. loan standards), and house prices, is thus a constraint on consumer spending. The evidence also strongly supported a collateral interpretation of the 'housing wealth effect' for South Africa. Housing wealth has a crucial role as collateral for mortgage borrowing, which implies that changes in housing wealth, mainly due to house price changes, induce large effects on consumer spending (missed when using a net worth assumption).

Credit conditions, though vital to capture in a model for consumption, are difficult to observe and measure. Loan standards vary over time, but modellers mostly lack the granular data that could detect the current rules used by banks and their complex credit scoring. One way forward is to deduce what credit conditions must have been by modelling the quantity of credit extended. If models can capture the drivers of credit in both consumer and mortgage markets, there is a hope of identifying the credit conditions. The 2013 Aron-Muellbauer model used a single credit conditions index, CCI, estimated as a latent variable common to equations for both total household debt and consumption. The 'Latent Interactive Variable Equation System' or LIVES approach (Duca and Muellbauer 2014), which models credit conditions as latent variables, is used in this paper and is detailed in Section 3.2.[5] Using this method, the evidence for France from Chauvin and Muellbauer (2018) and for Germany from Geiger et al. (2016) is that the effects of shifts in credit conditions on non-mortgage debt and mortgage debt are different. Thus two CCIs were modelled, for mortgage debt and for non-mortgage debt. It is likely that this would be particularly relevant in South Africa, where, especially in recent years, non-mortgage debt has accounted for a far larger share of total household debt than in most industrialized countries (it overtook mortgage debt in 2013).

Apart from work at the SARB (discussed in Section 4.7) and our previous work (Aron and Muellbauer 2013), there is a paucity of empirical work on aggregate consumption in South Africa that takes account of the available household balance sheet information. In this paper, we build on and extend our earlier work on modelling South African consumption using the 'credit-augmented consumption function', and bring it up to date, though omitting the pandemic period. Income expectations are handled through an econometric model for permanent household income, assuming a ten-year horizon. Our model splits net worth into liquid and illiquid financial assets, housing wealth, and debt. It controls separately for housing affordability, measured by the ratio of house price to income, and for housing wealth. We apply the LIVES approach to estimate separate CCIs for each type of debt in a five-equation model for consumption, mortgage debt, non-mortgage debt, house prices, and permanent income. The method of estimation is system

[3] The first version of a credit-augmented consumption model for South Africa was reported in Aron and Muellbauer (2000a), and in greater detail in Aron and Muellbauer (2000b). This was the first application of the latent variable method (defined below) of identifying credit conditions in the context of a consumption function.

[4] Johan Prinsloo, formerly head of National Accounts at the SARB and who worked with us, was important in realizing the adoption by the SARB of our household balance sheet estimates, their publication going forward, and their use in the SARB's Core Model.

[5] In the LIVES approach, the 'latent variable' is a function of dummy variables which appears in multiple behavioural equations. Known changes in financial architecture and regulation provide priors that influence the selection of dummies.

maximum likelihood for the first four of these equations. The credit conditions, which affect each of these variables, are common to the equations, helping to tie down the parameters of CCIs for the mortgage market (MCCI) and for non-mortgage debt (NCCI).

2 Macro theory, the consumption function, and the modelling framework[6]

2.1 Consumption models: theory background and formulation

Comprehensive surveys of an older literature on consumption functions include Muellbauer and Lattimore (1995), and Muellbauer (1994) for a less technical account. Cooper and Dynan (2016) survey the literature on wealth effects in consumption functions. Muellbauer (2022) critically assesses consumption functions in the current policy models of major European central banks.

The basic, aggregate, lifecycle/permanent income consumption function of Friedman-Ando-Modigliani has the form:

$$c_t = \gamma^* A_{t-1} + \omega^* y_t^P \qquad (1)$$

where c is real per capita consumption, which depends on permanent real per capita non-property income, y^P, and the real per capita level of net wealth, A, and $\gamma^*$and ω^* are parameters. Non-property income is the relevant income concept in standard lifecycle models. Here property income is defined by rates of return on assets, and the assets are choice variables. Income is therefore measured by non-property (labour plus transfer) income, which omits the dividends and interest earned on wealth that are embodied in asset prices. Permanent income, y^P, is defined as the constant amount of non-property income that corresponds to the present value of expected future non-property income streams.

Equation 1 captures in a specific form a basic comprehension of lifecycle budget constraints. A household wanting to sustain consumption will realize that not all of its assets can be spent now without damaging future consumption, and that future income has a bearing on sustainable consumption. Estimating this consumption function requires devising and estimating an income forecasting model to generate permanent non-property income (see discussion in Section 2.4).

Since consumption and income tend to grow exponentially, formulating the consumption function in logs has advantages. The log-linear approximation of Equation 1 as in Muellbauer and Lattimore (1995; see also Aron et al. 2012) is:

$$\ln c_t = \alpha_0 + \ln y_t + \gamma A_{t-1} / y_t + \ln(y_t^P / y_t) \qquad (2)$$

The marginal propensity to spend out of net worth is approximately γ, and $\gamma = \gamma^* / \omega^*$ and $\alpha_0 = \log \omega^*$. The log ratio of permanent to current income $ln(y^P/y)$, reflects expectations of income growth.

One important advantage of Equation 2 is that it avoids the log assets formulation employed in many studies of consumption. The log formulation of assets gives a poor approximation of the

[6] This section draws on our related papers, including Aron and Muellbauer (2013, 2022a, b), Aron et al. (2012), Chauvin and Muellbauer (2018), De Bonis et al. (2023), Muellbauer (2020, 2022), and Muellbauer and Lattimore (1995).

marginal propensity to consume out of assets when asset levels are low, as they are for many households and especially in emerging economies. It is also a poor approximation when disaggregating net worth into several components, since the log function is not additive.

A dynamic specification of the static form, for instance to introduce habits or adjustment costs, will imply a partial adjustment in the form of Equation 2. If real interest rates are variable, under standard consumption theory, the real interest rate, r_t, enters the model with the usual interpretation of inter-temporal substitution and income effects. The model can be extended to include a measure of income uncertainty, θ_t. These considerations suggest the following generalization of the canonical permanent income model of consumption in Equation 2 above:

$$\Delta \ln c_t \approx \lambda(\alpha_0 + \alpha_1 r_t + \alpha_2 \theta_t + \ln y_t + \alpha_3 E_t \ln(y_t^P / y_t) + \gamma A_{t-1}/y_t - \ln c_{t-1}) + \varepsilon_t \tag{3}$$

where λ measures the speed of adjustment of consumption to its long-run equilibrium level.

Three important modifications to Equation 3 allow a role for uncertainty and the different spendability of non-homogeneous assets, and the introduction of credit conditions. A first modification relaxes the present value formulation of permanent income, to allow for uncertainty concerning future income and liquidity constraint, reflected in a *higher* discount rate than the market real rate of interest. In practice, with aggregate data it is difficult to forecast income beyond around three years except by reversion to a trend. Short horizons are suggested if households anticipate future credit constraints, according to the buffer stock theory of saving explained in Deaton (1991). Precautionary behaviour also generates buffer stock saving, as in Carroll (2001a, b), where it is argued that plausible calibrations of micro-behaviour can give a practical income forecasting horizon of around three years. This horizon was originally suggested by Friedman (1963) in his application of the permanent income hypothesis to aggregate consumption data.

A second important modification is that the formulation of aggregate assets, A, in Equation 3 needs to be split into liquid and illiquid types of asset, each with different 'spendabilities', i.e. allowing different weights for the different types of asset. There are several strong reasons for this disaggregation of assets in empirical models of consumption. Housing wealth differs fundamentally from financial assets since it gives shelter (i.e. it has utility value) as well as having an asset value. Moreover, with credit constraints, housing wealth additionally has a vital collateral role (see Muellbauer 2020 or Aron et al. 2022a for further discussion). A third reason is that illiquid financial assets, which are subject to asset price volatility, and pensions, also subject to trading restrictions, have different and weaker effects on consumption than liquid financial assets[7] and debt. Muellbauer (2020, 2022) notes that the great majority of central bank policy models unfortunately retain the net worth restriction, which ignores these differences between the various household balance sheet components.

A third modification addresses the fact that variations in households' access to credit may induce time variation in key parameters of the consumption function. To counter asymmetric information, lenders use screening devices such as credit scores and evidence of borrowers' income, and for secured lending, especially for housing, they employ collateral requirements to reduce the risk of bad loans. As their willingness to lend increases given changes in their capital

[7] Otsuka (2004) has formalized a model in which trading costs for illiquid assets imply a higher 'spendability' for liquid assets.

base, the cost of funds, industry structure, and regulatory constraints, lenders tend to relax the stringency of their lending conditions. This has a corresponding impact on household demand, including for housing, and hence on house prices. This is why variations in credit conditions need to be controlled for in specifying the household sector in policy models, though they are rarely included in central bank policy models, as noted by Muellbauer (2020).

These considerations suggest the following 'credit-augmented' version of the Friedman-Ando-Modigliani consumption function:

$$\Delta \ln\, c_t \approx \lambda(\,\alpha_0\; + \alpha_{1M}\, MCCI_t + \alpha_{1N} NCCI_t + \alpha_{2t}\, r_t + \alpha_{3t}\, \theta_t + \alpha_{4t} E_t\, \ln\big(y_t^p/y_t\big) + \gamma_1 NLA_{t-1}/y_t + \gamma_2 IFA_{t-1}/y_t + \gamma_{3t} HA_{t-1}/y_t + \gamma_{4t} \ln(hp_{t-1}/y_t) + lny_t - lnc_{t-1}) + \beta_{1t}\, \Delta\, ln\, y_t\; + \beta_{2t}\, \Delta\, nr_t + \beta_{3t}\, \Delta\, \theta_t + \varepsilon_t \tag{4}$$

This is an equilibrium correction equation for log real per capita consumption, with the deviation between lagged log consumption and its long-run solution in parenthesis (potentially other dynamics in the long-run fundamentals may enter an empirical specification). The speed of adjustment of consumption to changes in its drivers is given by λ. Credit conditions are included via terms incorporating loan standards for both mortgage and non-mortgage credit—$MCCI_t$ and $NCCI_t$ respectively. As before, the real interest rate is r. The γ parameters measure the MPC for each of three types of household asset and for housing affordability measured by the log of the ratio of house prices to income. The ratio of net worth to income is disaggregated into liquid and illiquid elements: NLA/y is the ratio of liquid assets minus debt to income, IFA/y is the ratio of illiquid financial assets to income, and HA/y is the ratio of housing wealth to income.[8] hp/y is the ratio of house prices to income. The term $\Delta\, nr$ measures the cash flow impact on indebted households of changes in nominal rates, where nr is the nominal interest rate on debt, DB.[9] As before, θ_t captures income uncertainty. The evidence from several countries is that the change in the unemployment rate is a good proxy for income uncertainty, or for a shift in income uncertainty. The term in the log change of current income allows for the empirical possibility that some households' spending growth follows current income growth more closely than is implied by Equation 2. The relevance for this term may also reflect the fact that some, perhaps less sophisticated, households take current income growth as an indicator of future income growth. Equation 4 embodies the most basic lifecycle model (i.e. Equation 2) as a special case.[10] Finally, the time variation in some of the parameters is captured by their time subscripts. This time variation is induced by shifts in credit availability, for either mortgage or non-mortgage credit. This potentially applies to the real and nominal interest rates, uncertainty, income expectations, housing wealth, and house prices. Each may be altered by interaction with credit loan standards.

An important feature of the extended consumption function is that it introduces a credit channel for monetary transmission, completely absent from DSGE models and those semi-structural models where balance sheet and credit effects on consumption are captured only by a net worth measure. There are two main ways by which this credit channel operates. First, by affecting the

[8] Balance sheet data are measured at the end of each quarter (which is effectively the same as measuring at the beginning of the next quarter). We use ratios of nominal balance sheet data to nominal income, rather than ratios of real per capita data, so that in effect the price and population deflators cancel in the numerator and denominator.

[9] It is possible that the weight on $\Delta\, nr$ could increase with the debt-to-income ratio but decrease with increased access to credit. One could formulate the equation to account for and test for these effects.

[10] Note that $\lambda = 1$; $\alpha_1\; = \alpha_{2t} = \alpha_{3t} = 0$; $\alpha_{4t} = 1$; $\gamma_1 = \gamma_2 = \gamma_{3t}$; and $\beta_{1t} = \beta_{2t} = \beta_{3t} = 0$ are the restrictions which result in Equation 2.

balance sheets of banks, for example through bad loans, interest rate changes feed through to credit conditions. Second, changes in interest rates affect asset prices and the portfolio composition of households, both of which can interact with credit conditions, changing their influence on consumption. The credit channel for monetary transmission is reflected in the consumption function through the direct and indirect effects of the two measures of credit conditions; through the different MPCs for net liquid assets (i.e. liquid assets minus debt), housing, and illiquid assets; through the cash flow effect for borrowers via nominal interest rates; and by allowing for possible parameter shifts in several variables stemming from credit market liberalization or tightening. To illustrate, credit market liberalization potentially should: (i) raise $\alpha_{1M}\, MCCI_t + \alpha_{1N} NCCI_t$, implying a higher level of lnc/y because the required saving for a housing down-payment is reduced and because consumer credit is more freely available; (ii) make the real interest rate coefficient, α_2, more negative as scope for inter-temporal substitution of consumption rises (to the extent that the real interest rate effect is dominated by such substitution); (iii) lower α_3 and β_3 on the uncertainty effects, because easier credit reduces concerns with income uncertainty (though higher debt levels could cancel this tendency); (iv) raise α_4 by increasing the scope for the impact of expected income growth by relaxing the borrowing constraint;[11] (v) increase the MPC from housing wealth, γ_3, given the greater access to home equity loans;[12] (vi) lower the current income growth effect, β_1, because there will be fewer credit-constrained households depending mainly on their current income; and (vii) lower the cash flow impact, β_2, of a change in the nominal rate, since refinancing might become easier. On the other hand, with higher debt levels, the cash flow impact would be likely to increase, cancelling the former tendency. This discussion highlights the multiple potential channels by which credit conditions, both directly and in interaction with the above-mentioned economic variables, influence aggregate consumption.

With measurable indicators of the degree of credit market liberality, CCIs, it is possible to make each potentially time-varying parameter a linear function of the CCIs and test these hypotheses about time variation. It is a practical question as to how many of these potential interaction effects are empirically detectable in a relatively short sample, in an economy subject to large shocks and other more permanent structural changes.

As a further point, Equation 4 satisfies long-run homogeneity in income and assets: that is, doubling both doubles consumption. The long-run coefficient on $ln\, y$ is thus set to 1, as in Equation 2, and hence it is not being estimated. Then the income endogeneity issue highlighted in Hall (1978) ceases to be of concern for the measurement of the long-run income effects.[13] For the asset-to-income ratios, these are dominated by the movements of volatile, *lagged* asset prices, so

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[11] On the one hand, easier credit conditions should make it easier for households to make inter-temporal trade-offs, e.g. by borrowing to boost consumption in advance of higher expected income. This would raise α_4. On the other hand, extending access to credit to poorer households previously financially excluded can result in the profile of borrowers shifting, increasing the proportion with hand-to mouth behaviour. This would lower α_4.

[12] A theoretical foundation in optimizing behaviour for this effect is provided by Berger et al. (2018). They present a model of a household facing collateral constraints and lumpy transactions costs, with a collateral effect of house prices on consumption, and where the size of the effect increases as the down-payment constraint is relaxed. This implies that the house price or housing wealth effect on consumption varies with credit conditions.

[13] This could be more of concern in an extension of the approach to equations for, say, non-durable goods, durable goods, and services, with long-run income elasticities different from 1. It could be advisable to calibrate rather than estimate these. Also, an equation for expenditure on durable goods would need to take into account stock adjustment: in other words, the tendency for expenditure to be higher when stocks are low.

that the endogeneity of income for these ratios is in practice largely irrelevant. The change in log income, $\Delta \ln y_t$, will be endogenous, and may be estimated with a slight bias, but with little impact on the long-run solution.

Finally, the far greater consistency of Equation 4 with the modern view of the micro foundations of macroeconomics than that of the representative agent lifecycle/permanent income theory is an important feature. This formulation of the long-run drivers of consumption is consistent with micro-evidence and buffer-stock theory that the MPC out of current income varies according to the asset position of households. As Crawley and Kuchler (2023) show, the MPC out of current income is highest for the asset poor, intermediate for those holding illiquid but not liquid assets, and lowest for the doubly asset-rich. This is consistent with the long-run solution of Equation 4, which implies the following expression for the MPC of an individual household:

$$\frac{\partial c}{\partial y} = (c/y)[1 - \alpha_{4t} - \gamma_1 NLA_{t-1}/y_t - \gamma_2 IFA_{t-1}/y_t - \gamma_{3t} HA_{t-1}/y_t - \gamma_{4t}] \qquad (5)$$

For a given value of α_{4t}, which captures how forward-looking a household is, one without financial assets or housing wealth but with debt will have the highest MPC as γ_1 is positive. This is reinforced by the fact that such resource-poor households will tend to have a high average propensity to consume, c/y. A household with no debt but with both types of financial assets and housing wealth will have the lowest MPC, reinforced by the fact that such households will tend to have lower values of c/y. Moreover, as γ_1, the MPC for liquid assets, exceeds the MPCs for less liquid assets and housing, where the fraction of the portfolio in liquid assets is high, the MPC will be lower.

The flexibility of equation 4 and its consistency with micro-evidence makes it a suitable candidate for consumption heuristics in agent-based models of the economy using micro data. In these models, plausible decision heuristics for the economic agents—households, workers, firms, banks, and policy makers—replace the extreme rationality and informational assumptions made, for example, in DSGE models.

2.2 Models for house prices, mortgage debt, and non-mortgage debt

Household portfolios are key determinants for consumption and therefore themselves need to be modelled. An equilibrium correction framework is adopted, in which adjustment to the long-run solutions implied by theory takes time. The house price index as well as mortgage debt and consumer debt are endogenized in our model in separate equations. The key determinants of these are current and permanent income (with a positive coefficient), credit conditions (positive for debt and house prices), uncertainty (with a negative coefficient), and the age composition of population. They are also determined by arbitrage opportunities, represented here by their corresponding interest rates, real or nominal (with a negative coefficient for debt and house prices). House price and mortgage debt equations also include housing user costs and the rate of property tax (with a negative coefficient).

The house price equation

The theory background for the house price equation is an inverted log-linear demand function. The inverse demand approach to deriving a house price equation is based on the idea that while the demand for the stock of housing depends on real house prices, income, and other demand shifters, the housing stock is relatively fixed in the short run, while house prices are highly endogenous. In the inverted demand function, real house prices are the dependent variable, rhp, driven by household demand factors, conditional on the lagged housing stock.

$$\ln rhp_t = h_0 + h_1 MCCI_t + h_{2t} \ln nmr_t + h_{3t} \ln user_t + h_4(ln(y_t/hs_{t-1}) + h_{5t}E_t \ln(y_t^p/y_t)) + h_6\, demog_t + h_7 \ln(LA_{t-1}/y_t) + h_8 \ln(IFA_{t-1}/y_t) + h_9\, spillover_{t-1} + h_{10}\, property\ tax_t \quad (6)$$

In this equation, the intercept term, $h_0 + h_1 MCCI$, captures shifts in demand, which should increase with mortgage credit conditions, represented by an index, $MCCI$. The nominal effective mortgage rate, taking amortization into account, is nmr, and user cost, measuring interest rates minus expected house price appreciation (which resembles a real interest rate), is $user$. Both effects should be negative and potentially could vary with $MCCI$. The possible time variation in these effects is captured by the time subscripts on the corresponding parameters. The parameter h_4 for the log ratio of income to the lagged housing stock[14], is expected to be positive; from theory, this measures minus the inverse of the price elasticity of demand for housing (see above). The coefficient h_{5t} captures the relative effect of permanent to current income, analogous to a similar term in the consumption function. The expected sign is ambiguous, as there are two offsetting influences. Consider the situation where future income flows are expected to be higher than current income. The demand for housing as a current consumption item, as 'shelter', would then suggest a positive coefficient. If, however, future income flows are expected to fall relative to current income, say because of retirement, then investing in housing is a means of saving for the future. This would imply the opposite sign.[15] In principle, either factor could vary with mortgage credit conditions, $MCCI$. The remaining potential drivers of the real house price are demography, liquid financial assets, illiquid financial assets, spillover effects from other housing markets,[16] and the rate of property tax (unless incorporated into the user cost measure).

The role of demography is mixed. On the one hand, the proportion or changes in the proportion of households in the younger, first-time buyer age groups could be a factor influencing house prices, mainly derived from housing demand as a consumption good. However, the portfolio demand for housing among middle-aged and pre-retirement households is likely to be high. This suggests that the proportion of households in this age group could also be a positive factor for house prices. In principle, demography and the income distribution should interact, as the purchasing power of the different demographic groups, as well as their size, could be relevant. In practice, lack of data typically makes this impossible to test.

The different components of portfolio wealth could also have dual roles: *ceteris paribus*, higher wealth, whether liquid or illiquid, should increase the consumer good demand for housing. However, higher financial wealth would tend to diminish demand for housing as a store of value. South Africa is unusual in that mortgage market regulations permit pension wealth (an illiquid asset) to be used as part of collateral for housing purchases. Increases in pension wealth, for example as a result of extending pension coverage or from the appreciation of financial assets, could therefore increase the demand for housing and hence house prices.

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[14] This formulation imposes the constraint that the income elasticity of demand for housing is 1.

[15] Note that house price expectations (of appreciation) are already embodied in the user cost term.

[16] Spillover effects from housing markets in other countries could have an impact on local house prices through the investment choices of foreigners.

The long-run relationship expressed in Equation 6, when empirically estimated, is embedded in an equilibrium correction form. Conventionally, this would imply that the dependent variable is the change in $\ln rhp_t$, with the lagged deviation between the left-hand side and the right-hand side of Equation 6, as a key driver, together with changes in the other regressors and potentially in other variables such as the inflation rate, employment, and the exchange rate. However, while the long-run relationship is formulated in real terms, implying no money illusion in the long run, 'nominal inertia' is often found in short-run dynamics—for example, because of lags in perceptions of the price level. Reformulating the dynamic relationship with the change in the log of the *nominal* house price index as the dependent variable would imply a coefficient of 1 on the current inflation rate on the right-hand side *if* market participants were fully aware of the current price level and were able to make decisions in 'real' terms. In practice, for several other countries (e.g. for France, Chauvin and Muellbauer 2018), the hypothesis is strongly rejected that the coefficient on the current inflation rate is 1 when the dependent variable is the change in the log of the nominal house price index: the empirical evidence is for a coefficient not far from zero. This convinced us to apply a more parsimonious form of the equilibrium correction equation for South Africa, with the change in the log of the nominal house price index as the dependent variable, and testing for a (close-to-zero) coefficient on the freely estimated current inflation rate.

The household mortgage and non-mortgage debt equations

In contrast to the vast literature on consumption, little systematic econometric work exists on either for mortgage or non-mortgage household debt (see the reviews in Fernandez-Corugedo and Muellbauer 2006, Meen 1990, and Muellbauer 2022). The canonical rational expectations-lifecycle model of the representative consumer has little to contribute to understanding the determination of aggregate household debt. That model features a single asset, so it can explain only the evolution of aggregate net wealth. In practice, consumers have multiple motives for holding debt, and these differ between mortgage debt and non-mortgage debt (which consists of credit card debt, overdrafts, personal loans, and finance to acquire durables like cars and furniture). Both mortgage debt and consumer debt are expected to be driven by the purpose of the debts.

Beginning with mortgages, the potential motives for acquiring mortgage debt include for housing as a consumption item (i.e. to acquire a roof over one's head) and investment in housing to support future consumption. Another motive concerns the buffer stock role of housing equity, e.g. using housing as collateral via access to equity withdrawal. Increasing a mortgage can support spending in the event of a short-term need for cash as a result of an income drop or a medical emergency. These multiple motives suggest that no simple theoretical model can adequately explain the demand for mortgages. Moreover, the impact of income growth expectations on acquiring a mortgage remains uncertain: the consumption aspect of housing suggests a positive effect, while the saving aspect—acquiring housing as an asset—suggests the opposite.

These motives translate into the drivers of the (log) mortgage debt-to-income ratio, and several could potentially vary with the MCCI. Since mortgage debt finances housing purchases, higher house prices should increase the need for mortgages, though with the proviso that some potential first-time buyers might be priced out of the market. Paradoxically, mortgage access could be restricted through the credit market in periods when house prices are very high relative to average income, effectively constraining mortgage demand. The demand for mortgages should be affected by the level of interest rates, nominal and/or real, and by income, both current and expected, giving a role for permanent income. With a higher volume of housing stock, a larger mortgage stock would be needed, suggesting the ratio of housing stock to income as one of the drivers of the ratio of mortgage debt to income. Other household portfolio components might also affect the aggregate demand for mortgages. When liquid asset holdings increase, households find it easier to provide mortgage down-payments, raising the demand for mortgages. More affluent households tend to dominate aggregate liquid asset holdings, however, so this may be less relevant for lower-income borrowers. Illiquid financial assets, to an even greater degree, are mostly held by affluent households. In principle, this could affect these households' portfolio investment demand for housing and hence mortgage acquisition, but in aggregate this is likely to be a small effect (see above). High levels of non-mortgage debt might discourage the acquisition of mortgage debt, but this depends very much on the distribution of such debt.[17] Demography plays a role, since in general a higher proportion of young households in the population might be expected to raise the demand for mortgages. The rate of property tax could be relevant, since high tax rates would increase the financial burden of taking on mortgage debt to acquire housing.[18]

These potential drivers give rise to a long-run solution as in Equation 7. We assume that the income elasticity of the demand for mortgages is 1, so that the long-run equation is formulated in terms of the log mortgage debt-to-income ratio.

$$\ln\left(mdebt_t/y_t\right) = m_0 + m_1\, MCCI_t + m_{2t} \ln nmr_t + m_{3t} \ln user_t + m_{4t} E_t \ln\left(y_t^p/y_t\right) + m_{5t} \ln\left(hp_{t-1}/y_{t-1}\right) + m_6 ln\left(hs_{t-1}/y_t\right) + m_7 demog_t + m_8 ln\left(LA_{t-1}/y_t\right) + m_9 \ln\left(IFA_{t-1}/y_t\right) + m_{10t} ln\left(nmdebt_{t-1}/y_t\right) + m_{11}\, property\ tax_t \quad (7)$$

where $mdebt/y$ is the real per capita mortgage debt-to-income ratio.[19] $MCCI$ is an indicator of credit conditions in the mortgage market; nmr is the nominal effective rate of interest, taking account of amortization; $user$ measures user cost, as previously explained; y^P/y is the ratio of permanent to current per capita real HDI; hp/y is the ratio of the real house price index to per capita real HDI;[20] hs/y is the ratio of housing stock to income; $demog$ is a demographic indicator; LA/y is the ratio of liquid assets to income and IFA/y the corresponding ratio for illiquid financial assets; $nmdebt/y$ is the ratio of non-mortgage debt to income; and $property\ tax$ is the ratio of property tax payments to housing wealth, a proxy for the tax rate.

The long-run relationship in Equation 7 is embedded in an equilibrium correction form, as for the house price equation above. The above discussion of nominal inertia for the house price equation applies also to mortgage debt, implying a dynamic formulation with the change in the log of per capita mortgage debt in current prices as the dependent variable. This is confirmed by testing for a zero effect of the current inflation rate.

The possible time variation in the effects of the nominal interest rate, user cost, permanent income, house prices, and liquid assets, via their interactions with the MCCI, is captured by the time

[17] Potentially, the availability of unsecured credit to help fund a mortgage down-payment is another factor that could influence the relationship between non-mortgage and mortgage debt.

[18] Transaction costs are another potential factor discouraging the taking on of mortgage debt, as they reduce the cash available for a down-payment (see Chauvin and Muellbauer 2018 for evidence on France). We lack time series data on variations in rates of transfer duty in South Africa, and so we did not control for this factor.

[19] Expressing instead the dependent variable as the per capita mortgage debt in real terms, i.e. nominal debt divided by the consumer expenditure deflator, and including y, the per capita real household disposable income, on the right-hand side allows one to test this formulation. If the income elasticity of mortgage debt is 1, this confirms that the dependent variable can be formulated as the log of the mortgage debt-to-income ratio.

[20] Given that the same deflator is used for both house prices and income, the ratio of real house prices to real income is the same as the ratio of nominal house prices to nominal income.

subscripts on the corresponding parameters. Credit market liberalization could impact in several ways on these long-run relationships, broadly analogous to the impacts discussed for the consumption equation. Whether some of these subtle parameter shifts can be empirically detected in a relatively short sample is questionable but requires testing. To illustrate, credit market liberalization: (i) will raise the intercept $m_0 + m_1\, MCCI$, implying a higher level of mortgage debt, mainly from the relaxation of the housing down-payment and debt-service constraints; (ii) could make the user cost coefficient, m_{3t}, more negative, while nominal interest rates become less binding with liberalization, making m_{2t} less negative;[21] (iii) could cause an upward shift in m_{4t}, as liberalization refocuses people's decisions away from the present and income expectations weigh more heavily; [22] (iv) could raise m_{5t}, if the down-payment constraint is relaxed through liberalization, making even more pronounced the usual effect of higher house prices relative to income increasing the demand for mortgages; and (v) could make m_{10t} less negative, capturing the influence of easier mortgage credit conditions on the constraining effect of having high non-mortgage debt. [23]

Turning to non-mortgage debt (mainly unsecured borrowing), the motives for acquiring such debt, which includes credit card and hire purchase loans, are to finance consumption spending and to smooth fluctuations in income. Since consumer credit is mainly used to finance consumption, especially of durables, one might expect the long-run expression for the stock of consumer credit to have similar drivers to those for consumption. These effects potentially include liquid and illiquid wealth, real and nominal interest effects, the ratio of house prices to income, the ratio of permanent to current income capturing income expectations, and demography. Again, credit market liberalization could impact these long-run relationships.

However, there is a caveat concerning wealth effects where there is a highly unequal wealth distribution (as in South Africa). In this case, the wealth effects found relevant for aggregate consumption are unlikely also be relevant for *aggregate* non-mortgage debt because of distributional issues. For individuals, the stocks of liquid and illiquid assets held in the previous period might have been expected to have an effect on current choices on acquiring consumer credit. However, since the distribution of borrowers for consumer credit is likely to be skewed towards lower-income households with few assets, in practice, wealth effects concerning consumer credit are likely to be small or insignificant. This observation may hold too for the mortgage debt equation but to a lesser degree, as those acquiring mortgage debt tend to be in the upper 50 per cent of the income distribution.

Interest rate effects would be expected, but whether a real interest rate or a nominal rate (reflecting cash flow constraints) is more relevant is an empirical question. Unsecured borrowing is often taken on to supplement mortgage borrowing. Hence, the house price-to-income ratio or its recent rate of change may have a positive effect on unsecured borrowing. Existing owner-occupiers can

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[21] Real interest rates, here in the form of user cost, have more to do with inter-temporal substitution and the best time to acquire a mortgage, while nominal interest rates are closely connected with current cash flows and the ability to finance a mortgage.

[22] On the other hand, in the context of South Africa, broadening access to mortgages to households who may be more credit constrained and less financially sophisticated could have the reverse implication.

[23] A higher level of non-mortgage debt relative to income reduces the ability of households to take on mortgage debt and also may make lenders more cautious about mortgage lending. It is possible that when mortgage credit conditions are more relaxed, this negative effect becomes somewhat less pronounced. In practice, in short samples, identifying such interaction effects empirically can be very demanding. Nevertheless, testing for such possibilities is advisable.

refinance more expensive non-mortgage debt by increasing their mortgage debt on the basis of higher housing collateral. Thus, higher levels of housing wealth relative to income could reduce non-mortgage debt. Given the high correlation between housing wealth and house prices, such level effects would be hard to detect. Income growth expectations and demography should be included, as for the mortgage debt equation.

These potential drivers give rise to the following long-run formulation for the log of non-mortgage debt to income:

$$\ln(nmdebt_t/y_t) = u_0 + u_1 NCCI_t + u_{2t} \ln ncr_t + u_{3t}\, rcr_t + u_{4t} E_t \ln(y_t^p/y_t) + u_{5t} \ln(hp_{t-1}/y_{t-1}) + u_6 demog_t + u_7 ln(LA_{t-1}/y_t) + u_8 \ln(IFA_{t-1}/y_t) \tag{8}$$

where ncr and rcr are the nominal effective interest rate (this includes the repayment element of credit finance) and real interest rates on consumer credit, respectively; the other variables are defined as for the equations above. The possible time variation in the effects of the nominal interest rate, real interest rate, real permanent income, and house prices, via their interactions with $NCCI$, is captured by the time subscripts on the corresponding parameters. The intercept term, $u_0 + u_1 NCCI$, increases with $NCCI$, the credit conditions indicator applying to consumer credit. For the nominal effective interest rate on consumer credit, ncr and the real rate rcr, potential interaction effects with $NCCI$, are likely to be in the same direction as those discussed for the mortgage debt equation, for interactions with $MCCI$. For permanent income, because demand for consumer credit is probably dominated by lower-income households, credit liberalization is less likely to raise the coefficient, u_{4t}. Credit liberalization for non-mortgage credit is likely to increase u_{5t}, because borrowing to supplement a mortgage becomes easier, increasing access to housing even though house prices have risen.

2.3 The latent variable approach to addressing credit conditions

Since the GFC, the important role of shifts in credit conditions in mortgage and housing markets has been increasingly accepted (see the literature survey on housing markets by Duca et al. 2021). Mortgage lenders face endemic asymmetric information. They use credit scores and information on income (e.g. from payslips) to assess the credit-worthiness of potential borrowers. To set credit terms and to ration credit, banks set limits on loan-to-value ratios, debt-to-income or debt service-to-income ratios, and use risk pricing (i.e. charging higher interest rates on riskier loans). Well-capitalized lenders who are optimistic about the economy and have a higher risk appetite may relax credit conditions without necessarily cutting mortgage interest rates. They will tolerate more lenient credit scores and permit borrowing at higher loan-to-value and loan-to-income ratios.

Central banks have several potential information sources from which they could track developments in evolving credit conditions in mortgage and credit markets. For example, a reduction in the spreads of new lending relative to banks' own funding costs can often signal easing credit conditions. Other potential information sources include loan-to-value and loan-to-income or debt service-to-income ratios, especially for first-time borrowers, who are the most likely to face credit constraints.

If such data were available over a sufficiently long period, a measure for mortgage credit conditions could be directly captured. In the US, the work by Duca et al. (2016) in modelling US house prices uses household survey data on the median loan-to-value ratio for first-time home buyers to track mortgage credit conditions. The Federal Reserve's loan officer survey and the ECB's bank lending survey are other sources of information on credit conditions both for mortgages and for consumer credit, but both have their limitations.[24]

More typically, such survey data are unavailable, or not available for sufficiently long periods. Rather than adopting the extreme assumption of no changes in credit conditions, and hence ignoring the important endogenous shifts within the several equations that define consumption, the housing market, and debt, as discussed above, an alternative approach could be adopted. One of these is a latent variable approach christened LIVES (the 'Latent Interactive Variable Equation System') (see Duca and Muellbauer 2014). In this approach, the 'latent variable' is a function of dummy variables which appears in multiple behavioural equations. Known changes in financial architecture and regulation provide priors that influence the selection of dummies.

This is the approach adopted in this paper. We follow the methodology applied in France by Chauvin and Muellbauer (2018). As there were no data available with which to measure credit conditions directly in France over the whole estimation period, Chauvin and Muellbauer (2018) use the latent variable approach to estimate mortgage and non-mortgage credit condition indicators from a system of six equations, for house prices, mortgage debt, consumption, non-mortgage debt, liquid assets, and permanent income. They found that credit conditions for unsecured credit and other non-mortgage borrowing evolve rather differently from those in the mortgage market. The credit condition indicators for housing and non-housing loans were specified as a linear combination of ogive dummies which make a smooth transition from 0 to 1 over eight quarters. The selection of dummies was guided by institutional information on credit market liberalization and tightening. In this paper, unlike in Aron and Muellbauer (2013), we follow Chauvin and Muellbauer (2018) in distinguishing between non-mortgage and mortgage debt.[25]

2.4 Introducing an income forecasting equation

Income expectations provide an additional channel through which interest rates and asset prices may affect expenditure decisions. We thus propose a forward-looking approach to modelling consumption, by incorporating income expectations through modelling permanent income.

Permanent income is defined as the constant stream of real income that corresponds to the present discounted value of expected future income streams. In the absence of uncertainty, a discount factor, δ, equalling $1/(1 + r)$, would apply, where the discount rate, r, is a real rate of interest for horizon k. With income uncertainty and liquidity constraints, however, the discount rate will be higher, as less weight is placed on a more uncertain, distant future.

[24] While the US senior loan officer survey has quarterly data back to 1966 for consumer credit conditions, used successfully for modelling consumption in Aron et al. (2012) and in Duca and Muellbauer (2014), tracking mortgage market credit conditions only began in 1990. Multiple changes in loans coverage by the survey, such as the extension of the survey to non-prime and then subprime lending, make it impossible to extract a continuous, comparable series. Furthermore, fluctuating non-bank sources of credit for mortgages in the US also contributed to the overall state of mortgage credit conditions (not included in the survey). The ECB bank lending survey began only at the end of 2002. However, it is not clear whether respondents are focusing only on non-price aspects of lending standards, or whether some also regard an across-the-board interest rate increase as an aspect of tightening credit.

[25] Aron and Muellbauer (2013) used a three-equation latent variable model for household debt, consumption, and permanent income to estimate a *composite* South Africa CCI covering both mortgage and non-mortgage debt, for 1971 to 2005. Another application of the latent variable method was by Fernandez-Corugedo and Muellbauer (2006), who used proportions of mortgages with high loan-to-value and loan-to-income ratios and aggregated debt data to estimate a mortgage CCI for the UK.

Following Campbell (1987), expected income growth can be defined as the log ratio of permanent income to current income. This can be closely approximated by an expression in logs of expected future, non-property incomes:[26]

$$\ln(y_t^P / y_t) = (\Sigma_{s=1}^{k} \delta^{s-1} E_t \ln y_{t+s} \,/\, (\Sigma_{s=1}^{k} \delta^{s-1}) - \ln y_t \qquad (9)$$

Muellbauer and Lattimore (1995) argue that a discount rate of the order of 20 per cent per annum is appropriate for discounting future cash flows used in practical household decision-making under income uncertainty and liquidity constraints. This discount rate is supported by micro-evidence.[27] This implies a quarterly discount factor of $\delta = 0.95$, corresponding to a quarterly discount rate of 5 per cent.

To construct the dependent variable of Equation 9, at time t, forward-looking data on per capita income are required k quarters ahead, otherwise estimation would have to stop k quarters before the end of a sample. Hence, outside forecasts at time t from a reliable source (e.g. a commercial source or the International Monetary Fund) are required to replace the missing data for per capita income for quarters that extend beyond the estimation period.

A reduced-form equation for the dependent variable should incorporate factors affecting aggregate demand and supply, such as the labour force relative to population, interest rates, and the terms of trade, and variables such as asset prices likely to reflect the expectations of market participants. From time to time, large structural shifts occur in economies—for example, with the onset of the GFC. These can be incorporated in the equation as shifts in the intercept or in the trend.

Since the purpose is to proxy household expectations based on the information available at the time, the effect of such shifts that could not have been anticipated needs to be removed and an assumption made about how quickly households became aware of the shift in fundamentals. For example, with hindsight, households were over-optimistic about future incomes before the onset of the GFC and then had to adjust their expectations downwards. It is important that this correction for early over-optimism is captured via some learning assumption about the new fundamentals in the estimate of log permanent income.

3 South African statistics, empirical equations, and credit conditions

3.1 Statistics and variable definitions and sources

The data used in this paper are defined in Table 1, where summary statistics and sources are also presented.

[26] Equation 9 is also equivalent to a weighted moving average of forward-looking income growth rates.

[27] This is consistent with the empirical micro-estimates by Hausman (1979) and Warner and Pleeter (2001) of discounts for future cash flows. This high rate is also used by the FRB-US model of the Federal Reserve (Brayton et al. 1997), and the ECB-BASE model.

Table 1: Data definitions and sources

Variable	Definition	Mean	Standard deviation	Minimum	Maximum	Data source
Consumption equation						
Dependent variable						
Δ log (real consumption per capita)	Constant price, seasonally adjusted, consumption per head	0.00415	0.00805	−0.0167	0.0312	Quarterly Bulletin for consumption data; Stats SA and World Bank for population data
Independent variables						
Log real per capita income minus log real per capita consumption	Log scaled income, divided by the consumption deflator and population, minus log real consumption per head	0.150	0.0259	0.105	0.208	Quarterly Bulletin for consumption data; Stats SA, and World Bank for population data; Appendix 1 for scaled income
Mortgage CCI	A function of ogive dummies, estimated within the equation system	0.270	0.136	0.00463	0.621	MCCI is estimated
Non-mortgage CCI	A function of ogive dummies, estimated within the equation system	0.597	0.143	0.0775	0.860	NCCI is estimated
Dummy pension reform	Ogive dummy making smooth transition from 2015 Q1 to 2016 Q4	0.155	0.351	0.00	1.00	Constructed
Log (permanent income/current income)	Log permanent income, constructed from real per capita scaled income, is the learning-adjusted forecast from a reduced-form equation	0.0552	0.0466	−0.0411	0.127	Sections 2.4 and 4.1; Appendix 1
Net liquid assets/income	Liquid assets minus debt, lagged, divided by scaled income	−0.313	0.121	−0.544	−0.0690	Quarterly household balance sheet data from the SARB; income data, Appendix 1
Illiquid financial assets/income	Illiquid financial assets, excluding pensions, lagged, divided by scaled income	0.990	0.230	0.596	1.36	Quarterly household balance sheet data from the SARB; income data, Appendix 1
Log (house price/income)	The log of the house price index divided by per capita nominal scaled income	0.629	0.195	0.310	0.992	House price index, Appendix 2; income data, Appendix 1
Interaction term MCCI × (housing wealth/income)	Mortgage CCI multiplied by ratio of housing wealth to scaled income, minus the 2000 Q1 value of the ratio; housing wealth is a volume index of the residential	0.0833	0.0721	-0.000160	0.293	House price index, Appendix 2; MCCI is estimated; quarterly residential capital stock data from the SARB.

	capital stock multiplied by the four-quarter moving average of house prices					
Δ log (employment)	Quarterly change in log of employment	0.00153	0.00645	−0.0229	0.0177	Quarterly Bulletin
Δ_8 (prime rate)	Two-year change in nominal prime rate of interest	−0.00733	0.0291	−0.0883	0.0450	Quarterly Bulletin
Δ (Power outages)	Quarterly change in Eskom power outages	10.8	137	−736	670	Eskom data from the SARB
Δ Dummy 1993 Q2	Plus 1 minus 1 dummy					Constructed
Δ Dummy 2009 Q4	Plus 1 minus 1 dummy					Constructed
Δ Dummy 2018 Q4	Plus 1 minus 1 dummy					Constructed
Dummy 2010 Q3	Impulse dummy					Constructed
House price equation						
Dependent variable						
Δ log (nominal house price)	Quarterly change in log of house price index	0.0194	0.0214	−0.0342	0.0808	Appendix 2 for house price index
Independent variables						
Log (real house price index)	House price index divided by consumption deflator	4.32	0.306	3.84	4.80	Appendix 2 for house price index; Quarterly Bulletin for consumption deflator
Mortgage CCI	A function of ogive dummies, estimated within the equation system	0.270	0.136	0.00463	0.621	MCCI is estimated
Trend	Linear time trend	225	32.8	169	281	Constructed
User cost	$usercost = 0.2 + PRIME - \varphi \times 4 \times \Delta log\ hp_{t-1} - (1-\varphi) \times [\Delta_4 loghp_{t-1} + a^1 \Delta_4 loghp_{t-5} + a^2 \Delta_4 loghp_{t-9} + a^3 \Delta_4 loghp_{t-13}]/(1 + a^1 + a^2 + a^3)$; where $a = 0.5$, $\varphi = 0.5$, and $PRIME$ is prime interest rate/100	0.250	0.0845	0.0239	0.425	Constructed: see Section 3.2; Quarterly Bulletin for the prime rate; Appendix 2 for the house price index
Log (permanent income/current income)	Log permanent income, constructed from real per capita scaled income, is the learning-adjusted forecast from a reduced-form equation	0.0552	0.0466	−0.0411	0.127	Sections 2.4 and 4.1; Appendix 1
Log (income/housing stock)	Log of the ratio of real scaled income to the residential capital stock measure from the National Accounts (per capita, constant prices, lagged one quarter)	−0.0906	0.185	−0.395	0.185	Quarterly residential capital stock data from the SARB; Appendix 1 for income

Property tax rate (ma4)	Local government revenue from property taxes on residential property divided by value of total housing wealth (see above) (expressed as a four-quarter moving average); prior to 1998 there are no data on the household component of property tax revenue, so total local government property tax revenue for these years was spliced to the household component in 1998	2.69	0.730	1.46	3.98	Property tax revenue after 1998 from the SARB; earlier from Government Finance Statistics (1994–2012 and 1946–93)
(SA–US long bond spread) (ma4)	Yield on SA government long bond minus SA inflation less yield on ten-year US government bond minus US inflation; inflation defined as four-quarter change in log consumer expenditure deflator	0.0172	0.0190	−0.0378	0.0517	Quarterly Bulletin and Federal Reserve Economic Data (FRED for US data
(Δ_4 log (house price))/4	Average quarterly change over four quarters in log of house price index	0.0201	0.0207	−0.0147	0.0789	Appendix 2
Δ log (consumer expenditure deflator)	Quarterly change in log of consumer expenditure deflator	0.0163	0.00940	−0.00507	0.0493	Quarterly Bulletin
Δ Dummy 1992 Q1	Plus 1 minus 1 dummy					Constructed
Δ Dummy 1992 Q3	Plus 1 minus 1 dummy					Constructed
Δ Dummy 1992 Q4	Plus 1 minus 1 dummy					Constructed
Δ Dummy 1993 Q1	Plus 1 minus 1 dummy					Constructed
Mortgage debt equation						
dependent variable						
Δ log (mortgage debt per capita)	Quarterly change in log of mortgage debt (in current prices) divided by population	0.0214	0.0222	−0.0196	0.0977	SARB for quarterly mortgage data; Stats SA and World Bank for population data
Independent variables						
Log (mortgage debt-to-income ratio)	Log of mortgage debt divided by scaled income	−1.02	0.183	−1.26	−0.609	SARB for quarterly mortgage data; Appendix 1 for income
Log (house price/income)	Log of house price index divided by per capita nominal scaled income	0.710	0.184	0.387	1.10	Appendix 1 for scaled income; Appendix 2 for house price index
Log (housing stock/income)	Minus the log of the ratio of real per capita scaled income to the residential capital stock measure from	0.106	0.0923	−0.000387	0.376	Quarterly residential capital stock data from the SARB; Appendix 1 for income

	the National Accounts (per capita, constant prices, lagged one quarter)					
Interaction term MCCI × log (housing price/income)	Estimated MCCI multiplied by deviation from 2000 Q1 of log house price/income	0.091	0.185	−0.185	0.395	Appendices 1 and 2 for scaled income and house price index
Log (permanent income/current income)	Log permanent income, constructed from real per capita scaled income, is the learning-adjusted forecast from a reduced-form equation	0.0552	0.0466	−0.0411	0.127	Sections 2.4 and 4.1; Appendix 1
Log (effective mortgage rate)	Effective mortgage rate defined as $PRIME/(1-(1+PRIME)^{-8})$, where $PRIME$ is the prime interest rate/100	−1.56	0.127	−1.73	−1.31	Quarterly Bulletin
Log (property tax rate) (ma4)	Local government revenue from property taxes on residential property divided by value of total housing wealth from household balance sheets (expressed as a four-quarter moving average); prior to 1998 there are no data on the household component of property tax revenue, so total local government property tax revenue for these years was spliced to the household component in 1998	2.81	0.691	1.49	4.31	Property tax revenue after 1998 from the SARB; earlier from Government Finance Statistics (1994–2012 and 1946–93)
Demography	Ratio of population aged 25 to 44 to population aged 20 and above	0.508	0.0174	0.486	0.540	World Bank
Δ_2 log (mortgage debt)	Two-quarter change in log per capita mortgage debt (in current prices)	0.0430	0.0416	−0.00907	0.165	SARB for quarterly mortgage data; Stats SA and World Bank for population data
Δ_4 log (income)	Four-quarter change in log real per capita scaled income	0.0170	0.0192	−0.0265	0.0551	Appendix 1 for scaled income
Δ Dummy 2003 Q4	Plus 1 minus 1 dummy					Constructed
Dummy 1997 Q4	Impulse dummy					Constructed
Dummy 2001 Q1	Impulse dummy					Constructed
Dummy 2002 Q3	Impulse dummy					Constructed
Dummy 2006 Q1	Impulse dummy					Constructed
Non-mortgage debt equation						
Dependent variable						

Δ log (non-mortgage debt per capita)	Quarterly change in log of per capita non-mortgage debt (in current prices)	0.0232	0.0214	−0.0201	0.110	SARB for quarterly non-mortgage data; Stats SA and World Bank for population data
Independent variables						
Log ratio of non-mortgage debt to income	Log of non-mortgage debt divided by scaled income	−1.15	0.152	−1.46	−0.821	SARB for quarterly non-mortgage data; Appendix 1 for scaled income
Non-mortgage CCI		0.597	0.143	0.0775	0.860	Estimated
Log (effective non-mortgage rate) (ma8)	Effective non-mortgage rate (eight-quarter moving average) is defined as $PRIME/(1-(1+PRIME)^{-3})$, where $PRIME$ is the prime rate/100	−0.849	0.0635	−0.935	−0.739	Quarterly Bulletin
Demography	Ratio of population aged 25 to 44 to population aged 20 and above	0.508	0.0174	0.486	0.540	World Bank
Δ_4 log (house price/income)	Annual change in log of house price index divided by per capita nominal scaled income, with house prices as defined above	−0.00296	0.0771	−0.165	0.228	Appendix 1 for scaled income; Appendix 2 for house prices
Δ Dummy 1993 Q2	Plus 1 minus 1 dummy					Constructed
Δ Dummy 1999 Q1	Plus 1 minus 1 dummy					Constructed
Dummy 1995 Q1+ Dummy 1995 Q2	Impulse dummy					Constructed
Dummy 2002 Q3	Impulse dummy					Constructed
Income forecasting equation						
Dependent variable						
Log (permanent income/current income)	Log permanent income is constructed from per capita constant price scaled income (see Equation 9), with k = 40 quarters and a quarterly discount factor of 0.95	0.0582	0.0314	0.00515	0.124	Sections 2.4 and 4.1; Appendix 1
Independent variables						
Trend	Linear time trend	225	32.8	169	281	Constructed
Present value of the 2008 trend shift	Present value of trend shift from 2008 Q3	16.9	19.6	0	60.3	Constructed
Present value of the 1994 trend shift	Present value of trend shift from 1994 Q3	60.4	32.6	6.55	116	Constructed

Log (real per capita income)	Log of per capita constant price scaled income	3.61	0.177	3.33	3.84	Appendix 1 for scaled income
Real prime rate (MA4)	Prime rate of interest divided by 100, minus annual change in log of consumer expenditure deflator (all expressed as a four-quarter moving average)	0.0662	0.0269	0.0254	0.135	Quarterly Bulletin
Log (TOT) (MA4)	Log of terms of trade, as a four-quarter moving average	4.44	0.163	4.21	4.71	Quarterly Bulletin
$\Delta_4 \Delta_4$ (prime rate)	Annual acceleration in nominal prime rate of interest, as defined above	0.000206	0.0313	−0.118	0.0683	Quarterly Bulletin
Log (house price/income)	Log of house price index divided by per capita nominal scaled income, with house prices as defined above	0.710	0.184	0.387	1.10	Appendix 1 for scaled income; Appendix 2 for house prices

Note: the sample for the statistics is 1992 Q1 to 2020 Q1.

Source: authors' construction based on sources listed in column 7; data published in the Quarterly Bulletin of the SARB are available from the SARB's website; where it is indicated that the SARB provided data, these data are not in the public domain.

The models use balance sheet estimates of disaggregated wealth data developed in Aron and Muellbauer (2006) and Aron et al. (2006, 2008), later adopted and adapted for ongoing publication and use in models by the SARB, as mentioned in the introduction.

One important data choice concerned the measurement of current income, y, in South Africa. The theoretical measure from the textbook lifecycle/permanent income theory of real per capita non-property income, y, consists of tax-adjusted income from paid and self-employment and transfers from the government. Matching theoretical concepts with the National Accounts, in practice, can be difficult. Tax-adjusted measures of non-property and property income are not directly available in National Accounts data (see Aron and Muellbauer 2013 on possible approximations). A second measurement issue concerns developing a proxy for the change in the unemployment rate, a possible indicator for $\Delta\,\theta$, the measure of changes in uncertainty. South African data on the unemployment rate are not fully comparable over time, as the survey methodology changed in the 1990s from an annual October household survey to the biannual Labour Force Survey, and from 2008 to the Quarterly Labour Force Survey. The rate of growth of employment proved a useful alternative proxy (with the opposite sign). Statistics South Africa (Stats SA) has corrected the raw data for several breaks in the sampling frame to obtain an employment index that can be validly compared over time.

Time-consuming investigations eventually unveiled important data errors in income, house prices, and population measures for South Africa. These three data issues are briefly described here, with further extensive discussion in Appendices 1 and 2.

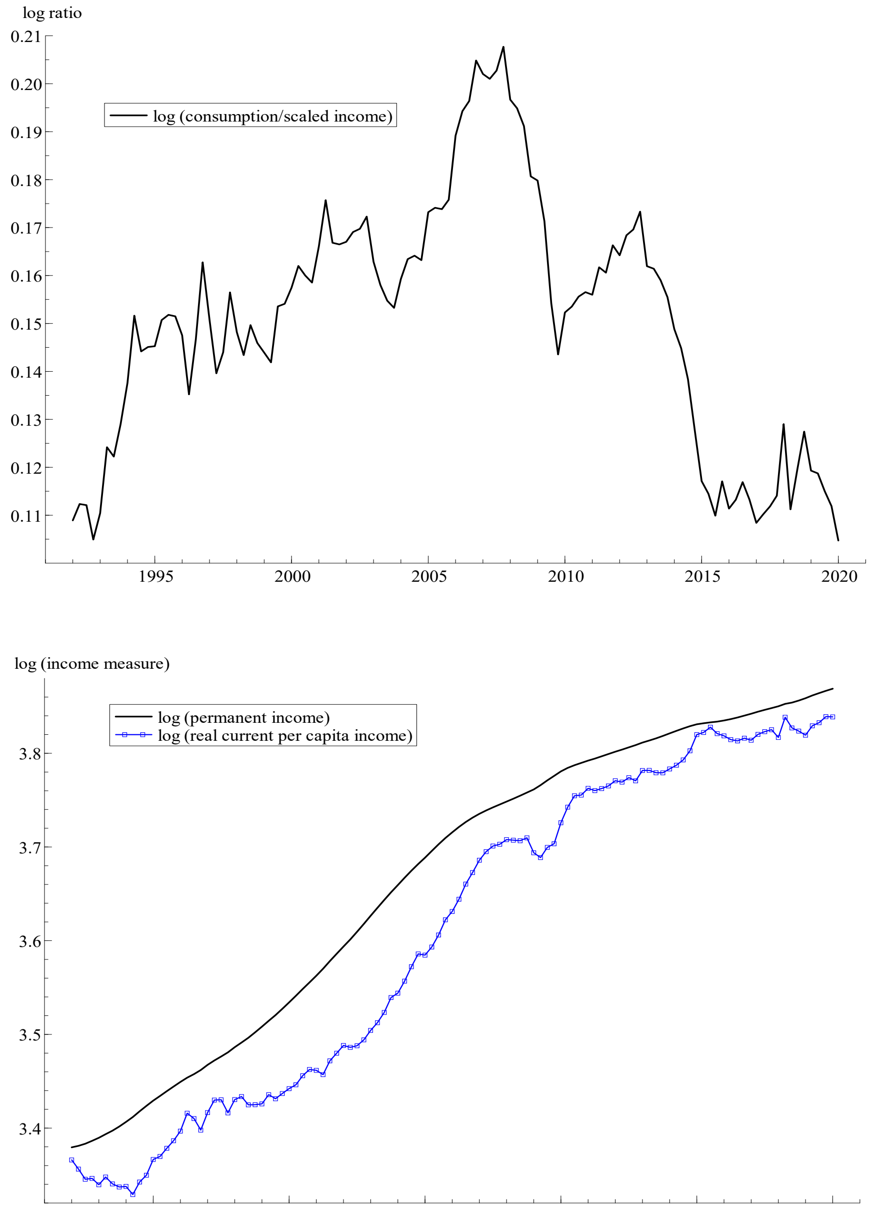
The first data error concerns the mismeasurement of household personal disposable income (HDI), referred to in the introduction using Figure 1. We established, after extensive investigation detailed in Appendix 1, that distortions have been introduced in the measurement of pre-1998 HDI, in the process of rebalancing the National Accounts in later years. We correct this error by splicing the HDI data in 1998 Q3 to an earlier data vintage from 2006, used in Aron and Muellbauer (2013), resulting in a far less noisy consumption-to-income ratio before 1998. As explained in Appendix 1, we also replace HDI with scaled income, which is a weighted average of after-tax labour income and HDI.

It proved more complex to find a reliable house price index. The index used internally at the SARB, based on the ABSA (Amalgamated Banks of South Africa) index before 2000 and then on a weighted average of ABSA data and data from other lenders, is seriously distorted. This is explained in Appendix 2. We replaced this index with a repeat-sales index from the data-purveying company, Lightstone, linked with earlier house price indices based on repeat sales, as explained in Appendix 2. This data correction also affected our measure of housing wealth, which is a volume measure of the housing stock scaled by the four-quarter moving average of our house price index.

The population data were also problematic. For population, we use annual mid-year data from Stats SA back to 2002 and splice it to World Bank/UN data for prior years. We use these data in preference to population data used internally at the SARB, which in some of the years has sudden jumps with implausible implications for the underlying net migration data (since births and deaths tend to be more stable).

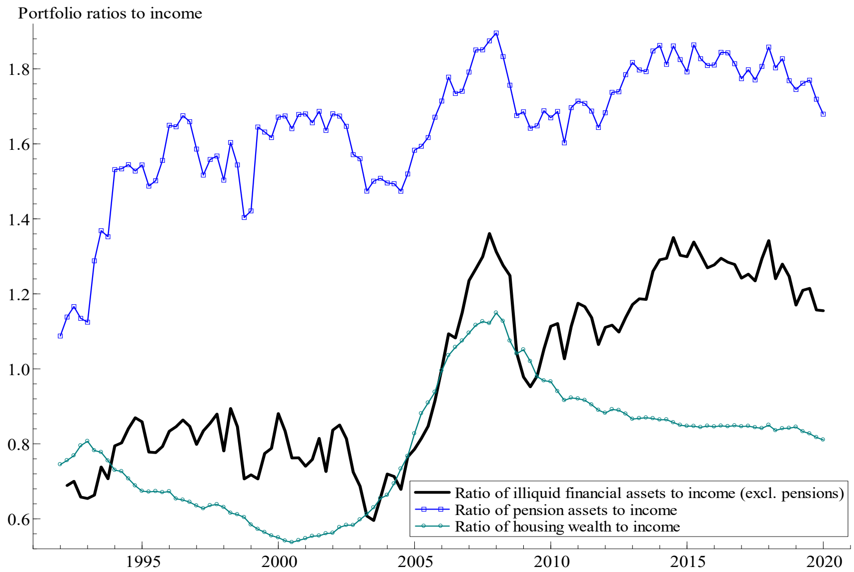
Figures 2, 3, and 4 each have three panels, which capture the variables underlying the regressions presented in this paper. These are: in Figure 2, the log of the ratio of consumption to income, log permanent income, and the log of the ratio of house prices to income; in Figure 3, the ratios of asset portfolio components to income and the log of the ratio of income to housing stock; and in Figure 4, the user cost, real prime rate of interest, and rate of property tax and demography.

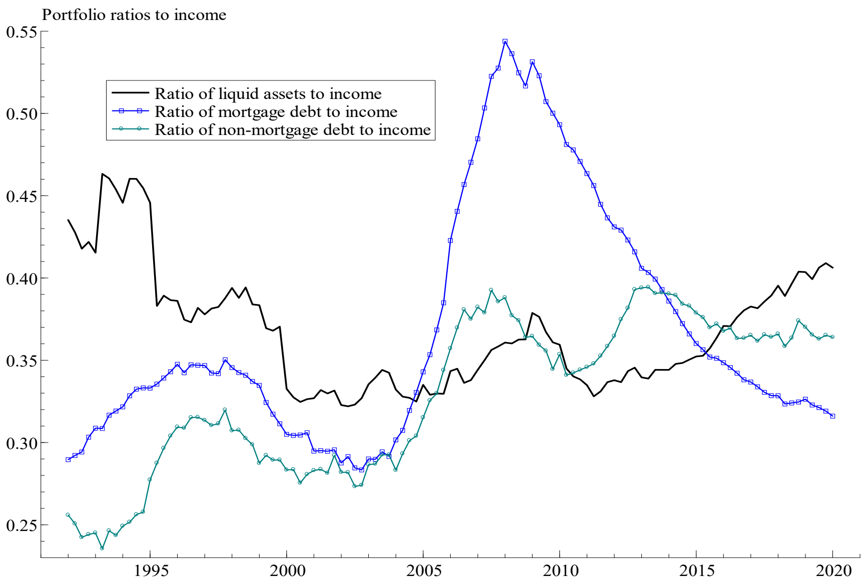
Figure 2: Panel of variables A

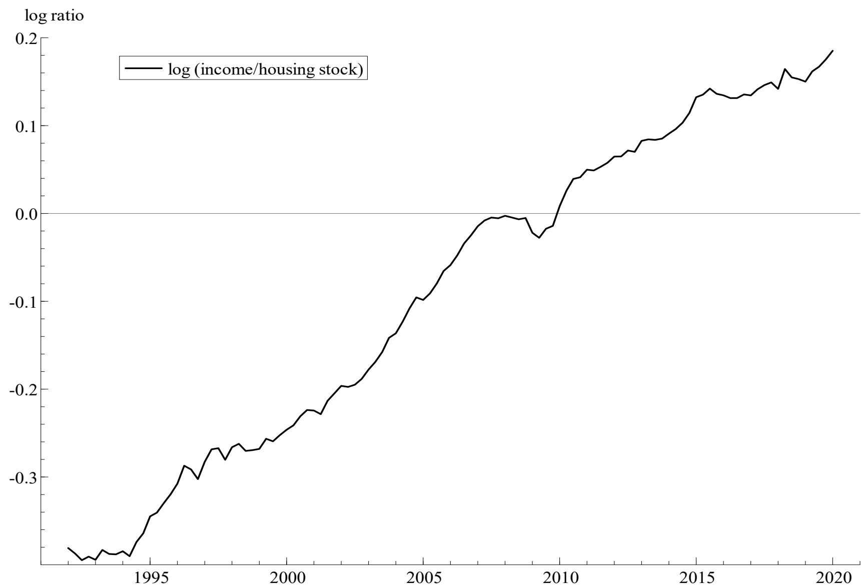


Source: authors' illustration based on data from Table 1.

Figure 3: Panel of variables B

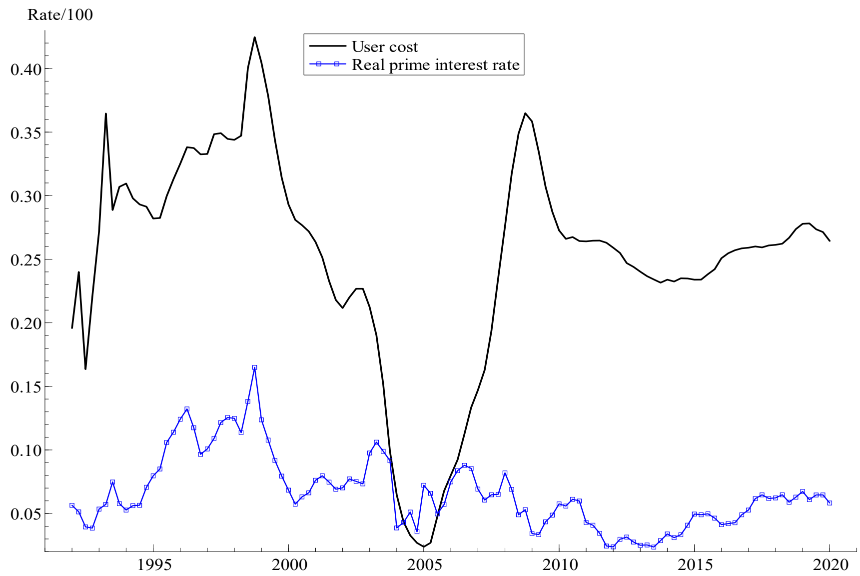


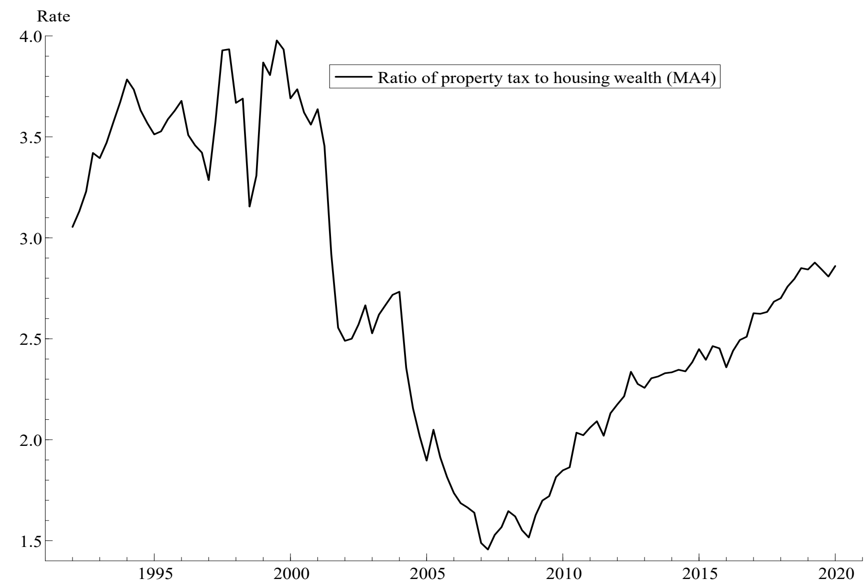


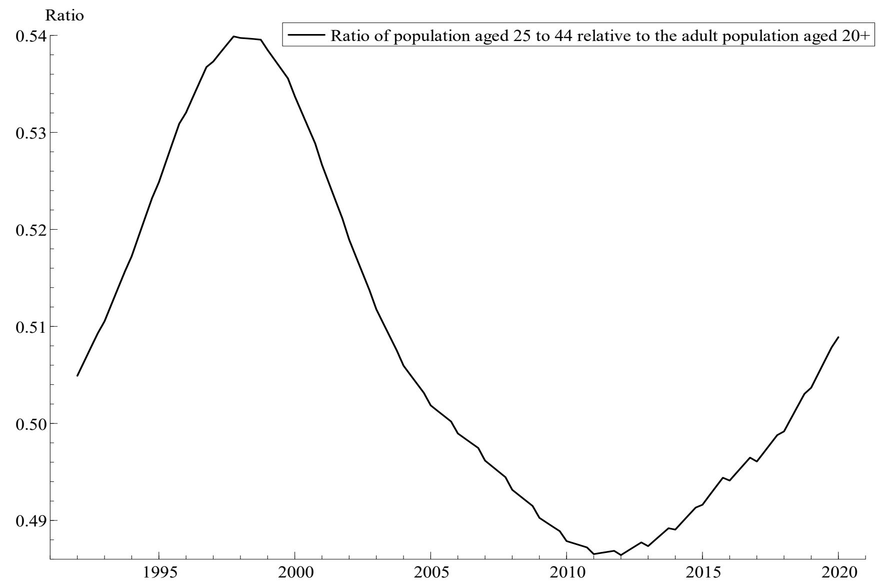


Source: authors' illustration based on data from Table 1.

Figure 4: Panel of variables C







Source: authors' illustration based on data from Table 1.

3.2 LIVES and Aron and Muellbauer (2013)

The most complete consumption function for South Africa corresponding to the above theoretical developments is found in Aron and Muellbauer (2013), analysing quarterly data for 1971–2005. It comes from a two-equation version of a 'latent interactive variable equation system'. They used the balance sheet estimates of disaggregated wealth data developed in Aron and Muellbauer (2006) and Aron et al. (2006, 2008).

The main empirical findings are in their table 3, corresponding to their equation 7 (a specific empirical version of Equation 4 above). The speed of adjustment, λ, was 0.45 per quarter and strongly significant. There was powerful evidence that the long-run ratio of consumption to income increased with greater access to credit. The negative effect of the real prime rate (measured as a four-quarter moving average) was strongly significant. The fitted log ratio of permanent to current income, capturing income expectations, was significant, and income expectations became more important with the easing of credit conditions.

Turning to the balance sheet estimates, the model found considerable heterogeneity for the estimated MPCs for the components of net worth: it implies around −0.11 to −0.16 for debt and 0.11 to 0.16 for liquid assets, while those for illiquid financial assets ranged from 0.022 to 0.028 and, at the peak of credit availability (since it varies with credit conditions), almost 0.1 for housing wealth. The implication is that liquid assets are far more 'spendable' than illiquid assets, and that debt has far more negative effects on consumption than the restrictive net worth formulation would have implied. Also, housing wealth does not act like a 'classical' wealth effect as in Equation 1, supporting the collateral interpretation of the 'housing wealth effect'.[28] In a boom, housing wealth rises strongly, but so does household debt.

[28] See Footnote 1.

3.3 A brief outline of the five empirical equations

For the **consumption equation**, the dependent variable is the change in the log of per capita consumer expenditure in constant prices. In the long-run equilibrium relationship for the log of consumer expenditure relative to income, the key drivers are the two credit condition indices (MCCI and NCCI); income growth expectations; the ratios to income of liquid assets minus debt, illiquid financial assets, and housing wealth; and housing wealth interacted with the MCCI, the indicator of mortgage credit conditions. The other important part of the long-run solution is 'housing affordability', proxied by the log ratio of house prices relative to income. After extensive testing of alternative dynamic specifications, the short-run dynamics are represented by the lagged rate of change of log consumption, lagged changes in the prime rate of interest, the lagged change in log employment, and the change in a measure of electrical power outages.

For the **house price equation**, the dependent variable is the change in the log of the nominal house price index. In the long-run equilibrium relationship for the log of real house prices, the key drivers are the MCCI; user cost; the log income per house measure; income growth expectations measured by the log ratio of permanent to current income; a measure of the rate of property taxes; and the spread between real long bond yields in South Africa and the US. The last of these is interpretable as an indicator of overseas investor demand for property in South Africa—the higher the spread, the lower the demand. The user cost term is defined as the prime rate of interest divided by 100, minus a weighted average of past house price appreciation,[29] plus a constant proxying a risk premium and transactions costs. Income per house is measured as real HDI divided by the previous quarter's housing stock, both from the National Accounts. The property tax rate is measured as the local government tax revenue from taxes charged on housing, divided by housing wealth.[30] As the tax revenue data are volatile, a four-quarter moving average is used. After extensive testing, the short-run dynamics are represented by the quarterly and annual changes in the lagged log house price index, the mortgage rate, and the current rate of consumer price inflation (measured by the four-quarter change in the log consumption deflator).

For the **mortgage debt equation**, the dependent variable is the change in the log of nominal mortgage debt per capita. In the long-run equilibrium relationship for the log of nominal mortgage debt relative to income, the key drivers are the MCCI; the log ratio of the lagged housing stock to income; the log of the nominal effective prime rate; income growth expectations measured by the log ratio of permanent to current income; the log ratio of house prices to income and its interaction with the MCCI; the property tax rate; and demography. The last variable is captured by the ratio of the population aged 25 to 44 to the adult population. After extensive testing, the short-run dynamics are represented by two variables: lags in the dependent variable, and the annual growth rate of income.

For the **non-mortgage debt equation**, the dependent variable is the change in the log of nominal non-mortgage debt per capita. In the long-run equilibrium relationship for the log of nominal non-mortgage debt relative to income, the key drivers are the NCCI, the indicator of non-mortgage

[29] Experimentation to decide the weights on the memory of past appreciation suggested using the average of the annualized appreciation for the last quarter and a declining weighted average of annual appreciation during the past four years; see Table 1 for details.

[30] These data provided by the SARB back to 1998 are spliced to data from government statistics on property tax revenue of local governments from all sources, including households. This assumes that the property tax revenue from households is a constant fraction of total property tax revenue before 1998, a plausible approximation judging from post-1998 data.

credit conditions; the log of the nominal effective prime rate;[31] and demography. As in the mortgage debt equation, demography is captured by the proportion of the adult population aged between 25 and 44. The short-run dynamics are represented by the lagged dependent variable and the four-quarter change in the log house price to income ratio.

In all four equations above, the finally selected specifications also include impulse dummies for outliers.

For the **income forecasting equation**, the dependent variable is the deviation of log permanent income from log current income, defined by Equation 9. The driving variables, apart from a trend and trend shifts, include the real prime rate of interest; the log terms of trade; log income; the log ratio of house prices to income; and a measure of the acceleration in the prime rate. The trend shifts take place in 1994 Q3, reflecting the peaceful democratic transition, and in 2008 Q3, reflecting the GFC and its aftermath. As neither shift was likely to have been predicted by households, we have removed the present value of these shift effects before these dates and assumed a learning process by which households then adjust their income expectations (see Table 1). The idea is to replicate what an econometrician might have been able to do at the time when faced with these large structural breaks.

3.4 What do we know about the evolution of credit conditions for South Africa?

Despite its importance, there is no general measure of changing credit conditions for South Africa. One way to obtain an aggregate CCI, or mortgage and non-mortgage CCIs, is to apply the LIVES method. Gathering as much ancillary information as possible about the likely evolution of credit conditions is important for identifying the latent variable(s) in the LIVES approach. Part of this ancillary information can be data for mortgage credit conditions from loan-to-value ratios and credit spreads, where available.

Evidence on credit conditions before 2003

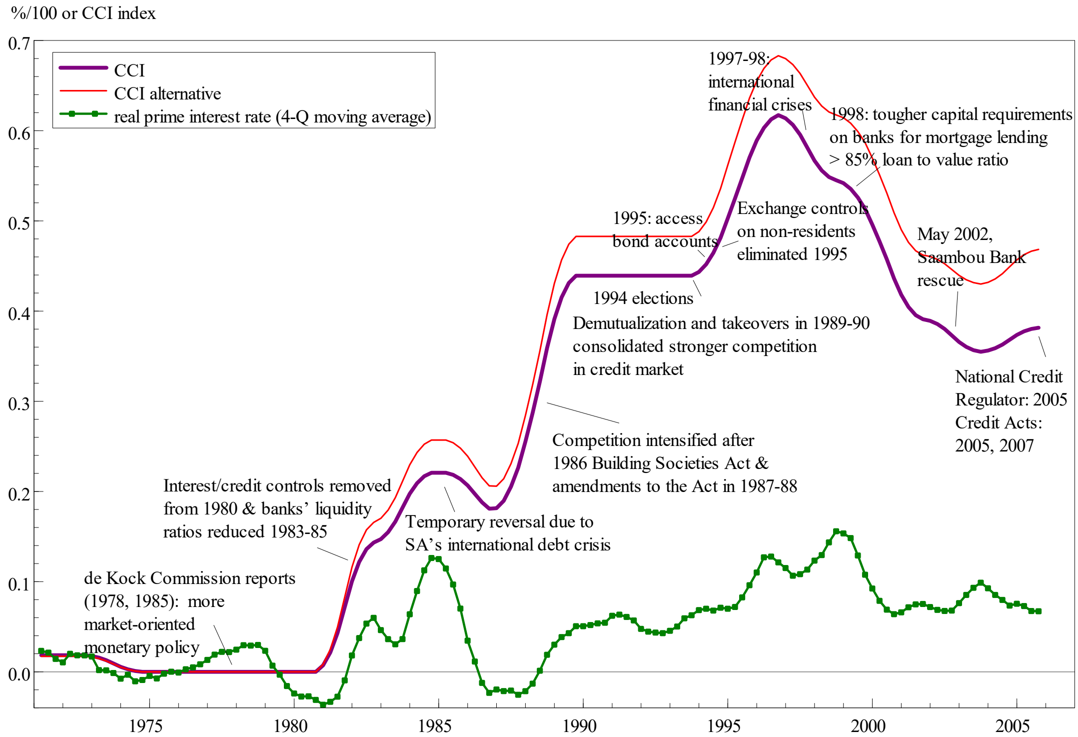
There is evidence on an *aggregate* CCI for 1971–2003 from Aron and Muellbauer (2013). There is also circumstantial evidence that throws some light on the likely different evolution of mortgage versus non-mortgage credit conditions from the early 1990s.

Estimation using the LIVES method in Aron and Muellbauer (2013), with a three-equation model and a latent variable to capture credit conditions, resulted in an estimate of an overall CCI for South Africa up to 2005.[32] Equations for consumption, total household debt, and permanent income were jointly estimated, using a latent variable composed of dummy variables. These dummies were selected with prior restrictions for periods when documented episodes of credit liberalization occurred. The estimated index in two variants is shown in Figure 5. The CCI has both an intercept effect, shifting up the average propensity to consume, and interaction effects (especially with the housing wealth to income ratio). This CCI measure was estimated for total debt, and as such is a mix of an index relevant for non-mortgage debt (NCCI) and an index for mortgage debt (MCCI).

[31] We assume that debt is amortized over three years; see Table 1.

[32] However, as consumption data after 2003 were subsequently upwardly revised, the estimates understate the rise in the CCI between 2003 and 2005.

Figure 5: Credit conditions index for South Africa and real interest rate to 2006



Source: reproduced from Aron and Muellbauer (2013).

Figure 5 covers the period 1971 to 2005. It suggests a liberalization of credit conditions in 1994–96, and tightening conditions in the emerging market crises that followed, including in South Africa's currency crisis in 1998/99. In the transition to democratic elections in 1994, there was pressure on lenders for greater financial inclusion of Black citizens. Transfers increased to the elderly and families with children, improving the credit-worthiness of many poor families. Initially, this probably resulted in a strategic switch by lenders from mortgage lending to other forms of credit. There was a large increase in unregulated unsecured lending which contributed to the failure of Saambou Bank in 2002 and seven other small lenders, with a peak in the aggregate credit impairment ratio of banks. The currency crisis and temporary rise in the prime rate to 24 per cent in September 1998 contributed to the high level of impairments. Possibly the 2002 bank failures led to a more cautious attitude among lenders regarding unsecured loans.

Evidence on credit conditions after 2003

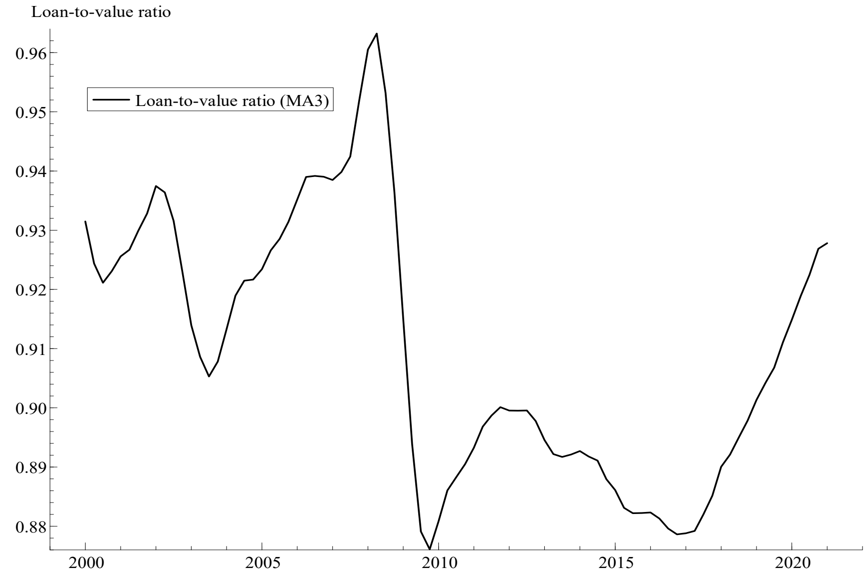
We have useful data on *mortgage* credit conditions from loan-to-value ratios and credit spreads, but there is only circumstantial evidence about *non-mortgage* conditions.

In the early 2000s, there was a strong economic recovery in the more stable environment of the new flexible inflation targeting regime. With falling interest rates, company profits rose strongly, resulting in large increases in deposits at banks, enabling lenders to increase credit provision and relax lending standards. There was a sustained drop in the credit impairments ratio. The 2005 National Credit Act reformed the legal framework and established the National Credit Regulator, putting non-mortgage lending on a sounder footing. Given the high deposit base at the banks, it seems likely that non-mortgage credit conditions were relaxed at this time.

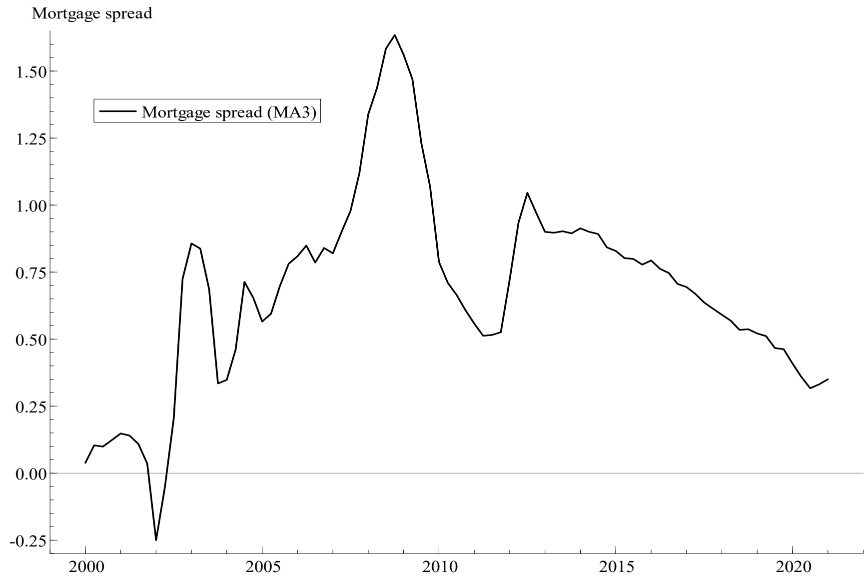
The GFC of 2008 resulted in credit tightening, especially given the elevated banking sector credit impairments. As the impact of the crisis was especially severe for the housing market, mortgage credit would have been particularly affected. Lending standards for unsecured lending were loosened substantially in around 2011, and the National Credit Regulator (NCR) raised concerns in March 2012 about reckless lending. This culminated in the failure of African Bank in 2014. With stringent bank supervision and regular stress testing of the banking system, non-mortgage credit was likely tightened.

Consistent with the broad picture outlined above, there is useful information from two indicators that are available from around 2000, closely related to credit conditions in the mortgage market. In Aron and Muellbauer (2022b) these were used to define proxies for the mortgage CCI. These proxies were used in three separate single equations for house prices, mortgage debt, and residential investment. The indicators are loan-to-value ratios and spreads between the actual mortgage rates paid and the base rate (or the interest rate on prime loans). Figure 6a illustrates the loan-to-value ratio and Figure 6b shows the mortgage spread.[33]

Figures 6a and 6b: Alternative measures of credit conditions



[33] The moving averages reduce the noisiness of the data but do not entirely remove a problem with the spreads data. An ambiguity is introduced because mortgage rates tend to respond with a short lag to a change in the policy interest rate. The prime rate moves in step with the policy rate. When the prime rate falls, the spread falls temporarily, and when the prime rate rises, the spread rises temporarily. However, in neither case does this signal a change in lending standards.



Note: the loan-to-value ratio is compiled from Deeds Office data by the First National Bank (FNB), and the mortgage spread is defined as the prime rate of interest minus the actual interest rate on new mortgage loans; both are shown as three-quarter moving averages.

Source: authors' illustration based on data provided by FNB on the loan-to-value ratio and by the SARB on the mortgage spread.

Together, Figures 6a and 6b suggest that mortgage credit conditions eased from about 2003 to 2008, followed by a sharp contraction associated with the GFC. After a modest recovery, there was renewed tightening until about 2016. From 2017 to 2021, the two graphs diverge, with the loan-to-value ratio trending upwards while the spread continues to narrow. Taken literally, the spreads data suggest continuing tightening of mortgage credit conditions from 2017, while the loan-to-value data suggest the opposite.

There are questions about the interpretation of loan-to-value data averaged over all mortgages versus applying only to first-time buyers. In the US, data on loan-to-value ratios for all mortgages show less of an association with evolving credit conditions than do data on loan-to-value ratios for first-time buyers (Duca et al. 2016). In the long housing market upswing from the late 1990s to 2006, many repeat buyers could use the increased equity in their homes to moderate the leverage needed to move up the housing ladder. Hence, average loan-to-value ratios in the US show far less of a rise than those for first-time buyers, many more of whom will have been credit constrained. In South Africa, credit constraints are prevalent among a greater fraction of all types of mortgage borrowers, and hence the average loan-to-value ratio may be a more reliable indicator of credit conditions than in the US. However, another problem in the measurement of loan-to-value ratios arises when house prices rise sharply. Because mortgages are based on lender-assessed valuations in the recent past rather than at the point the transaction occurs, when house prices rise sharply, the recorded loan-to-value ratio drops, because the recorded price is the transactions price rather than the lender's outdated assessment of value.[34]

Even with these provisos, the rise in the average loan-to-value ratio from 2017 is puzzling. Probably, with the low volumes of transactions after 2017, lenders were stricter about credit scores and income checks and so were able to offer higher loan-to-value ratios. Possibly, the fraction of

[34] When house prices fall, the bias goes in the opposite direction. This could explain some of the apparent rise in the loan-to-value ratio in 2010.

loans extended to borrowers able to access pension collateral increased. For such borrowers, lenders are able to offer higher loan-to-value ratios.[35] Overall, it seems likely from the joint information from loan-to-value ratios and spreads that post-GFC mortgage credit conditions were tighter, especially in an environment of tighter bank supervision and stress testing.

4 Empirical findings

4.1 The equation for log permanent income

The key variables in the log permanent income equation were given in Section 3.2. These were selected after testing down from more general specifications—for example, including a measure of the real stock market index and the real exchange rate. As the permanent income is necessarily a long forward-looking moving average of current real per capita income, it is unsurprising that smoothed versions of real interest rates and the terms of trade are found relevant. The former enters as a four-quarter moving average of the current year and the previous year's real prime rate, while the log terms of trade enters as a four-quarter moving average. A linear time trend with breaks in 1994 and 2008, and the log ratio of house prices to income are the other long-run drivers. A measure of the acceleration of the prime rate of interest is the only short-run variable selected.

Table 2 gives the parameter estimates for a sample from 1986 to 2020 Q1.[36] The log permanent income by construction is a weighted average of 40 observations of log income, and adjacent observations necessarily have a 38/40 overlap. Given the moving average nature of the dependent variable, the residuals are heavily serially correlated, biasing up the reported t-ratios as much as twofold; (see also the reported Lagrange multiplier (LM) tests. Visually, the fitted and actual perfect foresight measures of log permanent income are remarkably close (see Figure 7). The serial correlation is not a specification problem except for the reported standard errors and t-ratios. The parameter estimates are still consistent. Getting the best fit here is not necessarily the overwhelming objective, as we are trying to proxy what might have been in the mind of moderately well-informed households. Simple indicators such as terms of trade, real interest rates, and the house-price-to-income ratio and trends give a good fit: they do better than relying on, for example, ingredients of the consumer confidence survey from the Bureau for Economic Research.

[35] The Pension Funds Act (PFA) 1956 enables retirement funds to provide collateral for their members who would like to take out home loans, up to a maximum of 65% of their pension interest in the fund, though the actual percentage varies with specific fund rules. Borrowing directly from the fund is possible but subject to NCR registration and regulation. More common is the provision of security to a mortgage lender who receives monthly payments deducted by the employer from the member's salary and is then able to extend a mortgage at a lower loan-to-value ratio and/or lower interest rate than to borrowers without a pension-backed security.

[36] Pre-pandemic expectations of income growth from 2020 Q1 to 2030 Q1 were based on forecasts from Oxfordeconomics.com. However, as these substantially exceeded the three-year-ahead forecasts at the time from South Africa's Bureau for Economic Research, we halved the forecast growth rates from the former source.

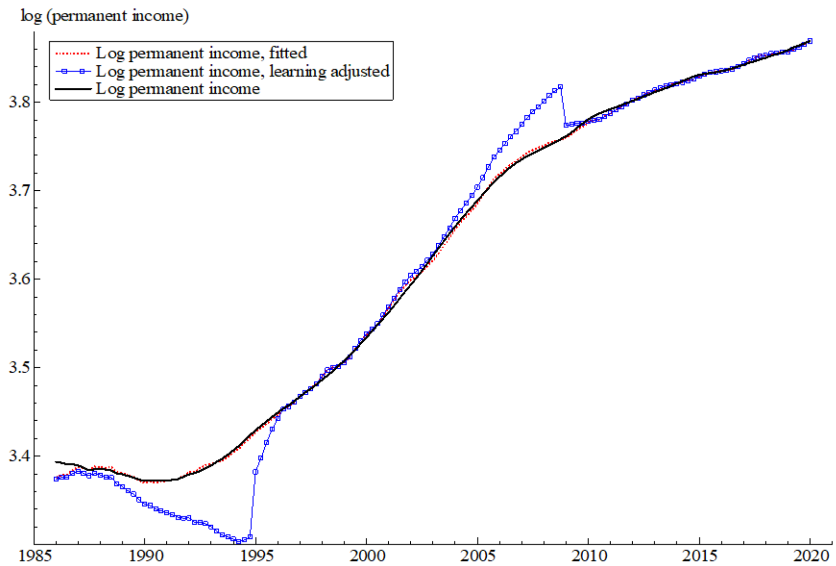
Table 2: Income forecasting model—results

Dependent variable: Δ log (permanent income) $_t$	1986 to 2020 Q1	
	Coefficient	t-statistic
Intercept	3.12	52.4
Trend	−1.63E-03	−10.1
Present value of the 2008 trend shift	−4.05E-03	−69.1
Present value of the 1994 trend shift	7.91E-03	34.9
Log (real per capita income) $_t$	−0.939	−54.0
Real prime rate (MA4) $_t$	−0.151	−9.29
Real prime rate (MA4) $_{t-4}$	−0.191	−11.1
Log (TOT) (MA4) $_{t-1}$	0.0629	6.93
Δ_4 Δ_4 (prime rate) $_t$	−0.0388	−4.38
Log (house price/income) $_{t-1}$	0.0355	15.0
Diagnostics		
Equation standard error		2.97E-03
Adjusted R-squared		0.995
LM het. test		25.4139 [.000]
Durbin-Watson statistic		0.256094

Note: single equation estimation performed in Time Series Processor (TSP) 5.0 (Hall and Cummins 2009); TOT denotes 'terms of trade'.

Source: authors' construction; see Table 1 for the definition of data sources.

Figure 7: Log of permanent income: actual, fitted, and adjusted



Source: authors' illustration based on results reported in Table 2, using data from Table 1.

There are clear breaks in the income process, with an improvement in trend growth after the democratic elections in 1994 and a peaceful transition, and a lower trend growth following the

GFC. As neither event would have been foreseen by households, the fitted values of forecast log permanent income are adjusted beginning 40 quarters earlier to remove the unanticipated breaks in the income process.[37] The aim here is to replicate what a forecaster would have been likely to forecast before each structural break. This implies that permanent income assessments would have been too pessimistic before 1995 and too optimistic before 2008. In each case, we assume a mix of quick and gradual learning. We assume that in 1994, half of the learning adjustment was instantaneous and the remainder took place over the following two years. In 2008, we assume that 70 per cent of the learning adjustment was instantaneous and the remainder took place over the following two years. In this context, the rational expectations approach, ignoring the huge forecast error everyone made just before the crisis, would not have been a good proxy for realistic income expectations.[38] Figure 7 contrasts the fitted value of log permanent income with the learning-adjusted level, suggesting that households may have underestimated permanent income by as much as 11 per cent in mid-1994 and overestimated permanent income by around 6 per cent in 2008 Q3.

An alternative approach could be to construct permanent income by running a one-sided Kalman or other filter, like a Hodrick-Prescott filter, through current income to extract the long-run, permanent income variable. However, it would then be hard to give the result an economic interpretation, and we put a high weight on economic interpretability. It would be difficult to handle the over- and under-optimism issue discussed above.

4.2 Credit conditions

We have fairly strong priors for the expected profile of the two credit indices, the mortgage and the non-mortgage CCIs, as discussed in Section 3.3, particularly for the mortgage CCI. Each CCI is a linear combination of ogive or smooth transition dummies, which increase gradually from 0 to 1 over eight quarters, following an S-curve. The signs on the expected coefficients are used to help eliminate those that violate these priors. After extensive testing, insignificant coefficients are sequentially eliminated. Model selection is not straightforward, as the starting point for each of the equations for consumption, house prices, and the two types of debt encompasses a range of possibilities—for example, whether interest rates enter in real or nominal form, the latter focusing on cash flow constraints faced by households. We also have some broad priors on speed of adjustment and on a few of the parameters based on international empirical evidence, which are helpful in achieving empirical identification.

[37] For robustness, we also checked an alternative model that included an earlier trend shift in the income process in 1990, following the release from prison of Nelson Mandela. Overall system estimates are very similar to those presented here.

[38] One question is whether a stochastic trend approach might have instead been feasible. Since the long-run drivers of permanent income are a mix of linear trends with breaks and some persistent and trend-like variables, the net outcome is necessarily not deterministic. The combination of linear trends with breaks—combined with a learning assumption about the new trend—provides a feasible way of handling the over-pessimism or over-optimism in expectations ahead of a major break in the income process. This would not have been feasible with a stochastic trend.

Table 3: Credit conditions—results

Variable	1992 Q1 to 2020 Q1		1995 Q1 to 2020 Q1		1992 Q1 to 2014 Q4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Non-mortgage CCI						
ND1992	0.569	3.62			0.630	3.26
ND1994	0.115	2.54			0.129	2.55
ND1997	−0.235	−4.15	−0.237	−4.41	−0.250	−3.65
ND2005	0.261	5.03	0.276	5.57	0.278	4.67
ND2011	0.111	2.61	0.116	2.77	0.120	2.44
ND2013	−0.356	−4.58	−0.328	−4.69	−0.399	−3.55
Mortgage CCI						
D1992	−0.570	−9.63			−0.540	−8.76
D1993	0.426	10.7			0.412	9.75
D1994	−0.223	−8.01			−0.204	−6.07
D1996	−0.121	−7.96	−0.122	−8.51	−0.113	−7.18
D1997	−0.089	−5.32	−0.088	−5.47	−0.080	−4.23
D1999	−0.030	−1.51	−0.044	−2.29	−0.023	−1.12
DM2002 Q1	−0.042	−2.21	−0.044	−2.41	−0.050	−2.63
D2002	0.241	8.33	0.234	8.19	0.237	7.94
D2003	0.188	6.56	0.168	5.79	0.181	6.08
D2005	0.123	5.25	0.114	4.47	0.127	5.39
D2007	−0.228	−11.2	−0.220	−10.6	−0.212	−8.77
D2012	−0.065	−5.65	−0.069	−6.25	−0.0584	−4.05

Note: ND(year) and D(year) denote, respectively, coefficients on smoothed transition dummies which are 0 before the beginning of the year and reach the value of 1 eight quarters later; DM2002 Q1 denotes the coefficient on a step dummy that is 0 before 2002 Q1 and 1 from 2002 Q1 onwards, proxying the effect of the Saambou Bank failure; OD is the ogive or smooth transition dummy and SD is the split dummy, 0 before 2002 and 1 from the first quarter of 2002; the two equations are:

$$NCCI_t = \sum_{1992}^{2018} ND_i \, OD_{it}$$

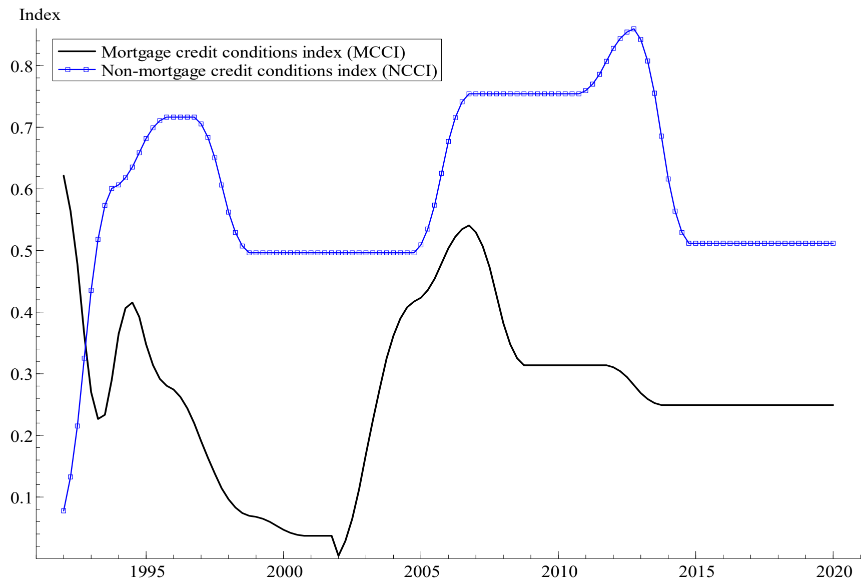
$$MCCI_t = \sum_{1992}^{2018} D_i \, OD_{it} + (\text{DM2002 Q1}) \, SD_{2002}$$

Source: authors' illustration based on system estimation reported in column 1 of results Tables 3 to 7 and single equation estimation for log permanent income reported in Table 2.

The final estimates of the coefficients on the ogive dummies are reported in Table 3, and the fitted values are graphed in Figure 8. The evidence suggests that in the 1992–95 period, there was indeed a switch from mortgage to non-mortgage lending, and a relaxing of lending standards for the latter, in line with the strong desire to improve financial inclusion for Black households.[39] In the emerging market crisis of 1997/98 and its aftermath in South Africa, credit conditions tightened across the board. After the bank failures of 2002, there seems to have been a temporary tightening of mortgage credit conditions, followed by successive relaxations as the economy grew and as the deposit base of banks expanded. Non-mortgage credit conditions, however, remained subdued for some years after 2002. Mortgage lending standards appear to have been at their most relaxed late in 2006. In 2005 to 2006, after the enactment of the National Credit Act, non-mortgage lending standards relaxed too.

Credit tightening in the GFC was sharpest for mortgages, with little change for non-mortgage lending. Indeed, in around 2011 there was renewed relaxation of lending standards for non-mortgage lending, probably mainly for unsecured lending. After the NCR's warning about reckless lending practices in 2012, and then the failure of the African Bank in 2014, credit appears to have been tightened for non-mortgage credit as well as for mortgages. The new emphasis on financial stability at the SARB after the GFC, with tougher supervision and regular stress tests for the banking system, probably helps to explain the continued tightness of both types of credit conditions.

Figure 8: Mortgage and non-mortgage credit condition indices for South Africa



Source: authors' illustration based on results reported in Table 3, using data from Table 1.

In the introduction, a link was made between restrictive lending behaviour by banks and high levels of non-performing loans (NPLs) held. The fact that CCIs prove useful in forecasting NPLs is an endorsement of the LIVES modelling approach and lends credibility to the estimated indices. This also confirms the important role that the indices play in the credit cycle. For France, Muellbauer (2022) demonstrates strong performance of the two CCIs (estimated in Chauvin and Muellbauer 2018) in forecasting the NPL ratio of French banks, both one and two years ahead. In a parallel

[39] This is broadly consistent with the flat profile found in the years 1990–94, for overall estimated credit conditions, based on an analysis using *total* household debt in Aron and Muellbauer (2013). The stronger rise in both CCIs in our current estimates compared with a small rise in the composite CCI reported in our 2013 paper reflects the subsequent upward revision of the consumption-to-income ratio compared with the 2006 (SARB) vintage data we were then using.

investigation for South Africa,[40] we find that the estimated values of NCCI and MCCI are both highly significant, together with four economic variables,[41] in forecasting a related concept—the credit impairment ratio for South African banks. For South Africa, successful forecasting requires lags up to four years for the CCIs, similar to the lags found for France.

4.3 The consumption equation

Our new credit-augmented consumption function has key roles in its long-run solution for the two CCIs (mortgage and non-mortgage), for disaggregated household portfolio wealth effects including housing wealth, housing affordability, and also for permanent income and current income. Remarkably, though the sample period from 1992 to 2020 is so different from that covered by Aron and Muellbauer (2013), the estimated speed of adjustment from the new model is similar, at over 0.4 (see Table 4), suggesting a well-determined long-run solution. Estimates of the MPC out of net liquid assets, at around 0.14 over different samples, are in line with the range in our earlier study. That study included pension wealth in the measure of illiquid financial assets, finding an MPC of around 0.025. In the current study, if we had imposed the same constraint, the coefficient on illiquid financial assets including pensions would be 0.018. However, testing for the separate effects revealed that the estimated MPC out of pension wealth was zero for the more recent sample. The result is therefore a higher coefficient in the current study, for illiquid financial assets excluding pensions, of around 0.04. A possible explanation for a zero effect of pension wealth in South Africa is the role that pension wealth plays as a source of funding for a mortgage down-payment. For affected households, the risk that their pension entitlement could be cut in the event of a mortgage default would make them more cautious about spending on current consumption in anticipation of their funded retirement pension. However, while the fit is a little worse when pensions are included in illiquid financial assets, most other parameters in the system are little changed—a welcome sign of robustness.

A major difference from our earlier findings concerns the role of permanent income, measured as the log ratio of permanent to current income. The lower value of the current estimate of around 0.45 is broadly in line with evidence from France in Chauvin and Muellbauer (2018), and for Italy in de Bonis et al. (2023). As with our current study, both of these studies used a learning-adjusted concept of permanent income to take into account structural breaks that could not have been anticipated. Aron and Muellbauer (2013) used a simpler measure of the fitted value of permanent income, without taking into account the over-pessimism of income expectations in the pre-1995 period. Yet this makes a major difference to the measurement of income growth expectations (see Section 4.1). Another improvement in the current model over our 2013 model is the explicit control for housing affordability, in the form of the log house price–income ratio, as well as for housing wealth (as in Chauvin and Muellbauer 2018 and de Bonis et al. 2023). Commensurate with those studies, the negative effect on aggregate consumption of raised house prices relative to income is statistically significant, as is the positive effect of higher housing wealth. Aggregate consumption sums that of house-owners and non-owners. For the latter, those aspiring to purchase a house through a mortgage need to save more when house prices rise relative to income. Moreover, as rents tend to follow house prices, renters are likely to be more cautious about spending when house prices rise relative to income. These effects lower the consumption of the

[40] Details are available from the authors on request.

[41] There are pre-pandemic data on the credit impairment ratio for 2002–19. The four variables are the recent log ratio of house prices to income (−), recent real interest rates (+), recent growth in real GDP per head (−), and recent level of power outages (+), with the signs on the economic variables in parenthesis (and these are as expected). For example, the negative coefficient for the log ratio of house prices to income, as found for France, signals that a slump in house prices relative to income exacerbates credit impairment.

non-owners. On the other hand, for those who already own a house, housing wealth rises with house prices, which allows greater consumption through equity withdrawal, if not immediately then in the future.

Table 4: Consumption model—results

Dependent variable: Δ log (real consumption per capita) $_t$	1992 Q1 to 2020 Q1		1995 Q1 to 2020 Q1		1992 Q1 to 2014 Q4	
	Equation 1		Equation 2		Equation 3	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Long-run coefficients						
Speed of adjustment	0.419	13.4	0.446	12.3	0.428	13.2
Intercept	0.100	7.18	0.087	3.89	0.115	7.26
(Mortgage CCI) $_t$	0.039	2.15	0.036	1.25	0.037	2.12
(Non-mortgage CCI) $_t$	0.118	4.05	0.115	4.12	0.092	3.43
Dummy pension reform	-0.030	-6.62	-0.027	-5.98	-0.030	0.000
Log (permanent income/current income) $_t$	0.463	11.5	0.515	11.3	0.426	10.9
(Net liquid assets $_{t-1}$ /income $_t$)	0.141	4.02	0.102	2.71	0.140	4.09
(Illiquid financial assets $_{t-1}$ /income $_t$)	0.042	3.99	0.041	3.49	0.038	3.73
Log (house price/income) $_{t-1}$	−0.103	−4.90	−0.098	−3.47	−0.112	−5.20
Interaction term: MCCI × (housing wealth $_{t-1}$ /income $_t$)	0.331	7.33	0.308	6.12	0.329	7.20
Log (real consumption per capita) $_{t-1}$ − log (income) $_t$	−1		−1		−1	
Short-run coefficients						
Δ log (real consumption per capita) $_{t-1}$	0.107	2.32	0.134	2.55	0.170	3.78
Δ log (employment) $_{t-2}$	0.102	2.21	0.111	2.28	0.125	2.80
Δ_8 (prime rate) $_{t-1}$	−0.044	−3.83	−0.044	−3.65	−0.034	−3.09
Δ (Electrical power outages) $_{t-1}$	−4.05	−2.22	−3.98	−2.12	−0. 128	−0.129
Diagnostics						
Equation standard error		0.00261		0.00267		0.00237
Adjusted R-squared		0.894		0.881		0.919
LM het. test		[.406]		[.386]		[.518]
Durbin-Watson statistic		2.00		2.02		2.08
AR1/MA1 LM test		[0.943]		[0.910]		[0.661]
AR4/MA4 LM test		[0.211]		[0.317]		[0.115]

Note: system estimation by maximum likelihood performed in TSP 5.0 (Hall and Cummins 2009); interaction term is in the form $MCCI_t \times x_t^*$ where $x_t^* = x_t - x_{2000Q1}$. The square brackets denote p-values for the LM tests.

Source: authors' construction; see Table 1 for the definition of data sources.

The evidence from the estimated model supports the collateral interpretation of the housing wealth effect. This is because an interaction effect between the MCCI and the ratio of housing wealth to income (i.e. easier credit promotes home equity withdrawal) dominates the housing wealth effect, interpreted like a classic financial wealth effect, and is highly significant. The point estimate of the freely estimated MPC out of housing wealth—that is, other than through the interaction term—is around 0.03. However, the precise value cannot be accurately pinned down as the standard error is three times as large as the coefficient. Clearly, the multicollinearity between housing wealth, house prices, and *MCCI* precludes precise estimation of this effect. For simplicity, we set the effect to zero.

Another new element in the long-run solution is a control for the 2014 pension reform,[42] which appears to have raised the saving rate by nearly three percentage points, other things being equal. We assume that the effect was not instantaneous but took two years to achieve a full adjustment, represented by one of the ogive dummies rising from 0 to 1 between the beginning of 2014 and the end of 2015.

Given that real interest rates play an important role in the permanent income equation and are therefore indirectly relevant through income expectations, it is not surprising that no significant direct real interest rate effect on consumption was found. However, the cash flow role of the change in the prime rate proved highly significant, with the empirical evidence supporting a lagged two-year change in the prime rate (the t-ratio is −3.8). The other controls for short-term dynamics include the lagged dependent variable, the lagged change in log employment, and the change in a measure of Eskom power outages—especially relevant in more recent years, when they became more protracted and widespread.

Testing for some of the other interaction effects suggested as theoretical possibilities in Section 3.3 led to no significant findings. For example, while in theory easier credit conditions should enhance the role of income growth expectations, this effect is clearly absent in South Africa. The coincidence of easier credit conditions with the financial inclusion of many poorer Black households with relatively short expectation horizons could be the explanation for this. There is also little evidence of shifts over time in the marginal effect on consumption of changes in the prime rate of interest. While easier credit conditions should allow borrowers to refinance to avoid the cash flow impact of higher interest rates, the higher debt levels that follow easier credit conditions increase the cash flow impact. Probably the two tendencies approximately cancel out.

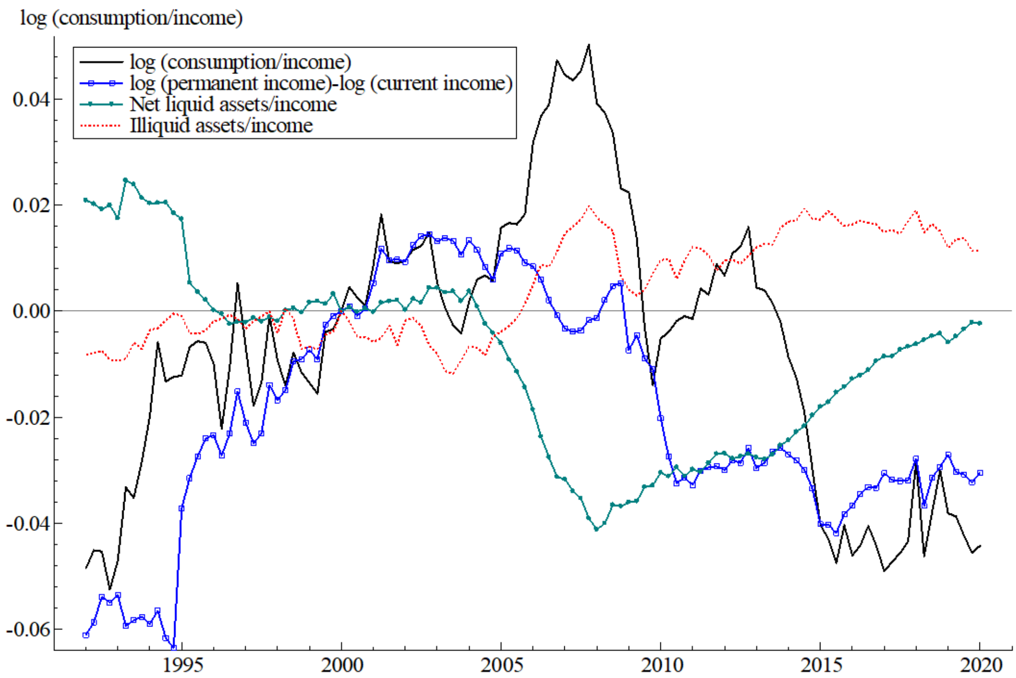
Parameter stability looks very satisfactory. Table 3 shows estimates for the periods 1995–2020 and 1992–2014. The model appears to have been able to capture the momentous changes in politics and the economy in the years 1992–94. Parameter estimates are also stable for the period 1992–2014, and they are almost all within one standard error of the full sample estimates.

For economic interpretability of relative magnitude of the various effects over time, the decompositions of the long-run effects of the various long-run drivers on the consumption-to-income ratio are shown in Figures 9 and 10. Figure 9 suggests that much of the rise in the consumption-to-income ratio from 1992 to 1996 was due to the relaxation of non-mortgage credit

[42] In 2014, the Treasury announced a set of retirement reforms, continuing proposals first made in 2012. These included making it mandatory for all employers to provide a retirement fund for their employees and removing the option for fund members, on withdrawing from a fund, to take the entire amount as a tax-free lump sum. Reforms designed to improve the portability and transparency of funds and to lower charges should also have made investing in such funds more attractive. These reforms, not all immediately implemented, are likely to have raised the household saving rate.

conditions, while Figure 10 suggests that more optimistic income expectations also played an important part in 1994–96. Figure 9 explains a major part of the rise in the consumption-to-income ratio from 2000 to 2007 in terms of the composite effect of the interaction of housing wealth and MCCI, not entirely offset by the negative effect of a higher house price-to-income ratio, together with the direct effect of the easier mortgage credit, joined in 2005/06 by easier non-mortgage credit conditions. These effects, added together, over-explain the rise in the consumption-to-income ratio. The offsetting factor is seen in Figure 10, which shows that the rise in debt in the 2000s, seen in the decline in net liquid assets, had a major effect in constraining consumption, offsetting the spending boost that came from easier credit and the house price boom.

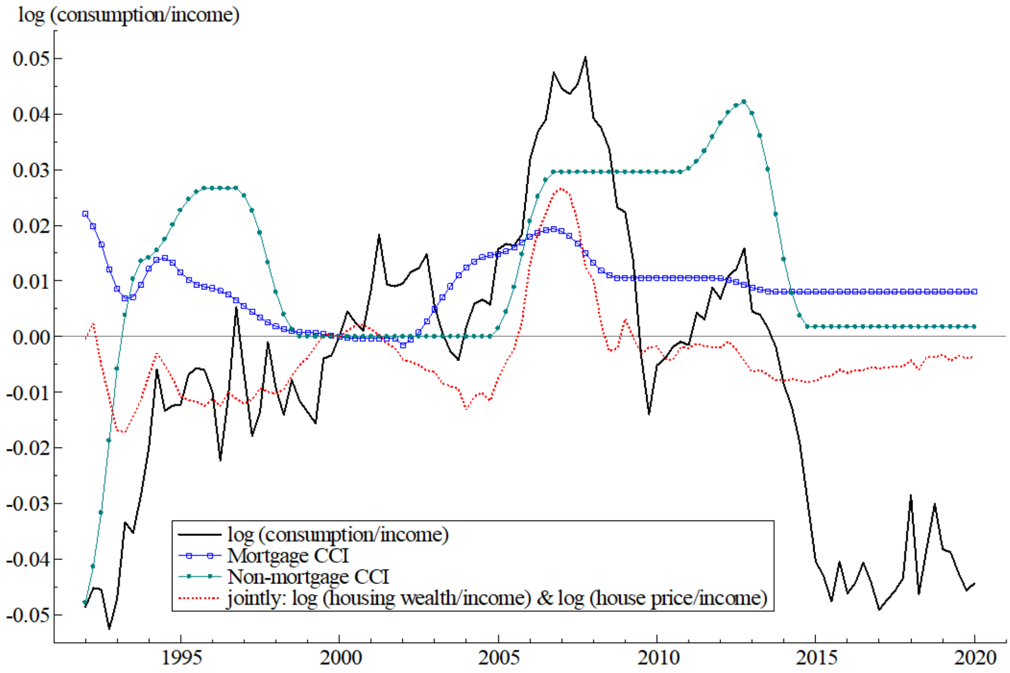
Figure 9: Fitted contributions to the log consumption-to-income ratio of net liquid assets and illiquid financial assets relative to income and log permanent income minus log current income



Note: log permanent income minus log current income is a measure of income expectations; illiquid financial assets excludes pensions.

Source: authors' illustration based on results reported in Table 4, using data from Table 1.

Figure 10: Fitted contributions to the log consumption-to-income ratio of the CCIs, and the composite effect of the log (housing wealth/income) interacted with MCCI and log (house price/income)



Source: authors' illustration based on results reported in Table 4, using data from Table 1.

The sharp fall in the consumption-to-income ratio after 2008 is explained by a combination of tighter mortgage credit conditions interacted with housing wealth, much more pessimistic income growth expectations, and a fall in financial wealth relative to income. A temporary partial recovery thereafter is connected with the temporary easing of non-mortgage credit conditions, the renewed fall from 2014 is mainly due to the 2014 pension reform (accounting for almost three percentage points of the fall in the consumption-to-income ratio), and tighter credit conditions in both debt markets. However, household de-leveraging seen in the rise of liquid assets minus debt relative to income since 2008, and the post-crisis recovery of stock markets seen in the rise of illiquid financial assets relative to income, provide some counter-balance to the above negative effects.

4.4 The house price equation

Estimation results for the house price equation are shown in Table 5. In the long run, house prices are driven by the ratio of income to the housing stock, income growth expectations in the form of the log ratio of permanent to current income, user cost, the property tax rate, the South Africa–US real long bond spread (a proxy for perceptions of risk) and a linear trend. The quarterly speed of adjustment is around 0.1, similar to a US estimate in Duca et al. (2016) and a little lower than the French estimate in Chauvin and Muellbauer (2018).

As explained in Section 3, the house price equation is based on an inverted demand framework in which, assuming an income elasticity of demand for housing of unity, the ratio of income to the housing stock plays a central role in capturing the supply-demand balance. For South Africa, this ratio is very trend-like (see Figure 3, last panel), making it hard to pin down precise estimates in the long-run solution for house prices. We therefore adopted a coefficient value of 1.7, the midpoint of international estimates, broadly in the range 1.4 to 2 (see Cavalleri et al. 2019).[43] However, tests also find a strongly significant, negative effect of a linear time trend, implying that measured income relative to measured housing stock has grown too fast to give a good explanation of the rise in real house prices, given the other factors. There are at least three interpretations: one is underestimation of the growth of the housing stock. This could be because the National Accounts failed to fully capture RDP (Reconstruction and Development Programme) housing or small-scale building, e.g. of shacks in back yards and informal settlements, or because the perpetual inventory method of measuring the housing stock used too high a depreciation rate.[44] A second interpretation could be due to an omitted demographic trend such as high levels of emigration by professionals in response to increasing crime. A third interpretation is in terms of the effective income of people acquiring housing: the composition of households acquiring housing could have changed because some of the affluent emigrated and because of an influx of young, poorer people into the cities, some of whom would have ended up buying less expensive houses. Then the growth of average per capita income from the National Accounts could be overstating the relevant income growth of those acquiring housing. A related possibility is that once Apartheid-era restrictions on movement were abandoned, people were better able to locate to where housing and infrastructure were available, so that there was a less bad match between the supply and demand for housing, analogous to increasing the effective supply of housing, hence a negative trend.

A highly significant driver in the long-run solution is user cost, which in our measure is effectively a real interest rate, using a proxy for expected house price appreciation to adjust the nominal prime rate.[45] Figure 4 (top panel) contrasts the user cost with a conventional measure of the real prime rate, subtracting the annual consumer price inflation rate from the prime rate. This reveals the important role of the proxy for past house price appreciation. The large fall in user cost in the 2000–05 period is dominated by recent house price appreciation.[46] No evidence could be found of an interaction effect between MCCI and user cost, though one might have expected more liberal credit conditions to have enhanced the effect of expected appreciation by allowing households higher levels of gearing. No significant evidence could be found either for the effective nominal mortgage rate, incorporating amortization of debt. This is different from France, with its largely fixed mortgage rate environment, where longstanding regulatory limits on the debt service-to-income ratio imply that lower nominal interest rates increase the amount of debt borrowers can take on, increasing the demand for housing. The lack of such limits in South Africa, and its floating rate environment, are consistent with the absence of such a nominal interest rate effect.

Income growth expectations, captured via the log ratio of permanent to current income, proved highly significant, with a coefficient around 0.9, compared with the coefficient of 1.7 on log income (entering via the housing stock to income term). It is interesting to calculate the relative weight of log permanent income to log current income, as this gives an indication of how forward-looking households are. A relative weight of 0.55 is calculated (0.9 divided by 1.7). This contrasts with a

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[43] An alternative value of 1.5 would give very similar results for the whole equation system, mainly raising a little the speed of adjustment in the house price equation. This indicates the robustness of the overall conclusions to the calibration of this parameter.

[44] We are grateful to Tsholofelo Shumba for information on the construction of the capital stock of residential housing.

[45] The level of user cost gives a slightly better fit than the log version, but the overall system results are very similar. Hence, non-linearity is unlikely to be a serious issue.

[46] Our measure (see Table 1) over-weights more recent appreciation, especially in the most recent quarter. It incorporates a measure of average appreciation over the last four years with a fading memory of past appreciation, with the lowest weight on annual appreciation four years ago.

relative weight of 0.45 for the consumption equation.[47] This suggests that on average, home buyers are more forward-looking than households in general.

The rate of property tax proved to have a strongly significant negative effect on real house prices. The last of the long-run level effects is the real long bond spread between South Africa and the US. We interpret this as a proxy for the perceived riskiness of South African assets, and when the rate rises, foreign investor demand for housing falls. The overall quantitative importance of these effects is discussed below.

The short-run dynamics include last quarter's rate of appreciation of house prices, with a positive sign, and the quarterly rate of appreciation averaged over the last year, with a negative sign. The difference between the two could be interpreted as a kind of shock or news on house price developments. Allowing these two terms to be freely estimated also gives some flexibility to the interpretation of the user cost, which incorporates past appreciation. Finally, there is a small effect from the current inflation rate, though far below the coefficient of 1 that would be relevant in the absence of nominal inertia. This could also suggest that investing in housing as an inflation hedge is of only very limited relevance in South Africa.

The only outlier corrections were in 1992 and 1993 and enter in the form of changes in impulse dummies. These probably suggest that the timing of quarterly changes derived from the Loos-FNB measure of the repeat-sales house price index are not exactly right.[48]

Parameter stability is strong over the three different samples shown in Table 5, and the fit is good.[49] However, one drawback is that the Durbin-Watson statistic indicates the presence of significant positive residual autocorrelation. Probably this arises because in the process of constructing repeat-sales indices, a degree of smoothing in the data has been introduced. This is likely also to have resulted in an upward bias in the coefficient on last quarter's change in the log of the house price index, and probably in a downward bias in the estimated speed of adjustment, but with little consequence for the long-run solution itself.

[47] For France, Chauvin and Muellbauer (2018) find a lower relative weight on permanent relative to current income in the house price equation. One interpretation is that the saving motive for acquiring housing in France is greater than in South Africa, where the consumption motive is more important. Note that in periods of negative income growth expectations, the desire to save would be greater.

[48] As Appendix 2 explains, the Loos-FNB measure for this period is derived from a graphic of four-quarter percentage changes, and small timing errors can arise in the process of digitalization.

[49] By contrast, attempts to estimate a similar model with the house price index used internally at the SARB reveal equation standard errors to be three times as large.

Table 5: House price model—results

Dependent variable: Δ log (nominal house price)$_t$	1992 Q1 to 2020 Q1		1995 Q1 to 2020 Q1		1992 Q1 to 2014 Q4	
	Equation 1		Equation 2		Equation 3	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Long-run coefficients						
Speed of adjustment	0.0945	10.6	0.101	9.69	0.100	9.43
Intercept	5.52	41.4	5.56	48.1	5.65	26.9
Mortgage CCI (fixed coeff.)	1		1		1	
Trend	−0.00405	−8.37	−0.00380	−8.37	−0.00472	−5.50
(User cost)$_t$	−0.896	−4.55	−1.09	−5.28	−0.931	−4.36
log (permanent income/current income)$_t$	0.937	6.98	0.911	7.37	0.802	5.10
log (income/housing stock)$_{t-1}$ (fixed coeff.)	1.7		1.7		1.7	
Property tax rate (ma4)$_{t-1}$	−0.0378	−3.47	−0.0413	−3.81	−0.0451	−3.67
(SA−US long bond spread) (ma4)$_{t-1}$	−0.884	−4.89	−0.919	−5.15	−0.898	−4.56
log (real house price)$_{t-1}$	−1		−1		−1	
Short-run coefficients						
Δ log (nominal house price)$_{t-1}$	0.742	10.52	0.631	7.81	0.711	8.90
(Δ_4 log (house price)$_{t-1}$)/4	−0.334	−6.97	−0.318	−5.74	−0.326	−6.15
Δ log (consumer expenditure deflator)$_t$	0.050	2.47	0.051	2.50	0.063	2.83
Diagnostics						
Equation standard error		0.00164		0.00162		0.00180
Adjusted R-squared		0.994		0.994		0.994
LM het. test		[.439]		[.860]		[.960]
Durbin-Watson statistic		1.27		1.28		1.25
AR1/MA1 LM test		[0.00]		[0.00]		[0.00]
AR4/MA4 LM test		[0.00]		[0.00]		[0.00]

Note: system estimation by maximum likelihood performed in TSP 5.0 (Hall and Cummins 2009); square brackets denote p-values for the LM tests.

Source: authors' construction; see Table 1 for the definition of data sources.

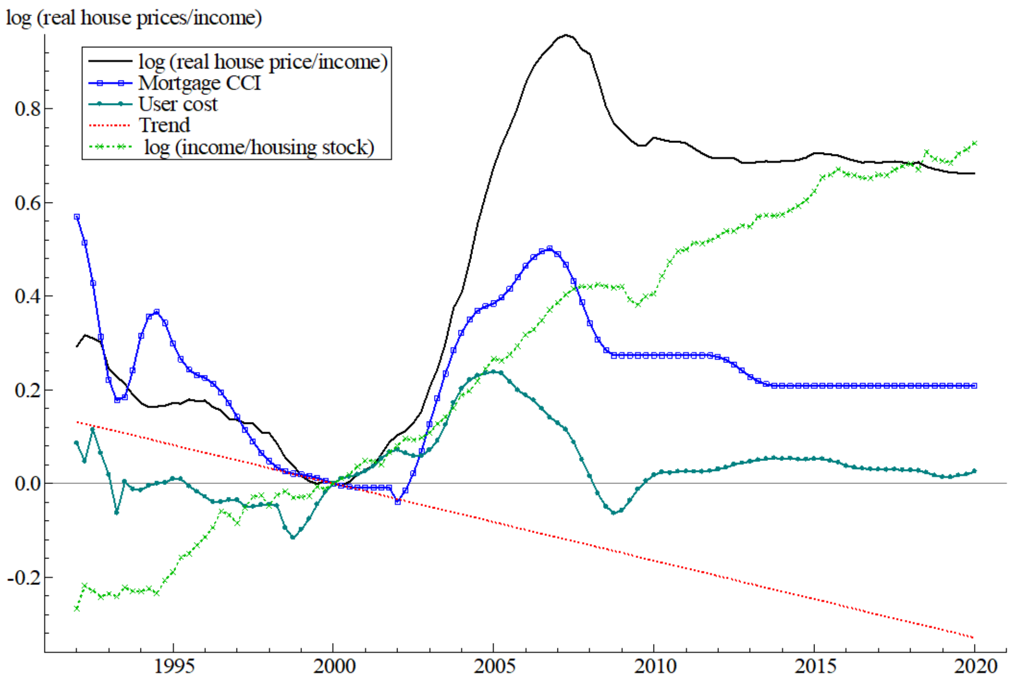
One qualification to these conclusions needs to be made. The rise in house prices in 1991/92 implied by the index from Loos, shown in Figures A2.1 and A2.2, is arguably implausibly large.[50] It is possible that the 1991 repeal of the Group Areas Act released demand for relatively lower-price properties in urban areas, causing large percentage rises in the prices of such properties. With

[50] This follows from comments gratefully received from Johan van den Heever and John Loos.

sparse data for this period from the Deeds Office used to construct the repeat-sales house price index, it is possible that the index was then less representative than usual of the entire market. This could have resulted in an overstatement of the rate of increase of the index in 1991/92 and of its level in 1992. This would imply that the estimated level of the *MCCI* in 1992 and its subsequent decline were overstated. If there is merit in these arguments, the reported results in the tables of estimates for consumption and debt, as well as for house prices, for the period 1995 Q1 to 2020 Q1 should be regarded as more robust than for samples beginning in 1992 Q1.

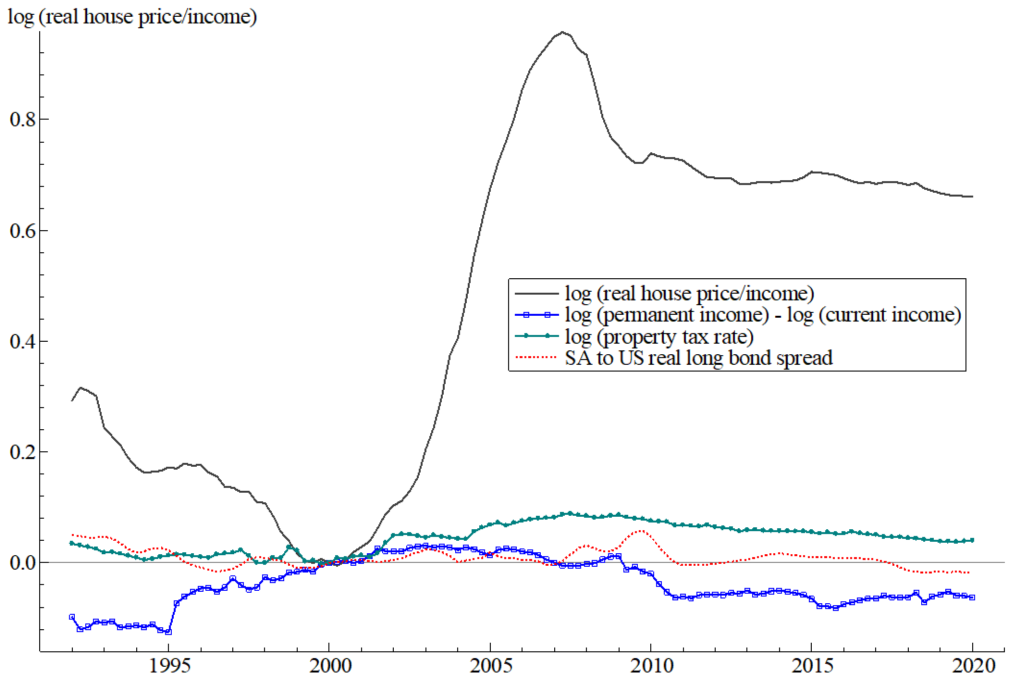
The graphical decomposition of the effects of the long-run drivers of house prices is shown in Figures 11 and 12. Figure 11 shows that much of the long-run upward trend in real house prices is the result of the rise in income relative to the housing stock, partly offset by the negative trend. The boom of the early to mid-2000s was driven by a combination of credit liberalization in the mortgage market and decline in user cost as housing market participants projected forward recent rates of house price appreciation. As boom turned to bust, these expectations of house price appreciation fell, driving up user cost. At the same time, considerable tightening took place in mortgage credit conditions. Figure 12 plots the long-run contributions of income growth expectations, the property tax rate, and the real long bond spread. Of these, greater growth pessimism after 2010 also contributed to the decline in real house prices.

Figure 11: Fitted contributions to the log real house price-to-income ratio of MCCI, user cost, log income per house, and a trend



Source: authors' illustration based on results reported in Table 5, using data from Table 1.

Figure 12: Fitted contributions to the log real house price-to-income ratio of the property tax rate, log permanent income minus log current income, and SA–US real long bond spread



Note: log permanent income minus log current income is a measure of income expectations; SA–US real long bond spread is defined as the real ten-year yield on SA government bonds minus the equivalent for the US (using the consumer expenditure deflator to measure annual inflation).

Source: authors' illustration based on results reported in Table 5, using data from Table 1.

4.5 The mortgage debt equation

Estimation results for the mortgage debt equation are shown in Table 6. The following have a role in the long-run solution for the log mortgage debt-to-income ratio: the log house price-to-income ratio, mortgage credit conditions, the log housing stock-to-income ratio, interest rates, demography, and the log ratio of permanent to current income, thereby capturing income growth expectations. The quarterly speed of adjustment is just over 0.06, broadly in line with UK estimates of a similar equation (Fernandez-Corugedo and Muellbauer 2006) and a little below estimates for France (Chauvin and Muellbauer 2018). As the UK had a rather similar financial structure and floating rate mortgages to South Africa, the similarity with UK estimates is reassuring. As with the above countries, South Africa's long duration of mortgages is typically reflected in a low speed of adjustment.

Table 6: Mortgage debt model—results

Dependent variable: Δ log (mortgage debt per capita) $_t$	1992:1 to 2020:1		1995:1 to 2020:1		1992:1 to 2014:4	
		Eq. 1		Eq. 2		Eq. 3
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Long-run coefficients						
Speed of adjustment	0.0630	8.81	0.0720	8.77	0.0643	7.78
Intercept	−3.68	−10.1	−3.49	−9.45	−3.66	−9.34
Log (house price/income) $_{t-1}$	0.643	2.45	0.745	2.72	0.599	1.86
Log (housing stock/income) $_{t-1}$	0.803	5.72	0.753	5.01	0.788	3.23
Log (permanent income/current income) $_t$	0.7	-	0.7	-	0.7	-
Interaction term: MCCI × log (house price/income) $_t$	1.02	2.31	1.39	2.61	1.02	2.01
Log (effective mortgage rate) (ma4) $_{t-1}$	−0.577	−3.17	−0.375	−2.26	−0.558	−2.62
Log (property tax rate) (ma4) $_{t-1}$	−0.0807	−2.08	−0.0594	−1.68	−0.0728	−1.47
Demography (fixed coeff.)	3		3		3	
Log (mortgage debt per capita/income) $_{t-1}$	−1		−1		−1	
Short-run coefficients						
Δ_2 (mortgage debt) $_{t-1}$	0.116	3.19	0.0554	1.41	0.114	2.83
Δ_4 log (income) $_t$	0.178	5.09	0.136	3.16	0.182	4.18
Diagnostics						
Equation standard error		0.00608		0.00580		0.00661
Adjusted R-squared		0.924		0.934		0.918
LM het. test		[.413]		[.558]		[.815]
Durbin-Watson test		1.78		2.00		1.81
AR1/MA1 Lagrange multiplier test		[0.262]		[0.992]		[0.391]
AR4/MA4 Lagrange multiplier test		[0.369]		[0.427]		[0.371]

Note: system estimation by maximum likelihood performed in TSP 5.0 of Hall and Cummins (2009); the interaction term is in the form of $MCCI_t \times x_t^*$ where $x_t^* = x_t - x_{2000Q1}$; the square brackets contain p-values for the LM tests.

Source: authors' construction; see Table 1 for the definition of data sources.

A key long-run determinant of the log ratio of mortgage debt to income is the log of the house price-to-income ratio, acting both on its own and, even more strongly, in interaction with the mortgage credit conditions indicator MCCI. In other words, when house prices rise relative to income, aspiring buyers need to take on more debt, and this process is reinforced when it is easier to access debt. These positive effects may also incorporate the incentive that some house-owners have when house prices rise to borrow more to release equity for spending purposes or to retire more expensive non-mortgage debt. A second long-run determinant of the log ratio of mortgage debt to income is the log ratio of the housing stock to income, since mortgage finance caters not only for higher priced housing but also for real investment in the stock of housing.

A third driver is the log of the effective interest rate, which includes amortization (assuming an eight-year duration of the mortgage) (see Table 1). Even if many repayment mortgages are nominally for 20 or 25 years, *de facto* the refinancing option in a floating rate environment suggests a shorter average expected mortgage duration. This interest rate enters as the lagged four-quarter moving average, suggesting lags in the process of obtaining a mortgage and in the adjustment of offered interest rates to the policy repo rate (with which the prime rate moves in step). No effect could be found for the user cost, found relevant in the house price equation and hence only indirectly relevant for mortgage debt. A fourth driver is the expected income growth, represented as previously by the log ratio of permanent to current income. The freely estimated coefficient exceeds unity, which seems implausible in view of the relative weights on permanent and current income estimated from the consumption and house price equations. We therefore calibrated the coefficient at a value of 0.7, at the upper end of plausibility as current income is surely relevant to many potential mortgage borrowers. This makes hardly any difference to the system estimates compared with the freely estimated coefficient. Another calibrated coefficient is applied to demography, as represented by the ratio of people aged 25 to 44 to adults aged 20 and above. Since the variable is very slowly evolving, with only two turning points between 1992 and 2020, our sample is unlikely to be long enough for robust estimates. The freely estimated coefficient is around twice that of the calibrated value of 3, the latter providing more plausible estimates of the long-run impact.[51] Finally, there is a small negative effect from the rate of property tax.

Short-run variables include the two-quarter change in the log mortgage stock lagged by two quarters,[52] the four-quarter growth rate of real per capita income, and five impulse dummies.[53]

Given the long duration of mortgages reflected in the low speed of adjustment, when we seek to graph the long-run solution to show the contribution of these variables to the dependent variable, the log ratio of mortgage debt to income, we run into the problem that the dependent variable typically lags behind its drivers. Therefore, we choose to graph instead the log mortgage debt to income plus the log change of per capita mortgage debt divided by the speed of adjustment. This is explained as follows.

An equilibrium correction model can be written in the form:

$$\Delta\, y_t = \lambda(\, f(x_t) - y_{t-1}) \; + short\ term\ variables \qquad (10)$$

where x is a vector of relevant long-term variables. Rather than plot the elements of $f(x_t)$ against y_t, we assume away the impact of the short-term variables on the right-hand side of Equation 10 and solve the equation for y_{t-1}. Then, the elements of $f(x_t)$ can be plotted against $y_{t-1} + \Delta y_t/\lambda$, which would approximate y_t in the long run.

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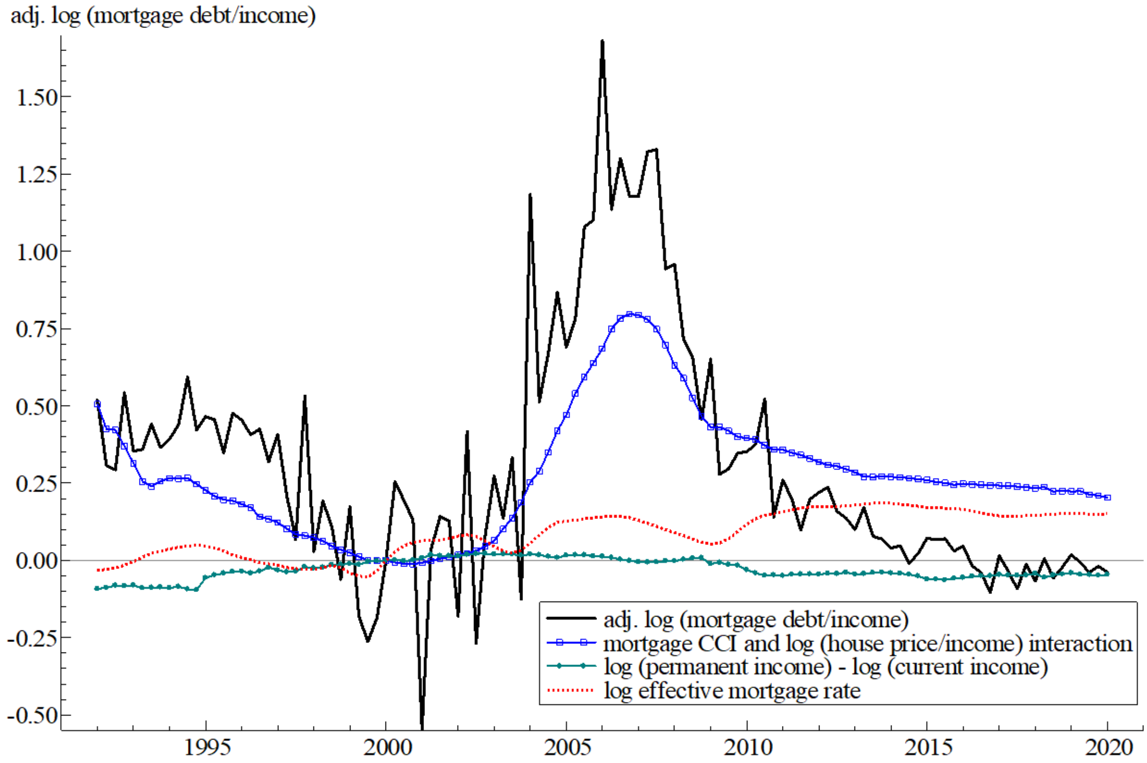
[51] Even with a longer sample of data, Chauvin and Muellbauer (2018) use similar calibrations for the mortgage debt equation for France.

[52] This may indicate a copycat effect in the process of competition among mortgage lenders struggling to maintain market share.

[53] These dummies may capture measurement issues, as the mortgage stock measure includes data from a variety of lenders both within and outside of the banking sector. The quality of the latter data, including local government data, may not always be as good as that of the banking data. Also, when the loan book of one lender is acquired by another, there can be temporary reporting gaps.

Figures 13 and 14 show these decompositions. Figure 13 shows that the dominant explanation for the rise in the ratio of mortgage debt to income in the 2000s is the rise in house prices relative to income and its interaction with easier mortgage credit conditions. Smaller contributions also came from lower interest rates and a fall in the property tax rate (proxied by property tax revenue relative to housing wealth). The earlier decline from 1992 to 2000 in the mortgage debt-to-income ratio and the renewed decline after 2008 also owe much to the combination of variations in house prices to income and in mortgage credit conditions.

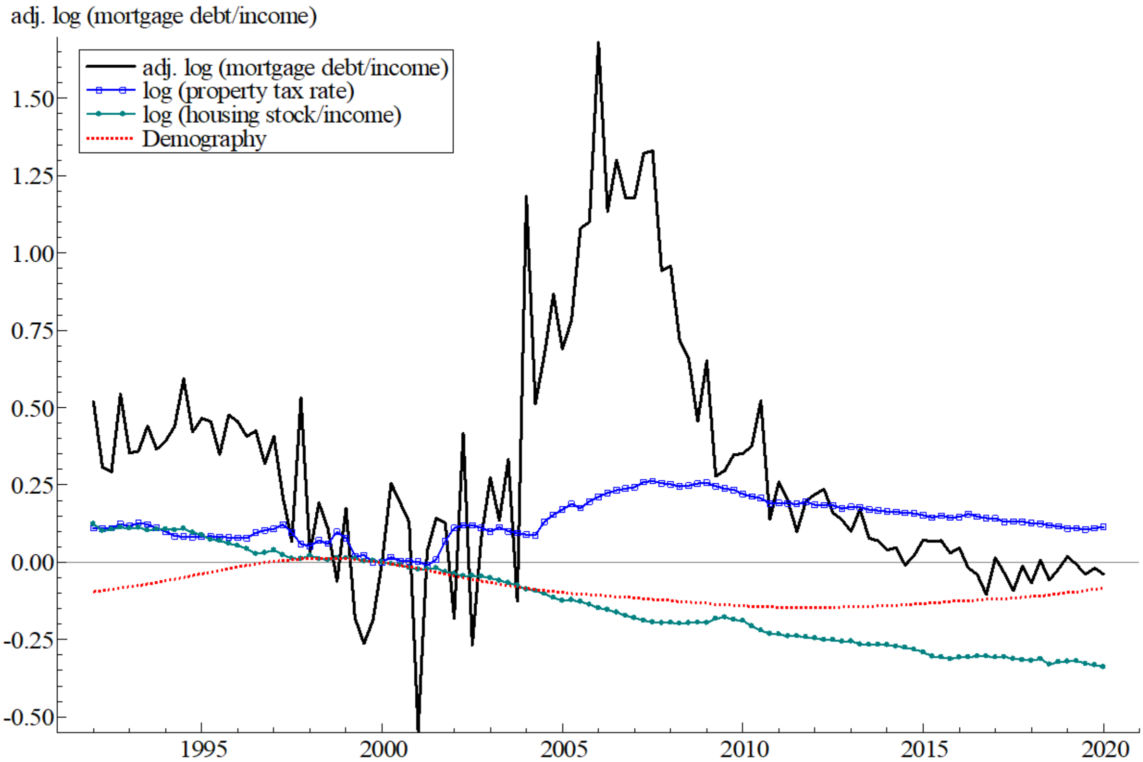
Figure 13: Fitted contributions to the log of the adjusted mortgage debt-to-income ratio of mortgage CCI and log (house price/income) interaction, log effective mortgage rate, and log (permanent income)/(current income)



Note: log permanent income minus log current income is a measure of income expectations; the adjustment of the dependent variable is defined in Equation 10; effective mortgage rate assumes amortization over eight years.

Source: authors' illustration based on results reported in Table 6, using data from Table 1.

Figure 14: Fitted contributions to the log adjusted mortgage debt-to-income ratio of the log of property tax rate, demography, and log housing stock-to-income ratio



Note: the adjustment of the dependent variable is defined in Equation 10.

Source: authors' illustration based on results reported in Table 6, using data from Table 1.

4.6 The non-mortgage debt equation

Estimation results for the non-mortgage debt equation are shown in Table 7. There are only three long-run drivers of the log ratio of non-mortgage debt to income. These are non-mortgage credit conditions, the effective interest rate, and demography, namely the proportion of adults aged between 25 and 44. The effective interest rate is based on the prime rate and amortization, assuming that the loan is repaid over three years.[54] For the same reasons as in the mortgage debt equation, the effect of demography is calibrated at 3, to avoid exaggerating it, as it cannot be robustly estimated over these relatively short samples. The estimated speed of adjustment is around 0.12, almost double that of mortgage debt, as befits the shorter duration of most non-mortgage debt. Two economic variables appear in the short-run dynamics. One is the lagged dependent variable, i.e. the previous quarter's change in the log of per capita non-mortgage debt in current prices. This has a negative coefficient, suggesting a tendency for debt growth to pull back a little after a quarter of high debt growth. The other highly significant variable is the lagged four-quarter change in the log house price-to-income ratio. Its positive sign suggests that when

[54] The effective rate enters as an eight-quarter moving average. In an alternative specification, checking for robustness, it enters as a four-quarter moving average. In this case, we find an additional positive effect from the annual change in the log of the effective mortgage rate, lagged one quarter. This suggests that when mortgage rates rise, some households increase their non-mortgage debt to ease the cash flow shock. The fit of the alternative specification is very similar, as are all other parameter estimates in the system.

house prices rise strongly relative to income, aspiring buyers use non-mortgage credit to help fund the down-payment needed to obtain a mortgage.

Table 7: Non-mortgage debt model—results

Dependent variable: Δ log (non-mortgage debt per capita)$_t$	1992:1 to 2020:1		1995:1 to 2020:1		1992:1 to 2014:4	
		Eq. 1		Eq. 2		Eq. 3
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Long-run coefficients						
Speed of adjustment	0.115	5.23	0.129	4.93	0.113	4.42
Intercept	−4.40	−14.0	−4.19	−12.82	−4.33	−11.0
Non-mortgage CCI (fixed coeff.)	1		1		1	
Log (effective mortgage rate) (ma8)$_t$	−1.65	−3.96	−1.37	−3.46	−1.48	−2.85
Demography (fixed coeff.)	3		3		3	
Log (non-mortgage debt$_{t-1}$/income$_t$)	−1		−1		−1	
Short-run coefficients						
Δ log (non-mortgage debt per capita)$_{t-1}$	−0.333	−4.90	−0.364	−4.98	−0.350	−4.71
Δ_4 log (house price/income)$_{t-1}$	0.154	6.73	0.167	6.62	0.166	6.44
Diagnostics						
Equation standard error		0.0114		0.0116		0.0118
Adjusted R-squared		0.716		0.704		0.718
LM het. test		[.592]		[.668]		[.954]
Durbin-Watson test		2.19		2.15		2.22
AR1/MA1 Lagrange multiplier test		[0.309]		[0.446]		[0.274]
AR4/MA4 Lagrange multiplier test		[0.903]		[0.963]		[0.899]

Note: system estimation by maximum likelihood performed in TSP 5.0 of Hall and Cummins (2009); the square brackets contain p-values for the LM tests.

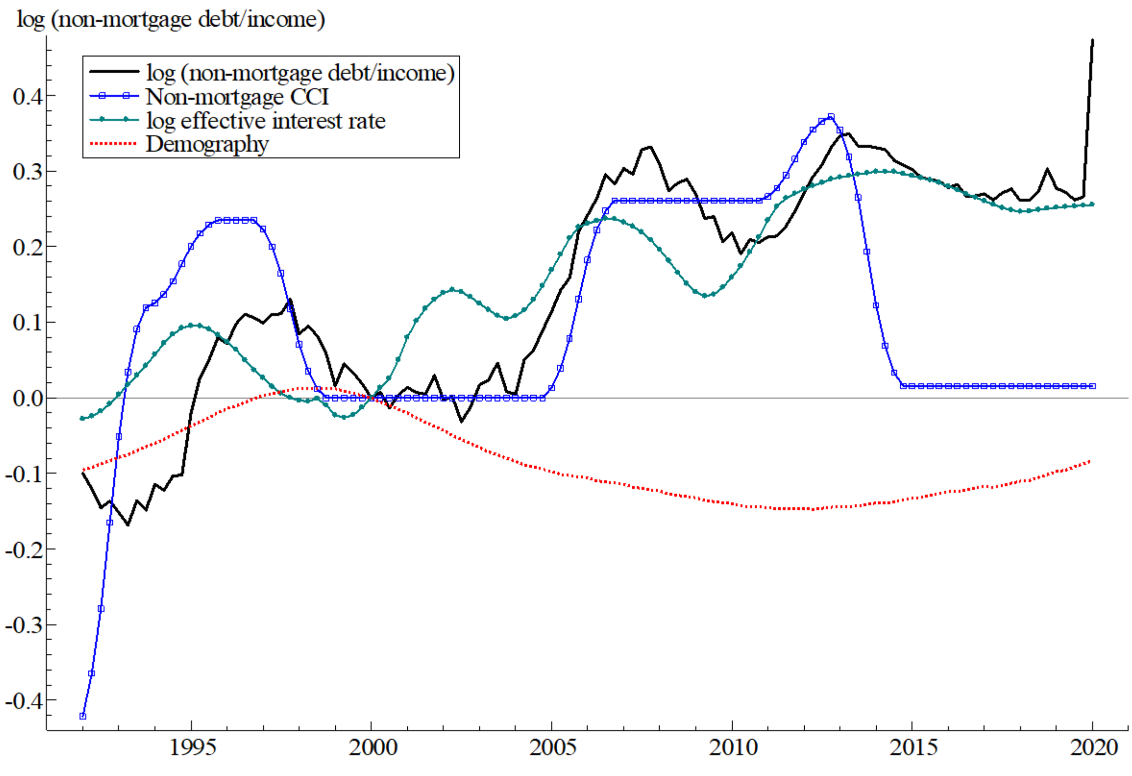
Source: authors' construction; see Table 1 for the definition of data sources.

One might have expected there to be a level as well as a rate of change effect of the log house price-to-income ratio for non-owners, with a positive coefficient. But higher house prices relative to income also drive up housing wealth relative to income, which, *for existing owners*, enables home equity withdrawal to substitute cheaper mortgage debt for more expensive non-mortgage debt. This would imply a negative coefficient on the housing wealth-to-income ratio in explaining the non-mortgage debt-to-income ratio of owners. For aggregate non-mortgage debt, this effect would at least partly offset the positive effect of the higher log ratio of house prices to income on the debt of the non-owners. In some specifications there was evidence for these partly offsetting level effects on aggregate non-mortgage debt, but parameter stability was less satisfactory. We therefore prefer the simpler formulation, omitting the two level effects, which has satisfactory parameter stability.

Another potential level effect is the log ratio of permanent to current income, capturing income expectations. This is not significant, unlike in the three other equations. A possible explanation is that non-mortgage debt typically involves a far shorter time horizon than mortgage debt. Also, some households, expecting a short-term income decline, may use non-mortgage borrowing as a buffer to maintain consumption levels, inducing a negative effect of income growth expectations on non-mortgage debt. This could cancel the opposite effect for other households with longer horizons.

Figure 15 shows a graphical decomposition of the long-run influences on the log ratio of non-mortgage debt to income, demonstrating the dominant role of non-mortgage credit conditions and the effective interest rate. These effects are apparent in the rise in the ratio of non-mortgage debt to income in the early to mid-1990s, its decline in the late 1990s, and its strong rise in 2005/06. The short-lived rise in the NCCI in around 2011 helps to account for the short-term rise in the log ratio of non-mortgage debt to income. The large fall in the NCCI, reflecting tightening from 2014, was partly offset by lower effective interest rates and the gradual rise in the adult population share of the 25–44 age group. To interpret the graphics, it is also important to be aware that with a speed of adjustment of 0.12, the log ratio of non-mortgage debt to income lags some way behind its drivers. This accounts for some of the apparent timing discrepancies in Figure 15.

Figure 15: Fitted contributions to the log ratio of non-mortgage debt to income of non-mortgage CCI, log effective interest rate, and demography



Note: the effective interest rate is defined in Table 1 and uses the prime rate with amortization of debt over three years.

Source: authors' illustration based on results reported in Table 7, using data from Table 1.

4.7 Comparisons of the treatment of consumption in our model versus the SARB's Core Model

The SARB's core forecasting model (see Smal et al. 2007) uses an equilibrium correction model linking log consumption with log HDI, log net worth, and the real interest rate, using data from 1985 to 2005. This was an important advance on earlier models for South African consumption, which all omitted the role of assets. The 2021 version of the Core Model's consumption equation, estimated on data for 1993 to 2015, has a similar long-run structure (de Jager et al. 2021; SARB 2019). The full model has been enhanced with more explicit linkages between the banking sector and the real economy, with a view to incorporating macroprudential policy settings.

However, the long-run solution for consumption has several shortcomings. It uses the *aggregate concept* of net worth as the only way in which household balance sheets and asset prices can affect consumption.[55] The assumption implicit in the restrictive net worth measure is that the different components of wealth all have the same effect on consumption, and this runs counter to modern economic theory. For example, liquid assets are necessarily more spendable than, say, pension wealth. The net worth restriction implausibly implies that there will be identical effects on consumption of a 100 rand (ZAR) increase in liquid assets, illiquid financial assets (such as pensions), and housing wealth, and of a ZAR100 decrease in debt. In contrast, our results indicate a far larger effect from a change in debt than from an equivalent change in illiquid financial wealth, and, in addition, the effect on consumption of housing wealth varies with credit conditions.

The long-run solution also does not explicitly consider permanent income. In reality, households are less ignorant of their future income (at least in the near term) than is implied by the Core Model. Moreover, households can adjust their portfolios by running down their assets or by borrowing more, to smooth out consumption fluctuations. Both of these behavioural features are addressed explicitly in our formulation.

In neglecting credit conditions, the time-varying impact of credit conditions on consumption including via the housing collateral channel is missed. A typical symptom of such omitted variables is a low estimated speed of adjustment. Indeed, in the equation the estimated speed of adjustment to the long-run equilibrium, after short- to medium-run perturbations, is very low, at 0.11 per quarter. By contrast, the speed of adjustment is around 0.42 in the consumption function of this paper (see Table 4) and a similar value was found in our earlier paper (Aron and Muellbauer 2013).

Monetary policy transmission to consumption is far stronger in our new model (and also in Aron-Muellbauer 2013) than in the Core Model. There is a *direct* effect of interest rates on consumption and *strong indirect* effects via housing wealth (which increase with greater credit availability) and via illiquid financial assets and permanent income. Since the effect of interest rates is so large, when there is a crisis, relaxing monetary policy potentially has powerful effects. In a boom, housing wealth rises strongly but so does household debt. This makes the household sector vulnerable to a subsequent contraction of credit conditions and falling housing wealth. The equation makes this vulnerability clear, which is of considerable importance to financial stability policy.

The Core Model is forced to calibrate the only wealth effect in the model, measured through net worth, as a robust estimate of the coefficient on net worth was not achieved. In contrast, our model has strong and highly significant balance sheet effects, highlighting the higher propensity to

[55] The 2021 version of the model does incorporate the lagged rate of change of private credit in the short-term dynamics, which brings in some influence of credit conditions and some small interest rate effects. However, this will not capture longer-term shifts in the supply of credit or differentiate demand-side from supply-side influences.

spend out of liquid assets, the negative effect of debt, and a robust estimate of the marginal propensity to spend out of interest-sensitive illiquid financial assets. Since interest rates transmit strongly to house prices, and therefore to housing wealth, our finding that the collateral effect on spending of housing wealth depends on credit conditions implies an important time-varying component in the transmission mechanism, also absent from the SARB's model. The crucial role of shifts in credit conditions is largely missing in the SARB's consumption equation. It might be argued that in their model, credit conditions are weakly proxied by the last quarter's rate of growth of real credit extension to the private sector. In principle, credit extension could provide another interest rate channel; however, the equations that drive credit extension in the Core Model show only very small and poorly estimated interest rate effects. Moreover, in our model, credit conditions are also important drivers of house prices and mortgage and non-mortgage debt. The insight into household vulnerability implied by high debt-to-income ratios is also missing in the Core Model.

By contrast with our finding of strong and long-lasting interest rate effects on consumption, in the Core Model interest rates have a weak direct effect on consumption and a relatively weak indirect effect via aggregated net worth. Net worth in the Core Model depends on the Johannesburg Stock Exchange (JSE) index and on house prices, but only temporarily—not in the long run. In the Core Model, house prices are affected by the interest rate on mortgages, but the JSE index is affected by interest rates only indirectly, through GDP and the consumer price index.

We further discuss new insights into the multiple channels of monetary transmission in the concluding section.

5 Conclusions

Our findings suggest that conventional approaches to modelling aggregate consumption, based on disposable income, net worth, and some measure of the real rate of interest, have seriously misleading implications for understanding the channels of monetary transmission via the household sector. Conventional approaches also fail to account for the important macroeconomic implications of variations in non-price credit conditions (i.e. loan standards), and hence they have little relevance for setting macroprudential policy.

In contrast, our approach controls for variations in credit conditions, and it disaggregates net worth into the key liquid and illiquid financial assets, debt, and housing wealth. We take into account the complex role of house prices and control for income growth expectations, and also for a cash flow impact of changes in nominal interest rates. None of the above controls is in the consumption equation in the SARB's published Core Model (2019). Critically, unlike in most emerging market countries, there are balance sheet estimates of disaggregated wealth data. These were developed by Aron and Muellbauer (2006) and Aron et al. (2006, 2008) and adopted for ongoing use by the SARB, and are available for improving on the net worth concept.

Our approach takes a more realistic view of the micro-foundations of household behaviour, and hence of monetary transmission, compared with the highly restricted textbook lifecycle/permanent income theory of consumption. This simplified theory, which underpins conventional approaches to modelling aggregate consumption, ignores liquidity and credit constraints, does not separately include housing, has only a single liquid financial asset, and allows virtually no role for income uncertainty. For a bird's eye view of the radical shift in the micro-foundations of macroeconomics that has taken place in the literature, and in the broader understanding of the professional community, especially since the GFC, see Appendix A1 in Muellbauer (2022).

A contribution of this paper is to clarify the various monetary transmission mechanisms in South Africa, which should be helpful for focusing discussion in the Monetary Policy Committee. On monetary transmission to aggregate consumption, our model is able to distinguish seven different channels. One important channel by which an increase in the repo policy rate affects aggregate consumption is through income growth expectations, measured as the log ratio of permanent to current income. Income growth expectations are strongly influenced by real interest rates. They are also influenced indirectly via the ratio of house prices to income, because this ratio is affected by interest rates. Our empirical model for permanent income suggests rather slow transmission in this channel through the average real prime rate over eight quarters and the indirect house price-to-income channel, though there is also a small shock effect from the four-quarter change in the prime rate compared with the previous year's change.

A second transmission channel to consumption is through house prices,[56] which have a dual role in transmission. For non-owners, a rise in the ratio of house prices to income has negative spending implications, as those aspiring to obtain a mortgage to purchase a home need to save for a higher down-payment. Similarly, renters without these aspirations can expect higher rents to follow house prices and are also therefore likely to be more cautious in spending. On the other hand, house-owners have the option of withdrawing home equity, by borrowing more as their available collateral increases in value with raised house prices. This withdrawal can be spent on consumption. This is termed the 'collateral effect' on consumption of higher housing wealth.[57] Home equity withdrawal, taking on more mortgage debt, can also be used to retire more expensive non-mortgage debt, improving the longer-term cash flow and therefore consumption opportunities of house-owners. Figure 10 showed the net impact on consumption of the operation of these dual effects: positive when credit conditions were most loose in 2005/07, and otherwise negative. The implication is that increasing the repo rate would have had a negative effect on consumption through the house price and collateral channel in 2005/07 but at other times a small positive effect through this channel by improving housing affordability. This also points to the danger of *decreasing* the repo rate when credit conditions are loose. These effects on aggregate consumption are far from instantaneous, however, since with an estimated adjustment speed of around 0.1 from the house price equation, it takes time for interest rates to feed through to house prices.

A third potential transmission mechanism of interest rates to consumption operates via credit conditions. Large increases in interest rates can trigger a downturn in which banks' NPLs increase, especially if previously loose credit conditions led to high levels of household debt and overvalued house prices.[58] Then, lenders are forced to tighten credit conditions, not just for households but also for firms with negative spending effects, discussed further below.

A fourth monetary transmission channel is via a strong cash flow effect of interest rates, acting directly on consumption through the change in the nominal prime rate. This is because in a floating

[56] There is another transmission channel operating through house prices to residential investment, which is another component of aggregate demand (Aron and Muellbauer 2022b).

[57] This differs from a classic wealth effect on housing from house price rises, as expressed in Equation 1, which does not involve increasing debt (similar to that of financial wealth).

[58] For evidence of such an effect in South Africa on the closely related concept of the banks' credit impairment ratio, see Aron and Muellbauer (2022c).

rate environment, the cash flow of borrowers quickly deteriorates when the nominal prime borrowing rate rises. Savers, on the other hand, see an improvement in their cash flow, as deposit rates follow the policy rate, though typically more slowly than rates charged to borrowers. There will be a smaller impact on aggregate consumption, since international evidence suggests the marginal propensity to spend a cash flow improvement is lower for savers. The evidence from our results is again that this effect is far from instantaneous, as it enters in the form of the eight-quarter change, lagged one quarter. This means that a jump in the prime rate will still have a negative effect on consumption for up to two years after it occurs.

A fifth monetary transmission channel to consumption is the relatively fast interest rate transmission effect through the prices of financial assets. We find a strongly significant MPC out of illiquid financial assets in South Africa. However, to quantify this further will require additional empirical equations to capture the transmission of the repo policy rate to the stock and bond markets (such as we have for the house price equation).

A sixth monetary transmission effect to consumption also involves assets but operates through their volumes rather than prices and is quite slow. A higher repo rate, feeding into loan and deposit rates, eventually results in higher levels of liquid assets and lower levels of debt, serving to boost consumption in subsequent years. Eventually this boost will partly offset the more immediate negative effect of the repo rate on consumption.

Finally, a seventh important transmission channel of monetary policy to consumption operates through current income. Our model shows how important current income is relative to permanent income. As the level of household income is determined by many sectors of the economy, the transmission of interest rates to household income also operates through multiple channels. These include residential investment (see Aron and Muellbauer 2022b), business investment, exports and imports (affected by the exchange rate), and employment. Our model conditions on the current level of real per capita household income; for a full assessment of how this multidimensional income channel operates, the model would need to be embedded in a larger semi-structural policy model.

These perspectives on both the speed and size of the multiple channels of monetary policy transmission in our model differ substantially from those in the SARB's Core Model. As explained in Section 4.7, the Core Model gives an oversimplified and limited view of the transmission mechanism of the policy interest rate operating via consumer spending. To begin with, its estimated speed of adjustment of 0.11 contrasts with ours of more than 0.4, which points to an underestimation of the speed of transmission of shocks from, for example, asset price changes. The very low speed of adjustment is a classic symptom of omitted variables, such as income expectations and more realistic balance sheet effects. The size of the estimated direct effect of interest rates, in the form of the real prime rate of interest, on consumption in the Core Model is small and estimated with a large standard error. The indirect effects acting through net worth and the growth of credit extension to the private sector are only short lived and are not accurately estimated. This contrasts with our relatively accurately estimated estimate of the direct effect of changes in the nominal prime rate. Moreover, we find a strong but slow-acting effect on consumption of the real prime rate, acting through income expectations. Income expectations are missing in the Core Model. Our finding that the interest rate transmission channel through house prices is potentially large when credit conditions are loose is also missed by the Core Model.

Our paper also makes a contribution to macroprudential policy. Conventional models of aggregate consumption fail to highlight important issues for macroprudential policy, because they exclude credit conditions. The macroeconomic implications of variations in credit conditions are missed. Easing credit conditions has a direct effect on consumption in the short run. Easier credit also has indirect effects on consumption via house prices in the short run. However, such easing results in a build-up of debt. This produces a far more negative effect on consumption than is implied by conventional consumption equations, since debt is buried as part of net worth, using restrictive assumptions (Section 1). This increase in debt takes time, but the stimulus from easing credit conditions is quick acting. This stimulus unfortunately disguises a rising vulnerability of indebted households. In a classic credit cycle, excessively loose credit conditions (i.e. loan standards) result in a build-up of financial vulnerabilities and the over-shooting of asset prices and credit beyond fundamentals, especially for real estate. The over-shooting is due in part, as Adrian (2017) argues, to the tendency of market participants to form extrapolative expectations about house prices. When negative shocks arrive, bad loans mount, and with higher non-performing loan ratios, the capability and appetite of lenders to provide credit to the private sector shrinks.

We find confirmation for the mechanisms underlying a classic credit cycle for South Africa. Our estimated CCIs are highly significant in forecasting models of the credit impairment ratio for South Africa's banks, one and two years ahead (see Section 4.2). With a jump in the credit impairment ratio (a concept related to NPLs), a rapid tightening of credit conditions then exacerbates the downturn, including in the housing market, with negative repercussions including higher levels of bankruptcy, home repossession, and loss of jobs and income. Such a credit cycle can occur without a widespread financial crisis, especially where the banking system is oligopolistic, generally profitable, and well capitalized enough to survive an otherwise damaging recession. We argue that in the 2000s, South Africa went through just such a credit cycle.

Tracking variations in credit conditions and understanding how those variations transmit to house prices and debt levels and affect consumer spending should be key elements in designing macroprudential policy. This design process involves both the selection of appropriate tools, such as borrower-based measures and risk weights, and consideration of the most appropriate macro-scenarios for the stress testing of the financial system. To accommodate these important practical macroprudential policy concerns, as well as those for enacting monetary policy, the insights into the multiple channels of transmission through the household sector via the models demonstrated in this paper, and their quantification, should prove useful.

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Appendix 1: The measurement of income and consumption.

There are problems with the current vintage of the available household income data, yet these are fundamental to any models of household behaviour. Before 1998, these data look especially volatile, see Figure A1.1. Fortunately, from earlier work, we have a data vintage from 2006 with which we could compare growth rates of real per capita household disposable income (HDI). The dotted line is from the current SARB data, and the solid line is from our 2006 vintage data. The volatility of the current data and its lack of correspondence with the older vintage data are notable, especially pre-1999. However, there are also some spikes in the vintage income growth rates in 1990 and 1992.

Clearly, the current vintage of HDI is far more volatile than the old vintage up to about 1998, and sometimes there are even movements in opposite directions. One difference in concept is that the old data vintage did not include an adjustment for the revaluation of pension reserves, whereas the new does, at least from 1995. But before 1995, the higher volatility of the new income data is also apparent.

For four-quarter changes of log per capita real HDI, the same disturbing pattern holds, see Figure A1.2. The differences in 1993–5 and 1995–7 are quite pronounced. In other words, this is not merely a seasonal problem. The dotted line is from the current SARB data, and the solid line is from our 2006 vintage data.

For consumption, the data revisions are minor in terms of annual growth rates, see Figure A1.3. However, the current data on the saving rate before 1998 are much more volatile than the vintage data, see Figure A1.4. Given the similarity in the consumption data, this means that revisions to the saving rate are almost entirely driven by revisions to the income data. The far greater volatility of the current SARB data on the saving ratio is especially concerning for our research as the consumption to income ratio (which is 1 minus the saving ratio) is a central feature of our consumption equation. If there are serious measurement errors in HDI before 1998, this would bias our results, probably quite badly. Unfortunately, trying to rely only on data from 1998 is also problematic, as our research requires relatively long time series of data to obtain robust estimates.

It is clear that the revisions in the income data are not primarily revisions in the compensation of employees. The revisions in labour income growth are quite minor (four-quarter growth rates of real per capita labour compensation, for current and for vintage data), see Figure A1.5. It follows that almost all the revisions in the disposable income data between the 2006 vintage and the 2023 vintage must be in the data on property and/or transfer income (and perhaps slight differences in the implied tax rates, though that seems less likely). The data error, if that is what it is, will be in the measure of non-labour income. Something has clearly changed in the process of rebalancing the National Accounts, and especially before 1998.

For 1990 to 2003, a regression of the growth rate of consumption, whether in quarterly or annual terms, on the growth rates of real per capita HDI for both the current SARB data and the vintage data show a strongly significant positive coefficient for the vintage data and an insignificant coefficient for the current data. While such regressions do not include all the controls that our work shows are important, they do provide circumstantial evidence against the accuracy of the current SARB income data.

This is the background to our decision to accept the current data vintage for data on consumption, both in current price and constant price terms, and for the compensation of employees, but to splice HDI data to the 2006 vintage in 1998 Q3. To be precise, we remove the revaluation adjustment for pension fund reserves from the current vintage of HDI data back to 1998Q3[59] and before 1998Q3 we splice to the 2006 vintage data which does not include the revaluation adjustment.

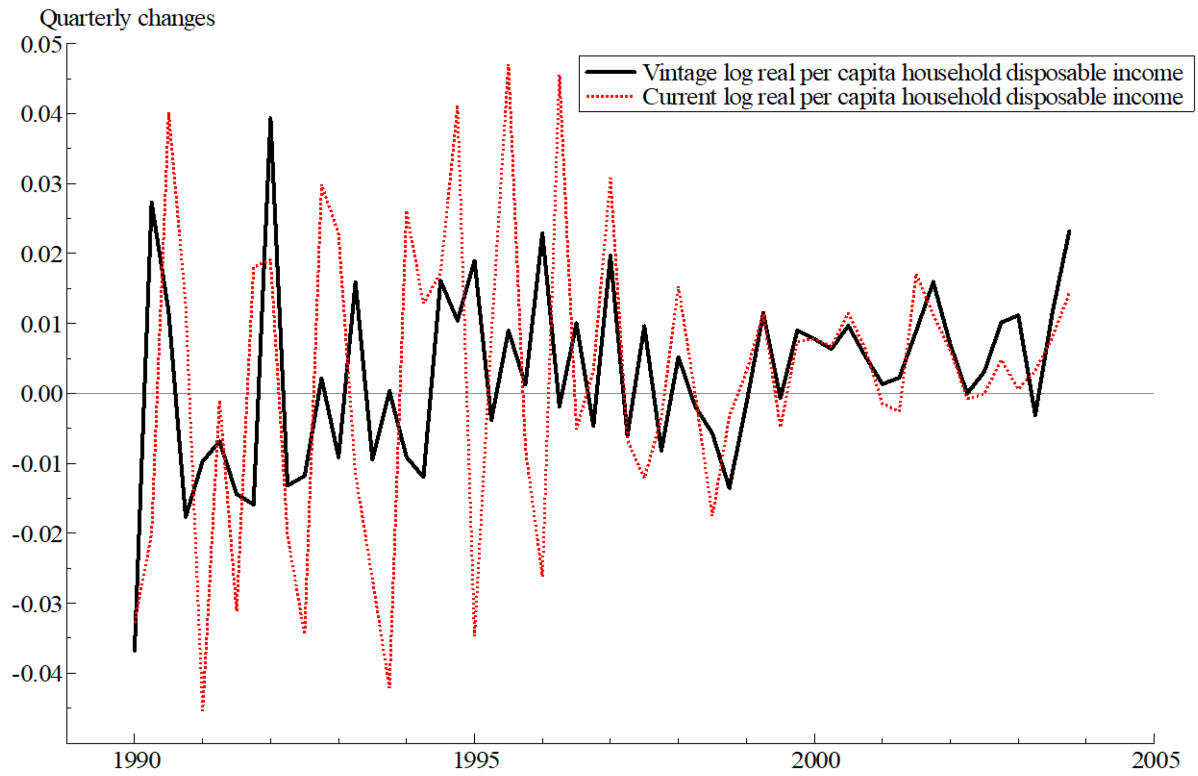
Textbook theory on the lifecycle/permanent income model of consumption presents an oversimplified model. It has only liquid assets, no liquidity constraints and no housing assets (see discussion around equation (1)). This model suggests that only relevant income concept is *non-property income*. Property income is captured by a real rate of return multiplied by financial wealth. However, in practice, property income is far from being a simple proportion of wealth. Moreover, aggregate consumption has a different relationship to labour income and some types of transfer income (benefits, pension and social security), than to property income. The FRB-US model of the Federal Reserve recognizes these differences by distinguishing the three types of income in their model. As a simplification, but still recognizing the distinction, we use a 'scaled income' concept for income, to drive consumption, house prices and the two types of debt. We define this as a weighted average of after-tax labour income and of HDI, thus over-weighting labour income in accordance with evidence for a higher propensity to consume out of labour income.[60] In our equation system, we can select the weight that gives the best overall fit. This puts a 30 per cent weight on tax-adjusted labour income and a 70 per cent weight on HDI. The tax adjustment of labour income is relatively crude: we multiply labour income (the compensation of employees) by the ratio of HDI, which is after-tax (and excluding the pension revaluation), to pre-tax income, a ratio fluctuating around 85 per cent.[61] On the current data vintage, this is only available for annual data, which entails using its moving average.

[59] As we do not have access to the quarterly data on this adjustment, we take the moving average of the annual data to make the adjustment.

[60] Unfortunately, quarterly data on transfer income are no longer available so that we could not incorporate these data in scaled income, except as part of HDI.

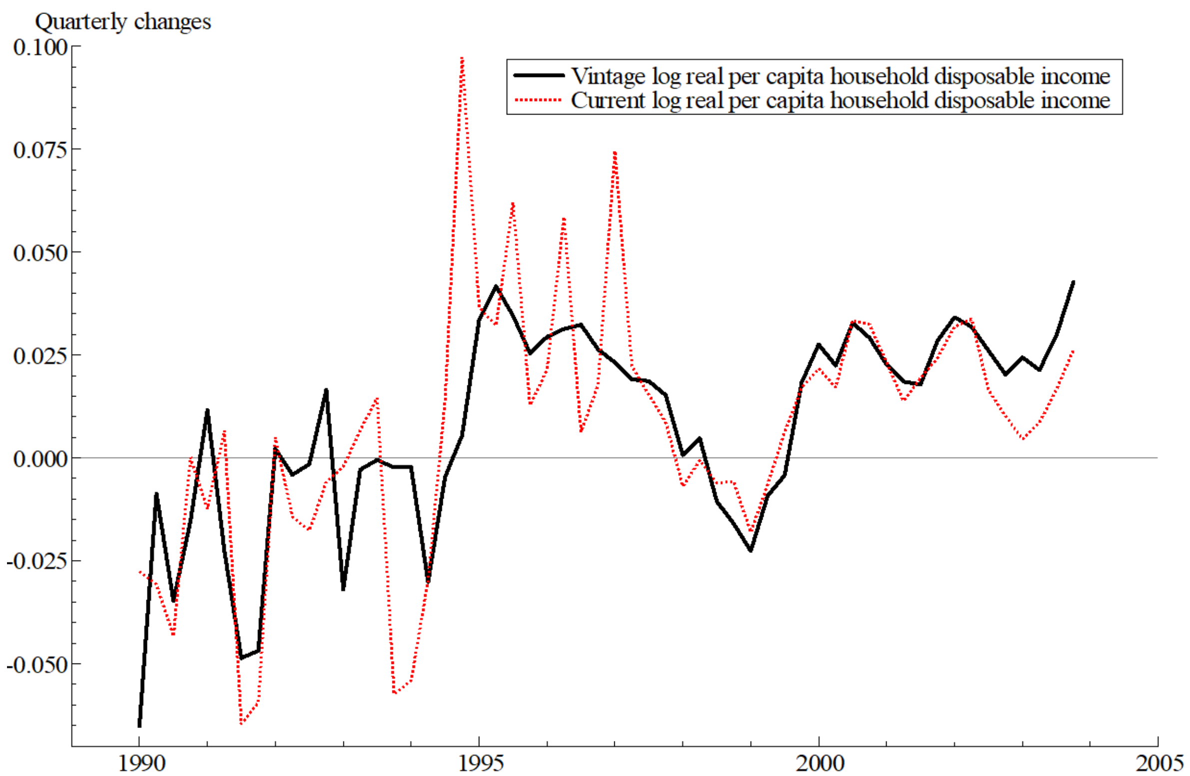
[61] Another reason for choosing to splice the data in 1998Q3 is that the ratio of HDI to pre-tax income is remarkably different for 1996 and 1997 for the current data vintage as compared with the 2006 data vintage. The earlier vintage data show little change in 1996 and 1997 compared with 1995, but the current data vintage shows a large jump in 1996/97 which then reverts to a lower level in 1998.

Figure A1.1: Current and vintage data on log real per capita household disposable income (quarterly)



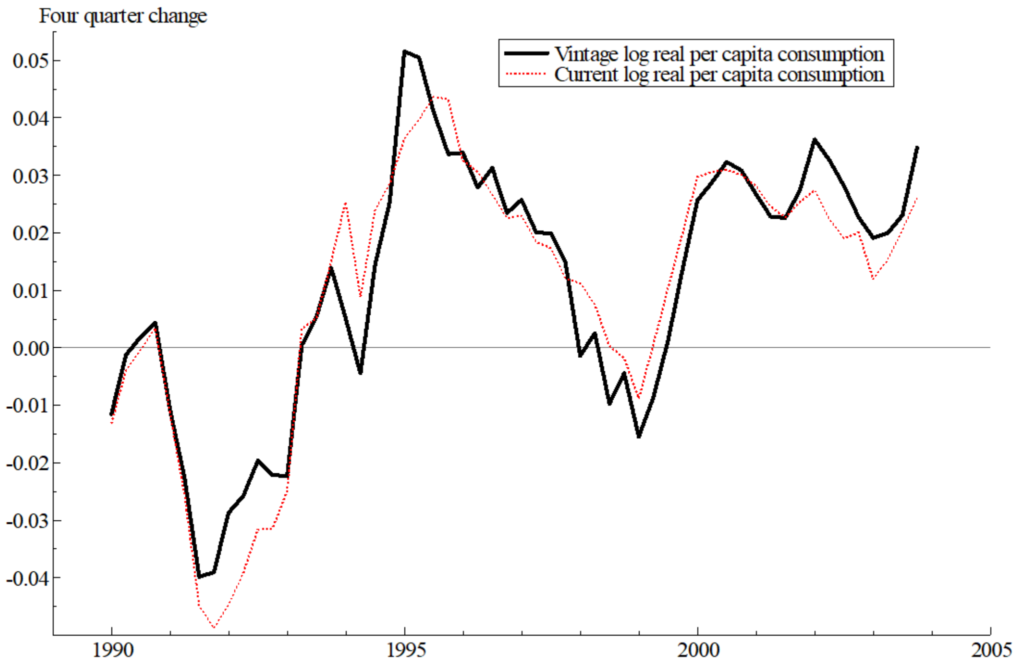
Note: SARB income data of different vintages (current and 2006), and the current consumption deflator.

Figure A1.2: Current and vintage data on log real per capita household disposable income (four quarter changes)



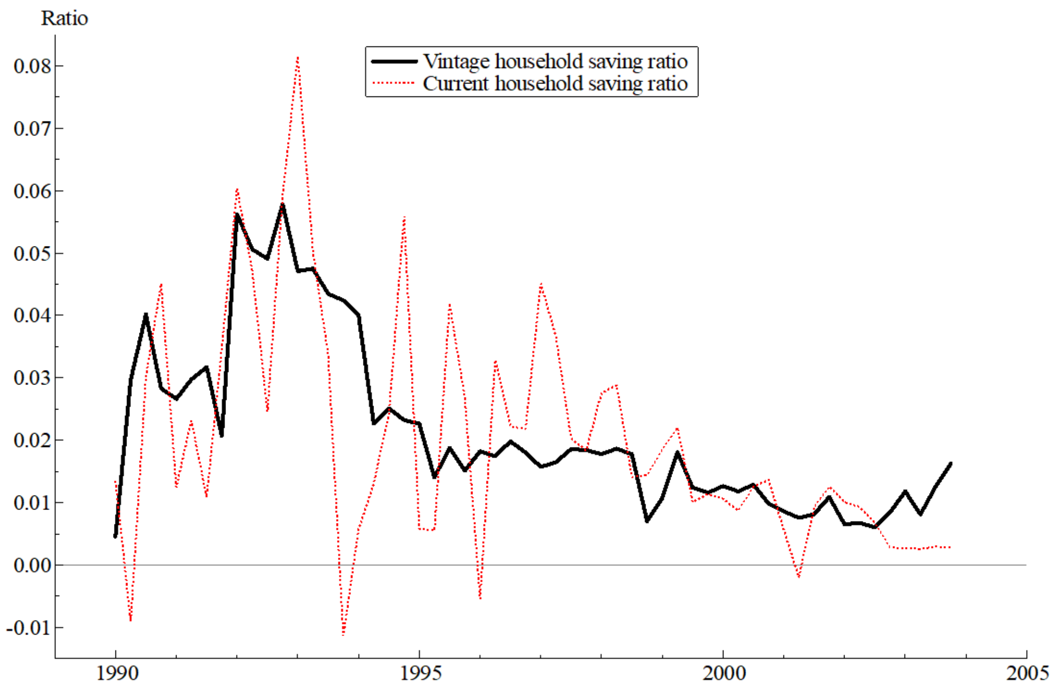
Note: SARB income data of different vintages (current and 2006), and the current consumption deflator.

Figure A1.3: Current and vintage data on log real per capita consumption (four quarter changes)



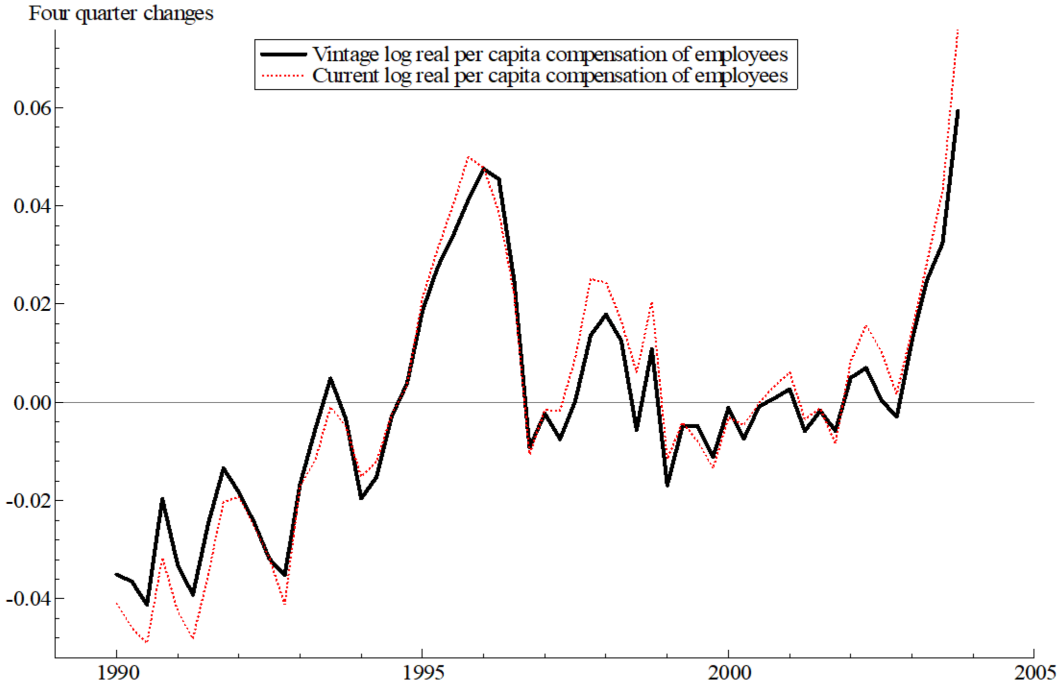
Note: SARB consumption data of different vintages (current and 2006), and the current consumption deflator.

Figure A1.4: Current and vintage data on the household saving ratio



Note: SARB saving ratio data of different vintages (current and 2006).

Figure A1.5: Current and vintage data on log real per capita compensation of employees (four quarter changes)



Note: SARB data on real per capita compensation of employees of different vintages (current and 2006).

Appendix 2: The measurement of house prices

The house price index the SARB is using, is based on an index published by ABSA (a large mortgage lender, once a subsidiary of the UK's Barclays Bank), and from 2000, based on an average of the ABSA index and indices from two other mortgage lenders. ABSA's methodology, at least before about 2000, was seriously defective, based on averages of transactions with little attempt to make like-for-like price comparisons, a fundamental element of proper index number methodology. Averages of transactions are skewed by the vagaries of the location of transactions. For example, a larger share of transactions in high priced Cape Town or Pretoria, will push up the index, and overstate the rise in the national index. Similarly, changes in the mix of property types transacted will distort index movements. Luüs (2005) documents differences in movements between house prices in different provinces, by size of homes and between newly built homes and existing homes. One aspect of the latter is the trend of construction towards gated communities, responding to rising crime and insecurity.

This also distorts estimates of housing wealth. The housing wealth in the SARB's household balance sheets multiplies the house price index by a volume measure of the residential housing stock. Housing wealth is a major component of household net worth, used in modelling, for example in the SARB's Core Model, and economic commentary.

Crucial for measuring housing wealth and modelling consumption, debt and residential construction are good data on the house price index. The OECD handbook for residential property price indices (2013) provides a clear account of the different methods of constructing house price indices. Basically, there are three reputable methods. One is the hedonic approach and Statistics South Africa has computed such a hedonic house price index, but only for recent years. The second method is the repeat-sales method. And the third, somewhat less satisfactory, are more traditional methods of index number construction, where fixed weights are used to compare movements in the prices of properties with similar characteristics, e.g. by size of property and location.

In the US, repeat-sales indices dominate practice, whether at the Fed or from private sector providers such as S&P Core Logic Case-Shiller. None of the different measures is ideal, see the OECD guide. Repeat-sales indices have the advantage of comparing like-for-like changes in house price levels and, being based on Deeds Office data, include cash as well as mortgage-financed transactions. However, they do not capture improvements, and so tend to somewhat overstate price rises. Also, they tend to overweight housing types for which transactions are more frequent. Hedonic methods typically rely on mortgage transactions, where the lender measures a range of housing characteristics, such as floor area, plot size, location, period of construction, number of bathrooms etc. These characteristics do not always fully capture what drives values, and the exclusion of cash transactions is a limitation. For SA, these data only cover recent years, which restricts the period for which hedonic methods can be applied, as well as more traditional fixed weight methods, that both control for composition by property type and locations. However, worst of all are price indices that take market averages without fully controlling for location and other differences in housing types. Then the index can be contaminated by variations in transactions volumes between high and low-priced locations, and different housing types, as noted above. The ABSA house price index, especially before 2000, does not even meet the standards of the traditional index number methods.

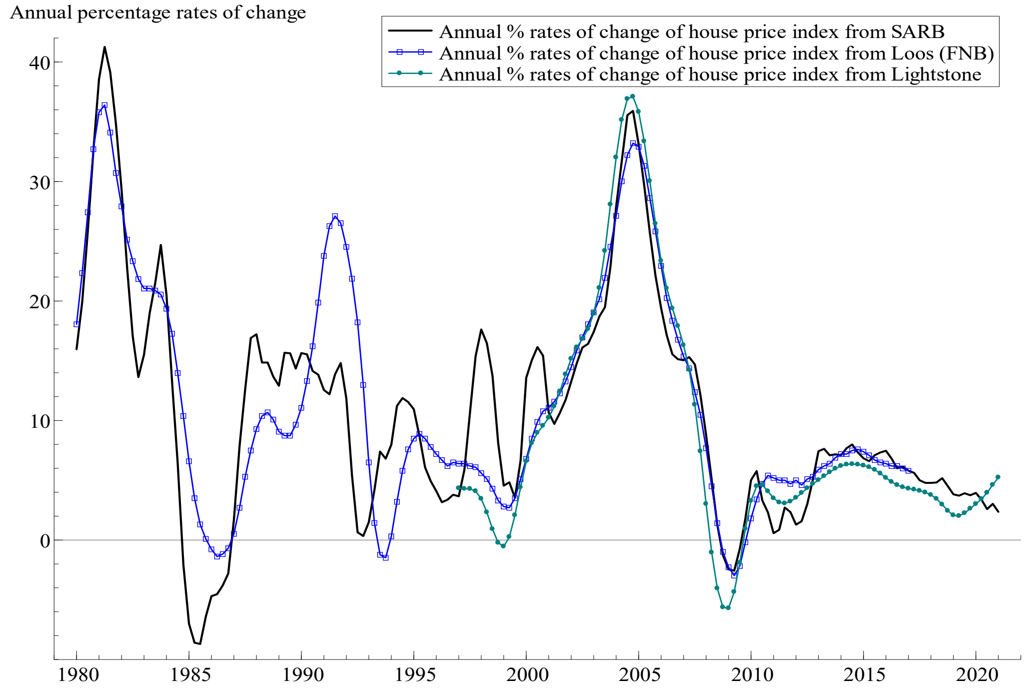
For longer historical data, the only sound alternative in South Africa is an index based on the repeat-sales method, widely used in the US and other countries. There are three sources for a repeat-sales house price index. The Lightstone index runs from 2000 to the present, but Lightstone have provided us with index points back to 1996, which they regard as less reliable. John Loos appears to have been the pioneer of repeat-sales indices for South Africa, beginning with his time at ABSA in 2000–2005 and reaching fruition from 2006 to 2018 when he was Property Economist at FNB. He advised Lightstone when they began their work on repeat-sales indices in the mid-2000s. His index, in the form of the four-quarter percentage growth rate runs from 1980 to 2017Q1.[62] Finally, Hermine Bester, in a remarkable Masters thesis at North-West University (2010), constructed a repeat-sales index for the period 1993 to 2009Q1.

Figure A1 compares the percentage four-quarter growth rates of three different indices. From about 2002 to 2016 there is a reasonably good match between the three measures. In particular, the two repeat-sales indices follow each other quite closely, though the Lightstone index is a little more cyclical, with a higher peak and lower trough than the index from Loos. This may indicate that there are a higher proportion of metropolitan transactions in the Lightstone data, as these tend to swing more widely than more rural or small town locations. In the period 2011–14, the index used by the SARB is rather more volatile, falling more sharply in 2011 and recovering more sharply in 2013–14. However, these differences are over-shadowed by major discrepancies in the period 1997–2001, and earlier.

Figure A2 concentrates on the period 1990 to 2003, in which the three repeat-sales indices follow each other fairly closely, but differ sharply from the ABSA index used by the SARB. Given the evidence against the ABSA index, for our modelling efforts we use the Lightstone index from 1998Q1 to 2020. For 1993Q1 to 1997Q4 we use Bester's index which, like Lightstone's, is more cyclical than the index from Loos, and link it to the Lightstone index in 1998Q1. Before 1993, we use the index from Loos, linked in 1993Q1 to the Bester-Lightstone measure. Our composite index results in more convincing and far better fitting econometric models of house prices and mortgage debt than the index used by the SARB.

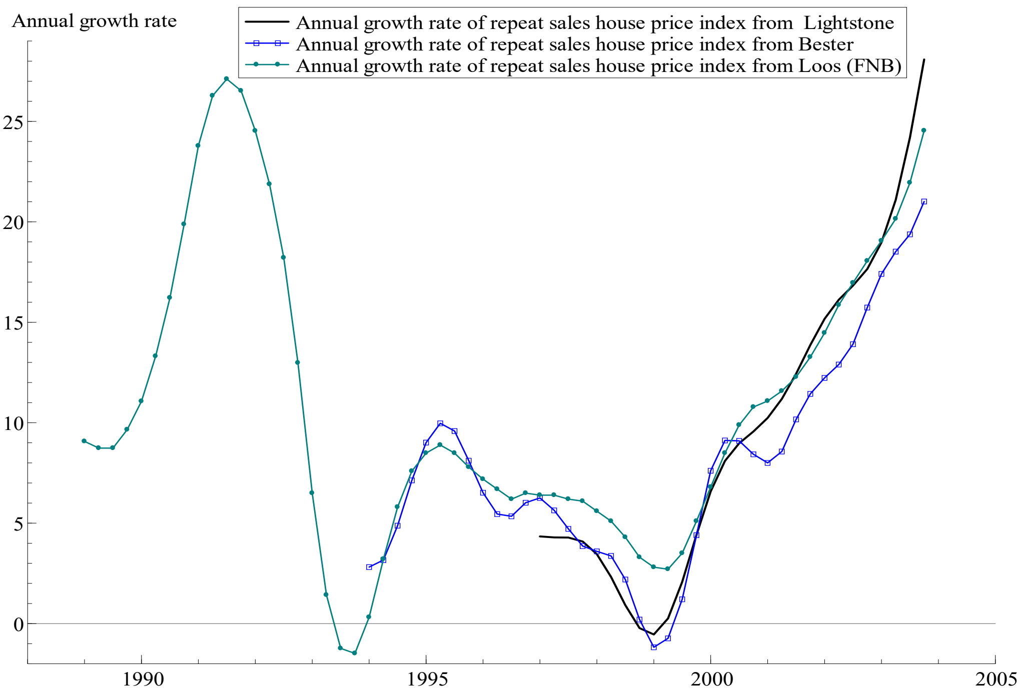
[62] It comes from a 2017 Property Barometer slide show. Unfortunately, FNB were unable to source the raw index whose growth rate is illustrated in the slide show. However, to a close approximation, it is possible to retrieve the numerical values of the data points from the graph.

Figure A2.1: Comparing 4-quarter growth rates of the index used by the SARB, and repeat-sales indices from Lightstone and Loos, 1980–2021.



Note: the index used at the SARB is based on the ABSA index before 2000, and is then a mix including indices from other lenders. Lightstone and Loos (FNB) indices are based on repeat-sales methodology, the latter a digitalization from a graphic.

Figure A2.2: Comparing four-quarter growth rates of house price indices from repeat-sales indices from Lightstone, Bester and Loos, 1989–2003.



Note: see note to Figure A2.1. We are grateful to Hermine Bester for providing her repeat-sales index in numerical form.