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

March 25, 2019

Christopher Carroll ¹  Jiri Slacalek ²  Martin Sommer ³

JHU  ECB  IMF

Abstract

We argue that an estimated version of a simple ‘buffer stock saving’ model can match the 30-year decline in the U.S. saving rate leading up to 2007, and the sharp increase during and after the Great Recession. In our tractable model, saving depends on the gap between the ‘target’ and actual wealth, with the target determined by credit availability and uncertainty. Estimates of our model suggest that, as a result of financial deregulation that began in the late 1970s, the expansion of credit availability (as measured using the Fed’s survey of bank Senior Loan Officers) accounts for the trend decline in saving, while fluctuations in measured wealth and consumer-survey-measured uncertainty capture the bulk of the business-cycle variation in saving, including the sharp rise during and after 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)


We thank Andra Buca, Kerstin Holzheu, Geoffrey Keim, Jakub Rybák, Camilla Sacca and Joanna Slawatyniec.
1 Introduction

The start of the Great Recession marks a striking break in the behavior of the US personal saving rate: After gradually declining over the previous 30 years, the rate more than doubled in 2007 (Figure 1(a)), and even 5 years later, exceeded its pre-crisis level by almost 5 percentage points (Figure 1(b)). Surprising weakness of consumption growth (relative to income growth) has been a key element in explanations of why the recovery from the Great Recession was repeatedly weaker than forecasters expected year after year after year. The “secular stagnation” hypothesis of Summers (2013, 2015), Krugman (2013, 2014), Gordon (2015) and others is the most provocative interpretation of these events, but even secular stagnation skeptics have acknowledged that weak consumption growth played a role in the anemic recovery (Hamilton, Harris, Hatzis, 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. But we are not aware of any work that has systematically attempted to

---

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.
quantify the 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 precautionary, wealth, and credit channels). The model’s key intuition is that, in the presence of income uncertainty, optimizing households have a target wealth–permanent income ratio that depends on the usual theoretical considerations (risk aversion, time preference, expected income growth, 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.

The structural model is able to capture the bulk of the variation in the saving rate over the historical period for which the necessary data are available — the fit is better than 0.90 in the $R^2$ sense. 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 easing of credit availability following the extended period of gradual financial deregulation that began in the Carter administration (cf Woolley (2012)) and extended to the brink of the Great Recession. Our measure of credit availability (based on the Fed’s survey of senior loan officers) shows a substantial tightening during the Great Recession, the first sustained and substantial tightening 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 rising precautionary motive (proxied by a measure of consumers’ unemployment expectations) also playing a substantial role.2

The rest of the paper is organized as follows. Section 2 presents the structural model and its mechanics. Section 3 briefly describes the main data; section 4 presents the estimates of the model and the empirical decomposition of the saving rate. Section 5 overviews the key competitor models of the saving rate; section 6 concludes.

2We 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 footnote 1) 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. See also our discussion in section 2.4 below.
2 Theory: Target Wealth and Credit Conditions

This section presents 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 that might be available to repay it).

2.1 Essentials of the Tracable Model

Under most specifications of uncertainty, Constant Relative Risk Aversion utility interacts with uncertainty in ways that rule out any closed form results.

The assumption that makes the CT model tractable despite their use of an intertemporally separable CRRA utility function $u(x) = (1 - \rho)^{-1} \cdot x^{-\rho}$ is that unemployment risk takes a particularly stark form: Employed consumers face a constant probability $\delta$ 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 derived almost instantaneously by backward iteration on a difference equation that terminates in the target.

Interpreting lower-case letters as the log of the corresponding upper-case factor (e.g., the growth rate $\gamma$ is the log of the growth factor $\Gamma$; the exception is time preference rate $\vartheta = -\log \beta$), CT show that for the special case of logarithmic utility, the target ‘market resources’ ratio $m$ (roughly, wealth-to-income ratio) for an employed consumer is

$$\tilde{m} \approx 1 + \left( \frac{1}{(\gamma - r) + \vartheta(1 + (\gamma + \vartheta - r)/\delta)} \right)$$  (1)

A “Growth Impatience Condition” guarantees that the expression $(\gamma + \vartheta - r)$ in the denominator is strictly positive. Using this fact, the equation has intuitive characteristics: Target wealth is higher when

- Human wealth is lower ($r - \gamma$ is larger)
- The time preference rate is lower (the consumer is more patient)
- Unemployment risk is higher (inducing a stronger precautionary motive)

Large literatures have examined the separate and the joint effects of $r$ and $\gamma$, and have consistently failed to find robust and reproducible results about the relationship between these variables and the saving rate. Our model does not have much to new
to say on that subject, so we will follow Campbell and Mankiw (1989) and many subsequent papers in assuming constant $r$ and $\gamma$.

2.2 The Consumption Function

Our only modification to the CT model is addition of an ‘unemployment insurance’ system that relaxes the natural borrowing constraint. (For the derivations, see appendix B.2). In the CT model, the necessity of arriving in the unemployment state with some minimal level of assets (to prevent zero consumption) prevents any borrowing. More generous UI benefits shift the consumption function of employed consumer to the left because households with little market resources are willing to borrow as they will not starve even if they become unemployed. Consumers will limit their indebtedness, however, to an amount small enough to guarantee that consumption will remain strictly positive even when unemployed (this requirement defines the ‘natural borrowing constraint’).³

The variables $m$ and $c$ are the levels of market resources $M$ (market wealth plus current income) and consumption $C$ normalized by the corresponding period’s labor income $\ell W$ (the product of individual labor productivity $\ell$ and the aggregate wage $W$, the combination of which is assumed to grow by $\Gamma$ per period; see CT for details). Next period’s market resources $m_{t+1}$ are the sum of current market resources $m_t$ net of consumption $c_t$, augmented by the growth-adjusted interest factor $R/\Gamma$; for the employed consumer, net normalized after-tax income is $1-\tau$, while for the unemployed consumer, unemployment benefits are $\varsigma$ (both expressed as a fraction of labor income). The unemployment benefit $\varsigma$ is financed on a pay-as-you-go basis by a lump sum tax $\tau$, changing the (normalized) dynamic budget constraint to

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

(2)

The steady-state target market resources ratio, $\tilde{m}^e$, depends on unemployment risk $\bar{\mathcal{U}}$, credit conditions (which we denote below as ‘CEA’) and other factors, such as the interest rate $r$, the growth rate of wages $\Gamma$, relative risk aversion $\rho$, and the discount factor $\beta$.⁴ and under our parameter values, the relationship of target wealth to the fundamentals of the model is characterized by

³We could easily add a tighter ‘artificial’ liquidity constraint, imposed exogenously by the financial system, that would prevent the consumers from borrowing as much as the natural borrowing constraint permits. But Carroll (2001) shows that the effects of tightening an artificial constraint are qualitatively and quantitatively similar to the effects of tightening the natural borrowing constraint. We describe the extension of the CT model for the unemployment insurance in an online appendix.

⁴Specifically, the appendix B.2 shows that the steady-state target wealth is:

$$\tilde{m} = \frac{(\eta + 1)(1 - \bar{\mathcal{U}}_k) - \eta K}{\eta + 1 - R/\Gamma},$$
\[ \hat{m} = f(U, \text{CEA}, R, \Gamma, \rho, \beta, \ldots) \]  

(3)

Target wealth \( \hat{m} \) increases with unemployment risk, because in response to higher uncertainty, consumers build up a larger precautionary buffer of savings. An easing of credit conditions—an increase in the CEA index (modelled as an increase in \( \zeta \))—makes it easier for households to borrow and reduces the need to accumulate wealth for consumption smoothing. A higher interest rate increases the rewards to holding wealth and thus increases the amount held. Faster wage growth translates into a lower wealth target because households who expect higher future income consume more now in anticipation of their future prosperity (the ‘human wealth effect’). Finally, risk aversion and the discount factor have effects on target wealth that are qualitatively similar to the effects of uncertainty and the interest rate, respectively.

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 the ratios of both consumption and market resources to labor income, \( c \) 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. 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).

Relaxation of the borrowing constraint (from an initial position of 0, in which no borrowing occurs, to a new value in which the natural borrowing limit is \( \bar{h} \) implying minimum net worth of \(-\bar{h}\)) leads to an immediate increase in consumption for a given level of resources (Figure 3c). But over time, the higher spending causes the consumer’s level of wealth to decline, forcing a corresponding gradual decline in consumption until wealth eventually settles at its new, lower target level.\(^6\)

\[ \eta = \kappa^u \Pi R / \Gamma, \quad \Pi = \left( \frac{\Gamma (R \zeta)^{-1} (1 - U)}{\kappa^u} \right)^{1/\rho} \]

where \( \eta = \kappa^u \Pi R / \Gamma, \quad \Pi = \left( \frac{\Gamma (R \zeta)^{-1} (1 - U)}{\kappa^u} \right)^{1/\rho} \) and \( \kappa^u \) is the (constant) marginal propensity to consume out of total wealth for the unemployed consumer.

\(^5\)The increase in \( U \) is a pure increase in risk (a mean-preserving spread in human wealth) because we assume that labor productivity \( \ell \) grows at the rate \( 1/U (1 - \ell) \) (which in turn implies that labor income grows at the rate \( \Gamma = G/(1 - U) \), where \( G \) is the growth rate of the wage \( W \)).

\(^6\)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 (2011) 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 $h$

(d) Saving Dynamics in a Buffer Stock Model
Figure 3d shows the consequences of a permanent increase in unemployment risk $\bar{U}$ for the dynamics of the personal saving rate (‘PSR’ henceforth), rather than the level of consumption (as 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 the new target $\bar{s}_t'$, followed by a gradual decline toward its new target $\bar{s}_t'$ (which is higher than the original one). This uneven adjustment of saving reflects the fact that, when the target level of wealth rises, not only is a higher level of steady-state saving needed to maintain a higher target level of wealth, an immediate further boost to saving is necessary to move from the current (inadequate) level of wealth up to the new (higher) target.

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).

2.4 Comparison to Alternative ‘Structural’ Models

Our goal has been to estimate a unified structural saving model whose “deep” parameters are identified using both business-cycle-frequency fluctuations AND long-term trends, since both cyclical and secular changes in the saving rate have been large.

We are not aware of prior papers that attempt this. Existing work in the consumption/saving literature (including the papers cited in footnote 1) has typically either been theoretical/calibrated (rather than structural and estimated to match aggregate data) or reduced-form (rather than structural). Furthermore, both literatures have mostly focused on business-cycle-frequency movements (e.g., by detrending the data using an HP filter), without any constraint that those dynamics be reconciled with longer-term trends (there are a few exceptions, e.g. Parker (2000b) and several papers by Muellbauer and coauthors cited below).

The tractability of our structural model has been instrumental in achieving our goals. But our model achieves tractability at the cost of making stylized assumptions, most notably about the nature of unemployment risk. 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 detailed elements of the microeconomic environment, and a flourishing literature today (in which two of the paper’s coauthors are active participants) explores the implications of these
complexities for many questions. (See Krueger, Mitman, and Perri (2016) for a survey of this literature.)

The core economic mechanisms in our model (precautionary, wealth, and credit effects) are present also in those models. A reader might wonder why we did not build our structural model using some adapted version of this appealing new generation of models.

Because of the difficulty of solving them, and because of the many detailed choices that go into their construction, until now rich microfounded models have usually been optimized for the purpose of examining of a single question (such as the mechanisms of transition of monetary policy, Kaplan, Moll, and Violante (2018)) in great depth rather than, as we are attempting, to address a number of different causal mechanisms, over different time horizons, simultaneously.

Perhaps more compelling is that, for our particular purposes, the extra microeconomic realism comes at too high a cost in transparency and tractability. Models with rich microeconomic environments require the calibration of many auxiliary parameters whose ultimate relationship to their quantitative results is sometimes opaque even to the authors (in part because of nonlinear interactions between the parameters), and even more obscure to readers. Our story is relatively simple and easily understood using the tractable model, but would have been much harder to explain if buried in a welter of microeconomic complexity.

Indeed, at the existing state of the computational art it was not clear to us that it would have been possible to conduct a structural estimation of the kind we sought. And, even if it had proven possible, it might not have been wise. When a novel approach to a question is proposed, it is almost always best to illustrate the technique with the simplest possible framework, rather than the richest possible framework, so that the essentials of the methodological contribution are easier to absorb. It will always be possible for subsequent researchers to see whether the results obtained using a simple model hold up when the model is made more realistic.

Arguably a deeper problem, both with our paper and with those 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 much of the increase in saving in the Great Recession begs the question of what caused those asset price movements (in stocks, housing, risky bonds, and most other asset categories other than safe 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.

A vast literature has attempted to model asset pricing in general equilibrium. While arguably some progress has been made in understanding the cross-section heterogeneity of asset holdings (cf. Gomes and Michaelides (2007)), for our purposes the what is needed is a model that can capture the cyclical and secular time series of returns.
If the aggregate time series asset pricing literature had found a consensus model that worked well, we would certainly have needed to incorporate some version of that consensus in our model. But 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 an exogenous but rare Great-Depression-like state, exogenous shocks to expectations, or endogenous changes in illiquidity of housing. The existence of this literature suggests that no single model of asset pricing is adequate for more “normal” times and the Great Recession; and, 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 particular model of asset pricing in our analysis, the paper would inevitably (and correctly) judged to be more about the performance of that asset pricing model than anything else.

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.

Finally, a central purpose of this paper was 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 reduced form estimates. After the exposition of our model and its estimation, our penultimate section 5 below 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.

---

7 In more detail, building on the literature on consumption disaster risk, Glover, Heathcote, Krueger, and Rios-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 the 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).
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.

Using the Federal Reserve’s Balance Sheets, if we define wealth Balances as \( B_{t+1} = (M_t - C_t)R(1 - \tau) \), we can obtain spendable resources by adding disposable income \((1 - \tau)\ell_{t+1}W_{t+1} \). Normalizing by disposable income yields a ratio of market resources to disposable income \( m_t \) measured as 1 plus the ratio of household net worth to disposable income (Figure 5a).

Our measure of credit availability, ‘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 debt-to-income ratio to account for the increasing trend in that variable, and normalizing it 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) which brings into grave 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.

---

\(^8\)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) The Credit Easing Accumulated (CEA) Index

(c) Unemployment Risk $E_t u_{t+4}$ and Unemployment Rate
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, a greater role of nonbanking financial institutions, and the increased use of securitization all contributed to the dramatic rise in credit availability from the early 1980s until the onset of the Great Recession in 2007. The subsequent significant drop in the CEA index was associated with the funding difficulties and de-leveraging of financial institutions.9

We measure a proxy $E_{t} u_{t+4}$ for unemployment risk $U_{t}$ using re-scaled answers to the question about the expected change in unemployment in the Thomson Reuters/University of Michigan Surveys of Consumers.10 In particular, we estimate $E_{t} u_{t+4}$ 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 $U\text{Exp}^{BS}$:

$$\Delta_{4} u_{t+4} = \alpha_{0} + \alpha_{1} U\text{Exp}^{BS}_{t} + \varepsilon_{t+4},$$

$$E_{t} u_{t+4} = u_{t} + \Delta_{4} \hat{u}_{t+4}.$$ 

The coefficient $\alpha_{1}$ is highly statistically significant, indicating that households do have substantial information about the direction of future changes in the unemployment rate. As expected, our $E_{t} u_{t+4}$ 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 roughly 4 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): “We show that much of the initial variation in the personal saving rate across time was meaningless noise.”11 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

---

9As 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).

10The question is: “How about people out of work during the coming 12 months—do you think that there will be more unemployment than now, about the same, or less?”

11In addition, there were substantial gyrations in the saving rate in 2012 due to a tax-related anomaly (income was boosted by accelerated and special dividend payments and by accelerated bonus payments in anticipation of changes in individual income tax rates).
the Mortgage Credit Availability Index of the Mortgage Bankers’ Association; see also Bhutta (2015)) document a substantial tightening in credit conditions after 2011. If, as this work suggests, 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 changed after the Great Recession due to the substantial shock of the Great Recession, e.g., 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). Finally, recall that our model implies that the saving rate “overshoots” and remains at levels different from its true equilibrium for a substantial period after a change in fundamentals (like a tightening of credit). During the period of continual expansion of credit, the saving rate should thus have been persistently below its long-run equilibrium level, and conversely after the arrival of a permanently tighter credit regime the saving rate should be elevated above its equilibrium value for a substantial 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. Households observe exogenous movements in three variables: wealth shocks $m_t$, unemployment risk $\bar{U}$ and credit supply conditions $CEA$. They consider the shocks to $\bar{U}$ and $CEA$ to be permanent, and do not expect the shocks to wealth to be reversed. Given these observables, consumers re-optimize their consumption–saving choice in each period. Collecting the parameters in vector $\Theta$ and denoting the wealth gap $m_t - \hat{m}_t$, the model implies a series of the saving rates $s_t^{\text{theor}}(\Theta; m_t - \hat{m}_t)$, which we match to those observed in the data, $s_t^{\text{meas}}$. Our estimates of $\Theta$ thus solve the problem:

$$\hat{\Theta} = \arg \min_{\Theta} \sum_{t=1}^{T} \left( s_t^{\text{meas}} - s_t^{\text{theor}}(\Theta; m_t - \hat{m}_t) \right)^2,$$

(4)

where target wealth $\hat{m}$ depends on credit conditions and unemployment risk, as described in section 2. In our baseline specification, the parameter vector $\Theta$ consists of the discount factor $\beta$ and scaling constants for credit conditions and unemployment.
risk:

\[ \Theta = \{ \beta, \theta_h, \theta_{CEA}, \theta_u \}, \]
\[ h_t = \theta_h + \theta_{CEA} CEA_t, \]
\[ \bar{U}_t = \theta_{t3} + \theta_u E_t u_{t+4}. \]

The re-scaling ensures that the unitless measure of credit conditions is re-normalized as a fraction of income and that the expected unemployment rate is transformed into the model-compatible equivalent of permanent risk. The model implies that \( \theta_{CEA} > 0 \) and \( \theta_u > 0 \).

Minimization (4) is a non-linear least squares problem for which the standard asymptotic results apply. The estimates have the asymptotic normal distribution:

\[ T^{1/2}(\hat{\Theta} - \Theta) \rightarrow_d N(0, D^{-1}ED'^{-1}), \]

where \( E = \text{var} \left( q_t(\Theta) \right) \) and \( D = \mathbb{E} \frac{ \partial q_t(\Theta) }{ \partial \Theta } \) are \( 5 \times 5 \) matrices and the scores \( q_t(\Theta) = \left( s_t \text{meas} - s_t \text{theor}(\Theta) \right) \frac{ \partial s_t \text{theor}(\Theta) }{ \partial \Theta } \).

4.2 Estimates and the Model Fit

Table 1 presents the estimation results. The calibrated parameters—the quarterly real interest rate \( r = 0.04/4 \), quarterly wage growth \( \Delta W = 0.01/4 \) and the coefficient of relative risk aversion \( \rho = 2 \)—take on standard values and meet (together with the estimated discount factor \( \beta \)) the conditions sufficient for the problem to be well-defined (see Carroll and Toche (2009)).

The estimated quarterly discount factor \( \beta = 1 - 0.0063 = 0.9937 \), or 0.975 at annual frequency, lies in the standard range. As for the horizontal shift in the consumption function \( h_t \) driven by credit availability, the estimates of the scaling factors \( \theta_h \) and \( \theta_{CEA} \) imply that \( h_t \) varies between \( 0.76/4 \approx 0.2 \) and \( (0.76 + 9.88)/4 \approx 2.7 \), 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 270 percent of annual income (for an average household)—not an unreasonable figure given the 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 \( \bar{U}_t \) peaks at \( 10 \times 10^{-5} \) per quarter. The magnitude of \( \bar{U}_t \) implies that over the life cycle of 50 years or 200 quarters, the workers face a probability of roughly 2 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 \( \bar{U}_t \) seems broadly plausible.
I’m confused about a number of things here. First, I can’t reconcile the following facts:

1. The relationship between the model-predicted saving rate and the constructed explanatory variables is almost perfectly linear (second-to-last column of Table 6 has an $R^2$ of 0.974)

2. We seem to be estimating two separate constants in the structural model

Take the second and third points first. If the structural model were exactly linear it would be writeable as

$$s_t = \nu_0 + \nu_1(\bar{\theta} + \theta_{\text{CEA}}) + \nu_2(\bar{\theta} + \theta_u \mathbb{E}_t u_{t+4}) + \epsilon$$

(5)

This equation appears to have THREE constant terms in it: $\nu_0, \nu_1, \nu_2, \bar{\theta}$, and $\nu_2 \bar{\theta}$. Maybe effectively there is no $\nu_0$ in the structural estimation, but even so there are effectively two constant terms. The computer doesn’t blow up presumably because there is a little nonlinearity. But this could explain why one of your constant terms is massively significant $\bar{\theta}_1$ and the other is massively insignificant.

I’d guess that this problem can be handled by demeaning both CEA and $\mathbb{E}_t u_{t+4}$ and allowing for an overall constant term.

1. In the reduced form regressions the coefficient on $\mathbb{E}_u$ is hugely statistically significant (table 5)

2. The estimated coefficient on the precautionary term is massively insignificant in our structural estimates (Table 1)

I can’t see how this can possibly make sense. I mean, if you were to set $\theta_u$ to zero (which is easily within the standard error band you report having obtained using the delta method), it shouldn’t meaningfully change the result, right? But how could that be, given the reduced form results? Maybe the answer is that the delta method is giving you a very local estimate of the standard errors (like, the data are largely indifferent between $\theta_u = 2.3$ or 2.4 times $10^{-4}$ but are MASSIVELY unhappy about $\theta_u = 0$.

These seem like first-order questions that must be addressed before we send the paper in.

The estimated risk $\bar{U}_t$ is highly counter-cyclical, reflecting movements in the unemployment rate and unemployment expectations. While the estimated sensitivity of $\bar{U}_t$ to expected unemployment, $\theta_u$, is not statistically significant, the range of $\bar{U}_t$ (between $7-10 \times 10^{-5}$) seems plausible: A 30 percent increase in uncertainty (e.g., during a recession) results in a roughly 3 percentage point increase in the saving rate, similar to the magnitudes predicted by model with more realistic heterogeneity (for example, Carroll, Slacalek, Tokuoka, and White (2017)).
Figure 6a shows the fit of the structural model. In terms of $\bar{R}^2$ (Table 1), the model captures more than 80 percent of variation in the saving rate, doing only slightly worse than our baseline reduced-form model (whose $\bar{R}^2$ is roughly 0.90). The Mincer–Zarnowitz horse race between the models puts weight of 0.72 on the structural model.

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: uncertainty, wealth, and credit conditions; Figure 6b. To gauge the relative importance of the three variables, we sequentially switch off the channels by setting the series equal to their sample means. 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 $\bar{U}$ rather than the total amount of saving attributable to uncertainty. 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.

Add: “A discussion of MPCs, and a comparison of your estimates with the reduced-form micro literature estimates that has estimated these channels, are also important to gauge whether your results are plausible.”

4.3.1 The MPC out of Wealth

The model (black circled line in Figure 6b) ascribes roughly 3 percentage points of the increase in the saving rate during the Great Recession 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 of $\frac{3}{200} = 0.015$. This value is on the low end of the range of estimates from the existing representative agent literature, which can range down to as low as 0.01 percent for models that incorporate habit formation. And it is very far below the estimates from the micro literature, which Carroll, Slacalek, Tokuoka, and White (2017) characterize as usually falling between 0.2 and 0.7. This reflects the usual tension between “representative agent” models like ours which aim to match aggregate statistics (like aggregate wealth or the aggregate saving rate) and models that incorporate a rich treatment of heterogeneity which allows them to better match the micro MPC evidence (e.g., Carroll, Slacalek, Tokuoka, and White (2017)). The reconciliation offered by the models with heterogeneity is that most of the wealth is held by wealthy people who, in equilibrium, have a much lower MPC than the median consumer. (The micro estimates typically report the MPC out of a uniform shock to income (say, in the form of stimulus checks to every taxpayer),
Figure 6  The Structural Estimation: Main Results

(a) Actual and Fitted Saving Rate

(b) Decomposition of Fitted Saving Rate
but data from surveys like the Survey of Consumer Finances show that a substantial proportion of consumption is done by households with very little wealth.\textsuperscript{12}

Combining all three channels in the model implies an increase in the saving rate of about 5 percentage points between 2007 and 2010 – not far from the actual change. Our model’s comparatively low MPC out of wealth but substantial roles for the other two channels 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 finding in line with much of the household-level evidence, including Hurst and Stafford (2004), Cooper (2013) and others, who stress the role of collateral constraints).

Probably drop the paragraph below (or move to the section on RF estimates)?

Table 6 replicates the estimates of Table 5 for the artificial saving series generated by the estimated structural model. The coefficient estimates closely mirror those obtained from actual data which means that the structural model captures well the key features of the saving data. Unsurprisingly, the standard errors are somewhat smaller than those in Table 5 and the $\bar{R}^2$s are higher because the process of generating artificial data by the model eliminates much of the noise present in the actual PSR data.

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 often used to model aggregate consumption dynamics (both literally and, effectively, in linearized DSGE models). The key distinction from our model of section 2 is that, in contrast to CRRA utility, under quadratic utility uncertainty has no effect on consumption dynamics, so that 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 that the variable $\bar{\theta}_{ij}$ enters significantly the structural model in Table 1. This evidence is confirmed in a reduced-form linear regression setup, where business-cycle variation in labor market uncertainty is estimated to significantly impact the PSR, both on its own and controlling for

other variables (columns 1 and 3 of Table 2, 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.\footnote{We have also considered other measures of uncertainty, such as financial market or economic policy uncertainty, but our measure of labor market uncertainty turns out to work better as a determinant of personal saving (which is in line with our model, in which uncertainty enters a labor market uncertainty).}

These results confirm a large body of complementary evidence on how uncertainty affects consumption and saving going back to 1990s (e.g., Carroll (1992) and many others). 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 (forthcoming) and the references in footnote 7) uncertainty amplified the drop in house prices, employment and consumption.

5.2 Demographics and Saving

There is a long tradition of work, stemming from the seminal work of Modigliani and Brumberg (1954), that evaluates the implications of demographic changes for saving using calibrations and simulations of various life-cycle models (often 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 (2000a) 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 changes in credit availability we have attributed to credit expansion over 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, 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.

Figure 8a shows that the old-age dependency ratio has been steadily increasing since the 1960s, and that the increase accelerated around 2010. In Table 2, 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, confirming the proposition that the correlations go the wrong
Figure 7: 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
way for a demographic story (confirming the large prior literature after Auerbach, Cai, and Kotlikoff (1991) that failed to find meaningful demographic effects).\footnote{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.}

5.3 Reduced-Form vs Structural Models of Saving

Let us now consider to what extent the main features of the structural model of section 2 can be summarized in a simple reduced-form regression:

$$s_t = \gamma_1 + \gamma_m m_t + \gamma_{\text{CEA}} \text{CEA}_t + \gamma_{\text{Eu}} \text{Eu}_t + \varepsilon_t. \quad (6)$$

This specification can be readily estimated using OLS estimators (Table 2, 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 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 consumption models that have had powerful trends like this, so the case for spurious correlation is weaker than it sometimes is). The point estimate of $\gamma_{\text{CEA}}$ 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).

Chris: Some new text below on why structural models are better than reduced-form models, please edit as you see fit:

Suggestion from RR: 8.4) The second would be a simple reduced-form relation: your equation 4. You now argue that model reforms reasonably well. But I think you need to argue the opposite: that this simple
linear regression actually performs significantly worse than your structural model. From your results, I think there is some truth to this, but you have to drive this new point home.

Given how well the baseline linear reduced-form model captures the saving rate, we may ask what is the value-added 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 $R^2$ is 0.974). Essentially, therefore, the 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 subset of nearly linear relationships that is a good approximation to the structural theory. The fact that the $R^2$ 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 is a structure that does no violence to the data.

The equally good fit of the structural model and the reduced form one make the case for structural estimation considerably stronger than in the usual case where there is a tradeoff in which the structural model does not fit the data as well as can be done in an unrestricted data-fitting exercise, but yields useful economic insights. Some of those advantages are:

- If the structure imposed is one that has considerable backing from other contexts or kinds of data, the likelihood that the fit of the model to the data is spurious is reduced;

- 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 superior to the reduced form fit. To the extent that those insights are correct, they could have important implications, for example, for optimal fiscal policies designed to fight aggregate shocks (particularly ones that might be related to uncertainty)

- 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 2 summarize the correlations of the personal saving rate with two variables the might realistically be related to it: government saving (Figure 8b) and income inequality (Figure 8c).

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 8c) 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 (2003a), we find little evidence of a substantial and statistically significant correlation between saving and income inequality.

6 Conclusions

We find 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 shocks. For example, the model suggests
that in a recession an optimizing government might wish 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 household heterogeneity (HANK) and a simple two-agent spender–saver setup (TANK).
References


Table 1 Calibration and Structural Estimates

\[
s_t^{\text{theor}} = s_t^{\text{theor}}(\Theta; m_t - \bar{m}(h_t, \bar{U}_t)),
\]

\[
l_t = \bar{h}_t + \theta_{\text{CEA}} CEA_t,
\]

\[
\bar{U}_t = \bar{\theta}_\delta + \theta_u E_t u_{t+4}.
\]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibrated Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(r)</td>
<td>Interest Rate</td>
<td>0.04/4</td>
</tr>
<tr>
<td>(\Delta W)</td>
<td>Wage Growth</td>
<td>0.01/4</td>
</tr>
<tr>
<td>(\rho)</td>
<td>Relative Risk Aversion</td>
<td>2</td>
</tr>
<tr>
<td><strong>Estimated Parameters</strong></td>
<td>(\Theta = {\beta, \bar{h}, \theta_{\text{CEA}}, \bar{\theta}_\delta, \theta_u})</td>
<td></td>
</tr>
<tr>
<td>(\beta)</td>
<td>Discount Rate</td>
<td>(1 - 0.0063^{***})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0010)</td>
</tr>
<tr>
<td>(\bar{h})</td>
<td>Scaling of (CEA_t) to (h_t)</td>
<td>0.7622</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.3016)</td>
</tr>
<tr>
<td>(\theta_{\text{CEA}})</td>
<td>Scaling of (CEA_t) to (h_t)</td>
<td>9.8760**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.1771)</td>
</tr>
<tr>
<td>(\bar{\theta}_\delta)</td>
<td>Scaling of (E_t u_{t+4}) to (\bar{U}_t)</td>
<td>(1.1781 \times 10^{-4}^{***})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.9002 \times 10^{-5})</td>
</tr>
<tr>
<td>(\theta_u)</td>
<td>Scaling of (E_t u_{t+4}) to (\bar{U}_t)</td>
<td>(2.3627 \times 10^{-4})</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.5073 \times 10^{-4})</td>
</tr>
<tr>
<td>(\bar{R}^2)</td>
<td></td>
<td>0.912</td>
</tr>
<tr>
<td>DW stat</td>
<td></td>
<td>0.818</td>
</tr>
<tr>
<td>Sample average of (CEA_t)</td>
<td></td>
<td>0.4389</td>
</tr>
<tr>
<td>Sample average of (E_t u_{t+4})</td>
<td></td>
<td>0.0620</td>
</tr>
</tbody>
</table>

Notes: Quarterly calibration. Estimation sample: 1966q2–2011q1. \{*, **, ***\} = Statistical significance at \{10, 5, 1\} percent. Standard errors (in parentheses) were calculated with the delta method. Parameter estimates imply sample averages of 5.10 and 0.000132 for \(h_t\) and \(U_t\), respectively.
Table 2 Reduced-Form Regressions

\[ s_t = \gamma_0 + \gamma_m m_t + \gamma_{CEA} CEA_t + \gamma_{Eu} E_t u_{t+4} + \gamma' X_t + \varepsilon_t \]

<table>
<thead>
<tr>
<th>Model</th>
<th>Uncertainty</th>
<th>Demographics</th>
<th>Reduced-Form</th>
<th>Additional Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Baseline</td>
<td>Time Trend</td>
</tr>
<tr>
<td>( \gamma_0 )</td>
<td>11.750***</td>
<td>29.504***</td>
<td>17.157***</td>
<td>15.535***</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
<td>(5.257)</td>
<td>(1.589)</td>
<td>(2.004)</td>
</tr>
<tr>
<td>( \gamma_m )</td>
<td>-1.596***</td>
<td>-0.894***</td>
<td>-0.618*</td>
<td>-0.862***</td>
</tr>
<tr>
<td></td>
<td>(0.362)</td>
<td>(0.261)</td>
<td>(0.341)</td>
<td>(0.269)</td>
</tr>
<tr>
<td>( \gamma_{CEA} )</td>
<td>-4.444***</td>
<td>-7.909***</td>
<td>-4.156**</td>
<td>-8.149***</td>
</tr>
<tr>
<td></td>
<td>(1.451)</td>
<td>(0.556)</td>
<td>(2.098)</td>
<td>(0.565)</td>
</tr>
<tr>
<td>( \gamma_{Eu} )</td>
<td>0.551***</td>
<td>0.264***</td>
<td>0.202***</td>
<td>0.347***</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.068)</td>
<td>(0.064)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>( \gamma_t )</td>
<td>-0.055***</td>
<td></td>
<td>-0.025</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{old} )</td>
<td>-0.861**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.365)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \gamma_{gov sav} )</td>
<td></td>
<td></td>
<td></td>
<td>-0.152**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.063)</td>
</tr>
<tr>
<td>( \gamma_{inc share} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( R^2 \) | 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 \\

Figure 9  The Fit of the Baseline Model and the Time Trend—Actual and Fitted PSR (Percent of Disposable Income)

Legend: Actual PSR: Thin black line, Baseline model: Thick red/grey line, Time trend: Dashed black line. Shading—NBER recessions.
Sources: Bureau of Economic Analysis, authors’ calculations.

Table 9 presents a second battery of specification checks of the baseline model shown again for reference as the first ‘model.’ The second model (Uncertainty) investigates the effects of adding to the baseline regression an alternative proxy for uncertainty: the Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) index of macroeconomic and financial uncertainty. The new variable is statistically insignificant and the coefficients on the previously included variables are broadly unchanged, suggesting that our baseline uncertainty measure is more appropriate for our purposes (which makes sense, as personal saving is conducted by persons, whose uncertainty is likely better captured by our measure of labor income uncertainty than by the Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) measure of firm-level shocks).

The third model (Lagged $s_{t-1}$) explores the implications of adding lagged saving to the list of regressors. Often in empirical macroeconomics, the addition of the lagged dependent variable is unjustified by the underlying theory, but nevertheless is required for the model to

---

See Baker, Bloom, and Davis (2011) for related work measuring economic policy uncertainty.
fit the data. Here, however, serial correlation in saving is a direct implication of the model (below we will show that the degree of serial correlation implied by the model matches the empirical estimate fairly well). The implication arises because deviations of actual wealth from target wealth ought to be long-lasting if the saving rate cannot quickly move actual wealth to the target. As expected, the coefficient is highly statistically significant. However, this positive autocorrelation only captures near-term stickiness and has little effect on the long-run dynamics of saving. Indeed, the coefficients from the baseline roughly equal their long-term counterparts from the model with lagged saving rates (that is, coefficient estimates pre-multiplied by $2.5$, or $1/(1 - \gamma_s) = 1/(1 - 0.60))^{16}$.

The fourth model (Debt) explores the role of the debt–income ratio. The variable could be relevant for two reasons. First, it could partly account for the fact that debt is held by a different group of people than assets and consequently net worth might be an insufficient proxy for wealth. Second, debt might also reflect credit conditions (although—as mentioned above—we prefer the CEA index because in principle it isolates the role of credit supply from demand). The regression can thus also be interpreted as a horse-race between the CEA and the debt–income ratio. In any case, while the coefficient $\gamma_d$ has the correct (negative) sign, it is statistically insignificant and its inclusion does not substantially affect estimates obtained under the baseline specification.

The seventh model (DB Pensions) examines whether the shift from defined benefit to defined contribution pension plans may also have had a measurable effect on the aggregate saving rate. Aggregate data on the size of defined-benefits pension plans are not readily available; the NIPA provides the relevant series only since 1988. As an initial experiment, we calculated the share of employer contributions accruing to the defined benefit plans as a percent of total contributions; however, this variable was not statistically significant in our regressions (sample 1988–2010). As an alternative, we compiled a measure of household saving adjusted for the defined-benefit pension plans from various research publications by the Bureau of Economic Analysis (BEA; Knitch (2010), Perozek and Reinsdorf (2002)) and Congressional Budget Office (CBO; Congressional Budget Office (1993)). Subsequently, we calculated “a pension gap,” defined as the difference between the headline saving rate and the BEA/CBO adjusted saving rate, and included this gap variable in our regressions (sample: 1960–2007). The gap is statistically significant with a coefficient of about 0.7. This suggests that the shift from defined benefit to defined contribution pension plans may have reduced the aggregate saving rate. However, this effect appears small in economic terms: the contribution of the changing pension system to the overall decline in the saving rate since the 1980s is only about 1 percentage point of disposable income. The coefficients on the baseline series (credit conditions, net wealth, unemployment expectations) remain highly statistically significant in this regression.

The eighth and ninth models (High Tax Bracket and Low Tax Bracket) provide a first-pass test of the effects of tax policy on aggregate saving by including the data on the highest and lowest marginal tax rates in our regressions. Neither of the two variables are statistically significant.

---

16 Note that with the inclusion of lagged saving, the Durbin–Watson statistic becomes close to 2, suggesting that whatever serial correlation exists in the other specifications reflect simple first order autocorrelation of the errors.
Figure 10  The Fit of the Baseline Model and the Model with Full Controls (of Table 9)—Actual and Fitted PSR (Percent of Disposable Income)

Legend: Actual PSR: Thin black line, Baseline model: Thick red/grey line, Model with full control variables: Dashed black line. Shading—NBER recessions.
Sources: Bureau of Economic Analysis, authors’ calculations.
Finally, to explore how much endogeneity may matter, the specification “IV” re-estimates the baseline specification using the IV estimator. Instruments are the lags of net wealth, unemployment risk and—crucially—the Financial Liberalization Index of Abiad, Detragiache, and Tressel (2010) (described in Appendix 1). The FLI is an alternative measure of credit conditions constructed using the records about legal and regulatory changes in the banking sector. The index intends to capture exogenous changes in credit conditions. While it is a rough approximation as it reflects only the most important events (see also Figure 11 in Appendix 1), the profile of the FLI matches well that of the CEA. The estimated coefficients remain broadly unchanged compared with the baseline specification.

6.1 Sub-Sample Stability

When the model is estimated only using the post-1980 data in Table 3 (Post-1980), its fit measured by the \( \bar{R}^2 \) actually improves, in contrast with many other economic relationships, whose goodness-of-fit deteriorated in the past 20 years. The F test does not reject the proposition that the regression coefficients have remained stable over the sample period. Allowing for a structural break at the start of the Great Recession in 2007q4 (column ‘Pre-2008’) does not much affect the baseline estimates. (The estimated values of the post-2007 interaction dummies and their standard errors are of course not particularly meaningful because the relevant sub-sample only consists of 13 observations.)

To anticipate the potential criticism that saving rate regressions are difficult to interpret because aggregate income shocks reflect a mix of transitory and persistent factors, we have also re-estimated our regressions with alternative measures of disposable income (see Appendix 2) which exclude a range of identifiable temporary shocks such as fiscal stimulus and extreme weather. There was little econometric evidence that transitory movements in aggregate disposable income are substantial and our econometric results basically did not change.

6.2 Saving Rate Decompositions

Table 4 reports an in-sample fit of the baseline model and the model Interact with the CEA–uncertainty interaction term of Table 5, together with the contributions of the individual variables to the explained increase in the saving rate between 2007 and 2010. Two principal conclusions emerge. First, both models (especially the latter) are able to capture well the observed change in the saving rate. Second, the key explanatory factors in saving were the changes in wealth and uncertainty, with credit conditions (as measured by CEA) playing a less important role. While the change in the trajectory of the CEA index is quite striking (see Figure 5b), and may explain the sudden academic interest in the role of household credit over the business cycle (see the papers cited in the introduction), this evidence suggests that the rise in saving cannot be primarily attributed to the decline in credit availability.

---

17 As mentioned above, wealth is lagged by one quarter to alleviate endogeneity in OLS regressions. However, a standard concern about reduced-form regressions like (6) is that the OLS coefficient estimates might be biased because the regressions do not adequately account for all relevant right-hand size variables (such as expectations about income growth; see also Appendix 2 for further discussion).
If correct, this finding is particularly important at the present juncture because it suggests that however much the health of the financial sector continues improving, the saving rate is likely to remain high so long as uncertainty remains high and household wealth remains impaired (compared, at least, to its previous heights).
Figure 11  Alternative Measures of Credit Availability

A Appendix 1: Comparison of Alternative Measures of Credit Availability

Figure 11 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.
Figure 12  Growth of Real Disposable Income (Percent)

Sources: Bureau of Economic Analysis, authors’ calculations.

B Appendix 2: Stochastic Properties of Aggregate Disposable Income

B.1 Measurement of Disposable Income

This appendix investigates the properties of three measures of disposable income: the official series produced by the BEA and two alternative “cleaned” series, in which we aim to exclude transitory income shocks due to temporary events, such as weather and fiscal policy. Specifically, we have removed the following events from the official disposable income series using regressions:

- Dummies for the 20 costliest tropical cyclones using data from the National Weather Service.
Figure 13  Personal Saving Rate (Percent of Disposable Income)

Legend: BEA personal saving rate: Thick red/grey line, PSR calculated with the “less cleaned” income series: Thin black line, PSR calculated with the “more cleaned” income series: Dashed black line. Shading—NBER recessions.
Sources: Bureau of Economic Analysis, authors’ calculations.
• Dummies for quarters with unusually high or low cooling degree days, and unusually high or low heating degree days (the dummy has a value of 1 whenever the seasonally-adjusted series are more than 2 standard deviations above or below its mean).

• Dummies for quarters with unusually high or low national temperature, and unusually high or low precipitation (again, using the 2 standard deviations criterion).

• Separate dummies for snowstorms or heat waves which were deemed unusually extensive and damaging (these events do not necessarily overlap with the episodes identified from the national temperature and cooling/heating degree days data).

The “less cleaned” disposable income series removes from published data the contributions of stimulus and heating/cooling day extremes. The “more cleaned” series removes all the sources of transitory fluctuations outlined above.

B.2 Stochastic Properties of Disposable Income and Saving for a Rainy Day

The classic paper by Campbell (1987) derived that the permanent income hypothesis implies that saving is negatively related to future expected income growth. This appendix investigates the univariate stochastic properties of disposable income and the relationship between saving and income, or the lack of it, in Tables 7 and 8, respectively.

Table 7 documents that all three disposable income series are statistically indistinguishable from a random walk. This means that (changes in) the series are unpredictable using their own lags. In particular, for the income series in log-level, the first autocorrelations are very close to 1 and the augmented Dickey–Fuller test does not reject the null of a unit root. In contrast, for income growth, the first and other autocorrelations are zero, as also documented by the p values of the Box–Ljung Q statistic, and the ADF test (of course) strongly rejects a unit root.

Table 8 reports the estimates of $\alpha_1$ the sensitivity of the saving rate to future income growth:

$$s_t = \alpha_0 + \alpha_1 \Delta y_{t+1} + \varepsilon_t,$$  

which is motivated by Campbell (1987), who derives that under the permanent income hypothesis the coefficient $\alpha_1$ is negative, as households save more when they are pessimistic about future income growth.

Overall, the estimates suggest that coefficient $\alpha_1$ is statistically insignificant and small, especially when the full sample, 1966q2–2011q1, is used and when income growth $\Delta y_{t+2}$ enters the regression (7), which might be justified because of time aggregation issues. While there is some evidence of a negative coefficient in the pre-1985 sample (which overlaps with the sample 1953q2–1984q4 considered by Campbell (1987)), the relationship seems to break down in the past 20 years.
Appendix 3: Extension of Derivation of Target Wealth to Include Unemployment Insurance

The model described in Carroll and Toche (2009) assumes that income for unemployed/retired households is zero. A step in the direction of realism is to recognize the existence (in most countries) of an unemployment insurance system that guarantees some level of income to unemployed persons. The implications of such a system are straightforward to model if we assume that the unemployment insurance benefit is a constant proportion of the labor income earned in the first year of unemployment if not losing job.

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 $S = \zeta \cdot \ell W$, which means individuals will receive one-period severance payment $S$ in the amount of a certain ratio $\zeta$ 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),

$$m^{t+1} = \begin{cases} b^{t+1} + \ell^{t+1} W^{t+1} - \tau^{t+1} & \text{w.p. } \bar{\mathbb{U}} \\ b^{t+1} + S^{t+1} & \text{w.p. } 1 - \bar{\mathbb{U}} \end{cases}$$

where $m$, $b$ and $\ell W$ denote market resources, assets and labor income respectively. We let $\tau = \bar{\mathbb{U}} \times S$ to ensure a balanced budget for the unemployment insurance system.\(^{18}\)

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

$$1 = \Gamma^{-\rho} R \beta \left\{ (1 - \bar{\mathbb{U}}) \left( \frac{c^{t+1}_e}{c^e_t} \right)^{-\rho} + \bar{\mathbb{U}} \left( \frac{c^{t+1}_u}{c^u_t} \right)^{-\rho} \right\}, \quad (8)$$

where nonbold variables represent the bold variables normalized by labor income $\ell W$. Superscripts $e$ and $u$ represent the two possible states.

To find the $\Delta c^e = 0$ and $\Delta m^e = 0$ loci, we let $c^{t+1}_e = c^e_t \equiv c^e$ and $m^{t+1}_e = m^e_t \equiv m^e$. Given $c^{t+1}_u = m^{t+1}_u \kappa^u$ ($\kappa^u$ is the MPC of an unemployed consumer), combined with the modified DBC above, we have

$$1 = \Gamma^{-\rho} R \beta \left\{ (1 - \bar{\mathbb{U}}) + \bar{\mathbb{U}} \left( \frac{\kappa^u (R (m^e - c^e) + \zeta)}{c^e} \right)^{-\rho} \right\}.$$  

---

\(^{18}\)Each period, proportion $\bar{\mathbb{U}}$ of employed consumers lose their jobs, i.e., the “exit rate” in the current labor market is $\bar{\mathbb{U}}$. In order to raise a corresponding amount of revenues, we need to assume that there is a “birth rate” $\bar{\mathbb{U}}$ of new employed consumers, which means a same proportion of consumers are entering the labor market each period. Combined with the assumption that $\tau = \bar{\mathbb{U}} \times S$, the severance payment and the severance payment are balanced.
Rearranging terms, the $\Delta c^e = 0$ locus can be characterized as

$$
\Pi \left( \Gamma^\rho (R^\beta)^{-1} - H \right)^{1/\rho} \left( \frac{c^e}{(R^e - c^e) + \varsigma \kappa u} \right).
$$

(9)

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

$$
m^e = R(m^e - c^e) + (1 - \Upsilon \varsigma).
$$

(10)

Given the two equations above, we are able to obtain the exact formula for target wealth $\hat{m}$, which is the steady state value of $m^e$. Following Carroll and Toche (2009), define $\eta \equiv R \kappa u \Pi$. We have

$$
\frac{\eta \hat{m} + \eta \varsigma}{\eta + 1} = (1 - R^{-1}) \hat{m} + \frac{1 - \Upsilon \varsigma}{R} = \hat{c}
$$

$$
\left( \frac{1}{R} - \frac{1}{\eta + 1} \right) \hat{m} = \frac{1}{R} \left( 1 - \Upsilon \varsigma - \frac{\eta \varsigma}{\eta + 1} \right)
$$

$$
\hat{m} = \frac{(\eta + 1)(1 - \Upsilon \varsigma) - \eta \varsigma}{\eta + 1 - R}.
$$

(11)

Clearly, target wealth decreases when the severance payment becomes more generous and it can even be negative if we make the severance ratio $\varsigma$ large enough.
Table 3 Additional Saving Regressions II.—Sub-sample Stability

\[ s_t = \gamma_0 + \gamma_m m_t + \gamma_{CEA} CEA_t + \gamma_{Eu} \bar{E}_t u_{t+4} + \varepsilon_t \]

<table>
<thead>
<tr>
<th>Model</th>
<th>Baseline</th>
<th>Post-1980</th>
<th>Pre-2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma_0 )</td>
<td>15.226***</td>
<td>16.692**</td>
<td>16.002***</td>
</tr>
<tr>
<td></td>
<td>(2.157)</td>
<td>(7.571)</td>
<td>(1.340)</td>
</tr>
<tr>
<td>( \gamma_m )</td>
<td>-1.183***</td>
<td>-1.503</td>
<td>-1.327***</td>
</tr>
<tr>
<td></td>
<td>(0.347)</td>
<td>(1.248)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>( \gamma_{CEA} )</td>
<td>-6.121***</td>
<td>-4.999**</td>
<td>-6.002***</td>
</tr>
<tr>
<td></td>
<td>(0.573)</td>
<td>(2.000)</td>
<td>(0.369)</td>
</tr>
<tr>
<td>( \gamma_{Eu} )</td>
<td>0.287***</td>
<td>0.298**</td>
<td>0.288***</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.136)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>( \gamma_{0\text{post}80}/\gamma_{0\text{post}07} )</td>
<td>-1.479</td>
<td>11.891</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.905)</td>
<td>(24.356)</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{m\text{post}80}/\gamma_{m\text{post}07} )</td>
<td>0.559</td>
<td>-1.234</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.289)</td>
<td>(1.556)</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{CEA\text{post}80}/\gamma_{CEA\text{post}07} )</td>
<td>-2.350</td>
<td>5.426</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.135)</td>
<td>(12.414)</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{Eu\text{post}80}/\gamma_{Eu\text{post}07} )</td>
<td>-0.098</td>
<td>-1.027</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.715)</td>
<td></td>
</tr>
<tr>
<td>( \bar{R}^2 )</td>
<td>0.895</td>
<td>0.899</td>
<td>0.903</td>
</tr>
<tr>
<td>F stat p val</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>F p val post-80/pre-08</td>
<td>0.16665</td>
<td>0.00012</td>
<td></td>
</tr>
<tr>
<td>DW stat</td>
<td>0.933</td>
<td>0.967</td>
<td>1.052</td>
</tr>
</tbody>
</table>

Notes: Estimation sample: 1966q2–2011q1. \{*, **, ***\} = Statistical significance at \{10, 5, 1\} percent. Newey–West standard errors, 4 lags. CEA is the Credit Easing Accumulated Index. Pre-2008: Heteroscedasticity robust standard errors (because post-2007 sample consists of only 13 observations).
### Table 4  Personal Saving Rate—Actual and Explained Change, 2007–2010

<table>
<thead>
<tr>
<th>Variable Baseline Interact Actual $\Delta s_t$</th>
<th>$\gamma m \times \Delta m_t$</th>
<th>$\gamma CEA \times \Delta CEA_t$</th>
<th>$\gamma Eu \times \Delta E_{t+4}$</th>
<th>$\gamma uC \times \Delta (E_{t+4} \times CEA_t)$</th>
<th>$\gamma_0 \times \Delta m_t$</th>
<th>$\gamma_0 \times \Delta CEA_t$</th>
<th>$\gamma_0 \times \Delta E_{t+4}$</th>
<th>$\gamma_0 \times \Delta (E_{t+4} \times CEA_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$-1.18 \times -1.39 = 1.64$</td>
<td>$-6.12 \times -0.11 = 0.64$</td>
<td>$0.29 \times 4.33 = 1.24$</td>
<td>$-0.32 \times 3.33 = -1.07$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0 \times \Delta m_t$</td>
<td>$-1.37 \times -1.39 = 1.90$</td>
<td>$-4.60 \times -0.11 = 0.48$</td>
<td>$0.38 \times 4.33 = 1.67$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0 \times \Delta CEA_t$</td>
<td>$\gamma_0 \times \Delta E_{t+4}$</td>
<td>$\gamma_0 \times \Delta (E_{t+4} \times CEA_t)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0 \times \Delta (E_{t+4} \times CEA_t)$</td>
<td>$\gamma_0 \times \Delta m_t$</td>
<td>$\gamma_0 \times \Delta CEA_t$</td>
<td>$\gamma_0 \times \Delta E_{t+4}$</td>
<td>$\gamma_0 \times \Delta (E_{t+4} \times CEA_t)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 5  Preliminary Saving Regressions and the Time Trend

$$s_t = \gamma_0 + \gamma_m \Delta m_t + \gamma_{CEA} \Delta CEA_t + \gamma_{Eu} \Delta E_{t+4} + \gamma_t \Delta t + \gamma_{uC}(\Delta (E_{t+4} \times CEA_t)) + \varepsilon_t$$

<table>
<thead>
<tr>
<th>Model</th>
<th>Time</th>
<th>Wealth</th>
<th>CEA</th>
<th>Un Risk</th>
<th>All 3</th>
<th>Baseline</th>
<th>Interact</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.608)</td>
<td>(1.727)</td>
<td>(0.574)</td>
<td>(0.420)</td>
<td>(2.558)</td>
<td>(2.157)</td>
<td>(2.556)</td>
<td>(0.456)</td>
</tr>
<tr>
<td>$\gamma_m$</td>
<td>$-2.606***$</td>
<td>$-1.124***$</td>
<td>$-1.183***$</td>
<td>$-1.368***$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.319)</td>
<td>(0.423)</td>
<td>(0.347)</td>
<td>(0.347)</td>
<td>(0.347)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_{CEA}$</td>
<td>$-14.138***$</td>
<td>$-5.472***$</td>
<td>$-6.121***$</td>
<td>$-4.604***$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.736)</td>
<td>(1.936)</td>
<td>(0.573)</td>
<td>(1.721)</td>
<td>(1.721)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_{Eu}$</td>
<td>$0.670***$</td>
<td>$0.316***$</td>
<td>$0.287***$</td>
<td>$0.385***$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.055)</td>
<td>(0.117)</td>
<td>(0.075)</td>
<td>(0.108)</td>
<td>(0.108)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_t$</td>
<td>$-0.044***$</td>
<td>$-0.025***$</td>
<td>$0.042***$</td>
<td>$-0.048***$</td>
<td>$-0.005$</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.011)</td>
<td>(0.002)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_{uC}$</td>
<td>$-0.321**$</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

Table 6  Preliminary Saving Regressions and the Time Trend—Saving Rate
Generated by the Structural Model

\[ s_t = y_0 + y_mm + y_{CEA}CEA_t + y_{Eu}E_tu_{t+4} + y_t + y_{uC}(E_tu_{t+4} \times CEA_t) + \varepsilon_t \]

<table>
<thead>
<tr>
<th>Model</th>
<th>Time</th>
<th>Wealth</th>
<th>CEA</th>
<th>Un Risk</th>
<th>All 3</th>
<th>Baseline</th>
<th>Interact</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.522)</td>
<td>(1.433)</td>
<td>(0.434)</td>
<td>(0.227)</td>
<td>(0.851)</td>
<td>(0.759)</td>
<td>(0.839)</td>
</tr>
<tr>
<td>(y_m)</td>
<td>-2.527***</td>
<td>-1.012***</td>
<td>-0.966***</td>
<td>-1.085***</td>
<td>(0.142)</td>
<td>(0.121)</td>
<td>(0.139)</td>
</tr>
<tr>
<td></td>
<td>(0.267)</td>
<td>(0.434)</td>
<td>(0.227)</td>
<td>(0.121)</td>
<td>(0.139)</td>
<td>(0.139)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>(y_{CEA})</td>
<td>-14.901***</td>
<td>-6.885***</td>
<td>-6.379***</td>
<td>-6.625***</td>
<td>(0.786)</td>
<td>(0.148)</td>
<td>(0.808)</td>
</tr>
<tr>
<td></td>
<td>(1.307)</td>
<td>(0.786)</td>
<td>(0.148)</td>
<td>(0.808)</td>
<td>(0.148)</td>
<td>(0.808)</td>
<td>(0.808)</td>
</tr>
<tr>
<td>(y_{Eu})</td>
<td>-0.044***</td>
<td>-0.026***</td>
<td>0.047***</td>
<td>-0.048***</td>
<td>0.004</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>(y_uC)</td>
<td>-0.0696</td>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.065)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Series</th>
<th>Official BEA</th>
<th>Less Cleaned</th>
<th>More Cleaned</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Disposable Income—Log-level</td>
<td>Disposable Income—Growth Rate</td>
<td>Personal Saving Rate</td>
</tr>
<tr>
<td>First Autocorrelation</td>
<td>0.983</td>
<td>0.983</td>
<td>0.983</td>
</tr>
<tr>
<td>Box–Ljung Q stat, p value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Augmented Dickey–Fuller test, p value</td>
<td>0.505</td>
<td>0.515</td>
<td>0.501</td>
</tr>
<tr>
<td>First Autocorrelation</td>
<td>−0.043</td>
<td>−0.033</td>
<td>−0.024</td>
</tr>
<tr>
<td>Box–Ljung Q stat, p value</td>
<td>0.604</td>
<td>0.446</td>
<td>0.334</td>
</tr>
<tr>
<td>Augmented Dickey–Fuller test, p value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>First Autocorrelation</td>
<td>0.953</td>
<td>0.953</td>
<td>0.952</td>
</tr>
<tr>
<td>Box–Ljung Q stat, p value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Augmented Dickey–Fuller test, p value</td>
<td>0.628</td>
<td>0.600</td>
<td>0.539</td>
</tr>
</tbody>
</table>

Notes: Box–Ljung statistics: 8 lags, ADF test: 4 lags.
<table>
<thead>
<tr>
<th>Series</th>
<th>Official BEA</th>
<th>Less Cleaned</th>
<th>More Cleaned</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Sample: 1966Q2–2011Q1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$s_t = \alpha_0 + \alpha_1 \Delta y_{t+1} + \varepsilon_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>$-0.046$</td>
<td>$-0.054$</td>
<td>$-0.065$</td>
</tr>
<tr>
<td></td>
<td>$(0.052)$</td>
<td>$(0.050)$</td>
<td>$(0.051)$</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td>$-0.002$</td>
<td>$-0.000$</td>
<td>$0.002$</td>
</tr>
<tr>
<td>$s_t = \alpha_0 + \alpha_1 \Delta y_{t+2} + \varepsilon_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>$0.017$</td>
<td>$0.009$</td>
<td>$-0.009$</td>
</tr>
<tr>
<td></td>
<td>$(0.050)$</td>
<td>$(0.047)$</td>
<td>$(0.047)$</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td>$-0.005$</td>
<td>$-0.006$</td>
<td>$-0.006$</td>
</tr>
<tr>
<td><strong>Pre-1985 Sample: 1966Q2–1984Q4</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$s_t = \alpha_0 + \alpha_1 \Delta y_{t+1} + \varepsilon_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>$-0.108^{***}$</td>
<td>$-0.105^{***}$</td>
<td>$-0.117^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.031)$</td>
<td>$(0.031)$</td>
<td>$(0.033)$</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td>$0.143$</td>
<td>$0.128$</td>
<td>$0.150$</td>
</tr>
<tr>
<td>$s_t = \alpha_0 + \alpha_1 \Delta y_{t+2} + \varepsilon_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>$-0.056$</td>
<td>$-0.060^*$</td>
<td>$-0.083^{**}$</td>
</tr>
<tr>
<td></td>
<td>$(0.039)$</td>
<td>$(0.036)$</td>
<td>$(0.033)$</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td>$0.029$</td>
<td>$0.034$</td>
<td>$0.070$</td>
</tr>
</tbody>
</table>

Notes: {*, **, ***} = Statistical significance at {10, 5, 1} percent. Newey–West standard errors, 4 lags.
Table 9 Additional Saving Regressions I.—Robustness to Explanatory Variables

\[ s_t = \gamma_0 + \gamma_m m_t + \gamma_{CEA} CEA_t + \gamma_{EU} EU_t + \gamma_s s_t + \gamma_d d_t + \gamma_{top5\%} top5\%_t + \ldots + \gamma_d db_t + \gamma_{hitax} hitax_t + \gamma_{lotax} lotax_t + \gamma_m m_t + \gamma_{GS} GS_t + \gamma_{CS} CS_t + \epsilon_t \]

<table>
<thead>
<tr>
<th>Model</th>
<th>Baseline</th>
<th>Uncert</th>
<th>Leged stt-1</th>
<th>Debt</th>
<th>Inc Ineq</th>
<th>DB Pnsn</th>
<th>Hi Tax Br</th>
<th>Lo Tax Br</th>
<th>Multi Cntls</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\gamma_0)</td>
<td>15.226***</td>
<td>15.080***</td>
<td>5.323***</td>
<td>13.884***</td>
<td>14.866***</td>
<td>11.394***</td>
<td>15.597***</td>
<td>17.162***</td>
<td>17.459***</td>
<td>21.323***</td>
</tr>
<tr>
<td>(2.157)</td>
<td>(2.180)</td>
<td>(1.667)</td>
<td>(2.190)</td>
<td>(2.182)</td>
<td>(2.114)</td>
<td>(2.231)</td>
<td>(2.893)</td>
<td>(1.877)</td>
<td>(2.746)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_m)</td>
<td>-1.183***</td>
<td>-1.211***</td>
<td>-0.307</td>
<td>-0.803**</td>
<td>-0.814*</td>
<td>-0.683*</td>
<td>-1.100***</td>
<td>-1.086***</td>
<td>-1.304***</td>
<td>-2.022***</td>
</tr>
<tr>
<td>(0.347)</td>
<td>(0.363)</td>
<td>(0.222)</td>
<td>(0.360)</td>
<td>(0.478)</td>
<td>(0.398)</td>
<td>(0.344)</td>
<td>(0.385)</td>
<td>(0.308)</td>
<td>(0.492)</td>
<td></td>
</tr>
<tr>
<td>(0.573)</td>
<td>(0.648)</td>
<td>(0.531)</td>
<td>(0.732)</td>
<td>(1.013)</td>
<td>(0.524)</td>
<td>(0.805)</td>
<td>(0.554)</td>
<td>(0.628)</td>
<td>(1.166)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{EU})</td>
<td>0.287***</td>
<td>0.282***</td>
<td>0.143***</td>
<td>0.345***</td>
<td>0.314***</td>
<td>0.302***</td>
<td>0.293***</td>
<td>0.314***</td>
<td>0.117</td>
<td>0.084</td>
</tr>
<tr>
<td>(0.075)</td>
<td>(0.094)</td>
<td>(0.053)</td>
<td>(0.071)</td>
<td>(0.076)</td>
<td>(0.078)</td>
<td>(0.076)</td>
<td>(0.078)</td>
<td>(0.088)</td>
<td>(0.133)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_s)</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
<td>0.257</td>
</tr>
<tr>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td>(0.466)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_d)</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
<td>0.574***</td>
</tr>
<tr>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{top5%})</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
<td>-1.905</td>
</tr>
<tr>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td>(1.162)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{hitax})</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
<td>0.666**</td>
</tr>
<tr>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td>(0.321)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{lotax})</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.011</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_t)</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
</tr>
<tr>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{GS})</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
<td>0.129***</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
<td></td>
</tr>
<tr>
<td>(\gamma_{CS})</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
<td>-0.121</td>
</tr>
<tr>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.895</td>
<td>0.896</td>
<td>0.927</td>
<td>0.898</td>
<td>0.896</td>
<td>0.905</td>
<td>0.896</td>
<td>0.896</td>
<td>0.910</td>
<td>0.00000</td>
</tr>
<tr>
<td>F st p val</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>DW stat</td>
<td>0.933</td>
<td>0.940</td>
<td>2.134</td>
<td>0.924</td>
<td>0.923</td>
<td>0.940</td>
<td>0.936</td>
<td>0.945</td>
<td>0.954</td>
<td>0.740</td>
</tr>
</tbody>
</table>

Notes: Estimation sample: 1966q2–2011q4. \{*, **, ***\} = Statistical significance at \{10, 5, 1\} percent. Newey–West standard errors, 4 lags. CEA is the Credit Easing Accumulated Index, top5% is the income share of the top 5 percent households (including capital gains, taken from Piketty and Saez (2003b)), db is the gap between the BEA saving rate and the saving rate adjusted for defined-benefit pensions plans, hitax and lotax are top and bottom marginal tax rates respectively, GS is the government saving as a fraction of GDP, CS is the corporate saving as a fraction of GDP. In model IV, m, CEA and EU are instrumented with lags 1 and 2 of m, EU and the Abiad, Detragiache, and Tressel (2010) Index of Financial Liberalization; the sample for the IV model is 1973q1–2005q4. OID p val denotes the p-value from the Hansen’s J statistic for overidentification.