Dissecting Saving Dynamics: Measuring Wealth, Precautionary, and Credit Effects

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Abstract
We show that an estimated tractable 'buffer stock saving' model can match the 30-year decline in the U.S. saving rate leading up to 2007, the sharp increase during the Great Recession, and much of the intervening business cycle variation. In the model, saving depends on the gap between 'target' and actual wealth, with the target determined by measured credit availability and measured unemployment expectations. Following financial deregulation starting in the late 1970s, expanding credit supply explains the trend decline in saving, while fluctuations in wealth and consumer-survey-measured unemployment expectations capture much of the business-cycle variation, including the sharp rise during the Great Recession.

Keywords Consumption, Saving, Wealth, Credit, Uncertainty
JEL codes E21, E32

Web: http://econ.jhu.edu/people/ccarroll/papers/cssUSSaving/
PDF: http://econ.jhu.edu/people/ccarroll/papers/cssUSSaving.pdf
Slides: http://econ.jhu.edu/people/ccarroll/papers/cssUSSaving-Slides.pdf
Repo: https://github.com/llorracc/cssUSSaving
(Contains data and estimation software producing paper's results)

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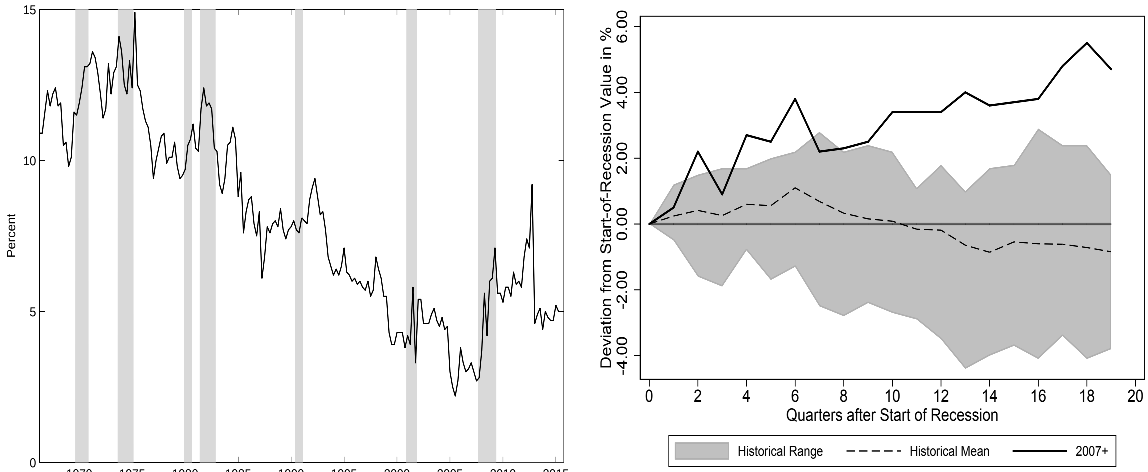
Figure 1 US Personal Saving Rate ('PSR')



Notes: The left panel shows the personal saving rate, 1966q1–2015q4. The right panel shows the deviation of the saving rate from its value at the start of recessions (in percentage points), over a historical range that includes all recessions after 1960q1. Source: BEA.

1 Introduction

The start of the Great Recession marked a striking break in the behavior of the US personal saving rate. After gradually declining over the previous 30 years, the saving rate doubled during the recession (Figure 1(a)), and even 5 years later, exceeded its pre-crisis level by 4 percentage points (Figure 1(b)). Surprising weakness of consumption growth (relative to income growth) was a key element in explanations of why, year after year, the recovery was weaker than forecasters expected. The "secular stagnation" hypothesis of Summers (2013, 2015), Krugman (2013, 2014), Gordon (2015), and others is the most provocative interpretation of these facts, but even skeptics of secular stagnation have acknowledged that surprisingly weak consumption growth played a role in the anemic recovery (Hamilton, Harris, Hatzius, and West (2016)).

Standard consumption models incorporate several mechanisms that interact with income dynamics to generate the saving rate; the channels that have received the most attention include 'wealth effects,' the availability of credit, and precautionary motives.[1] But we are not aware of any work that has attempted to quantify the

[1] The literature is large; see among many others the analyses of Carroll (1992) on precautionary saving during

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relative importance of these channels using the full (secular and cyclical) variation in the available historical data. Our contribution is to use a simple structural model of saving to construct such a quantitative decomposition. Specifically, we estimate a tractable 'buffer stock saving' model (an extended version of Carroll and Toche (2009)) with explicit and transparent roles for the three factors emphasized above (the wealth, credit, and precautionary channels). The model's key intuition is that, in the presence of income uncertainty, optimizing households have a target ratio of wealth to permanent income that depends on the usual theoretical considerations (the coefficient of relative prudence, see Kimball (1993); time preference; etc.) and on two features that have been harder to incorporate into analytical models: The degree of labor income uncertainty and the availability of credit.

Over the historical period for which the necessary data are available, the structural model is able to capture the bulk of the variation in the saving rate—with a fit better than 0.90 in the R^2 sense.[2] We find a statistically significant and economically important role for all three explanatory variables. The trend decline in saving between the mid-1970s and 2007 is explained by the continual easing of credit availability during the period of gradual financial deregulation that began in the Carter administration (see Woolley (2012) for the history) and extended to the brink of the Great Recession. Our measure of credit supply (based on the Fed's Survey of Senior Loan Officers) shows a substantial tightening during the Great Recession, the first sustained curtailment since the 1970s. But according to the model's estimates, a larger contributor to the sharp increase in the saving rate during the Great Recession was the collapse in household wealth, with an increased precautionary motive (proxied by a measure of consumers' unemployment expectations) playing the next most important role. We find that, contra Eggertsson and Krugman (2012) and Guerrieri and Lorenzoni (2017), redit contraction as the least important of the three factors.[3]

The rest of the paper is organized as follows. Section 2 presents the structural model and its mechanics. Section 3 briefly describes our data sources; section 4 presents the

recessions, Carroll, Otsuka, and Slacalek (2011), Mian, Rao, and Sufi (2011), Berger, Guerrieri, Lorenzoni, and Vavra (2018) and others on wealth effects, and Muellbauer (2007) and Parker (2000) on credit availability and financial liberalization. Some work (e.g., Hall (2011), Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2017)) has argued (though without much attempt at quantification) that a sudden sharp reversal of the credit-loosening trend played a large role in the recent saving rise. Finally, a series of recent papers investigates the role of housing for the dynamics of consumption (e.g., Justiniano, Primiceri, and Tambalotti (forthcoming), Huo and Ríos-Rull (2016), Garriga and Hedlund (2018), Kaplan, Mitman, and Violante (2017) and Gorea and Midrigan (2018)), but this work focusses on the dynamics during the global financial crisis (rather than also covering 'normal' recessions over the last several decades, as we do).

[2] Below we address the econometric challenges involved in evaluating this statistic.

[3] We treat the three driving variables as exogenous inputs into our partial equilibrium model. This is unsatisfying, because all three variables are to some degree endogenous to deeper forces; in particular, the collapse in asset prices in the Great Recession is presumably at least partly attributable to the increase in uncertainty and perhaps to the credit tightening. If there were anything approaching a consensus about the appropriate way to endogenize asset prices (of stocks and, more recently, of housing) we would have preferred to do so, but no such consensus has emerged (see, e.g., the work we refer to in footnotes 1 and 7 for an overview). In this choice, we follow many papers (including Landvoigt (2017) and recently Hubmer, Krusell, and Smith, Jr. (2018)), who model asset returns as exogenous (on exogeneity of asset prices see also our discussion in section 2.4).

estimates of the model and the empirical decomposition of the saving rate. Section 5 compares our framework to the key competing frameworks for thinking about the saving rate; section 6 concludes.

2 Theory: Target Wealth and Credit Conditions

Here we introduce the model that we will later estimate, a simple representative-consumer buffer-stock saving model derived from Carroll and Toche (2009) (henceforth CT). We extend the CT model to incorporate unemployment insurance, which gives the model a mechanism to capture changes in credit availability (because borrowing is assumed to be limited by the minimum possible income available to repay it).

2.1 Essentials of the Tractable Model

Under most specifications of uncertainty, Constant Relative Risk Aversion utility interacts with uncertainty in ways that rule out any transparent analytical formulation of the forces at work. The assumption that makes the CT model tractable despite its use of CRRA utility is that unemployment risk takes a particularly stark form: Employed consumers face a constant probability $\mho$ of becoming unemployed, and, once unemployed, can never become employed again. The sense in which the model is tractable is that there is a closed form solution for the level of target wealth, and the full consumption function (though numerical) can be constructed from the target almost instantaneously using a simple difference equation.

CT show that for the special case of logarithmic utility, the target 'market resources' ratio for an employed consumer (roughly, spendable wealth) is:

$$\check{m}^e \approx 1 + \left(\frac{1}{(\gamma - \mathsf{r}) + \vartheta\big(1 + (\gamma + \vartheta - \mathsf{r})/\mho\big)} \right), \tag{1}$$

where γ is the growth rate of labor income, r is the interest rate and $\vartheta = -\log \beta$ is the time preference rate.

A "Growth Impatience Condition" guarantees that the expression $(\gamma + \vartheta - \mathsf{r})$ in the denominator is strictly positive. Using this fact, the equation has intuitive implications: Target wealth is higher (the consumer saves more) when

- The consumer is more patient (the time preference rate ϑ is lower)
- Unemployment risk $\mho$ is higher (inducing a stronger precautionary motive)
- Expected future income is lower (that is, $\gamma - \mathsf{r}$ is smaller)

2.2 Determinants of Target Wealth

We modify the CT model by adding an 'unemployment insurance' (UI) system that relaxes the natural borrowing constraint. In the CT model, households accumulate positive wealth to prevent zero consumption when they become unemployed. But, in the model in this paper, employed households are willing to borrow, because they know they will not starve even if they become unemployed; their consumption function shifts to the left. However, such consumers will limit their indebtedness to an amount small enough to guarantee that consumption will remain strictly positive even if they become unemployed (so, it is the 'natural borrowing constraint' that shifts).

The budget constraint depends on the consumer's employment status. We denote with lower-case m and c the levels of market resources M (market wealth plus current income) and consumption C normalized by the corresponding period's pretax labor income $\ell\mathsf{W}$ (the product of individual labor productivity ℓ and the aggregate wage W); $\ell\mathsf{W}$ grows by $\Gamma = 1 + \gamma$ per period. Next period's market resources ratio m_{t+1} is the sum of current market resources m_t net of consumption c_t, augmented by the (growth-adjusted) interest factor R/Γ and income. For the employed consumer (normalized) after-tax labor income is $1 - \tau$, while for the unemployed consumer the unemployment benefit is ς (both expressed as a fraction labor income). The unemployment benefit ς is financed on a pay-as-you-go basis by a lump sum tax τ. Under these assumptions the (normalized) dynamic budget constraint is:

$$m_{t+1} = \begin{cases} (m_t - c_t)\mathsf{R}/\Gamma + \varsigma & \text{with prob.} \quad \mho \quad \text{(unemployed in } t+1\text{)} \\ (m_t - c_t)\mathsf{R}/\Gamma + 1 - \tau & \text{with prob.} \quad 1-\mho \quad \text{(employed in } t+1\text{)} \end{cases} \tag{2}$$

Generalizing formula (1) for relative risk aversion $\rho > 1$ and allowing for UI benefits ς, the employed consumer's target market resources ratio $\check{m}^e$ can be written as a function characterized by:[4]

$$\check{m}^e = f\Big(\underset{(+)}{\mho}, \underset{(-)}{\text{CEA}(\varsigma)}, \underset{(+)}{\mathsf{R}}, \underset{(-)}{\Gamma}, \underset{(+)}{\rho}, \underset{(+)}{\beta}, \ldots\Big). \tag{3}$$

The target wealth $\check{m}^e$ increases with unemployment risk $\mho$, as consumers build up a larger precautionary buffer of savings. An easing of credit conditions (which we denote as 'CEA')—an increase in the CEA index (modelled as an increase in ς)—allows households to borrow more and thus reduces the need to accumulate wealth for consumption smoothing. A higher interest rate R increases the rewards to holding wealth and thus increases the amount held. Faster expected growth of labor income

[4] Specifically, in online appendix A we show that the steady-state target wealth is:

$$\check{m}^e = \frac{(\eta+1)(1-\mho\varsigma) - \eta\varsigma}{\eta + 1 - \mathsf{R}/\Gamma},$$

where $\eta = \kappa^u \Pi \mathsf{R}/\Gamma$, $\Pi = \left(\frac{\Gamma^\rho (\mathsf{R}\beta)^{-1} - (1-\mho)}{\mho}\right)^{1/\rho}$ and κ^u is the (constant) marginal propensity to consume out of total wealth for the unemployed consumer. The relationship holds under our estimated parameter values; some of these relationships do not hold for all parameter values.

Γ translates into a lower wealth target because optimists consume more now in anticipation of their future prosperity (the 'human wealth effect'). Increasing risk aversion ρ raises target wealth in a way that is qualitatively similar to the effects of an increase in uncertainty. And of course, making the consumer more patient (increasing β) increases target wealth.[5]

2.3 The Three Channels: A Graphical Exposition

Figure 3a shows the phase diagram for the CT model. The (concave) consumption function is indicated by the thick solid locus, which is the saddle path that leads to the steady state (at which both consumption and market resources, c and m, are constant). Because the precautionary motive diminishes as wealth rises, the model says the saving rate is a declining function of market resources, an implication of consumption concavity.

This consumption function can be used directly to analyze the effects of the three channels affecting the saving rate. For a consumer who starts with market resources equal to the target, $m_t = \check{m}^e$, the consequences of a pure negative shock to wealth, depicted in Figure 3b, are straightforward: Consumption declines upon impact, to a level below the value that would leave m constant (the leftmost red dot); because consumption is below permanent income, m (and thus c) rises over time back toward the original target (the sequence of dots).

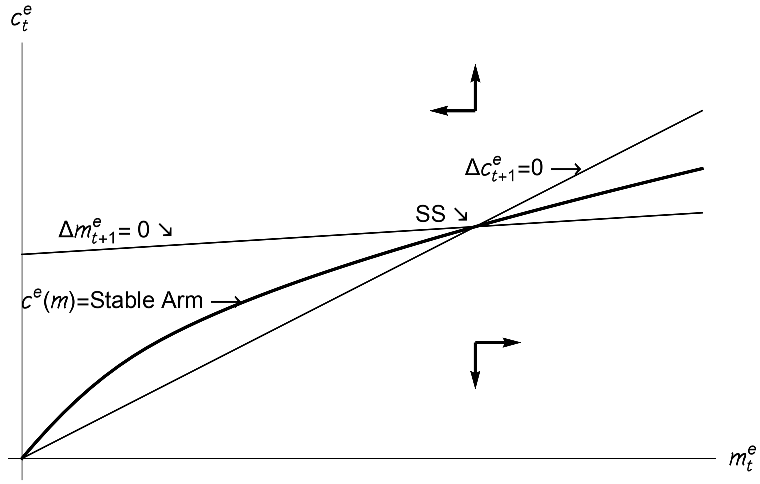
From an initial borrowing limit of 0 that requires wealth to be positive (m must be strictly greater than c), an expansion of unemployment benefits results in a more generous natural borrowing limit $\underline{h}$ (implying minimum net worth of $-\underline{h} < 0$) and causes an immediate increase in consumption for a given level of resources (Figure 3c). But over time, the higher spending makes the consumer's level of wealth decline, forcing a corresponding gradual decline in consumption until wealth eventually settles at its new, lower target level.[6]

Figure 3d shows the consequences of a permanent increase in unemployment risk $\mho$ for the dynamics of the personal saving rate ('PSR' henceforth), rather than the level of consumption shown before. Qualitatively, the effects of a human-wealth-preserving spread in risk are essentially the opposite of a credit loosening: On impact, the PSR jumps upward, 'overshooting' (cf. Dornbusch (1976)) the new target $\check{s}'$, followed by a gradual decline toward $\check{s}'$ (which is higher than the original $\check{s}$). This nonmonotonic adjustment of saving to shocks reflects the fact that, when target wealth rises, not only

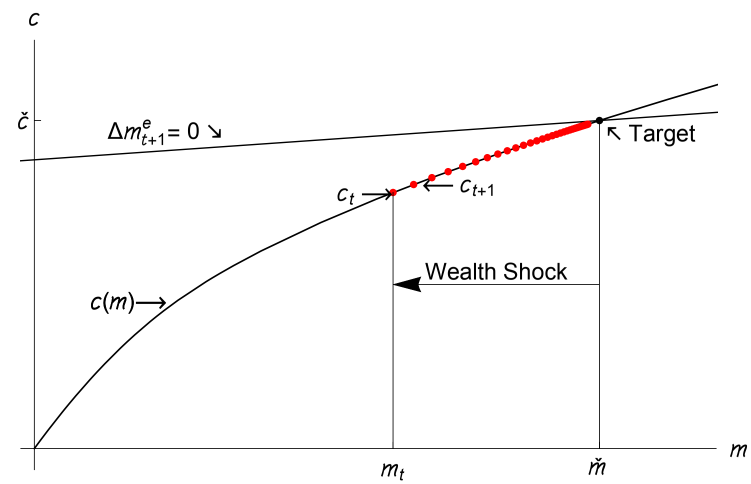
[5]Our final modeling assumption is that we can capture most of the variation in the saving rate by considering the behavior of an economy populated by a single 'employed' agent (who is always afraid of becoming unemployed but never does). (Carroll and Jeanne (2009) show that the simulated behavior of an economy populated by a continuum of agents who draw unemployment shocks as specified in the model – so that at any given time there is a population of employed and of unemployed consumers – is very well represented by the behavior of the 'representative employed consumer' we use here).

[6]Our setup thus reproduces the standard result from the literature on the effects of borrowing constraints; see, e.g., Carroll (2001), Muellbauer (2007), Guerrieri and Lorenzoni (2017) and Hall (2011).

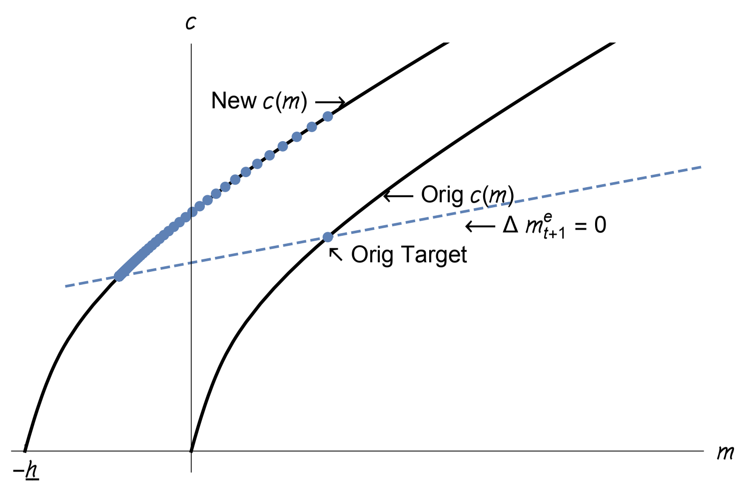
Figure 2 Consumption/Saving Dynamics in a Simple Buffer Stock Model



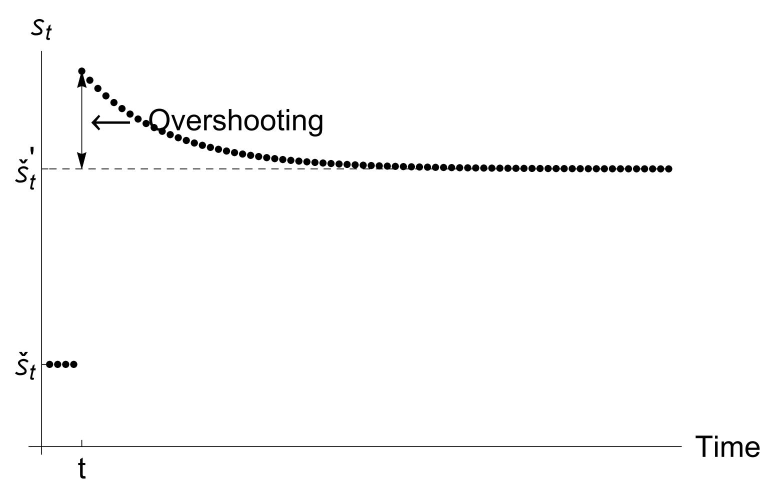
(a) Consumption Function (Stable Arm of Phase Diagram)



(b) A Wealth Shock



(c) Relaxation of Natural Borrowing Constraint from 0 to $\underline{h}$



(d) Saving After an Increase in Uncertainty $\mho$

is a higher level of steady-state saving needed to maintain higher target wealth, an immediate *further* boost to saving is necessary to move from the current (inadequate) level of wealth up toward the new (higher) target.

2.4 Comparison to Alternative 'Structural' Models

We use this simple, partial-equilibrium framework (instead of a richer but less tractable HA-GE model) because our goal is to estimate a unified structural saving model whose "deep" parameters are jointly identified using both business-cycle-frequency fluctuations AND long-term trends. Both cyclical and secular changes in the saving rate have been large, and a model that matched one set of facts (secular, or cyclical) but had strongly counterfactual implications for the other would not be a satisfying description of history.

We are not aware of prior papers that attempt this. Essentially all of the "structural" literature has focused on cyclical dynamics, using one of two frameworks:

1. Complex Heterogeneous Agent New Keynesian models (HANK) with serious treatments of uncertainty

2. Simple spender–saver Two-Agent New Keynesian models (TANK)

For the first class of models, the last decade or so has seen impressive progress in the degree of realism achievable in the treatment of uncertainty, liquidity constraints, household structure, and other first-order elements of households' microeconomic environment. A flourishing literature today explores the implications of these complexities for many questions; see Krueger, Mitman, and Perri (2016) for a survey. However, at the current state of the art, estimating such a model would be a considerable challenge, as estimation is generally several orders of magnitude more computationally demanding than simulating a calibrated version (which is what the existing literature has done). Furthermore, rich microfounded models have usually been optimized for the specialized purposes of examining in great depth a single question (such as the mechanisms of transmission of monetary policy, Kaplan, Moll, and Violante (2016)) rather than, as we are attempting, to address a number of different causal mechanisms, over different time horizons, simultaneously. Finally, even if such a rich HA-GE model could be estimated, it is not clear that the extra microeconomic realism would be worth the cost in transparency and tractability.

Indeed, in advocating the use of TANK models, Debortoli and Galí (2017) argue that the simplicity and transparency of models with only two agents more than make up for their lack of fidelity to microeconomic facts. This point is reflected in the fact that, at present, central banks and other entities that require a workhorse model for current analysis, have (to our knowledge) not gone further than TANK models in their incorporation of heterogeneity. Nonetheless, a major drawback of the TANK models is that they allow no role for uncertainty either as an impulse or a propagation mechanism, despite the large literature in recent years that has argued the uncertainty is a core element of business cycle dynamics (see, e.g., cf. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)).

Our model occupies a middle ground. We have only a single agent (making our model simpler in one respect even than the TANK models), but that agent's consumption function is nonlinear (making it harder to analyze analytically). This nonlinearity brings a major benefit, though, in providing a way to accommodate two mechanisms that do not meaningfully exist in TANK models: Uncertainty and credit constraints. Furthermore, like a TANK model, its parameters can be straightforwardly estimated to match targeted macroeconomic facts (in our case, the saving rate).

Likely because of its tractability and simplicity, our model (as introduced in a draft version of this paper) has been found useful as a tool to understand saving dynamics in a number of countries in addition to the US. The model has been used explicitly to forecast consumption and the saving rate at the Bank of England (Burgess, Fernandez-Corugedo, Groth, Harrison, Monti, Theodoridis, and Waldron (2013)). Mody, Ohnsorge, and Sandri (2012) use a version of it to motivate an empirical exercise which concludes that labor income uncertainty contributed by at least two fifths to the increase in the saving rate in advanced economies during the Great Recession (consistent with our structural estimates below). Trichet (2010) argues (referring to our model) that the precautionary motive contributed to the high saving rate in advanced economies after 2008.

2.4.1 Why We Do Not Endogenize Asset Prices

Arguably a deeper problem, both with our paper and with the other literature cited above, is the choice to take as exogenous some of the variation that we would most urgently like to understand. In particular, our model's finding that a 'wealth effect' explains part of the increase in saving in the Great Recession begs the question of what caused the asset price movements that underlie the wealth effect (in stocks, housing and bonds). If, as seems likely, an important driver of asset prices is the degree of uncertainty (cf. Bekaert, Engstrom, and Xing (2009), Drechsler (2013)), then our method will substantially underestimate the cyclical importance of uncertainty, attributing part of uncertainty's true effect to developments (asset prices; credit availability) that are themselves consequences of uncertainty.

A vast literature has attempted to model asset pricing in general equilibrium. While some progress has been made in understanding the cross-sectional heterogeneity of asset holdings (cf. Gomes and Michaelides (2007)), for our purposes what is needed is a model that can capture the cyclical and secular time series of returns. The extent to which no consensus exists is highlighted by the diversity of the recent literature that has sought to endogenize the precipitous decline of net worth and house prices during the Great Recession. In this attempt, different authors have built into their models a number of alternative mechanisms, including the presence of a exogenous but rare Great-Depression-like state, exogenous shocks to expectations, or endogenous changes in illiquidity of housing.[7] The existence of this literature suggests that no single model of asset pricing is adequate both for "normal" times and for the Great Recession; more broadly, it seems fair to say that no single asset pricing model has come to be viewed as robustly applicable to most times and places, or for both high-frequency cyclical and low-frequency secular movements in asset prices. If we were to incorporate any non-consensus model of asset pricing (and, at this point, *all* asset-pricing models are non-consensus models), our paper would inevitably (and correctly) judged to be more about the performance of that asset pricing model than anything else.[8]

The exogeneity assumptions bring us to a final reason for using our tractable model, which is that a central purpose of this paper has been to bring to light the existence of some surprisingly simple empirical relationships between the saving rate and our three explanatory variables. The construction of an elaborate model that required many pages to set up and explain, and many more pages to estimate, might have drawn attention away from the simplicity of the empirical foundations of the paper, in which the key results are evident even in the OLS reduced form estimates. Our penultimate section 5 examines the empirical performance of our model in comparison with a number of alternatives (including the reduced form model) and argues that our structural model has advantages over any of them.

3 Data and Measurement Issues

This section describes how we measure our key variables (shown in Figure 4).

The saving rate is from the BEA's National Income and Product Accounts and is expressed as a percentage of disposable income.

Motivated by equation (2), we measure household's normalized market resources m_t as 1 plus the ratio of household net worth to disposable income (Figure 5a). For net worth we use data from the Federal Reserve's Financial Accounts; this variable

[7] In more detail, building on the literature on consumption disaster risk, Glover, Heathcote, Krueger, and Ríos-Rull (2017) adopted a setup in which the aggregate shock includes a Great-Depression-like state. Related work attempted to capture the dynamics of house prices during the last boom and (deep) bust. For example, Kaplan, Mitman, and Violante (2017) show that changes in beliefs about future housing demand can match the volatile dynamics of house prices and house price–rent ratios; but invoking unobservable changes in opinions about the future demand for assets is only a small step from explicitly assuming that asset prices are exogenous. Garriga and Hedlund (2018) argue that an endogenous decline in housing liquidity (induced by directed search to buy houses) amplifies recessions by contracting credit and depressing consumption. The debate on the role of beliefs about house prices, changes in credit supply or mortgage market arrangements includes important contributions of Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Kaplan, Mitman, and Violante (2017), Justiniano, Primiceri, and Tambalotti (forthcoming), and Garriga and Hedlund (2018).

[8] Essentially the same points could be made about our choice to take credit supply as exogenous. Again, to the extent that movements in credit supply are caused by movements in uncertainty, our estimates may seriously underestimate the contribution of uncertainty to business cycle fluctuations.

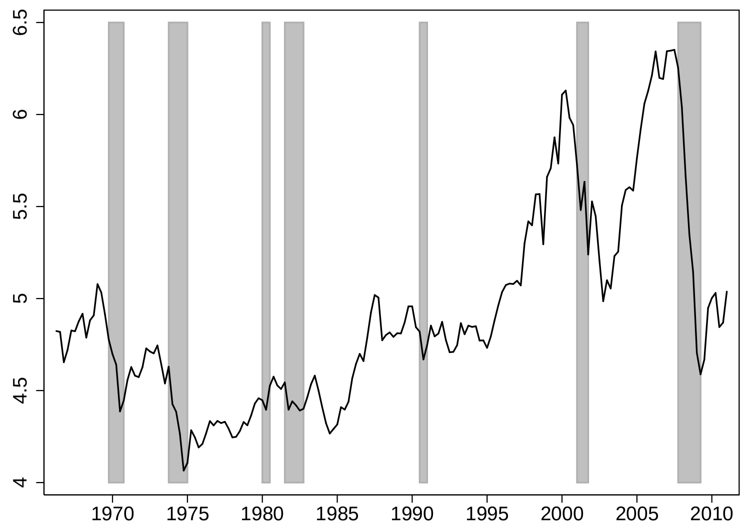
is lagged by one quarter to account for the fact that data on net worth are reported as the end-of-period values.[9]

Our measure of credit availability, which we call the 'Credit Easing Accumulated' index (CEA; Figure 5b) is adapted from work by John Muellbauer and various coauthors (Muellbauer (2007), Duca, Muellbauer, and Murphy (2010) and Aron, Duca, Muellbauer, Murata, and Murphy (2011); for a related approach, see Hall (2011)). It is constructed using a question from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices. The question asks about banks' willingness to make consumer installment loans now as opposed to three months ago. To calculate a proxy for the *level* of credit conditions, the scores from the survey were accumulated, weighting the responses by the contemporaneous debt-to-income ratio to account for the increasing trend in that variable, and normalizing the result to range between 0 and 1 to make the interpretation of regression coefficients straightforward. We use the question on installment loans because it is available since 1966; other measures of credit availability, such as for mortgage lending, move closely with the index on consumer installment loans over the sample period when both are available until 2008. While the two indices diverge in the Great Recession and afterward, this corresponds to the period when there was a massive shift of mortgage origination from banks (the respondents to the SLOOS) to government sponsored entities (Fannie Mae, Freddie Mac, and others). That shift brings into question the continued relevance of the direct SLOOS index of mortgage lending conditions. There was no similar profound institutional change in the market for installment lending, which is one reason it might reasonably be interpreted as a consistent indicator of the overall credit environment (given its high correlation with other credit supply indices in the period before the Great Recession).

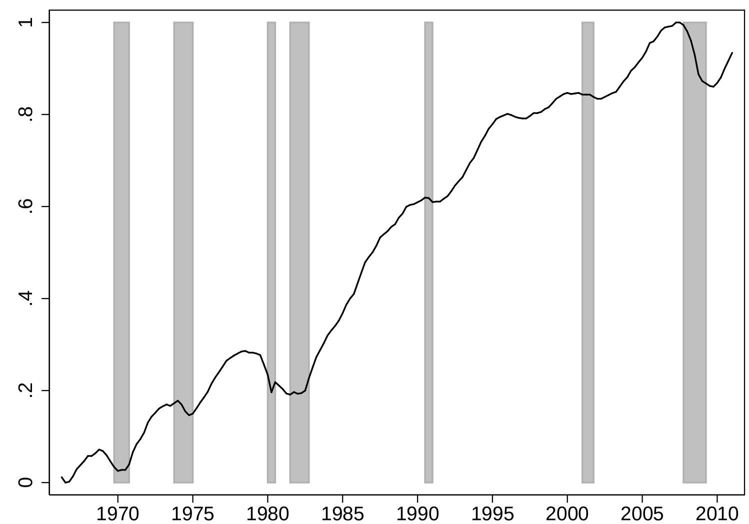
The CEA index is taken to measure the availability/supply of credit to a typical household as it is affected by factors other than the level of interest rates—for example, through constraints on loan-to-value or loan-to-income ratios, availability of mortgage equity withdrawal and mortgage refinancing. The broad trends in the CEA index seem to reflect well the key developments of the US financial market institutions, which we summarize as follows: Until financial deregulation began in the late 1970s, consumer lending markets were heavily regulated and segmented. After the phaseout of interest rate controls beginning in the early 1980s, the markets became more competitive, spurring financial innovations that led to greater access to credit. Technological progress leading to new financial instruments and better credit screening methods (Pagano and Jappelli (1993)), a greater role of nonbanking financial institutions, and the increased use of securitization all contributed to the

[9]Our simple model does not distinguish between the role of various wealth components and does not specifically look into the role of housing wealth as distinct from other kinds of wealth. While in a reduced form approach it would be straightforward to separately estimate the role of housing and financial wealth (as many papers estimating the wealth effects on consumption have done), it would be much more challenging to estimate a structural model with portfolio choice and illiquid housing.

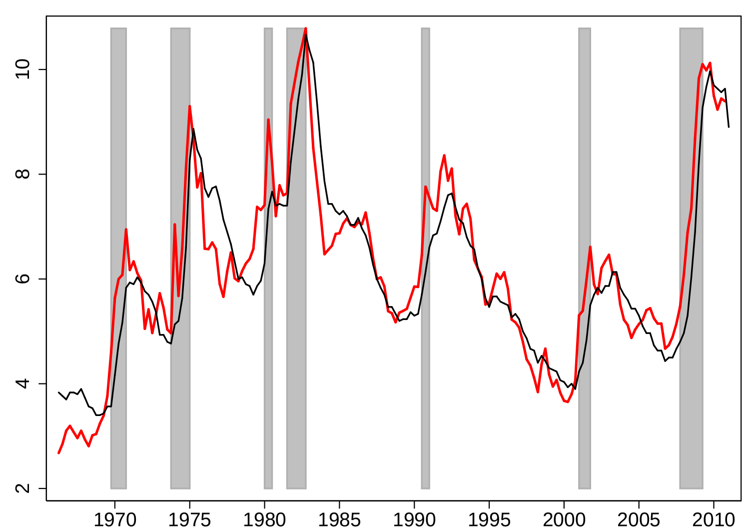
Figure 4 Key Data Series



(a) Net Worth–Disposable Income Ratio



(b) Credit Availability: 'The Credit Easing Accumulated' (CEA) Index



(c) Expected Unemployment Risk $\mathbb{E}_t\, u_{t+4}$ (Red) and Actual Unemployment Rate (Black) dramatic rise in credit availability from the early 1980s until the onset of the Great Recession in 2007, at which point a substantial drop in the CEA index was associated with the funding difficulties and de-leveraging of financial institutions.[10]

We measure a proxy $\mathbb{E}_t\, u_{t+4}$ for unemployment risk $\mho_t$ using re-scaled answers to the question about the expected change in unemployment in the Thomson Reuters/University of Michigan Surveys of Consumers. In particular, we estimate $\mathbb{E}_t\, u_{t+4}$ using fitted values $\Delta_4 \hat{u}_{t+4}$ from the regression of the four-quarter-ahead change in unemployment rate $\Delta_4 u_{t+4} \equiv u_{t+4} - u_t$ on the answer in the survey, summarized with the balance statistic $\texttt{UExp}_t^{BS}$:

$$\begin{aligned} \Delta_4 u_{t+4} &= \alpha_0 + \alpha_1 \texttt{UExp}_t^{BS} + \varepsilon_{t+4}, \\ \mathbb{E}_t\, u_{t+4} &= u_t + \Delta_4 \hat{u}_{t+4}. \end{aligned}$$

The coefficient α_1 is highly statistically significant, indicating that households do have substantial information about the direction of future changes in the unemployment rate. As expected, our $\mathbb{E}_t\, u_{t+4}$ series is strongly correlated with unemployment rate and predicts its dynamics (Figure 5c).

Data for our empirical measure of credit conditions are available starting 1966q2, and the data we use in estimation cover that date to 2011q4.

We do not use data after 2011 for several reasons. First, personal saving rate statistics are subject to large revisions until some five years after the first data release (after the BEA receives much higher quality personal income data from the IRS). To quote Nakamura and Stark (2007): "[M]uch of the initial variation in the personal saving rate across time was meaningless noise."[11] As their paper documents, it is not uncommon for the saving rate to be revised by 3–5 percent of disposable income after several benchmark revisions.

Second, our index of credit availability is increasingly questionable after 2011 because of the apparent divergence in credit conditions for installment and mortgage loans: Various sources (including the Mortgage Credit Availability Index of the Mortgage Bankers' Association; see also Bhutta (2015)) document continued tight credit conditions after 2011. If, as this work suggests, mortgage credit remained tighter than indicated by our installment loans index after 2012, that could explain part of the continued high saving rate in the post-2012 period, which would be mispredicted by a mismeasured credit conditions index. Alternatively, saving attitudes may have

[10] As a caveat, it is important to acknowledge that CEA might to some degree be influenced by developments from the demand rather than the supply side of the credit market. But whatever its flaws in this regard, indexes of this sort seem to be gaining increasing acceptance as the best available measures of credit supply (as distinguished from credit demand).
The CEA index correlates strongly with measures financial reforms of Abiad, Detragiache, and Tressel (2010), and measures of banking deregulation of Demyanyk, Ostergaard, and Sørensen (2007) (see panel A of their Figure 1, p. 2786 and Appendix 1).

[11] In addition, there were substantial gyrations in the saving rate in 2012 due to a tax-related anomaly (in late 2012 income was boosted by accelerated and special dividend payments and by accelerated bonus payments in anticipation of changes in individual income tax rates in 2013).

changed after the Great Recession due to the substantial shock of the Great Recession, perhaps because of "scarring" effects (see, e.g., Malmendier and Shen (2018), Jordà, Schularick, and Taylor (2015), Hall (2012)); for evidence that financial crises have much longer-lasting effects than usual business cycle fluctuations, see Reinhart and Rogoff (2009). All of these are reasons to worry about data from the post-Great-Recession period.

4 Structural Estimation

This section estimates the structural model of section 2 by minimizing the distance between the saving rate implied by the model and its empirical counterpart.

4.1 Estimation Procedure

In more detail, the structural estimation proceeds as follows. We assume that households observe exogenous movements in unemployment risk $\mho$ and credit availability $\underline{h}$,[12] and that there are simple mappings from our credit availability index CEA_t to the location of the consumers' borrowing constraint $\underline{h}_t$ and from measured unemployment expectations $\mathbb{E}_t\, u_{t+4}$ to $\mho_t$:[13]

$$\begin{aligned}\underline{h}_t = \underline{h}(\text{CEA}_t) &= \theta_{\text{CEA}}\text{CEA}_t,\\ \mho_t = \mho(\mathbb{E}_t\, u_{t+4}) &= \bar{\theta}_{\mho} + \theta_u\, \mathbb{E}_t\, u_{t+4}.\end{aligned} \tag{4}$$

Collecting the parameters $\Theta = \{\beta, \theta_{\text{CEA}}, \bar{\theta}_{\mho}, \theta_u\}$, and the time-$t$ observable variables as $z_t = \{m_t, \text{CEA}_t, \mathbb{E}_t\, u_{t+4}\}$, the model implies a "saving rate function" $\text{s}(z_t;\Theta)$ which we aim to compare to the saving rates observed in the data, s_t^{meas}. Our objective is therefore to find the parameter vector $\hat{\Theta}$ that minimizes the distance between actual saving rates and those implied by the model:

$$\hat{\Theta} = \arg\min \frac{1}{T}\sum_{t=1}^{T}\Big(s_t^{\text{meas}} - \text{s}(z_t;\Theta)\Big)^2. \tag{5}$$

Minimization of (5) is a non-linear least squares problem for which the standard

[12] We assume that consumers consider the shocks to $\mho$ and $\underline{h}$ to be permanent. This assumption is necessary for us to be able to use our tractable model. While indefensible as a literal proposition (presumably nobody believes the unemployment rate will remain forever where it is today), the high serial correlation of these variables means that the assumption may not be too objectionable.

[13] We have also considered a model in which the CEA equation contains an intercept, $\underline{h}(\text{CEA}_t) = \bar{\theta}_h + \theta_{\text{CEA}}\text{CEA}_t$. In that model $\bar{\theta}_h$ is estimated to be insignificant and close to 0. But, as we discuss below, even our reduced model is close to being linear; adding a constant to a nearly linear model only confuses matters. Theoretical considerations suggest that if one of the two linear coefficients should be excluded, it is probably the one for the CEA equation, so we made that choice. Our substantive conclusions are robust to this choice.

asymptotic results apply. The estimates have the asymptotic normal distribution:

$$T^{1/2}(\hat{\Theta} - \Theta) \to_d \mathcal{N}\Big(0, \sigma^2 \times \big(\lim_{T\to\infty} \mathbb{E}(\mathbf{F}'\mathbf{F}/T)\big)^{-1}\Big),$$

where the variance matrix can consistently be estimated with

$$\hat{\sigma}^2 \times \left(\hat{\mathbf{F}}'\hat{\mathbf{F}}\Big/T\right)^{-1}$$

for $\hat{\sigma}^2 = \frac{1}{T}\sum_{t=1}^{T}\left(s_t^{\text{meas}} - \text{s}(z_t;\hat{\Theta})\right)^2$ and the $T \times 4$ gradient matrix of the saving rate function $\hat{\mathbf{F}} = \nabla_{\Theta'}\text{s}(z_t;\hat{\Theta})$ evaluated at $\hat{\Theta}$ (which is calculated numerically).

4.2 Estimates and the Model Fit

Table 1 presents the estimation results. The calibrated parameters—the quarterly real interest rate $\mathsf{r} = 0.04/4$, quarterly wage growth $\Delta\mathsf{W} = 0.01/4$ and the coefficient of relative risk aversion $\rho = 2$—are conventional and meet (together with the estimated discount factor β) the conditions sufficient for the problem to have a well-defined solution (see Carroll and Toche (2009)).

The estimated quarterly discount factor $\beta = 1 - 0.0065 = 0.9935$, or 0.974 at an annual frequency, lies in the standard range. As for the horizontal shift in the consumption function $\underline{h}_t$ driven by credit availability, the estimates of the scaling factor θ_{CEA} implies that $\underline{h}_t$ varies between 0 and $8.89/4 \approx 2.2$, implying that financial deregulation resulted at its peak in an availability of credit in 2007 that was greater than credit availability at the beginning of our sample in 1966 by an amount equal to about 220 percent of annual income (for an average household)—not an unreasonable figure given the now-prevailing rule of thumb that homebuyers can afford a house costing three times their annual income.

The estimated intensity of perceived unemployment risk reflects that fact that the risk in our setup is purely permanent: the estimated risk $\mho_t$ ranges between 1.25×10^{-4} and 1.5×10^{-4} per quarter. The peak magnitude of $\mho_t$ (of 1.5×10^{-4}) implies that over the life cycle of 50 years or 200 quarters, the workers face a probability of roughly 3 percent to become (permanently) unemployed. Given the average aggregate unemployment rate of roughly 6 percent in our sample and given that much of this risk is in reality transitory, the estimated scaling of $\mho_t$ seems broadly plausible. The estimated risk $\mho_t$ is highly counter-cyclical, reflecting movements in the unemployment rate, further magnified by unemployment expectations.

The quantitative interpretation of the coefficients in the model can be summarized by calculating that a 20 percent increase in uncertainty (not out of line for a recession) results in a roughly 1-percentage-point increase in the saving rate. A way to judge the plausibility of this prediction is to consider a similar increase in uncertainty in a microeconomically richer model, such as Carroll, Slacalek, Tokuoka, and White

(2017). A 20 percent increase in the variance of permanent shocks in that model predicts a similar increase in the saving rate, as that implied by our estimates above.

4.3 What Drives the Saving Rate? A Decomposition

Time-variation in the fitted saving rate arises as a result of movements in its three time-varying determinants: wealth, uncertainty and credit conditions; Figure 6.

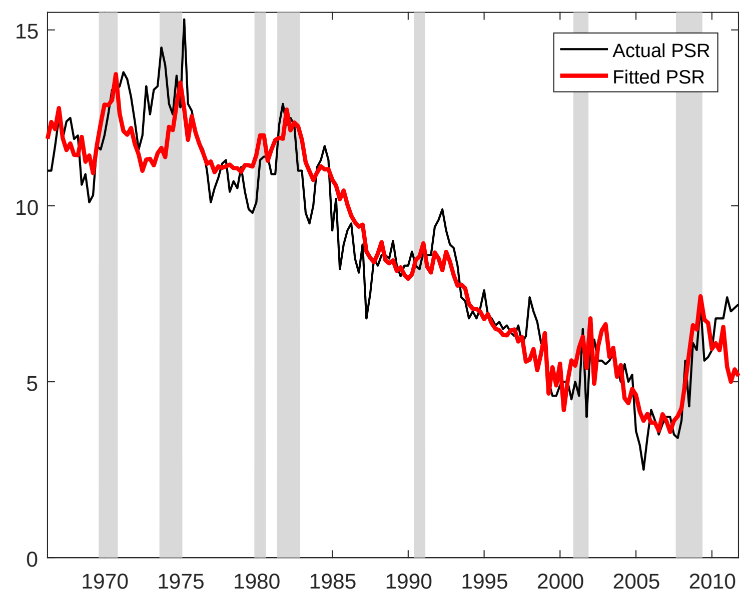
Overall, the estimated structural model provides a good explanation for both low-frequency and business-cycle variation in the saving rate (red line in Figure 7a). The model matches both the 30-year decline in the saving rate before 2007 and the cyclical increases in saving during recessions. For the Great Recession, Table 2 shows that the model implies an increase in the saving rate of about 2.6 percentage points between the 2006–2007 period (immediately before the GR) and the 2009–2010 period (skipping the transitional year of 2008). This matches exactly the 2.6 point measured change in the saving rate. Of that 2.6 point change, the drop in wealth accounts for about half, with the increase in uncertainty accounting for a bit more of the remainder than the decrease in credit. (Recall also our earlier point that this decomposition understates the full role of uncertainty, if the drop in asset prices or the tightening of credit were themselves partly the result of increases in uncertainty).

To gauge the relative importance of the three variables over the full sample, we sequentially switch off the channels by setting the series equal to their sample means.[14] The main takeaway is that the CEA is essential in capturing the trend decline in the PSR between the 1980s and the early 2000s. The wealth fluctuations contribute to a good fit of the model at the business-cycle frequencies, and the cyclical fluctuations in uncertainty magnify the increases in the PSR during recessions, including in the Great Recession.

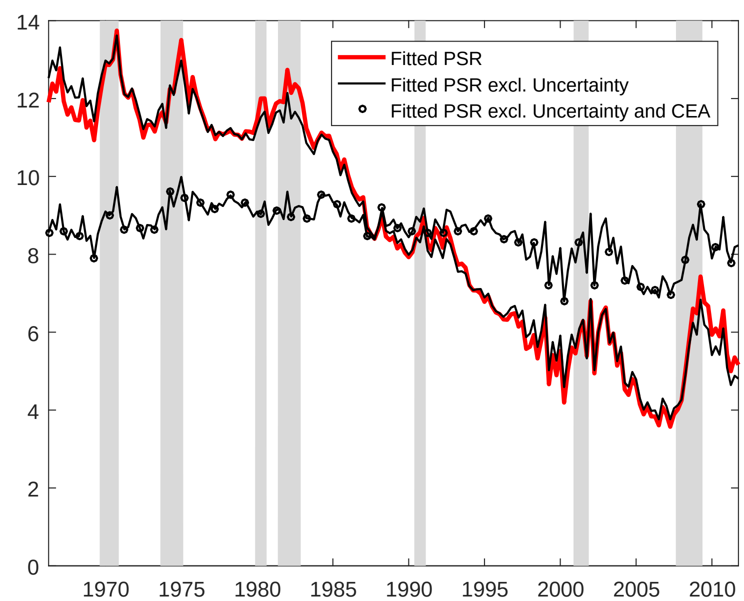
The implied estimates of the wealth effect on consumption are on the low end of the range produced by existing empirical estimates, which lie between 0.02–0.07 (Carroll, Otsuka, and Slacalek (2011), Mian, Rao, and Sufi (2011), Berger, Guerrieri, Lorenzoni, and Vavra (2018) and many others). For example, during the Great Recession, of the 5-percentage-point increase in the saving rate the model (black circled line in Figure 7b) ascribes roughly 3 percentage points to the drop in net worth, which amounted to roughly 200 percent of disposable income (Figure 5a), implying a marginal propensity consume out of wealth (MPCW) of $3/200 = 0.015$. The key reason for this contrast is that our structural estimates attribute a substantial role to uncertainty and credit conditions. This finding suggests that much of what has been interpreted as pure "wealth effects" in the prior literature may actually have reflected precautionary or credit availability effects that are correlated with wealth (a result in

[14] Note that the difference between the fitted series (red/grey line) and the fitted series excluding uncertainty (black line) should be interpreted as the effect of *time variation* in unemployment risk $\mho$ rather than the *total amount* of saving attributable to uncertainty.

Figure 6 The Structural Estimation: Main Results



(a) Actual and Fitted Saving Rate



(b) Decomposition of Fitted Saving Rate line with much of the household-level evidence, including Hurst and Stafford (2004), Cooper (2013), Aruoba, Elul, and Kalemli-Ozcan (2019) and others, who stress the role of credit availability and collateral constraints). (This explanation is supported by our reduced form results in section 5.3, in which the coefficient on wealth in the saving rate equation is substantially higher in the univariate regression, than when controlling for uncertainty and credit conditions.)

Finally, our simple model does not adequately account for household heterogeneity. In a model like that of Carroll, Slacalek, Tokuoka, and White (2017), wealth shocks mostly hit wealthy people who have low MPCs, while income shocks (like stimulus checks) hit the whole population which includes many low-wealth people who have high MPCs. If this is the right explanation, an RA model (ours included) is by its fundamental nature incapable of reconciling the conflict. In addition, a substantial proportion of shocks to net worth are driven by housing wealth, for which evidence suggests that the MPC is likely lower than for liquid assets (including increases from income tax rebates; for a compelling quasi-natural experiment on the size of housing wealth effects, see Kessel, Tyrefors, and Vestman (2019)).

5 Empirical Evaluation of Alternative Models

Here we argue that our model has advantages over the chief alternatives that can be readily evaluated.

5.1 Quadratic Utility

Since Hall (1978), an optimizing model with quadratic utility has been an influential benchmark for aggregate consumption dynamics (especially once one understands that linearized DSGE models are basically indistinguishable from the Hall model). The key distinction from our theoretical model in section 2 is that, in contrast to CRRA utility, under quadratic utility uncertainty has no effect on consumption dynamics; quadratic-utility households do not engage in precautionary saving and do not have a wealth target (other than the current level of wealth).

The model without uncertainty turns out to be distinctly inferior to our buffer stock saving model. We have already seen above in Table 1 that the intercept $\bar{\theta}_{\mho}$ and the sensitivity to uncertainty θ_u enter very significantly the unemployment risk equation (4) of the structural model. This evidence is confirmed in a reduced form linear regression estimation, where business-cycle variation in labor market uncertainty is strongly related to the PSR, both on its own and controlling for other variables (columns 1 and 3 of Table 3, respectively). The results imply that a 1 percentage point increase in expected unemployment rate increases the saving rate by roughly 0.2–0.6 percentage points.[15]

These results confirm a large body of complementary evidence on how uncertainty affects aggregate consumption and saving going back to 1990s. Recently, the evidence based on household-level data has shown that uncertainty is also important for macroeconomic outcomes (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), Kaplan and Violante (2018) and many others). These findings, mostly based on 'normal' (shallow) recessions, were further strengthened during the Great Recession when (according to Krueger, Mitman, and Perri (2016) and the references in footnote 7) uncertainty amplified the drop in house prices, employment and consumption.

5.2 Demographics and Saving

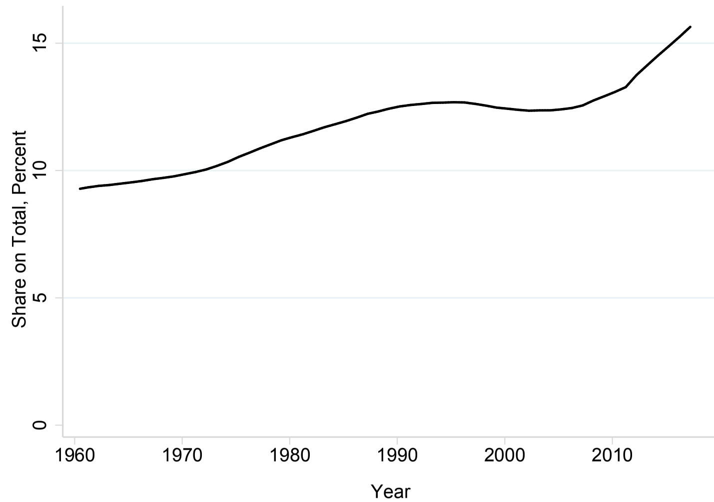
A long tradition of work, stemming from the seminal work of Modigliani and Brumberg (1954), examines the implications of demographic change for saving using calibrations and simulations of various life-cycle models (usually in an OLG setup). Overall, this strand of work has concluded that at the higher frequencies (e.g., annual) demographic changes do not substantially affect changes in saving because they are both small and very slow-moving (Summers and Carroll (1987), Parker (2000) and many others).

If demographic trends could provide a compelling explanation for the long-term decline in the saving rate leading up to 2007, that might constitute a plausible alternative to our story based on increased credit availability in the era of financial deregulation. But Auerbach, Cai, and Kotlikoff (1991) and related papers argued persuasively in the early 1990s that the first-order implication of demographics was that there should be a sustained *rise* in the saving rate for many years until the baby boom generation hit its peak earnings years around 2000–2005, and a declining saving rate thereafter. This is precisely the opposite of the actual pattern (the baby boom generation began exiting the "high-saving" phase of life and entering the supposedly "low-saving" retirement phase during exactly the interval when the saving rate stopped declining and then rose).

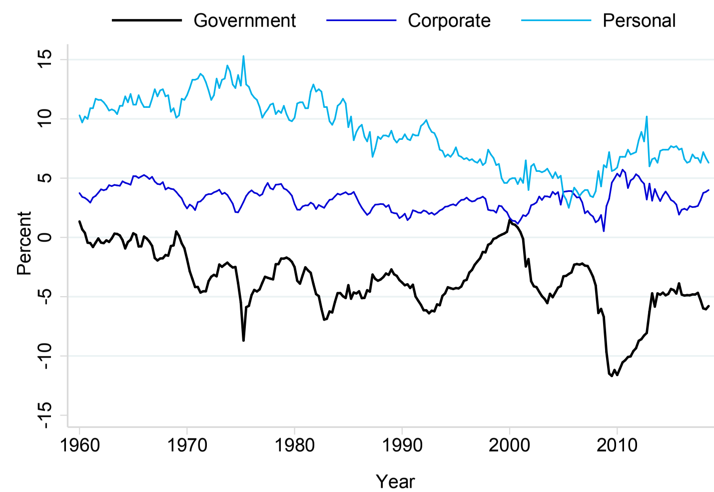
This point is roughly captured in Figure 9a which plots the old-age dependency ratio, which began rising faster around 2010 when large numbers of baby boomers began reaching retirement age. In Table 3, column 2 we estimate that the coefficient on the old-age dependency ratio is negative, which would suggest that the increase in the share of people older than 65 years should have *reduced* the saving rate, so the correlations go the wrong way for a demographic story (confirming the large prior

[15] We have also considered other measures of uncertainty, such as financial market or economic policy uncertainty (Baker, Bloom, and Davis (2016)), but our measure of labor market uncertainty, which is much more closely tied to a rigorous theory, also turns out to work better as a determinant of personal saving.

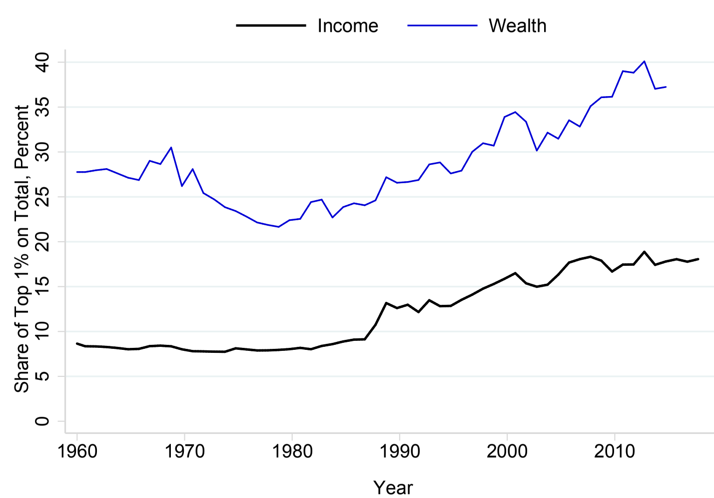
Figure 8 Additional Data Series: Demographics, Government Saving and Inequality



(a) Share of Population Above 65 Years (Old-Age Dependency Ratio)



(b) Government and Corporate Saving (as Fraction of GDP)



(c) Share of Top 1 Percent, Income and Wealth literature after Auerbach, Cai, and Kotlikoff (1991) that failed to find meaningful demographic effects).[16]

5.3 Reduced-Form vs Structural Models of Saving

We now ask to what extent the main features of the structural model of section 2 can be summarized in a simple reduced-form linear regression:

$$s_t = \gamma_1 + \gamma_m m_t + \gamma_{\text{CEA}}\text{CEA}_t + \gamma_{Eu}\,\mathbb{E}_t\,u_{t+4} + \varepsilon_t. \tag{6}$$

This specification can be readily estimated using OLS estimators (Table 3, column 3) and, at a minimum, can be interpreted as summarizing basic stylized facts about the data.

We have mentioned (in section 5.1) that the estimates of the "Baseline" model (6) are significant and explain more than 90 percent of variation in the saving rate. As expected from the structural model, the point estimates indicate a strong negative correlation of saving with net wealth and credit conditions, and a positive correlation with unemployment risk.

The coefficient on the Credit Easing Accumulated index is highly statistically significant with a t-statistic of more than 14. (Of course, this t-statistic should be taken with a several grains of salt given the obvious trends in both variables, and the cautionary literature about regressions of trends on trends; but aside from demographics (which go the wrong way), there are no other variables that are core constituents of standard saving models that have had powerful trends like this, so the case for spurious correlation is weaker than it sometimes is). The point estimate of γ_{CEA} implies that increased access to credit over the sample period until the Great Recession reduced the PSR by about 8 percentage points of disposable income. In the aftermath of the Recession, the CEA index declined between 2007 and 2010 by roughly 0.11 as credit supply tightened, contributing roughly 0.64 percentage point to the increase in the saving rate. Finally, once the three variables are included jointly, the time trend ceases to be significant (column 4).

Given how well the baseline linear reduced-form model captures the saving rate, one might wonder what value is added by construction of the structural model we proposed earlier. A first point to make here is that when we simulate the estimated version of our model and perform linear regressions on the corresponding generated data, the result is very close to being linear (the $\bar{R}^2$ is 0.975). Essentially, therefore, the

[16] For China a separate strand of work (e.g., Curtis, Lugauer, and Mark (2015) and Imrohoroglu and Zhao (2018)) uses a newer generation of these models to investigate the implications of demographic change. This work typically argues that demographic change did substantially contribute to the massive increase in saving (from around 5 percent in the 1970s to more than 25 percent in the 2010s). On the other hand, the importance of population aging in cross-country studies of household saving (for example, Bloom, Canning, Mansfield, and Moore (2007) and Bosworth and Chodorow-Reich (2007)) appears to be largely driven by the experience of Japan and Korea—countries well ahead of the United States in the population aging process.

difference between the two approaches is that the OLS regression puts no restrictions at all on the linear relationships between the variables, while the structural estimation puts stringent requirements that those linear relationships be tightly constrained to the small subset of nearly linear relationships that is a good approximation to the structural theory. The fact that the $\bar{R}^2$ from the structural estimation is essentially the same as for the unrestricted model (both of them round to 0.91) was by no means inevitable and indicates that the structure imposed by the model does no violence to the data.

5.3.1 Why Estimate a Structural Model When OLS Works Fine?

Because structural estimation restricts empirical relationships to those that are compatible with a theory, structural models by their intrinsic nature fit the data worse than an unrestricted data-fitting exercise; the advantages of structural modeling (articulated below) can nevertheless make such estimation worth the sacrifice in data-fitting ability. In the case at hand, however, the structural model fits the data nearly as well as an unrestricted OLS regression. Thus, in our context, the case for structural modeling is stronger than in the usual case where there is a significant penalty in data-fitting ability.

Some of the advantages of having a structural model are:

- If the structure imposed is one that has considerable backing from other contexts or kinds of data, it is less likely that the fit of the model to the data is spurious (in the sense of failing to capture any reliable or causal economic relationship).

- The structural model can provide insights that could not be obtained from the reduced form model. For example, the "overshooting" result implied by the structural model might have important consequences for business cycle dynamics even if the fit of the structure that embodies those dynamics is statistically inferior to the reduced form fit.

- The structural model has implications for ways to test the ideas using data other than those on which it was estimated. In this case, for example, the structural model would suggest that it would be useful to look at regional or local data in which the endogeneity of aggregate asset prices and credit conditions could be controlled for by looking at differences in unemployment expectations and saving responses across regions in an aggregate economy where most of the movements in the other explanatory variables are not region-specific.

5.4 Further Robustness Checks

Columns 5 and 6 of Table 3 summarize the correlations of the personal saving rate with two variables that some theories suggest might be related to it: government saving (Figure 9b) and income inequality (Figure 9c).

Column 5 reports that there is indeed a negative correlation between government and personal saving, though the size of the coefficient, -0.15, implies only a modest crowding out. More than a support for the Ricardian equivalence—the hypothesis that households observing higher government saving should save less themselves (as they should expect lower taxes in the future)—the finding seems to reflect reverse causality between private and public saving, the fact that during recessions government saving falls (e.g., due to higher outlays on unemployment insurance), while personal saving rises for precautionary reasons (see work of Elmendorf and Mankiw (1999) and many others).

Finally, in column 6 we evaluate whether growing income inequality (shown in Figure 9c) has resulted in an increase in the aggregate saving rate: Microeconomic evidence points to high personal saving rates among the higher-permanent-income households (Carroll (2000); Dynan, Skinner, and Zeldes (2004)), whose share on total income has been rising. Having experimented with numerous measures of the top shares of Piketty and Saez (2003), we find little evidence of a substantial and statistically significant correlation between saving and income inequality.

6 Conclusions

We show that a simple representative-consumer model of buffer stock saving can match most of the time-series variation in the aggregate US personal saving rate over the past 50 years. In the model, saving depends on the gap between the 'target' and actual wealth, with the target determined by credit availability and uncertainty.

We estimate that these three factors—credit availability, shocks to household wealth, and movements in income uncertainty proxied by unemployment risk—have all been important in driving the saving rate. In particular, the relentless expansion of credit supply between the early-1980s and 2007 (likely largely reflecting financial innovation and liberalization), along with higher asset values and consequent increases in net wealth (possibly also partly attributable to the credit boom) encouraged households to save less out of their disposable income. At the same time, the fluctuations in wealth and labor income uncertainty, for instance during and after the burst of the information technology and credit bubbles of 2001 and 2007, can explain the bulk of business cycle fluctuations in personal saving.

The model we estimate could be extended to analyze the implications of the 'overshooting' of saving in response to business-cycle shocks. For example, the model suggests that in a recession an optimizing government might want to counteract the part of the consumption decline that reflects overshooting. In an economy rendered non-Ricardian by liquidity constraints and/or uncertainty, the existence of precautionary saving thus provides a potential rationale for counter-cyclical fiscal policy.

More generally, the simple buffer stock saving model we estimate could provide insights into the current debate about the role household heterogeneity for macroeconomic outcomes. The model is both easy to solve and provides a setup to meaningfully analyze the effects on uncertainty on the macro-economy. Consequently, the model could be a useful middle ground between a setup with a realistic but complex description of household heterogeneity (HANK) and a simple two-agent spender–saver setup (TANK) that cannot accommodate roles for credit availability or uncertainty.

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Table 2 Actual and Explained Change of the Saving Rate: Structural and Reduced Form Models, 2006/07–2009/10

	Model Decomposition		
Variable	Structural	Reduced Form	Actual Δs_t
m_t	1.3	$-0.89 \times -1.19 = 1.1$	
CEA_t	0.6	$-7.91 \times -0.12 = 1.0$	
$\mathbb{E}_t\, u_{t+4}$	0.7	$0.20 \times 4.6 = 0.9$	
Explained/Actual Δs_t	2.6	3.0	2.6

Notes: The table shows the change of the personal saving rate between the two-year averages of years 2006–2007 and 2009–2010 (in percentage points) implied by the structural model, the baseline reduced form model of Table 3 and in actual data.

Table 1 Calibration and Structural Estimates

$$\mathrm{s}_t = \mathrm{s}\Big(\{m_t, \mathrm{CEA}_t, \mathbb{E}_t\, u_{t+4}\}; \Theta\Big),$$
$$\underline{h}_t = \theta_{\mathrm{CEA}}\mathrm{CEA}_t,$$
$$\mho_t = \bar{\theta}_{\mho} + \theta_u\, \mathbb{E}_t\, u_{t+4}.$$

Parameter	Description	Value
Calibrated Parameters		
r	Interest Rate	0.04/4
$\Delta\mathsf{W}$	Wage Growth	0.01/4
ρ	Relative Risk Aversion	2
Estimated Parameters $\Theta = \{\beta, \theta_{\mathrm{CEA}}, \bar{\theta}_{\mho}, \theta_u\}$		
β	Discount Factor	$1 - 0.0065^{***}$
		(0.0005)
θ_{CEA}	Scaling of CEA_t to $\underline{h}_t$	8.8943^{***}
		(0.8403)
$\bar{\theta}_{\mho}$	Scaling of $\mathbb{E}_t\, u_{t+4}$ to $\mho_t$	$1.2079 \times 10^{-4***}$
		(0.2757×10^{-4})
θ_u	Scaling of $\mathbb{E}_t\, u_{t+4}$ to $\mho_t$	$2.6764 \times 10^{-4***}$
		(0.6490×10^{-4})
$\bar{R}^2$		0.906
DW stat		0.780
	Sample average of CEA_t	0.4289
	Sample average of $\mathbb{E}_t\, u_{t+4}$	0.0620

Notes: Quarterly calibration. Estimation sample: 1966q2–2011q4. $\{^{*}, ^{**}, ^{***}\}$ = Statistical significance at $\{10, 5, 1\}$ percent. Standard errors (in parentheses) were calculated with the delta method. Parameter estimates imply sample averages of 3.82 and 0.000137 for $\underline{h}_t$ and $\mho_t$, respectively.

Table 3 Reduced-Form Regressions

$$s_t = \gamma_0 + \gamma_m m_t + \gamma_{\text{CEA}}\text{CEA}_t + \gamma_{Eu}\,\mathbb{E}_t\,u_{t+4} + \gamma' X_t + \varepsilon_t$$

			Reduced-Form		Additional Variables	
Model	Uncertainty	Demographics	Baseline	Time Trend	Gov Sav	Ineq
γ_0	11.750***	29.504***	17.157***	15.535***	17.588***	18.553***
	(0.462)	(5.257)	(1.589)	(2.004)	(1.589)	(1.804)
γ_m		−1.596***	−0.894***	−0.618*	−0.862***	−1.321***
		(0.362)	(0.261)	(0.341)	(0.269)	(0.410)
γ_{CEA}		−4.444***	−7.909***	−4.156**	−8.149***	−9.545***
		(1.451)	(0.556)	(2.098)	(0.565)	(1.249)
γ_{Eu}	0.551***	0.264***	0.202***	0.347***	0.028	0.181***
	(0.059)	(0.068)	(0.064)	(0.105)	(0.074)	(0.065)
γ_t	−0.055***			−0.025		
	(0.002)			(0.015)		
γ_{old}		−0.861**				
		(0.365)				
$\gamma_{\text{gov sav}}$					−0.152**	
					(0.063)	
$\gamma_{\text{inc share}}$						0.190
						(0.144)
$\bar{R}^2$	0.910	0.918	0.911	0.914	0.916	0.913
F stat p val	0.000	0.000	0.000	0.000	0.000	0.000
DW stat	0.761	0.848	0.732	0.769	0.682	0.771

Notes: Estimation sample: 1966q2–2011q4. $\{^*, ^{**}, ^{***}\}$ = Statistical significance at $\{10, 5, 1\}$ percent. Newey–West standard errors, 4 lags.

Supplemental Materials—Not for Publication

A Extension of Derivation of Target Wealth to Include Unemployment Insurance

This appendix introduces an unemployment insurance system into the model of Carroll and Toche (2009) (which assumes that income for unemployed/retired households is zero). The UI system guarantees a minimum (positive) level of income to the unemployed. For ease of modelling we assume that the unemployment insurance benefit is a constant proportion of the labor income that the unemployed would counterfactually earn in the first year of unemployment if they had not become unemployed.

In the perfect foresight context, receiving a constant payment with perfect certainty is equivalent to receiving a lump sum "severance" payment whose value is equal to the PDV of the stream of future UI payments. Thus, for simplicity, we assume $\mathcal{S} = \varsigma \cdot \ell \mathsf{W}$, which means individuals will receive one-period severance payment $\mathcal{S}$ in the amount of a certain ratio ς to labor income of the period when they first lose their jobs. After that, they will not receive any unemployment insurance benefit.

The only modifications of the decision problem are to add the severance payment and a corresponding lump-sum tax into the dynamic budget constraint (DBC) of employed consumers in Carroll and Toche (2009),

$$m_{t+1} = \begin{cases} (m_t - c_t)\mathsf{R}/\Gamma + \varsigma & \text{with prob.} \quad \mho \quad \text{(unemployed in } t+1) \\ (m_t - c_t)\mathsf{R}/\Gamma + 1 - \tau & \text{with prob. } 1-\mho \quad \text{(employed in } t+1) \end{cases}$$

where we denote with lower-case m and c the levels of market resources (market wealth plus current income) and consumption normalized by the corresponding period's pretax labor income $\ell \mathsf{W}$. We let $\tau = \mho \times \mathcal{S}$ to ensure a balanced budget for the unemployment insurance system.[17]

Following Carroll and Toche (2009), we have the following condition derived from the Euler equation,

$$1 = \Gamma^{-\rho}\mathsf{R}\beta \left\{ (1-\mho)\left(\frac{c^e_{t+1}}{c^e_t}\right)^{-\rho} + \mho \left(\frac{c^u_{t+1}}{c^e_t}\right)^{-\rho} \right\}.$$

Superscripts e and u represent the two possible employment states.

To find the $\Delta c^e = 0$ and $\Delta m^e = 0$ loci, we let $c^e_{t+1} = c^e_t \equiv c^e$ and $m^e_{t+1} = m^e_t \equiv m^e$. Given $c^u_{t+1} = m^u_{t+1}\kappa^u$ (κ^u is the MPC of an unemployed consumer), combined with the modified DBC above, we have (for $\mathcal{R} \equiv \mathsf{R}/\Gamma$):

$$1 = \Gamma^{-\rho}\mathsf{R}\beta \left\{ (1-\mho) + \mho \left(\frac{\kappa^u(\mathcal{R}(m^e - c^e) + \varsigma)}{c^e}\right)^{-\rho} \right\}.$$

[17] Each period, proportion $\mho$ of employed consumers lose their jobs, i.e., the "exit rate" in the current labor market is $\mho$. In order to raise a corresponding amount of revenues, we need to assume that there is a "birth rate" of $\mho$ of new employed consumers, which means a same proportion of consumers are entering the labor market each period. Combined with the assumption that $\tau = \mho \times \mathcal{S}$, the severance payment and the severance payment are balanced.

Rearranging terms, the $\Delta c^e = 0$ locus can be characterized as:

$$\overbrace{\left(\frac{\Gamma^\rho(\mathsf{R}\beta)^{-1} - (1-\mho)}{\mho}\right)^{1/\rho}}^{\Pi} = \frac{c^e}{(\mathcal{R}(m^e - c^e) + \varsigma)\kappa^u}.$$

Given the modified DBC of employed consumers, the $\Delta m^e = 0$ locus becomes:

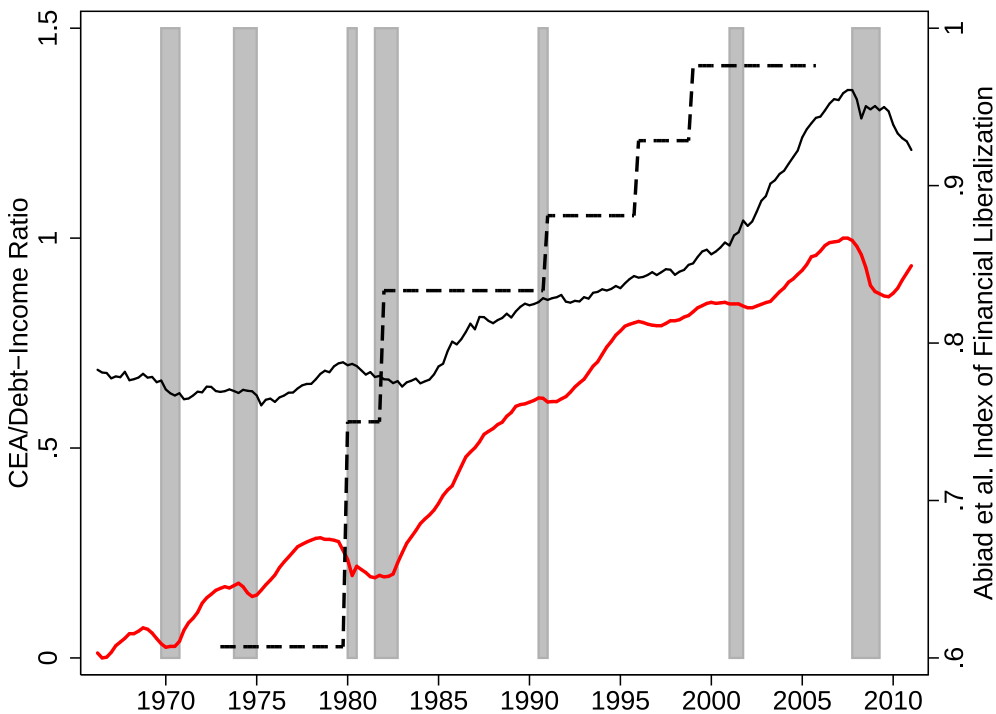
$$m^e = \mathcal{R}(m^e - c^e) + (1 - \mho\varsigma).$$

Given the last two equations, we are able to obtain the exact formula for target wealth $\check{m}^e$, which is the steady state value of m^e. Defining $\eta \equiv \mathcal{R}\kappa^u\Pi$, following Carroll and Toche (2009), we have:

$$\begin{aligned}
\frac{\eta\check{m}^e + \frac{\eta\varsigma}{\mathcal{R}}}{\eta+1} &= (1-\mathcal{R}^{-1})\check{m}^e + \frac{1-\mho\varsigma}{\mathcal{R}} = \check{c}^e \\
\left(\frac{1}{\mathcal{R}} - \frac{1}{\eta+1}\right)\check{m}^e &= \frac{1}{\mathcal{R}}\left(1 - \mho\varsigma - \frac{\eta\varsigma}{\eta+1}\right) \\
\check{m}^e &= \frac{(\eta+1)(1-\mho\varsigma) - \eta\varsigma}{\eta + 1 - \mathcal{R}}.
\end{aligned}$$

Clearly, target wealth decreases when the severance payment becomes more generous and it can even be negative if we make the severance ratio ς large enough.

Figure 10 Alternative Measures of Credit Availability



Legend: Debt–disposable income ratio: Thin black line, CEA index: Thick red/grey line, the Abiad, Detragiache, and Tressel (2010) Index of Financial Liberalization: Dashed black line. 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/`; Abiad, Detragiache, and Tressel (2010); US Financial Account (Flow of Funds), Board of Governors of the Federal Reserve System.

B Comparison of Alternative Measures of Credit Availability

Figure 10 compares three measures of credit availability: our baseline CEA index, the Index of Financial Liberalization constructed by Abiad, Detragiache, and Tressel (2010) for a number of countries including the United States, and the ratio of household liabilities to disposable income.

The Abiad, Detragiache, and Tressel index is a mixture of indicators of financial development: credit controls and reserve requirements, aggregate credit ceilings, interest rate liberalization, banking sector entry, capital account transactions, development of securities markets and banking sector supervision. The correlation coefficient between this measure and CEA is about 90 percent.

For comparison, the figure also includes the ratio of liabilities to disposable income (from the Flow of Funds), which is however determined influenced by the interaction between credit supply and demand.

Table 4 Reduced-Form Regressions with Saving Rate Estimated by the Structural Model

$$s_t = \gamma_0 + \gamma_m m_t + \gamma_{\text{CEA}}\text{CEA}_t + \gamma_{Eu}\,\mathbb{E}_t\,u_{t+4} + \gamma' X_t + \varepsilon_t$$

			Reduced-Form		Additional Variables	
Model	Uncertainty	Demographics	Baseline	Time Trend	Gov Sav	Ineq
γ_0	11.689***	18.994***	16.254***	16.093***	16.215***	16.330***
	(0.182)	(1.126)	(0.636)	(0.710)	(0.633)	(0.646)
γ_m		−0.912***	−0.756***	−0.729***	−0.759***	−0.780***
		(0.110)	(0.099)	(0.113)	(0.099)	(0.117)
γ_{CEA}		−7.316***	−8.085***	−7.713***	−8.064***	−8.174***
		(0.292)	(0.112)	(0.621)	(0.114)	(0.309)
γ_{Eu}	0.555***	0.237***	0.223***	0.238***	0.239***	0.222***
	(0.025)	(0.018)	(0.017)	(0.030)	(0.021)	(0.016)
γ_t	−0.055***			−0.002		
	(0.001)			(0.004)		
γ_{old}		−0.191***				
		(0.071)				
$\gamma_{\text{gov sav}}$					0.014	
					(0.014)	
$\gamma_{\text{inc share}}$						0.010
						(0.033)
$\bar{R}^2$	0.975	0.989	0.988	0.988	0.988	0.988
F stat p val	0.000	0.000	0.000	0.000	0.000	0.000
DW stat	1.167	2.331	2.213	2.219	2.237	2.217

Notes: Estimation sample: 1966q2–2011q4. $\{^{*}, ^{**}, ^{***}\}$ = Statistical significance at $\{10, 5, 1\}$ percent. Newey–West standard errors, 4 lags.

C Reduced Form Regressions with Saving Rate Generated by the Structural Model