What Drives Household Saving?

Examining the Role of Target Wealth

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Abstract

Researchers have traditionally related movements in the personal saving rate to fluctuations in net wealth, credit conditions, unemployment, and other relevant factors. We argue that the empirical research has not fully taken on board implications of the precautionary saving literature, which links household saving decisions to the concept of optimal (target) wealth holdings. Using the state space methods, we identify the unobserved time-varying target wealth from U.S. quarterly data. Our results confirm the effects of uncertainty, interest rates, and expected income on target wealth suggested by the theoretical literature and also indicate that a "wealth gap," the difference between the actual and target wealth, explains an important part of saving rate volatility. Since household net worth is currenly below the estimated target level, the U.S. personal saving rate could remain elevated above the pre-recession levels for a considerable period of time.

Keywords Saving, Target Wealth, Credit Availability, Uncertainty

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1 Introduction

Rarely has any nation's personal saving behavior been subjected to the same degree of scrutiny as the U.S. household saving rate. The recent sharp increase in saving is unprecedented in the post-war period—at the end of the Great Recession in 2009, the personal saving rate (PSR) exceeded its pre-crisis value in 2007 by more than five percentage points, twice the maximum increase during previous recessions (see Figure 1). This surge followed a period of ever-declining saving rates, from over 10 percent of disposable income (DI) in the early 1980s to a mere 1 percent in the mid-2000s.

There is no shortage of potential explanations for the recent jump in the PSR—the consumption theory would have predicted, for example, that the enormous drop in net worth during the Great Recession provided a strong incentive for households to boost their wealth holdings through higher saving from current income. Tighter credit conditions and greater uncertainty have also surely played role as discussed, for example, by Carroll in Council of Economic Advisers (2010).

That said, we argue that the existing empirical research has not fully taken on board implications of the precautionary saving literature which links household saving decisions to the concept of optimal (target) wealth. Specifically, in the presence of the precautionary motive, consumers should boost their saving whenever their actual wealth is below the optimal target level, and vice versa, which establishes the target wealth as a potentially important object of interest.

The main purpose of this paper is to estimate (to our knowledge, for the first time) this unobserved and perhaps time-varying wealth target and verify whether the wealth gap—deviation between actual and target wealth—is indeed an important driver of saving behavior.

Our empirical framework is motivated by several strands of the existing literature. First, our work is conceptually related to the papers estimating the natural rate of unemployment (NAIRU), the natural rate of interest, potential output, or the inflation target, as we estimate unobserved series suggested by the economic theory from observed data using the state space methods.[1] Second, the theory for our target wealth specification is provided by Carroll and Toche (2009), who distilled the key insights from the large literature on consumption and saving under uncertainty into a tractable model with the closed-form solution for target wealth. In Carroll and Toche, consumer's target wealth can be explicitly linked to macro-financial factors such as uncertainty, impatience, income growth, and interest rates. Third, besides the precautionary saving channel, our model allows for the personal saving rate to be affected by a number of other traditional factors such as the fiscal deficits, corporate saving and demographics.[2] We also build on the growing

[1] See Staiger et al. (1997) and Laubach (2001); Laubach and Williams (2003); Kuttner (1994); and Leigh (2008), respectively.

[2] The saving rate literature offers a number of possible determinants of saving: papers exploring linkages between personal saving, fiscal deficits, expected income growth, and habit formation include Barro (1974), Campbell (1987), and Carroll et al. (2000). For reduced-form saving regressions exploring the relationship of household saving with other potential determinants such as net wealth, unemployment, corporate profits and foreign saving, see for example Summers and Carroll (1987), Callen

literature about the macroeconomic effects of changing credit availability (e.g., Muellbauer (2007), Guerrieri and Lorenzoni (2010), and Hall (2011)). In this line of work, increasing availability of credit (as reflected, for example, by easing bank lending standards such as the required minimum loan-to-value or loan-to-income ratios) helps consumers increase—albeit possibly temporarily—their consumption for a given level of income.[3]

Our estimation framework consists of two key equations. The first (observation) equation links household saving to the gap between the actual and target net wealth, and many other possible determinants of saving, including the availability of credit. The second (transition) equation links the unobserved target wealth to its theoretical determinants such as uncertainty, expected interest rates, and expected income growth. We estimate the resulting state space system using the Kalman filter algorithm.

Our empirical model of household saving captures very well the broad trend in the PSR over the past four decades and confirms the recent findings of Carroll in Council of Economic Advisers (2010) and Carroll et al. (2012), who argue using different empirical frameworks that the U.S. household saving behavior can be explained well with a parsimonious model of net wealth, credit conditions, and uncertainty. In this paper, we extend these results along several dimensions by highlighting the important role of time-varying target wealth.

In particular, the estimated target wealth fluctuates substantially over time and exerts significant influence on the saving rate. Mincer–Zarnowitz regressions place a much greater weight on a model with time-varying wealth than a traditional model with (implicitly) constant target wealth. Looking at the experience of the past several years, the large negative gap between the actual and target wealth contributed about 4 percentage points to the increase in the saving rate between the 2005 trough and the 2009 peak, of which around 1.5 percentage point is attributable to the higher wealth target. Indeed, the increase in target wealth during recessions typically tends to exacerbates the negative effects of falling asset prices on consumption.[4] As for the determinants of target wealth more generally, the regression results are consistent with the theoretical priors. Higher uncertainty and real interest rates are associated with higher household target wealth in percent of disposable income. More optimistic income expectations tend to reduce target wealth, although this particular result is often statistically insignificant, potentially due to data measurement issues.

Our results are also informative about one of the key policy issues of today—the pace of US economic recovery. With household wealth below the optimal level, the household

and Thimann (1997), Masson et al. (1998), Loayza et al. (2000), Horioka and Wan (2007), and Council of Economic Advisers (2010).

[3]For a recent complementary perspective on the implications of credit expansion for household leverage, consumer default, spending and employment using disaggregated data, see the series of papers by Mian and Sufi (e.g., Mian and Sufi (2009), Mian and Sufi (2010) and Mian and Sufi (forthcoming)) and Dynan and Kohn (2007). Dynan et al. (2006) reviews literature documenting the sustained increase in credit availability before the Great Recession.

[4]These findings are broadly in line with the complementary household-level evidence reported in Bricker et al. (2011), who document using SCF data higher desired precautionary saving among most families during the Great Recession.

saving rate could remain elevated above the pre-recession levels for a considerable period of time, reducing the likelihood of a speedy recovery.

2 Empirical Framework

2.1 Theory: Target Wealth and Credit Conditions

This section describes the key theoretical underpinnings of our empirical framework. The first strand of the literature upon which we build is Carroll and Toche (2009), who provided a tractable framework for analyzing the impact of uncertainty, especially the unemployment risk, on household saving.

The key feature, which makes it possible for Carroll and Toche to solve analytically for target wealth even under the CRRA utility, is the simple form of unemployment risk: the employed consumers face a constant probability $\mho$ of becoming unemployed, while the unemployed consumers remain without a job forever. Under these assumptions, Carroll and Toche show that the steady-state target wealth m^* depends on unemployment risk $\mho$, interest rate r, growth rate of wages Δy and preferences:[5]

$$m^* = f(\underset{(+)}{\mho}, \underset{(+)}{r}, \underset{(-)}{\Delta y}, \text{preferences}).$$

The target wealth increases with the unemployment risk, because in response to higher uncertainty, consumers choose to build up a larger precautionary buffer of wealth to protect their spending.[6] Meanwhile, a higher interest rate increases target wealth as consumers shift resources from current consumption to saving. Stronger income growth translates into a lower wealth target because households consume more now, anticipating additional resources in the future. Finally, risk aversion and discount factor have a qualitatively similar impact on target wealth as uncertainty and interest rate, respectively. While the unemployment risk in Carroll and Toche (2009) is of a simple form, the key mechanisms at work are the same as those in more sophisticated setups with a realistic specification of uninsurable risks (building on the work of Skinner (1988), Zeldes (1989), Deaton (1991), Carroll (1997) and others).

In our empirical framework, we do not intend to identify the slowly-moving deep parameters such as risk aversion or the discount rate. Instead, we aim to estimate the dynamics of the target wealth with respect to risk, interest rates, and expected income:

$$m_t^* = m_0 + \delta_\sigma \sigma_{t-1}^{2*} + \delta_r r_{t-1}^* + \delta_y \Delta y_{t-1}^* + \eta_t^m, \tag{1}$$

[5] Specifically, the steady-state target wealth is

$$m^* = 1 + \frac{R}{\Gamma + \zeta\Gamma - R},$$

where $R = 1 + r$, $\Gamma = (1 + \Delta y)/(1 - \mho)$, $\zeta = R\kappa^u\Pi/\Gamma$, $\kappa^u = 1 - R^{-1}(R\beta)^{1/\rho}$, $\Pi = \left(\frac{((R\beta)^{1/\rho}/\Gamma)^{-\rho} - (1-\mho)}{\mho}\right)^{1/\rho}$, β denotes the discount factor and ρ denotes the coefficient of relative risk aversion.

[6] Note that the increase in $\mho$ is a pure increase in risk because productivity is assumed to grow by the factor $1/(1 - \mho)$ each period, $\ell_{t+1} = \ell_t/(1 - \mho)$ (see Carroll and Toche (2009), p. 6).

where σ^{2*} denotes uncertainty, r^* is the ex ante real interest rate and Δy^* denotes expected income growth. All four starred variables are assumed to be unobserved—the target wealth series is a theoretical construct, while the available measures of uncertainty, ex ante real interest rates and expected income do not perfectly match their (starred) theoretical counterparts.[7]

The second strand of the literature on which we build our model is related to Muellbauer (2007), Guerrieri and Lorenzoni (2010), Council of Economic Advisers (2010), Hall (2011) and others. In this literature, relaxation of credit constraints leads to an immediate increase in consumption for a given level of income as the previously constrained consumers accumulate new debt. In this light, financial liberalization, which accelerated in the 1980s as Dynan et al. (2006) as document, could be interpreted as a process of continual easing of credit constraints which put a downward pressure on the saving rate independently of net wealth.

In sum, personal saving is in our empirical framework allowed to be driven by a number of factors. First, due to the precautionary motive, saving rises whenever actual wealth m drops below the target wealth m^* ($\beta_m < 0$). Second, the model is augmented with a measure of credit supply conditions CCI, which are meant to proxy the effect of credit constraints on consumption and saving. Additional variables which could influence the saving rate separately, such as the unemployment rate, demographics, or government and corporate savings, are collected in the vector X_t,

$$s_t = \beta_0 + \beta_s s_{t-1} + \beta_m(m_t - m_t^*) + \beta_{\mathrm{CCI}}\mathrm{CCI}_t + \beta' X_t + \varepsilon_t^s.$$

Credit conditions are measured by an index that increases when credit supply is loosened; the coefficient β_{CCI} is therefore expected to be negative, so that higher supply of credit implies lower saving.[8] The sluggishness in the saving rate adjustment is captured by its lagged value, $\beta_s > 0$.

2.2 The State Space Model

Our empirical model has a state space representation consisting of four measurement and four transition equations. The first measurement equation links the saving rate to its lagged value, the wealth gap (a difference between the actual and target wealth), credit conditions, and other controls:

$$s_t = \beta_0 + \beta_s s_{t-1} + \beta_m(m_t - m_t^*) + \beta_{\mathrm{CCI}}\mathrm{CCI}_t + \beta' X_t + \varepsilon_t^s. \tag{2}$$

The remaining three measurement equations postulate that the empirical measures of uncertainty, interest rates and expected income track their underlying theoretical counterparts (denoted by stars) only imperfectly, either because of pure measurement error

[7]To keep the estimation tractable, we impose a linearity of the model and normality of disturbances. While neither holds in reality, our estimation approach (which also allows for measurement error) seems to capture the key properties of the data well.

[8]Given the smoothness of the CCI (Figure 2), we do not complicate the model further by introducing a measurement error in this variable because the implied "true" CCI_t^* would practically coincide with the measured CCI_t.

or timing mismatches (e.g., due to the approximations used in the calculation of the real interest rate):

$$\begin{aligned}
\sigma_t^2 &= \sigma_t^{2*} + \varepsilon_t^\sigma, && (3)\\
r_t &= r_t^* + \varepsilon_t^r, && (4)\\
\Delta y_t &= \Delta y_t^* + \varepsilon_t^y. && (5)
\end{aligned}$$

The disturbances ε_t^s, ε_t^σ, ε_t^r and ε_t^y are assumed to follow normally distributed independent white noise processes.

The first transition equation expresses the target wealth as a function of uncertainty, expected interest rates and expected income growth:

$$m_t^* = \delta_\sigma \sigma_{t-1}^{2*} + \delta_r r_{t-1}^* + \delta_y \Delta y_{t-1}^* + \eta_t^m. \tag{6}$$

The remaining transition equations have a standard simple random-walk form to allow flexibility in the dynamics of state variables:

$$\begin{aligned}
\sigma_t^{2*} &= \sigma_{t-1}^{2*} + \eta_t^\sigma, && (7)\\
r_t^* &= r_{t-1}^* + \eta_t^r, && (8)\\
\Delta y_t^* &= \Delta y_{t-1}^* + \eta_t^y. && (9)
\end{aligned}$$

In sum, the state space representation of the system can be written as follows:

$$\begin{aligned}
\tilde{y}_t &= Z\alpha_t + Bx_t + \varepsilon_t,\\
\alpha_t &= T\alpha_{t-1} + \eta_t,
\end{aligned}$$

where

$$\tilde{y}_t = \begin{bmatrix} s_t \\ \sigma_t^2 \\ r_t \\ \Delta y_t \end{bmatrix}, \qquad Z = \begin{bmatrix} -\beta_m & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \qquad \alpha_t = \begin{bmatrix} m_t^* \\ \sigma_t^{2*} \\ r_t^* \\ \Delta y_t^* \end{bmatrix},$$

$$B = \begin{bmatrix} \beta_{\mathrm{CCI}} & \beta_s & \beta_m \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \qquad x_t = \begin{bmatrix} \mathrm{CCI}_t \\ s_{t-1} \\ m_t \end{bmatrix}, \qquad \varepsilon_t = \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^\sigma \\ \varepsilon_t^r \\ \varepsilon_t^y \end{bmatrix},$$

$$T = \begin{bmatrix} 0 & \delta_\sigma & \delta_r & \delta_y \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \qquad \eta_t = \begin{bmatrix} \eta_t^m \\ \eta_t^\sigma \\ \eta_t^r \\ \eta_t^y \end{bmatrix}$$

and ε_t and η_t are iid zero-mean normal variables with diagonal variance matrices $\mathrm{var}(\varepsilon_t) = H$ and $\mathrm{var}(\eta_t) = Q$.

2.3 Data for Estimation

We use U.S. quarterly data for 1966Q2–2009Q3, with the first and last periods determined by the availability of our preferred measures of credit conditions and uncertainty, respectively. The saving rate from the BEA's national accounts is expressed in percent of disposable income,[9] while wealth is measured as the ratio of household net worth to disposable income, in line with Carroll and Toche (2009).[10] The wealth ratio is lagged by one quarter to account for the fact that the net worth data are reported as the end-of-period values.

The measure of credit supply conditions CCI (see Figure 2) is constructed similarly as in Muellbauer (2007) and Duca et al. (2010) by cumulating responses about the availability of consumer installment loans from the Federal Reserve's Senior Loan Officer Opinion Survey (see also Fernandez-Corugedo and Muellbauer (2006) and Hall (2011)).[11] The Credit Conditions Index (CCI) measures the availability/supply of credit to a typical household through factors other than the level of interest rates—for example, through loan to value and loan to income ratios, availability of mortgage equity withdrawal and mortgage refinancing. The broad trends in the CCI index—that is, the rising availability of credit following financial liberalization in the early 1980s and shrinking credit supply during the recent financial crisis—seem to reflect well the key developments of the U.S. financial market institutions as described in McCarthy and Peach (2002), Dynan et al. (2006) and Green and Wachter (2007), among others.[12] Indeed, the CCI index is highly correlated with an alternative index of financial liberalization of Abiad et al. (2008) based fully on the readings of laws and regulations—the correlation is about 90 percent. However, this alternative index is only available through 2005, which renders it unhelpful for the analysis of the Great Recession.

Our measure of macroeconomic and financial uncertainty is from Bloom et al. (2009) and is calculated as the first principal component extracted from the following proxies for uncertainty: aggregate output growth volatility (measured by a stochastic model), stock market return volatility (measured using the VIX implied volatility index), market participants' disagreement about GDP and unemployment rate forecasts (from the Survey

[9]As a robustness check, we have also re-estimated our model with an alternative measure of the PSR calculated from the Flow of Funds (FoF) as the sum of the net acquisition of financial assets and tangible assets minus the net increase in liabilities. Because this FoF-based measure is substantially more volatile, the fit of the model is worse than for the NIPA-based PSR. However, the main messages of the paper remain unchanged.

[10]The literature on precautionary savings typically measures wealth as a fraction of *permanent* income. We have checked that such variable very closely tracks the indicator we use. This is not surprising because, as is well-known, almost all shocks to the level of aggregate income are permanent.

[11]The question asks about banks' willingness to make consumer installment loans now as opposed to three months ago. To calculate a proxy of the *level* of credit conditions, the scores from the survey were accumulated, and for convenience normalized to lie between zero and one. As in Muellbauer, we use the question on consumer installment loans rather than mortgages because the latter is only available starting in 1990Q2 and the question changed in 2007Q2.

[12]Our results do not materially change when we use the credit conditions index of Duca et al. (2010), which slightly differs from our CCI in that Duca et al. explicitly remove identifiable effects of interest rates and the macroeconomic outlook from the SLOOS data using regression techniques.

of Professional Forecasters), the dispersion in firm-level sales growth and stock market returns, and the dispersion in industry-level output and productivity growth.[13]

The real interest rate r_t is approximated as the difference between the ten-year Treasury bond yield and a one-year-ahead inflation forecast from the Survey of Professional Forecasters (SPF).[14] Income growth expectations Δy_t are proxied using the one-year-ahead GDP growth forecast from the SPF.[15]

3 Estimation

As noted above, we identify the unobserved target wealth ratio from (2)–(9) using the Kalman filter. Conceptually, this approach draws on the large existing empirical literature employing the Kalman filter to estimate unobservable macroeconomic concepts such as potential output, the natural rate of unemployment, the natural rate of interest, or the inflation target. More recently, the Kalman filter has also been used to estimate the dynamic stochastic general equilibrium models.

3.1 Baseline Specification

Since the signal to noise ratios $\lambda \equiv \sqrt{\operatorname{var}(\eta_t)/\operatorname{var}(\varepsilon_t)}$ for uncertainty, interest rates and income are small, their maximum likelihood estimates are subject to "the pileup problem," i.e., the likelihood function has a positive probability mass at $\operatorname{var}(\eta_t) = 0$ even if the true $\operatorname{var}(\eta_t)$ is positive. Consequently, the maximum likelihood procedure often estimates $\operatorname{var}(\eta_t) = 0$. The standard remedy proceeds in two steps. First, we apply the median-unbiased procedure of Stock and Watson (1998) to estimate the variances of state variables $\operatorname{var}(\eta_t)$. Second, given these values, we estimate the remaining parameters of the model with maximum likelihood.

Figure 3 shows the in-sample fit of the baseline model. The state space system captures the broad stability of the personal saving rate until the early 1980s, its subsequent trend decline through the mid-2000s, as well as the rebound over the past several years.

The first column of Table 1 reports parameter estimates and their standard errors for the *baseline specification* of the model. In the observation equation for the saving rate, the coefficient on wealth gap β_m is negative and statistically significant, suggesting that consumers indeed tend to boost their saving whenever their actual wealth lies below the target. On average, a 100 percentage point wealth gap (in percent of disposable income) raises the saving rate by 0.6 percentage points in the short term. The eventual effect is

[13]The Bloom et al. measure of uncertainty does not capture *idiosyncratic, household-specific* household income volatility, which has risen since the 1970s, as documented by Dynan et al. (2007) and Moffitt and Gottschalk (2007). We leave this issue for future research. However, attitudinal questions in the Survey of Consumer Finances suggest that the fraction of saving held for precautionary reasons has remained broadly stable over time—see Dynan and Kohn (2007).

[14]The ten-year-ahead inflation forecast is available from the SPF only starting in 1991Q4, and is in any case strongly correlated with the one-year-ahead expectations. The error term ε_t^r in equation (4) is meant to soak up any measurement errors related to the horizon mismatch.

[15]Similarly as for the real interest rate, the error term ε_t^y in equation (5) is meant to capture any approximation error.

$\beta_m/(1-\beta_s) = 0.643/(1-0.519) \approx 1.3$ percentage points. The estimated coefficients thus imply a relatively small direct marginal propensity to consume out of wealth (MPCW) compared to the typical estimates for the United States. It should be kept in mind, however, that the model is formulated in terms of the wealth gap rather than the wealth level, while also including a measure of credit conditions. When the CCI index is omitted from the regression, the eventual MPCW more than doubles to 2.8 (this is implied by the second model in Table 1).[16] The coefficient on the credit conditions index is also negative and highly statistically significant. The finding that easier credit conditions tend to reduce the saving rate is in line with Fernandez-Corugedo and Muellbauer (2006), Council of Economic Advisers (2010), Guerrieri and Lorenzoni (2010) and Hall (2011).

The estimated transition equation for target wealth (1) is broadly consistent with the theoretical priors. First, target wealth is strongly positively correlated with the Bloom measure of uncertainty. To the extent that uncertainty sharply rises during recessions (see Bloom et al. (2009), Sandri (2009) and Dovern et al. (forthcoming)), the saving rate effectively becomes more sensitive to any decline in asset prices. Second, the estimated target wealth rises with the real interest rate. Third, higher expected income growth reduces the saving rate in the baseline model, in line with Campbell (1987); however, the coefficient is not statistically significant. This could in part be due to the difficulties with approximating expected income using one-year ahead GDP growth.

3.2 Properties of Target Wealth and the Wealth Gap

Figure 4 compares the Kalman smoother estimates of the state variables—target wealth m^*, uncertainty σ^{2*}, interest rate r^* and income growth Δy^*—with their measured counterparts. Our principal focus is on the target wealth ratio to the extent that the other state variables were estimated with simple filters (7)–(9). That said, it is notable that that the estimated profile of the nature rate of interest resembles quite well the results from a dedicated model of Laubach and Williams (2003).

The estimated path for target wealth m_t^* has a number of plausible characteristics (see the first panel of Figure 4). The wealth target varies substantially over time, mostly fluctuating between 450 and 600 percent of disposable income with two notable exceptions. The target rose toward 620 percent in the early 1980s due to elevated uncertainty and high real interest rates. At the other extreme, the wealth target fell close to 400 percent of disposable income during the mid-2000s when the perceived uncertainty of the economic environment was unusually low (a period of the "Great Moderation") and the real interest rate fell to within-sample lows.

The estimates of the target wealth are understandably subject to considerable uncertainty. The point estimate of target wealth at the end of 2009 is about 523 percent of

[16] Muellbauer (2007) finds that the estimate of MPCW is positively correlated with credit conditions. We do not examine such interactions in this paper which focuses on the first-order effects. In any case, the potential nonlinearity cannot be explored in the Kalman filter framework because state variables cannot be interacted with the observables. Linearization would not be sensible as the credit conditions index does not tend to return to a given steady state.

disposable income, but one standard deviation of this estimate taking into account both parameter and filter uncertainty (calculated using the Ansley and Kohn (1986) method) is 140 percent of DI, the bulk of which is due to parameter uncertainty. Such a degree of uncertainty is common in the literature identifying unobservable concepts such as the natural rate of interest or non-accelerating inflation rate of unemployment (NAIRU). That said, in our case (as in Laubach and Williams (2003)), the large standard errors seem to be caused by the joint estimation of several state variables—in contrast with the NAIRU literature where, in contrast, the primary reason seems to be a low statistical significance of the Phillips curve slope (Staiger et al. (1997) and Laubach (2001)). Note also that the signal-to-noise ratios λ in the third panel of Table 1 are significantly different from zero.

From the economic perspective, accounting for the effects of time-varying target wealth considerably improves the explanatory power of the saving rate model. A horse-race regression of the fitted values of the baseline model in Table 1 against the fitted values from the analogous model with a constant target wealth puts a much greater weight on the former model, suggesting that the time variation in the target wealth is important for understanding the dynamics of the PSR.[17]

Figure 5 examines how the two key determinants of saving—wealth gap and credit conditions—contribute to the fit of the model. For convenience, we back out the long-term contributions of both variables $\frac{\beta_m}{1-\beta_s}(m_t - m_t^*)$ and $\frac{\beta_{\text{CCI}}}{1-\beta_s}\text{CCI}_t$. Credit conditions account well for the trend decline in the saving rate since the early 1980s, but do poorly at accounting for the cyclical volatility of saving, including saving rate increases during the recessions of 1973–75, the early 1980s and 2007–09. Meanwhile, the wealth gap contributes to explaining the saving rate dynamics by capturing variation in both actual and target wealth. The wealth gap contributed about 4 percentage points to the increase in the saving rate between the 2005 trough and the 2009 peak, of which around 1.5 percentage points is attributable to the higher household wealth target and the remaining 2.5 percentage points are attributable to lower asset values.

3.3 Alternative Specifications

Figure 6 makes it clear that our estimate of target wealth extracts a considerable amount of information from the theory-based determinants of saving in equation (2) and differs considerably from univariate filters such as the Christiano and Fitzgerald (2003) bandpass

[17] In particular, we estimate the Mincer–Zarnowitz regression

$$s_t = \tilde{\lambda}^{\text{TV}} \hat{s}_t^{\text{TV}} + (1 - \tilde{\lambda}^{\text{TV}})\hat{s}_t^{\text{OLS}} + \varepsilon,$$

where $\hat{s}_t^{\text{TV}}$ denotes the fitted values implied by the (time-varying) baseline model of Table 1 and $\hat{s}_t^{\text{OLS}}$ denotes the fitted values from the OLS regression

$$s_t = \beta_0 + \beta_s s_{t-1} + \beta_m m_t + \beta_{\text{CCI}}\text{CCI}_t + \varepsilon_t.$$

The Mincer–Zarnowitz regression yields $\tilde{\lambda}^{\text{TV}} = 1.14$.

filter or the random-walk-plus-noise (local-level) model, which do not allow for sustained departures of target wealth from actual wealth.[18]

Table 1 and Figure 7 compare the baseline Kalman filter estimates of target wealth to two other alternative models: (i) the baseline model (2)–(9) which excludes the credit conditions (i.e., imposes $\beta_{\text{CCI}} = 0$) and (ii) the random walk model with a flexible transition equation for target wealth à la Staiger et al. (1997): $m_t^* = m_{t-1}^* + \eta_t^m$. The results from the no-CCI model highlight the key role of credit conditions in explaining the dynamics of saving over the long term: to match the saving rate data, this alternative model forces the target wealth to fall over time, which seems implausible, especially given the dramatically higher uncertainty faced by consumers during the Great Recession. When the target wealth is modeled as a random walk (an agnostic approach), the coefficients on wealth target and credit conditions remain correctly signed (negative) and statistically significant, but the estimated target wealth varies little over time because the estimated signal to noise ratio λ_m is substantially lower that for the other two specifications in Table 1.

Table 2 reports results for several other alternative specifications of the Kalman filter. The estimation results change little when we use alternative measures of uncertainty and expected interest rate—model M2 proxies uncertainty with the Bloom et al. (2009) stock market uncertainty index (based on the VIX/VXO implied stock market volatility) and the three-month interest rate (rather than the ten-year rate as in the baseline). In the specification M3, which excludes the lagged PSR, the estimated coefficients on the wealth gap and CCI roughly double which is consistent with the estimated coefficient on lagged saving of about 1/2 in specification M1. Model M4 contains the full set of control variables in X_t including corporate and government saving, real interest rate and unemployment rate. Although some these variables may be statistically significant, they make only a marginal contribution to the goodness-of-fit in economic terms. Demographics variables such as the old-age and young-age dependency ratios were not significant in our specifications and are not reported here.[19] As additional checks, specifications M5 and M6 drop expected income growth and the expected real interest rate from the baseline, respectively. The estimated end-of-sample target wealth ratios vary across specifications, but the target wealth is in all cases but one above the current net worth-to-disposable income ratio of 495 percent.

4 Conclusions

In this paper, we build on the precautionary saving literature and establish target wealth as an important object of empirical interest, similarly as are the natural rate of unemployment,

[18] The random-walk-plus-noise (local-level) model is:

$$\begin{aligned} z_t &= \mu_t + \tilde{\varepsilon}_t, \\ \mu_t &= \mu_{t-1} + \tilde{\eta}_t, \end{aligned}$$

where $(\tilde{\varepsilon}_t \ \tilde{\eta}_t)'$ are iid zero-mean normal variables with the variance matrix $\text{var}(\tilde{\varepsilon}_t \ \tilde{\eta}_t)' = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_\eta^2 \end{pmatrix}$.

[19] In cross-country studies, the effect of changing demographics on saving is usually identified from the experiences of Japan and Korea, which are well ahead of the United States in the population aging process.

inflation target, or natural rate of interest in other macroeconomic fields. We find that target wealth fluctuates considerably over time, primarily due to changes in uncertainty and the real interest rate. Changes in target wealth exert significant influence on the household saving behavior, in particular during recessions when a spike in target wealth exacerbates an upward pressure on saving from lower asset prices. While the saving rate behavior is ultimately driven by a variety of factors, our results do suggest that the PSR could remain higher than before the crisis for some time since net wealth remains below the estimated target wealth.

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Table 1 Three models with time-varying target wealth

$$s_t = \beta_0 + \beta_s s_{t-1} + \beta_m (m_t - m_t^*) + \beta_{\text{CCI}} \text{CCI}_t + \varepsilon_t^s$$
$$m_t^* = \delta_\sigma \sigma_{t-1}^{2*} + \delta_r r_{t-1}^* + \delta_y \Delta y_t^* + \eta_t^m$$

Model	Baseline	Baseline without CCI	Random Walk
Parameter		Measurement equation for s_t	
β_0	4.598***	2.575**	4.049***
	(1.183)	(1.054)	(0.894)
β_s	0.519***	0.677***	0.583***
	(0.099)	(0.092)	(0.097)
β_m	−0.643**	−0.915***	−0.764***
	(0.270)	(0.282)	(0.276)
β_{CCI}	−2.332***		−2.371***
	(0.664)		(0.751)
		Transition equation for m_t^*	
δ_σ	4.447***	3.077***	
	(1.577)	(0.808)	
δ_r	0.254*	0.103	
	(0.139)	(0.082)	
δ_y	−0.290	0.282	
	(0.439)	(0.200)	
		Signal-to-noise ratios $\lambda = \sigma_\eta / \sigma_\varepsilon$°	
λ_σ	0.0080**	0.0080**	
90% CI for λ_σ	(0.0013, 0.0971)	(0.0013, 0.0971)	
λ_r	0.0191**	0.0191**	
90% CI for λ_r	(0.0032, 0.1536)	(0.0032, 0.1536)	
λ_y	0.0091**	0.0091**	
90% CI for λ_y	(0.0012, 0.1034)	(0.0012, 0.1034)	
λ_m			0.0029**
90% CI for λ_m			(0.0003, 0.0355)
Log-likelihood	−748.39	−755.33	−203.03
		Point estimates for m_t^*	
Mean	4.919	4.520	5.096
End-of-sample	5.231	4.419	5.186
		Standard errors for $m_t^{*\diamond}$	
Mean	1.401	1.336	1.814
End-of-sample	1.513	1.145	1.633

Notes: $\{^*, ^{**}, ^{***}\}$ = Statistical significance at $\{10, 5, 1\}$ percent. Standard errors in the parentheses. Target wealth for the random walk model M3: $m_t^* = m_{t-1}^* + \eta_t^m$. ∘: Signal-to-noise ratios were estimated using the median unbiased procedure of Stock and Watson (1998) (and the Quandt likelihood ratio (QLR)/sup Wald statistic). ⋄: Standard errors for m_t^* were calculated with the Ansley and Kohn (1986) procedure (and account both for filter and parameter uncertainty).

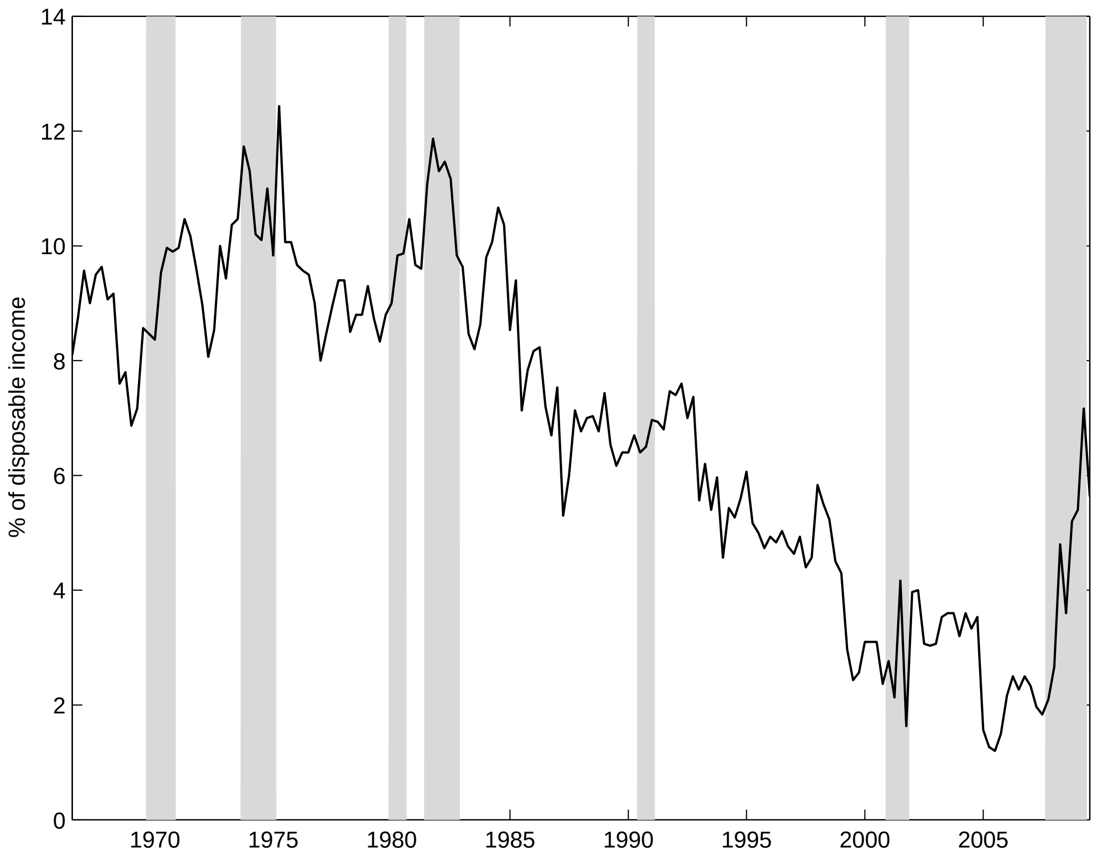
Table 2 Additional models with time-varying target wealth

$$s_t = \beta_0 + \beta_s s_{t-1} + \beta_m(m_t - m_t^*) + \beta_{\text{CCI}}\text{CCI}_t + \beta' X_t + \varepsilon_t^s$$
$$m_t^* = \delta_\sigma \sigma_{t-1}^{2*} + \delta_r r_{t-1}^* + \delta_y \Delta y_t^* + \eta_t^m$$

Model	M1	M2	M3	M4	M5	M6
Description	Baseline	Alt IR & Unc	No Lagged Saving	Full Controls	Baseline ex Y	Baseline ex IR
Parameter	Measurement equation for saving rate s_t					
β_0	4.598***	4.090***	8.365***	5.810***	4.462***	4.259***
	(1.183)	(1.184)	(0.907)	(1.418)	(1.167)	(1.165)
β_s	0.519***	0.601***		0.484***	0.516***	0.607***
	(0.099)	(0.095)		(0.105)	(0.099)	(0.088)
β_m	−0.643**	−0.552*	−1.506***	−0.623*	−0.751***	−0.479*
	(0.270)	(0.282)	(0.289)	(0.335)	(0.234)	(0.251)
β_{CCI}	−2.332***	−2.519***	−4.310***	−2.939***	−2.067***	−2.017***
	(0.664)	(0.924)	(0.789)	(0.907)	(0.556)	(0.641)
β_u				−0.263*		
				(0.149)		
β_r				0.180*		
				(0.105)		
β_{GS}				−0.217**		
				(0.092)		
β_{CS}				−0.092		
				(0.128)		
	Transition equation for target wealth m_t^*					
δ_σ	4.447***	4.696*	4.550***	6.014**	3.778***	5.076**
	(1.577)	(2.738)	(0.952)	(2.926)	(0.929)	(2.341)
δ_r	0.254*	0.785	0.293***	−0.036	0.232**	
	(0.139)	(0.636)	(0.094)	(0.243)	(0.112)	
δ_y	−0.290	−0.629	−0.160	−0.461		−0.555
	(0.439)	(0.894)	(0.276)	(0.698)		(0.656)
Log-likelihood	−748.39	−834.04	−759.10	−743.07	−468.42	−472.47
	Point estimates for target wealth m_t^*					
Mean	4.919	5.002	5.526	5.172	4.936	3.996
End-of-sample	5.231	5.631	5.680	5.780	5.014	4.797
	Standard errors for target wealth $m_t^{*\diamond}$					
Mean	1.401	1.802	0.714	1.833	1.649	3.132
End-of-sample	1.513	2.245	0.822	1.877	1.485	2.786

Notes: $\{^*, ^{**}, ^{***}\}$ = Statistical significance at $\{10, 5, 1\}$ percent. Standard errors in the parentheses. GS: government surplus/deficit as a fraction of GDP, CS: corporate saving as a fraction of GDP. $\diamond$: Standard errors for m_t^* were calculated with the Ansley and Kohn (1986) procedure (and account both for filter and parameter uncertainty).

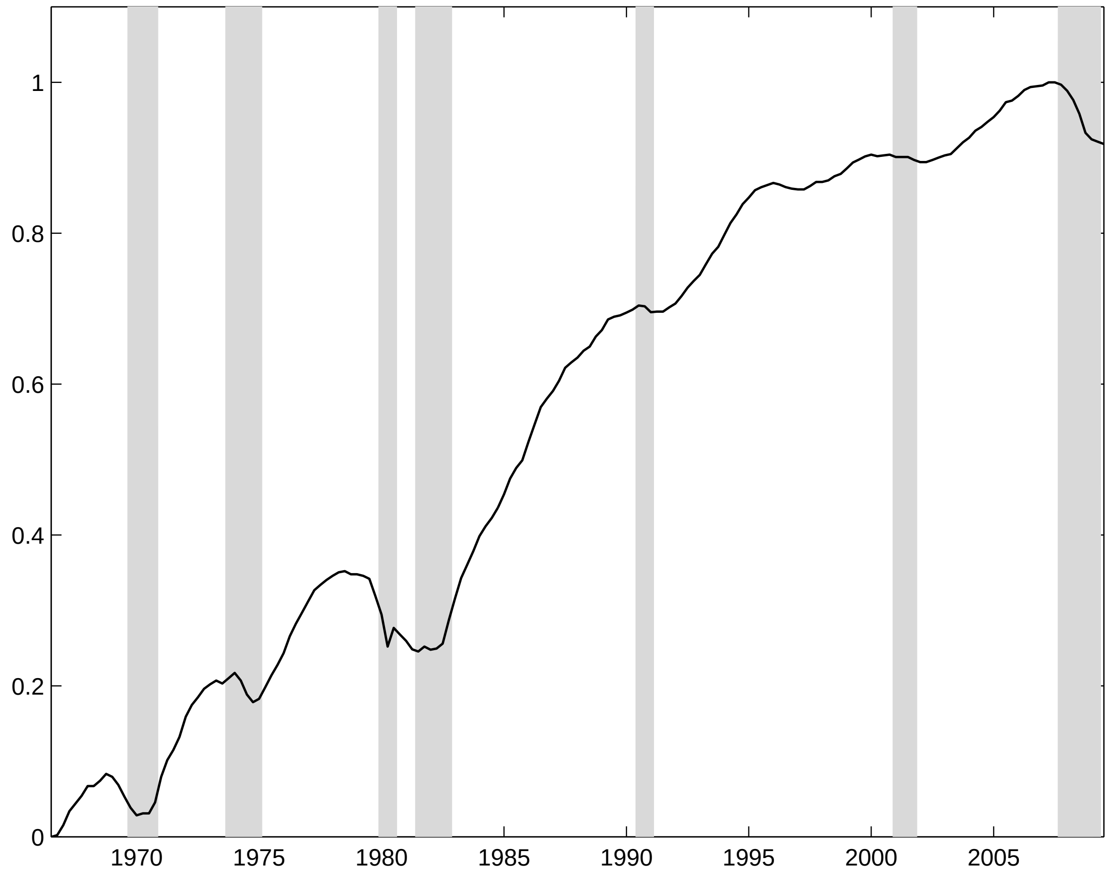
Figure 1 Personal saving rate



Notes: Shading—NBER recessions.

Source: Bureau of Economic Analysis, US Department of Commerce.

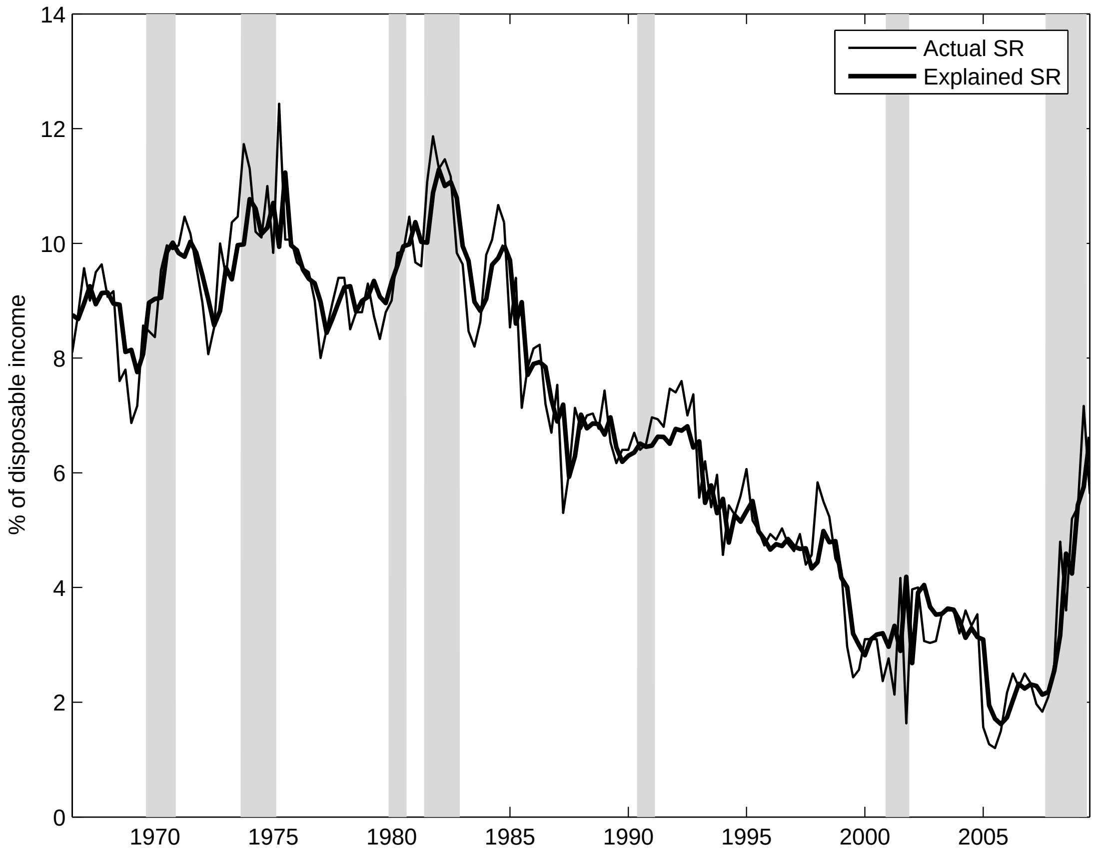
Figure 2 The Credit Conditions Index



Notes: Shading—NBER recessions.

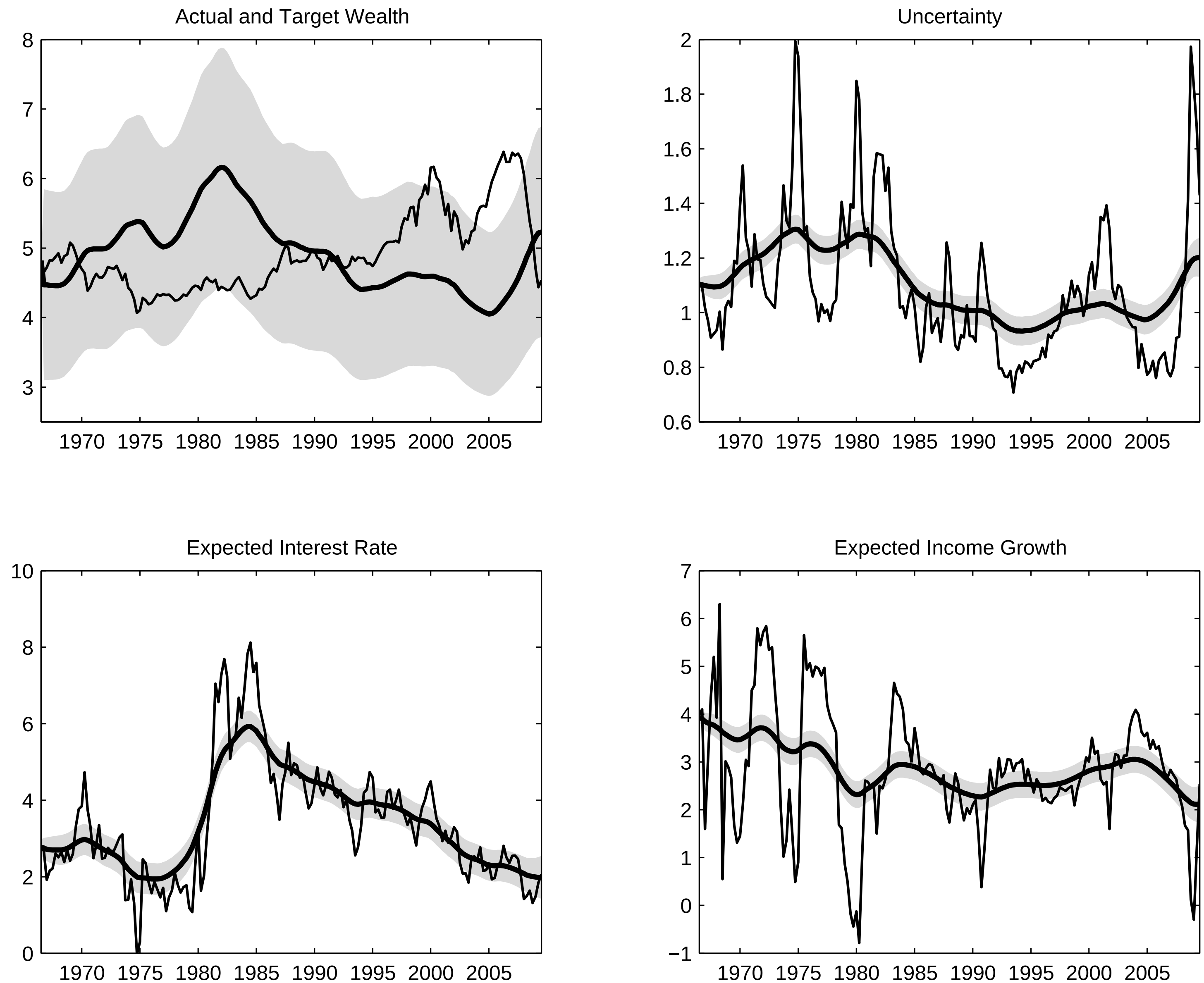
Sources: Federal Reserve, accumulated scores from the question on change in the banks' willingness to provide consumer installment loans from the Senior Loan Officer Opinion Survey on Bank Lending Practices, `http://www.federalreserve.gov/boarddocs/snloansurvey/`.

Figure 3 Actual and explained saving rate



Notes: Shading—NBER recessions. "Explained SR" shows the fit of the baseline model of Table 1.

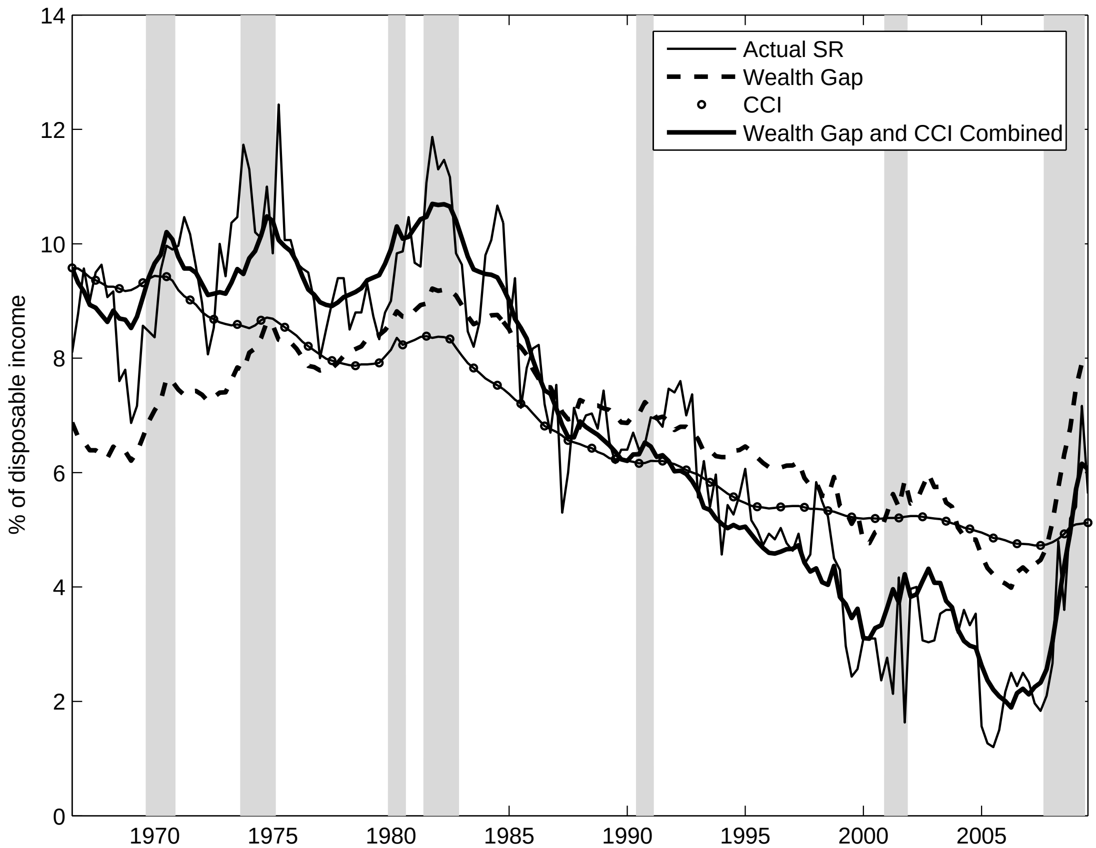
Figure 4 Key variables and their unobserved counterparts



Notes: Thin line—Actual series, thick line—Kalman smoother, shaded bands—68 percent standard error bands for the Kalman smoothers calculated using the Ansley and Kohn (1986) procedure. Target wealth is expressed in hundreds of percent of annual disposable income.

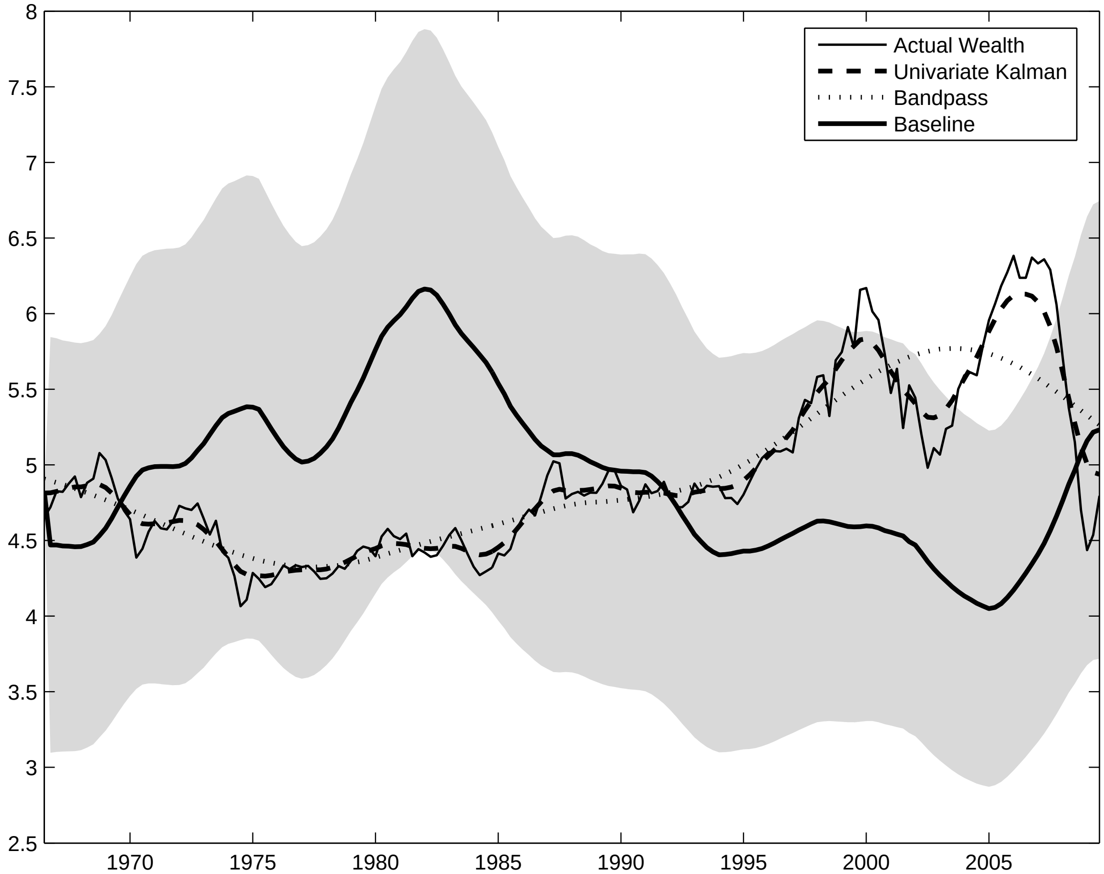
Sources: Net worth–disposable income ratio—Flow of Funds, Board of Governors of the Federal Reserve System, US Department of Commerce, Bureau of Economic Analysis; Uncertainty—Bloom et al. (2009); Expected interest rate: Board of Governors of the Federal Reserve System, Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia; Expected income growth: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia.

Figure 5 Contributions of the wealth gap and credit conditions (CCI) to the saving rate



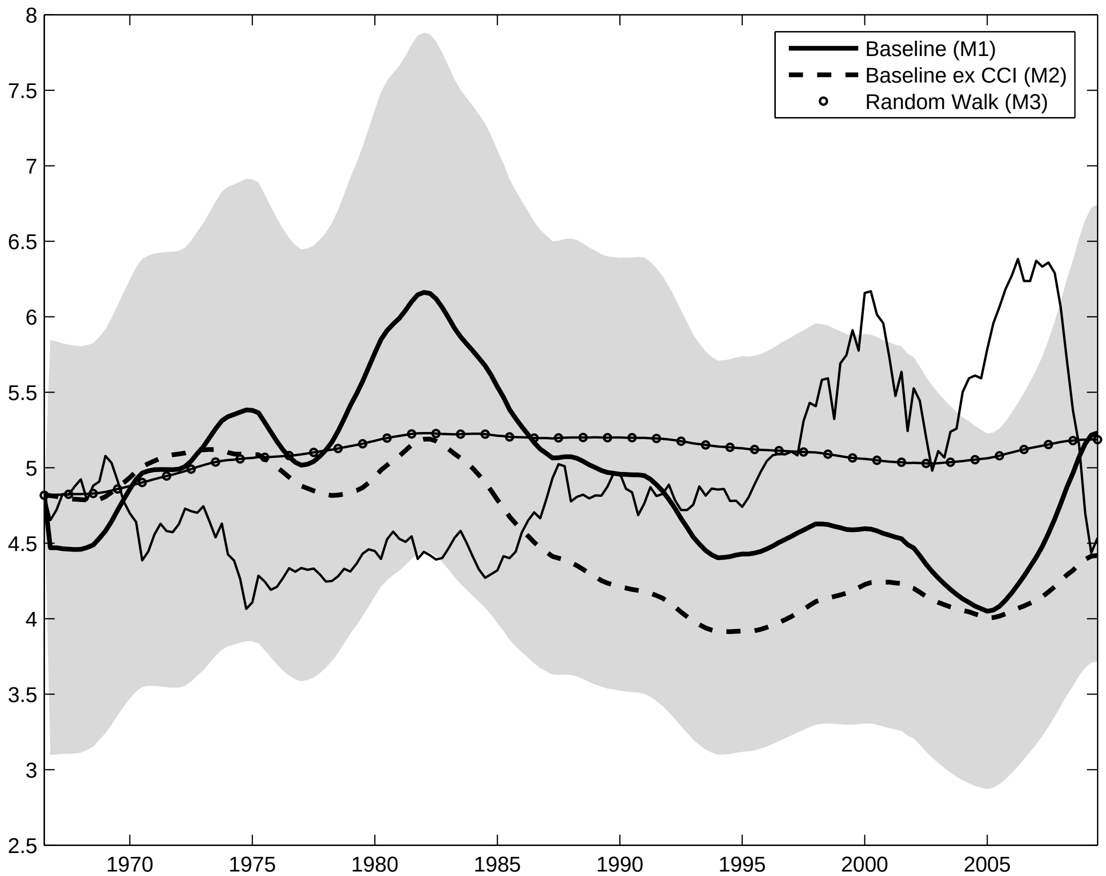
Notes: Shading—NBER recessions. Contributions of the wealth gap and credit conditions are calculated as $\frac{\beta_m}{1-\beta_s}(m_t - m_t^*)$ and $\frac{\beta_{\text{CCI}}}{1-\beta_s}\text{CCI}_t$, respectively. They are normalized to have the same mean as the actual PSR.

Figure 6 The time-varying target wealth m^*: Baseline and *univariate* filters



Notes: Target wealth is expressed in hundreds of percent of annual disposable income. Shaded band—68 percent standard error band for the Kalman smoother. "Univariate Kalman": random-walk-plus-noise model specified in footnote 18. "Bandpass": bandpass filter of Christiano and Fitzgerald (2003); lower cut-off frequency: 60 quarters. "Baseline": Baseline model of Table 1.

Figure 7 The time-varying target wealth m^*: Baseline and other *multivariate* filters



Notes: Target wealth is expressed in hundreds of percent of annual disposable income. Shaded band—68 percent standard error band for the baseline Kalman smoother of Table 1. "Baseline ex CCI": Second model of Table 1. "Random Walk": Third model of Table 1.