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Aggregate consumption and wealth in the long run: the impact of financial liberalization*

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Abstract

This paper investigates the impact of financial liberalization on the relationship between consumption and total wealth (i.e., the sum of asset wealth and human wealth). Financial liberalization is persistent and may signal changes in expected future consumption growth rates and/or in rates of return on wealth that, through the intertemporal budget constraint, affect the current consumption-wealth ratio. We estimate the long-run relationship between consumption, total wealth and financial liberalization by state space methods using quarterly US data. The results show that the trend in the consumption-wealth ratio is well-captured by our baseline liberalization indicator. We find that the increase in this indicator over the sample period has increased the consumption-wealth ratio with about ten percent. Investigating the responsible channel, additional estimates show that financial liberalization has predictive power for aggregate consumption growth rather than for returns, a result that supports an incomplete markets interpretation of the link between liberalization and the consumption-wealth ratio.

JEL Classification: E21, C32, C11

Keywords: consumption, wealth, financial liberalization, incomplete markets, state space model

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1 Introduction

The debate on the time series behavior of the consumption to total wealth ratio, an important but unobserved macroeconomic variable used e.g. for predicting future consumption changes and asset valuation, is still ongoing. One issue centers around whether or not this ratio is stationary. Lettau and Ludvigson (2001) and Lettau and Ludvigson (2004) construct a widely used proxy for the log of this ratio, i.e., the variable 'cay' as the residual from a time series regression for the US of log consumption on a constant, on log asset wealth and on log labor income where the latter serves as a proxy for log human wealth. They argue that 'cay' is stationary. More recent findings, however, suggest otherwise. Rudd and Whelan (2006) reject the stationarity of the consumption-wealth ratio in the US upon using data in the construction of 'cay' that is fully in line with the underlying theoretical framework. Bianchi et al. (2018), who follow Lettau and Ludvigson (2015) in using total personal consumer expenditures as a measure for consumption instead of nondurables and services, argue that the non-stationarity of the consumption-wealth ratio is due to regime shifts caused by monetary policy changes. They propose an alternative proxy for the consumption-wealth ratio obtained from a regression of log consumption on log assets and log labor income that includes a two-state Markov switching intercept. Similarly, Chang et al. (2019) propose a proxy for the consumption-wealth ratio obtained from a regression of log consumption on log assets and log labor income with time-varying slope parameters.

In a recent paper, Carroll et al. (2019) attribute the structural decline observed in the US saving rate, another important macroeconomic ratio, from the late 1970's until the Great Recession to financial liberalization. They find that, over this period, the expanding credit supply has decreased the fraction of disposable income that households save by about eight percentage points. Given that financial deregulation can explain the non-stationarity of the US saving rate, the question remains whether the non-stationarity of the consumption-wealth ratio can similarly be linked to financial reform, i.e., it is conceivable that financial liberalization has not only decreased the fraction of income that households save, but that it has also increased the fraction of wealth that they consume. Indeed, to the extent that wealth is correlated with income, we would expect to find that both ratios are, at least to some extent, driven by similar trends.

We therefore investigate the impact of financial liberalization on the long-run relationship between consumption and total wealth, i.e., on the trend in the consumption-wealth ratio. The empirical framework used is based on the intertemporal budget constraint of a representative consumer. As financial liberalization is persistent, it may signal changes in expected future consumption growth rates and/or in rates of return on wealth. With respect to the former, financial liberalization may affect expected consumption growth because it changes market completeness and consumption smoothing opportunities. With respect to the latter, financial liberalization may affect expected returns because it changes the cost of capital. These changes in expected consumption growth rates and/or expected returns then, through the intertemporal budget constraint, affect the current consumption-wealth ratio. From this framework, we derive a long-run relationship between consumption, total wealth and financial liberalization which we estimate using quarterly US data. Following Lettau and Ludvigson (2001), we use labor income to proxy unobserved human wealth. The data that we use for consumption, asset wealth and labor income correspond to the data used in recent estimations of the 'cay' variable by Lettau and Ludvigson (2015) and Bianchi et al. (2018). To measure financial liberalization, we use the 'credit easing accumulated' (CEA) index as our baseline indicator (see e.g., Carroll et al., 2019, and references therein). We conduct robustness checks, however, with alternative datasets that include alternative measures of financial liberalization. As far as the estimation method is concerned, we note that the derived long-run regression equation consists of stochastically trended variables with a regression error term that, for different reasons, could be non-stationary as well. Estimations therefore occur within a state space framework (see Harvey, 1989; Durbin and Koopman, 2001). This framework allows to test and control for a potentially non-stationary error term by adding an unobserved stochastic trend to the regression equation and estimate it jointly with the regression parameters (see e.g., Harvey et al., 1986; Canarella et al., 1990; Planas et al., 2007; Everaert, 2010). We further empirically investigate the channels through which financial liberalization affects the consumption-wealth ratio by investigating whether financial liberalization has predictive power for aggregate consumption growth and/or returns on wealth.

When estimating the regression model without the financial liberalization variable included, we find strong evidence in favor of the presence of an unobserved stochastic trend in the regression error. This supports the evidence reported in the literature on the non-stationarity of the traditional 'cay' variable as a proxy for the consumption to wealth ratio and is in line with a preliminary unit root test that we conduct on the 'cay' variable. Our baseline financial liberalization indicator, i.e., the CEA index, succeeds in capturing this non-stationarity and therefore the trend in the estimated consumption-wealth ratio. We find that the increase in this indicator over the sample period has increased the consumption-wealth ratio with about ten percent. A battery of robustness checks that we conduct along several dimensions confirm the positive impact of financial liberalization on the consumption-wealth ratio. When investigating the channel that is responsible for this relationship, we find that liberalization has some predictive power for aggregate consumption growth, i.e., it reduces expected future consumption growth. We do not find evidence, however, that liberalization has predictive ability for returns on wealth over the sample period. We argue that this evidence supports an incomplete markets interpretation of the relationship between financial liberalization and the consumption-wealth ratio, i.e., liberalization signals improvements in market completeness which reduces expected consumption growth rates and this, through the intertemporal budget constraint, increases the current consumption-wealth ratio.

The structure of the paper is as follows. Section 2 presents and discusses the empirical framework used to conduct our estimations. Section 3 deals with the estimation of the long-run relationship between consumption, wealth and financial liberalization. We present the baseline results as well as several robustness checks. Section 4 investigates the channels that are put forward in the paper to explain the impact of financial liberalization on the consumption-wealth ratio. Section 5 concludes.

2 Empirical framework

A preliminary unit root test conducted on the consumption-wealth ratio as proxied by the standard 'cay' variable, strongly suggests, in line with the literature, that this ratio is non-stationary. We refer to Appendix C for the results of this test. This paper argues that this non-stationarity is related to financial liberalization. To this end, in this section, we present the framework used to investigate the impact of financial liberalization on the long-run relationship between aggregate consumption and wealth. First, we present and discuss the expression for the log consumption to total wealth ratio that is derived from the intertemporal budget constraint of a representative consumer. Second, we use this expression to argue that financial liberalization, which we model as a persistent process, can affect the current consumption to total wealth ratio by signalling future changes in expected consumption growth rates and/or in rates of return on wealth. Third, we implement steps to obtain an estimable long-run aggregate time series relationship between the considered variables.

2.1 Intertemporal budget constraint and the consumption-wealth ratio

From the log-linearized and forward solved budget constraint of a representative consumer, we can write the period t log consumption-wealth ratio $c_t - w_t$ as,

$$c_t - w_t = E_t \sum_{j=1}^{\infty} \rho^j \left(r_{t+j} - \Delta c_{t+j} \right) \tag{1}$$

with $c_t = \ln C_t$ where C_t is real consumption, with $w_t = \ln W_t$ where W_t is real total wealth which is the sum of asset wealth and human wealth, with E_t the conditional expectations operator based on period t information, with r_t the real rate of return on total wealth (see e.g., Campbell and Mankiw, 1989). The parameter ρ (with $0 < \rho < 1$) is a discount factor which equals $\frac{W-C}{W}$ where C and W are the steady state values of consumption and total wealth and which is expected to be close to one. The unimportant linearization constant is omitted from the expression. We refer to Appendix A for the derivation. Eq.(1) states that if the consumer's consumption-wealth ratio is high in period t, subsequent rate of return increases or lower subsequent growth rates of consumption are necessary for the consumer's budget constraint to hold intertemporally. We note that, while we impose a transversality condition when deriving eq.(1) to exclude the possibility of a non-stationary log consumption-wealth ratio $c_t - w_t$ due to the occurrence of bubbles, this ratio can still be non-stationary if the variables r_t and/or Δc_t are non-stationary.

2.2 Financial liberalization and the consumption-wealth ratio

From eq.(1), we note that financial liberalization may affect the current log consumption-wealth ratio if it affects expected rates of return on wealth and/or expected consumption growth rates. With respect to the former channel, financial liberalization may affect expected returns because it reduces the cost of capital (see e.g., Arouri et al., 2010, pages 45-47 and references therein). With respect to the latter channel, financial liberalization may affect expected consumption growth because it increases market completeness, i.e., by lifting the restrictions that consumers face to transfer resources across time or across uncertain states of the world, financial liberalization may improve consumption smoothing opportunities (see e.g., Parker and Preston, 2005). We capture these possibilities by assuming the following processes for returns and consumption growth,

$$r_{t+1} = \psi_0^r + \psi_1^r fl_t + \chi_{t+1}^r \tag{2}$$

$$\Delta c_{t+1} = \psi_0^{\Delta c} + \psi_1^{\Delta c} fl_t + \chi_{t+1}^{\Delta c} \tag{3}$$

where fl_t denotes financial liberalization in period t, where ψ_1^r and $\psi_1^{\Delta c}$ capture the impact of financial liberalization on expected returns and expected consumption growth and where χ_{t+1}^r and $\chi_{t+1}^{\Delta c}$ are unobserved components that capture all other factors that affect r_{t+1} and Δc_{t+1}. These components can be persistent, but they are assumed to be stationary.

From the liberalization measures presented below in Section 3.2 - in particular, our baseline credit easing accumulated (CEA) index - we observe that liberalization is trended over the considered sample period. As such, we model financial liberalization as a stochastically trended variable using a random walk process. This gives,

$$fl_{t+1} = fl_t + \xi_{t+1} \tag{4}$$

where ξ_{t+1} is a stationary process for which we have $E_t \xi_{t+1} = 0$.

Substituting eqs.(2) and (3) written for period $t + j$ into eq.(1), we obtain,

$$c_t - w_t = \sum_{j=1}^{\infty} \rho^j (\psi_0^r - \psi_0^{\Delta c}) + E_t \sum_{j=1}^{\infty} \rho^j (\psi_1^r - \psi_1^{\Delta c}) fl_{t+j-1} + E_t \sum_{j=1}^{\infty} \rho^j (\chi_{t+j}^r - \chi_{t+j}^{\Delta c}) \tag{5}$$

Upon noting that $\sum_{j=1}^{\infty} \rho^j = \frac{\rho}{1-\rho}$ and using the result that $E_t fl_{t+j-1} = fl_t$ which follows from the random walk process assumed for fl_{t+1} in eq.(4), we can write the log consumption-wealth ratio as,

$$c_t - w_t = \gamma fl_t + \epsilon_t^c \tag{6}$$

where $\gamma \equiv \frac{\rho}{1-\rho}(\psi_1^r - \psi_1^{\Delta c})$, where $\epsilon_t^c \equiv E_t \sum_{j=1}^{\infty} \rho^j \left[\chi_{t+j}^r - \chi_{t+j}^{\Delta c}\right]$ is a stationary error term, and where we have omitted the constant of the equation.

The parameter γ is the impact of financial liberalization on the consumption to total wealth ratio. Since $0 < \rho < 1$, the sign of γ, which captures whether financial liberalization increases or decreases the consumption-to-wealth ratio over time, depends on the sign of the parameters ψ_1^r and $\psi_1^{\Delta c}$. Suppose that financial liberalization has no impact on expected consumption growth but reduces expected returns because it reduces the cost of capital, i.e., we have $\psi_1^r < 0$ and $\psi_1^{\Delta c} = 0$. Then, an increase in fl_t implies an expected decrease in future returns on wealth which, through the intertemporal budget constraint eq.(1), implies a decrease in the log consumption-wealth ratio, i.e., we have $\gamma < 0$. Suppose, on the other hand, that financial liberalization has no impact on expected returns but reduces expected consumption growth because it increases market completeness and consumption smoothing opportunities, i.e., we have $\psi_1^r = 0$ and $\psi_1^{\Delta c} < 0$. Then, an increase in fl_t implies an expected decrease in future consumption growth rates which, through the intertemporal budget constraint eq.(1), implies an increase in the log consumption-wealth ratio, i.e., we have $\gamma > 0$.

While in Section 3 we deal with the direct estimation of the parameter γ, in Section 4 we report the values for ψ_1^r and $\psi_1^{\Delta c}$ obtained from estimating eqs.(2)-(3). These estimates shed light on the channel through which financial liberalization affects the consumption-wealth ratio. We further note that since ϵ_t^c is assumed to be stationary, the only source of non-stationarity in the model and therefore in the consumption-wealth ratio $c_t - w_t$ stems from financial liberalization. Our empirical approach detailed below, however, allows for the possibility that there are additional sources of non-stationarity.

2.3 Deriving an estimable long-run relationship

Eq.(6) cannot be estimated since log total wealth w_t is unobservable. Since total wealth is the sum of asset wealth and human wealth, we have $W_t = A_t + H_t$ where A_t is asset wealth and H_t is human wealth and where the former is observed but the latter is not. Log-linearizing this sum, we write,

$$w_t = \alpha a_t + \beta h_t \tag{7}$$

where $a_t = \ln A_t$, $h_t = \ln H_t$, $\alpha = \frac{A}{W} > 0$ and $\beta = \frac{H}{W} > 0$ with A and H the steady state values of asset wealth and human wealth. Substituting eq.(7) into eq.(6), we obtain,

$$c_t = \alpha a_t + \beta h_t + \gamma fl_t + \epsilon_t^c \tag{8}$$

Then, following Lettau and Ludvigson (2001, 2004), we proxy the unobserved log human capital variable h_t with the observed log labor income variable y_t to obtain,

$$c_t = \alpha a_t + \beta y_t + \gamma fl_t + \epsilon_t \tag{9}$$

where the error term ϵ_t is assumed to be the stationary. We note that if $\gamma = 0$, then eq.(9) becomes the standard 'cay' regression equation considered in the literature. In the next section, we discuss the estimation of eq.(9) and the obtained results.

3 Estimating the long-run relationship between consumption, wealth and financial liberalization

Regression equations containing non-stationary variables such as the equation put forward in eq.(9) do not necessarily have a stationary error term. While in Section 2, we assume stationarity of the error term ϵ_t, this assumption may be false. At the most fundamental level, the finding of a non-stationary error term may suggest that the theoretical model considered is incomplete as one or more relevant non-stationary variables have been omitted from the derived long-run regression equation and are therefore relegated to the error term. Alternatively, a non-stationary error term could occur because some model assumptions - i.e., the validity of the transversality condition - do not hold or because some model approximations - i.e., the applied linearizations - are inaccurate. As such, we use an estimation methodology that allows to test and control for a potentially non-stationary error term. To this end, we employ an unobserved component or state space framework (see Harvey, 1989; Durbin and Koopman, 2001) through which we can reliably estimate the long-run relationship of eq.(9) even if its error term is non-stationary. We do this by explicitly adding an unobserved stochastic trend - i.e., a random walk component - to the regression equation and estimate it jointly with the model parameters (see e.g., Harvey et al., 1986; Canarella et al., 1990; Planas et al., 2007; Everaert, 2010). We also test for the presence of an unobserved stochastic trend in the regression error using the methods of Frühwirth-Schnatter and Wagner (2010). While stationarity of the error term is not required to estimate the parameters of eq.(9), concluding in favor of stationarity provides support for the model and its assumptions.

Section 3.1 presents the empirical specification. Section 3.2 elaborates on the data while the estimation methodology is discussed in Section 3.3. The results are presented in Section 3.4.

3.1 Empirical specification

We write eq.(9) in general form as,

$$c_t = x_t \phi + \epsilon_t \tag{10}$$

where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix}'$. We also estimate the model without including the financial liberalization variable fl_t, in which case we have $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta \end{bmatrix}'$.

The unobserved error term ϵ_t is modelled as the sum of a non-stationary unobserved component or stochastic trend μ_t and a stationary unobserved component v_t. As such, we have,

$$\epsilon_t = \mu_t + v_t \tag{11}$$

The non-stationary component μ_t is modelled as a random walk process $\mu_t = \mu_{t-1} + \eta_t$ with $\eta_t \sim iid\mathcal{N}\left(0, \sigma_\eta^2\right)$. A random walk provides a simple but flexible way to capture the potential non-stationarity in the regression error term. Following Frühwirth-Schnatter and Wagner (2010), we write down this process in non-centered form as,

$$\mu_t = \mu + \sigma_\eta \mu_t^* \tag{12}$$

$$\mu_t^* = \mu_{t-1}^* + \eta_t^* \tag{13}$$

where μ is the initial value of μ_t, where $\mu_0^* = 0$ and where we $\eta_t^* \sim iid\mathcal{N}(0,1)$. We discuss the advantages of using this non-centered specification in Section 3.3 below.

The stationary component v_t is modelled as consisting of an error term e_t and lags, leads and contemporaneous values of the first difference of the regressors x_t, i.e.,

$$v_t = \sum_{j=-p}^{p} \Delta x_{t+j} \kappa_j + e_t \tag{14}$$

where $e_t \sim iid\mathcal{N}\left(0, \sigma_e^2\right)$. This specification follows the literature where dynamic OLS (DOLS) is typically applied to the estimation of regression equations between consumption, labor income and asset wealth (see Lettau and Ludvigson, 2001). For most of the estimations reported in the paper, we follow Bianchi et al. (2018) and set $p = 6$. Robustness checks discussed and presented in Section 3.4.5 and Appendix E show, however, that our main results are not affected when we use alternative values for p.

3.2 Data

We estimate eq.(10) using quarterly US data. Full details on the sources and on the construction of the data are provided in Appendix B.

The variables c_t, a_t and y_t are constructed exactly as in Lettau and Ludvigson (2015) and Bianchi et al. (2018) and are calculated over the period $1951Q4 - 2016Q4$. For consumption, total personal consumption expenditures are used. For asset wealth, we use household net worth (including consumer durables) while for income, we use disposable labor income. Consumption, disposable labor income and assets are all deflated by the price deflator for total personal consumption expenditures and then divided by total population to obtain per capita variables. Finally, the natural logarithm of the resulting series are taken which gives us the variables c_t, y_t and a_t. We note that other measures for the variables c_t, a_t and y_t have been suggested in the literature. In Appendix E, we show that our baseline estimations are robust to the use of alternative measures for c_t, a_t and y_t.

To measure financial liberalization fl_t, our baseline indicator is the 'credit easing accumulated' (CEA) index considered also by Carroll et al. (2019). It is constructed from a survey that inquires on the willingness of US banks to make consumer installment loans. This measure is advantageous because of its availability - from 1966 onward - and because it captures credit supplied to consumers while being relatively less driven by credit demand. A second indicator for fl_t that we consider in the robustness checks, i.e., the household debt to disposable income ratio, has even better availability - i.e., from 1951 onward - but it is conceptually much less appealing as a measure of liberalization and expanding credit supply as it is determined by both supply and demand.[1] A third measure for fl_t that is also considered in the robustness checks is the index of financial reform of Abiad et al. (2008) which is a mixture of financial development indicators and hence reflects credit supply conditions. The main advantage of this measure is that it can be considered a more exogenous measure of liberalization when compared to our baseline CEA index. The index of Abiad et al. (2008) is based on legislation and regulation, whereas the CEA index is also affected by the business cycle and the financial situation of the banks that extend loans.[2] The downside of this measure is its limited availability - i.e., only over the period $1973 - 2005$ - and its limited variability as it is a step function that takes on only six values. All three measures used for fl_t are presented in Figure 1. All measures suggest that liberalization in the US has increased drastically over the considered period. The financial deregulation that started in the early 1980's and the later financial market technological advancements and financial innovations are clearly visible in all the measures. Our preferred CEA indicator and, to a lesser extent, the household debt to income ratio also reveal a clear cyclical pattern, i.e., during recessions, credit availability diminishes.

[1] Justiniano et al. (2015) discuss the limitations of this indicator to measure liberalization, in particular in the context of housing.

[2] Legislation and regulation are less affected by the real economy than the willingness of banks to extend loans. Moreover, the ability and willingness of banks to extend loans is affected by legislation and regulation as regulations and restrictions affect the cost of lending.

3.3 Methodology

Eqs.(10)-(14) constitute a state space system that we estimate using Bayesian methods. In particular, we use a Gibbs sampling approach which is a Markov Chain Monte Carlo (MCMC) method used to simulate draws from the intractable joint posterior distribution of the parameters and the unobserved state using only tractable conditional distributions. The general outline and technical details of the Gibbs sampling algorithm together with a convergence analysis of the sampler are provided in Appendix D. In the following subsections, we discuss how we test for a stochastic trend in the error term of the regression equation and we discuss which prior distributions we employ for the fixed parameters of the state space system.

3.3.1 Testing for a stochastic trend in the regression error term

We test whether to include or exclude the stochastic trend or unobserved random walk component in the regression equation using the stochastic model selection approach for Bayesian state space models as developed by Frühwirth-Schnatter and Wagner (2010). In a Bayesian setting, a prior probability can be assigned to each of two potential models - i.e. one with and one without an unobserved stochastic trend in the error term - and the posterior probability of each model is then calculated conditional on the data. Testing whether or not the unobserved component μ_t is present in eq.(10) amounts to testing $\sigma_\eta^2 > 0$ against $\sigma_\eta^2 = 0$. This is a non-regular testing problem from a classical viewpoint as the null hypothesis lies on the boundary of parameter space. To this effect, the non-centered parameterization of the unobserved random walk put forward in eq.(12) is useful as the transformed component μ_t^*, in contrast to μ_t, does not degenerate to a static component if the innovation variance equals zero. This means that if the variance $\sigma_\eta^2 = 0$, then $\sigma_\eta = 0$ in eq.(12) and the time-varying part μ_t^* of the unobserved component μ_t drops out of the equation. Hence, using the non-centered parameterization, the presence or absence of a non-stationary unobserved component can be expressed as a standard variable selection problem. In particular, we rewrite eq.(12) as,

$$\mu_t = \mu + \iota \sigma_\eta \mu_t^* \tag{15}$$

where ι is a binary inclusion indicator which is either zero or one. If $\iota = 1$, there is an unobserved random walk in the regression error, μ is the initial value of μ_t and σ_η is estimated from the data. If, on the other hand, $\iota = 0$, there is no unobserved random walk, μ_t becomes constant as $\mu_t = \mu$ and σ_η is set to zero. The binary indicator ι is sampled together with the other parameters so that from its posterior distribution we can calculate the posterior inclusion probability of an unobserved stochastic trend in the regression equation.

3.3.2 Parameter priors

In Table 1, we report the prior distributions assumed for the regression parameters. In the robustness checks discussed and presented in Section 3.4.5 and Appendix E, we provide evidence concerning the robustness of our main results to a number of alternative parameter prior configurations.

For the binary indicator ι used to calculate the posterior inclusion probability of a stochastic trend in the regression, we assume a Bernoulli prior distribution with probability $p_0 = 0.5$. Using the alternative prior inclusion probabilities $p_0 = 0.25$ and $p_0 = 0.75$ does not affect the conclusions of the paper.[3] For the variance σ_e^2 of the error term e_t, we use an inverse gamma (IG) prior with belief equal to 0.1 and a low strength equal to 0.01 which implies a prior distribution that has support over a relatively wide range of parameter values (see Bauwens et al., 2000, for details on prior beliefs and strengths). For the intercept parameter μ and for the parameters in κ, i.e., the coefficients on the contemporaneous values and leads and lags of the first differences of the regressors, we assume Gaussian prior distributions with mean zero and unit variance. This relatively high prior variance implies relatively flat priors for these parameters.

From Table 1, we further note that we also use Gaussian prior distributions for the regression coefficients in ϕ, i.e., the coefficient α on assets, the coefficient β on disposable labor income and the coefficient γ on financial liberalization. We set the prior mean for γ, our main coefficient of interest, equal to zero to let the data fully determine the direction of the impact of financial liberalization. From Section 2, we know that, theoretically, the coefficients α and β reflect the weight in steady state of respectively asset and human wealth in total wealth. Previous estimates for the ratio of human wealth to total wealth in the US vary from about 0.60 (see e.g., Lettau and Ludvigson, 2001, 2004) to about 0.90 (see e.g., Lustig et al., 2013). Hence, we set the prior mean for β to the average of these values which is 0.75, and this then implies a prior mean for α equal to 0.25. A relatively high variance equal to one is chosen for all parameters in ϕ, again implying relatively flat priors.

Finally, we elaborate on the prior choice for the parameter σ_η of the unobserved random walk component μ_t, i.e., the square root of its innovation variance σ_η^2. Using the non-centered parameterization for the random walk μ_t implies that σ_η is basically a regression coefficient in the consumption equation. Hence, rather than using a standard IG prior for the variance parameter σ_η^2, we use a Gaussian prior centered at zero for σ_η.[4] We again impose a unit variance so that the prior distribution has support over a wide range of parameter values. As noted by Frühwirth-Schnatter and Wagner (2010), this approach

[3]Results unreported but available upon request.

[4]Centering the prior distribution at zero makes sense as the posterior distribution for σ_η is also symmetric around zero, both when $\sigma_\eta^2 = 0$ and when $\sigma_\eta^2 > 0$. In the former case, it is unimodal at zero; in the latter case, it is bimodal at $\pm|\sigma_\eta|$.

Table 1: Prior distributions of parameters regression equation $c_t = x_t\phi + \mu_t + v_t$

Gaussian priors $\mathcal{N}(b_0, V_0)$				Percentiles	
		mean (b_0)	variance (V_0)	5%	95%
Coefficient on a_t	α	0.25	1.00	−1.39	1.89
Coefficient on y_t	β	0.75	1.00	−0.89	2.39
Coefficient on fl_t	γ	0.00	1.00	−1.64	1.64
Initial value random walk/regression intercept	μ	0.00	1.00	−1.64	1.64
Square root variance random walk error	σ_η	0.00	1.00	−1.64	1.64
Coeff. on lags/leads of Δx_t (DOLS terms)	κ	0.00	1.00	−1.64	1.64
Inverse Gamma prior $IG(\nu_0 T, \nu_0 T \sigma_0^2)$				Percentiles	
		belief (σ_0^2)	strength (ν_0)	5%	95%
Variance error term e_t	σ_e^2	0.1	0.01	0.03	1.2
Bernoulli prior $\mathcal{B}(p_0)$					
		mean (p_0)	variance ($p_0(1-p_0)$)		
Binary indicator ι		0.50	0.25		

Notes: The main regression equations that we estimate are $c_t = \alpha a_t + \beta y_t + \mu_t + v_t$ (model without financial liberalization) and $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$ (model with financial liberalization). Other specifications in Sections 3.4.2 and 3.4.4 below consider an additional fl_t variable or alternatives for the fl_t variable. The coefficient priors on these variables are identical to the prior used for γ. The random walk component (stochastic trend) is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ (model without financial liberalization) or $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$ (model with financial liberalization).

avoids the shortcomings of using an IG prior distribution on the innovation variance of a random walk component when we want to decide on the inclusion or exclusion of this component in the regression.[5]

3.4 Results

This section presents the results of estimating the long-run relationship between the consumption-wealth ratio and financial liberalization. The baseline results using the CEA index for financial liberalization are presented in Section 3.4.1. Then, we consider a series of robustness checks. First, in Section 3.4.2, we check whether trended but less appealing proxies of financial liberalization can explain the trend in the consumption-wealth ratio. Second, in Section 3.4.3, we explore the causality of the relationship between financial liberalization and the consumption-wealth ratio. Third, in Section 3.4.4, we consider two alternative theories that could potentially explain the presence of a stochastic trend in the consumption-wealth ratio. Finally, in Section 3.4.5, we discuss the results obtained when using alternative estimation

[5]In particular, when using the standard IG prior distribution for variance parameters, the choice of the shape and scale hyperparameters that define this distribution has a strong influence on the posterior distribution when the true value of the variance is close to zero. More specifically, as the IG distribution does not have probability mass at zero, using it as a prior distribution tends to push the posterior density away from zero. This is of particular importance when estimating the variance σ_η^2 of the innovation to the unobserved random walk μ_t as we want to decide whether or not to include this component in the regression equation. Frühwirth-Schnatter and Wagner (2010) show that the posterior density of σ_η is much less sensitive to the hyperparameters of the Gaussian distribution and is not pushed away from zero when $\sigma_\eta^2 = 0$.

settings and datasets.

3.4.1 Baseline results

Table 2 presents the posterior probabilities that the regression error term of different estimated regression models contains a stochastic trend, i.e., a random walk component. The upper panel of the table contains the results for the models estimated in this section. The prior probability is set to 50% in all cases. From the posterior probabilities reported in the table, we conclude that there is strong evidence in favor of the presence of an unobserved stochastic trend in the regression error term for the model without the liberalization variable fl_t included. This is the case also when we estimate the model without liberalization over a shorter period, i.e., the period over which our baseline CEA index of liberalization is available. This result supports the evidence reported in the literature on the non-stationarity of the traditional 'cay' variable as a proxy for the consumption to wealth ratio. It is also in line with the results from the unit root test that we apply to the 'cay' variable and that we report in Appendix C. The result for the baseline model with the 'credit easing accumulated' or CEA index included as a measure of financial liberalization suggests that this model provides an adequate characterization of the non-stationarity of the regression error as the posterior probability that a stochastic trend is present in the error term drops considerably when considering this model and lies well below 0.5.

The results obtained when estimating the model without financial liberalization and the baseline model with the 'credit easing accumulated' (CEA) index used as the financial liberalization indicator fl_t are presented in Tables 3 and 4. In these tables, we report the means and 90% highest posterior density (HPD) intervals of the posterior distributions of the fixed parameters of the estimated state space system given by eqs.(10)-(15) with the exception of the κ coefficients which are excluded due to space constraints. The results are reported both for the case without and with a stochastic trend included in the regression error, i.e., for $\iota = 0$ and for $\iota = 1$. In the latter case, the innovation standard deviation $|\sigma_\eta|$ of the included random walk is also reported.

From the results for the model without liberalization reported in Table 3, we note that the estimates for the elasticities α and β are close to the values typically reported in the 'cay' literature. The estimates vary somewhat depending on the sample period considered and according to whether or not the unobserved stochastic trend is included in estimation. We note that excluding the unobserved stochastic trend by setting $\iota = 0$ is in line with the 'cay' models estimated in the existing literature, i.e., the non-stationarity in the error term of the regression is typically not accounted for. Estimating the regression model under the restriction $\iota = 1$, on the other hand, is in line with the posterior inclusion probabilities for the unobserved random walk component reported in Table 2 which are equal to one, i.e., the stochastic trend

Table 2: Posterior probability $p(\iota = 1)$ of an unobserved stochastic trend in the regression error

Model	Sample period	Probability
1. Baseline results (Section 3.4.1)		
Baseline model with CEA index for financial liberalization	1966Q3-2016Q4	0.28
Model without financial liberalization (full period)	1951Q4-2016Q4	1.00
Model without financial liberalization (CEA period)	1966Q3-2016Q4	1.00
2. Alternative trended variables (Section 3.4.2)		
Model with linear deterministic trend	1966Q3-2016Q4	0.67
Model with household debt to income ratio	1966Q3-2016Q4	0.93
3. Causality (Section 3.4.3)		
Model with Abiad et al. measure for financial liberalization	1973Q1-2005Q4	0.02
4. Other theories (Section 3.4.4)		
Model with unemployment risk	1961Q4-2016Q4	1.00
Model with old-age dependency ratio	1959Q4-2016Q4	1.00

Notes: The regression equation is either $c_t = \alpha a_t + \beta y_t + \mu_t + v_t$ (model without financial liberalization) or $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$ (model with financial liberalization) or $c_t = \alpha a_t + \beta y_t + \gamma trend_t + \mu_t + v_t$ (model for other tested theories). Reported is the posterior inclusion probability of the unobserved random walk component $\mu_t = \mu + \iota \sigma_\eta \mu_t^*$. It is calculated as the average ι obtained over the iterations of the Gibbs sampler. The prior distribution of ι is Bernoulli with probability $p_0 = 0.5$. Details on the data are provided in Section 3.2 and Appendix B. The effective sample periods and sample sizes are reduced compared to the reported sample periods due to the use of first-differences, lags and leads.

is relevant, so it is included in the model and estimated.

The results obtained when estimating the model with the 'credit easing accumulated' (CEA) index as the baseline financial liberalization indicator fl_t are presented in Table 4. The table again reports both the case without and with a stochastic trend included in the regression error, i.e., for $\iota = 0$ and for $\iota = 1$. We note that setting $\iota = 0$ is in line with the posterior inclusion probability reported in Table 2 above for the baseline model where liberalization is measured using the CEA index. This probability is well below 50%. From the table, we note that our main parameter of interest γ, which captures the impact of liberalization on the consumption-wealth ratio, is positive. Hence, we find that liberalization increases the consumption to wealth ratio. In particular, for the more relevant regression without the unobserved stochastic trend ($\iota = 0$), we find that the increase in the CEA index from zero to one over the sample period (see Figure 1) has increased the consumption to total wealth ratio with about 10%. We further note that the elasticities α and β are of different magnitude as compared to those obtained from the model without financial liberalization reported in Table 3. In particular, the elasticity α - which reflects the ratio of asset wealth to total wealth in steady state - is considerably lower, while the elasticity β - which reflects the ratio of human wealth to total wealth in steady state - is considerably larger. These values, in particular those obtained when we set $\iota = 0$, are in accordance with the human wealth to total

Table 3: Model without financial liberalization: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \mu_t + v_t$

	Period $1951Q4 - 2016Q4$		Period $1966Q3 - 2016Q4$	
	(1)	(2)	(3)	(4)
	$\iota = 0$	$\iota = 1$	$\iota = 0$	$\iota = 1$
α	0.2357	0.2156	0.2538	0.2028
	[0.1758,0.2949]	[0.1286,0.3027]	[0.1640,0.3419]	[0.1046,0.3020]
β	0.7873	0.7616	0.7616	0.7758
	[0.7211,0.8552]	[0.6573,0.8673]	[0.6496,0.8755]	[0.6557,0.8958]
μ	-0.5064	-0.0465	-0.4657	-0.0553
	[-0.6356,-0.3778]	[-0.2710,0.1839]	[-0.6518,-0.2810]	[-0.2900,0.1808]
$\lvert\sigma_\eta\rvert$	-	0.0033	-	0.0037
	[-,-]	[0.0021,0.0049]	[-,-]	[0.0023,0.0056]
σ_e^2	0.0024	0.0021	0.0025	0.0021
	[0.0021,0.0028]	[0.0018,0.0025]	[0.0021,0.0030]	[0.0018,0.0025]

Notes: Depicted are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. The effective sample period for the period $1951Q4 - 2016Q4$ results is $1953Q3 - 2015Q2$ with effective sample size $T = 248$, i.e., 261 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$. The effective sample period for the $1966Q3 - 2016Q4$ results is $1968Q2 - 2015Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

wealth ratio estimates of about 90% and more reported recently in the literature (see e.g., Lustig et al., 2013, and references therein).

Figure 2 presents the time-varying part of the random walk components that we estimate when setting $\iota = 1$, i.e., the term $\sigma_\eta\mu_t^*$. As $\mu_t^* = \mu_{t-1}^* + \eta_t^*$ and $\mu_0^* = 0$, $\sigma_\eta\mu_t^*$ is initialized at zero. The left panel shows this component for the model without liberalization. It shows a clear upward evolution which suggests that the model without liberalization is not fully specified and therefore incomplete. The right panel shows this component for the model with the CEA index as a measure of liberalization. Although the posterior inclusion probability reported in Table 2 above suggests that it is not necessary to include a stochastic trend in this model (i.e., setting $\iota = 0$ is preferred over setting $\iota = 1$ as the probability is well below 0.5), we are nonetheless interested to see how the estimated trend in this model differs from the estimated trend in the model without liberalization. While there is still some time variation in this component in the model with financial liberalization, the upward trend observed in the random walk component of the model without liberalization is far less prominent here and therefore seems to have been well captured by the inclusion of the CEA index to the regression model.

Table 4: Baseline model with CEA index for fl_t: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$

	(1)	(2)
	$\iota = 0$	$\iota = 1$
α	0.1336	0.1694
	[0.0380,0.2259]	[0.0681,0.2706]
β	0.8510	0.8090
	[0.7401,0.9655]	[0.6885,0.9307]
γ	0.1014	0.0865
	[0.0669,0.1361]	[0.0092,0.1583]
μ	0.0224	0.0031
	[-0.2196,0.2627]	[-0.2331,0.2403]
$\lvert\sigma_\eta\rvert$	-	0.0029
	[-,-]	[0.0013,0.0049]
σ_e^2	0.0022	0.0021
	[0.0019,0.0027]	[0.0018,0.0025]

Notes: The CEA index is used as a measure of financial liberalization. Reported are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Data are available over the period $1966Q3 - 2016Q4$ while the effective sample period is $1968Q2 - 2015Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

We proxy the evolution of the log consumption to total wealth ratio $c_t - w_t$ by calculating $c_t - \mu - \alpha a_t - \beta y_t$.[6] Figure 3 shows the posterior means and 90% HPD intervals of the log consumption-wealth ratio where the blue graph depicts the log consumption-wealth ratio obtained from the model without an unobserved stochastic trend ($\iota = 0$) and the red graph depicts the log consumption-wealth ratio obtained from the model with an unobserved stochastic trend ($\iota = 1$). The left panel shows this ratio for the model without liberalization. Here, the log consumption wealth ratio obtained when $\iota = 0$ (i.e., the blue graph) corresponds to the standard 'cay' variable reported recently by Bianchi et al. (2018). The log consumption-wealth ratio obtained when $\iota = 1$ (i.e., the red graph) shows, as expected, a clearer upward trend as it is not restricted to be stationary.[7] This discrepancy between both ratios suggests that

[6] The level of the log consumption to total wealth ratio is not identified in our model because, among other things, we approximate human wealth through labor income. Hence, we can subtract the intercept μ when calculating the log consumption-wealth ratio.

[7] From the figure, we note that the HPD intervals for the log consumption-wealth ratio obtained under $\iota = 1$ (red) are wider than those obtained under $\iota = 0$ (blue). This stems from the fact that the estimation of the former entails the estimation of both fixed parameters and a time-varying state - i.e., the unobserved random walk component μ_t^* - while the

not dealing with the unobserved trend in the regression error term has important consequences for the estimation of the evolution of the consumption-wealth ratio. The right panel shows the log consumption-wealth ratio for the model with the CEA index included as a measure of liberalization. The discrepancy observed between the $\iota = 0$ and $\iota = 1$ cases is rather small which suggests that, in the model with financial liberalization, whether or not an unobserved stochastic trend is included in the regression makes little difference. This again confirms that the CEA index as an indicator of financial liberalization does a good job of capturing the non-stationarity and therefore the trend that is present in the consumption to wealth ratio. Figure 3 further depicts the US recessions as determined by the NBER (grey shaded areas). From these, we can observe that the calculated consumption-wealth ratios are cyclical, i.e., the consumption-wealth ratios tend to fall during and/or shortly after a recession. The cyclicality of the consumption-wealth ratio is driven by the relative cyclical evolution in the consumption, assets and labor income variables that are used in its construction as well as by the cyclicality of the CEA index which we documented in Section 3.2 above (see Figure 1).

We end this section by comparing the out-of-sample performance of the models with and without financial liberalization. To this end, we sample the distributions of the root mean squared error (RMSE) of both models, both at the one-quarter and four-quarter horizons.[8] Based on these, we calculate the distributions of the following three statistics: the ratio between the RMSE of both models ('RMSE ratio'), the difference between the RMSE of both models ('RMSE diff.') and the out-of-sample R-squared ('R^2_{oos}'). The means and 90% HPD intervals of these distributions are presented in Table 5. From the table, we conclude that, in accordance with the in-sample results, the model with the CEA index as a measure of financial liberalization performs unequivocally better than the standard model without liberalization.

3.4.2 Alternative trended variables

This section investigates whether alternative upward trended but less appealing proxies of financial liberalization can also explain the observed trend in the consumption-wealth ratio. We consider both a simple deterministic linear time trend and the household debt to income ratio. The latter is discussed in Section 3.2 above where we note that it is less interesting as a measure of expanding credit supply as it is determined also by demand. We compare the performance of these measures with that of the CEA index over the period that the latter is available, i.e., over the period $1966Q3 - 2016Q4$. From Table 2 above, we note that when including each of these variables separately to the regression equation, the

estimation of the latter entails only the estimation of fixed parameters.

[8] Both models are compared over the same period 1966Q3-2016Q4 with, given $p = 6$, effective sample period $1968Q2 - 2015Q2$. The first sample used for out-of-sample forecasting is $1968Q2 - 1979Q4$ so that forecasting begins in $1980Q1$ for horizon $h = 1$ and in $1980Q4$ for $h = 4$. The second sample used for forecasting is $1968Q2 - 1980Q1$, and so on.

Table 5: Out-of-sample performance: model with versus without financial liberalization

	Measure		
Horizon	RMSE ratio	RMSE diff.	R^2_{oos}
h=1	0.8607	0.0042	0.2592
	[0.7743,0.9551]	[0.0013,0.0072]	[0.0877,0.4004]
h=4	0.8895	0.0036	0.2088
	[0.8005,0.9872]	[0.0004,0.0067]	[0.0253,0.3591]

Notes: Reported are the means and the 90% HPD intervals (in square brackets) of the posterior distributions of the three statistics comparing the out-of-sample performance of the models with and without liberalization. The horizon h is expressed in number of quarters. With $RMSE^{fl}$ ($RMSE^{nofl}$) denoting the RMSE of the model with (without) financial liberalization, 'RMSE ratio' is given by $\frac{RMSE^{fl}}{RMSE^{nofl}}$, 'RMSE diff.' is given by $RMSE^{nofl} - RMSE^{fl}$ and 'R^2_{oos}' is given by $1 - \left(\frac{RMSE^{fl}}{RMSE^{nofl}}\right)^2$. The model with financial liberalization uses the CEA index for fl_t. Both models are estimated over the same period 1966Q3-2016Q4 with, given $p = 6$, effective sample period $1968Q2 - 2015Q2$. The first sample used for out-of-sample forecasting is $1968Q2 - 1979Q4$. Estimation occurs using the prior distributions reported in Table 1. Both models are estimated without an unobserved stochastic trend included in the regression (i.e., for $\iota = 0$).

posterior probabilities that there is still an unobserved stochastic trend in the regression, while reduced compared to the standard model without liberalization, are still well above 50%. In Table 6, we present the parameter estimates for the regressions estimated with these alternative measures for fl_t. We note that the values for γ imply that the linear time trend and especially the household debt ratio have a positive impact on the consumption-wealth ratio when no stochastic trend is included in the regression error, i.e., when we set $\iota = 0$. The posterior inclusion probabilities reported in Table 2 suggest to set $\iota = 1$ however. In this case, the values for γ show that neither of these alternative liberalization measures has an impact on the consumption-wealth ratio.

We also check which measures of liberalization have an impact on the consumption-wealth ratio when the CEA index and either the linear time trend or the household debt ratio are included in the model simultaneously. The results presented in Table 7 show that, in both cases, the CEA index has a substantial positive impact on the consumption-wealth ratio while both less appealing liberalization measures have no discernable effect. To summarize, the results presented in this section show that not just any measure of liberalization or, more generally, not just any upward trended variable is capable of capturing the non-stationarity that is present in the consumption-wealth ratio. We find that, over the period over which it is available, our preferred baseline CEA measure of liberalization performs better than less appealing alternatives.

Table 6: Model with alternative trended variables for fl_t: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$

	Linear deterministic trend		Household debt to income ratio	
	(1)	(2)	(3)	(4)
	$\iota = 0$	$\iota = 1$	$\iota = 0$	$\iota = 1$
α	0.1661	0.1923	0.1621	0.1867
	[0.0720,0.2573]	[0.0924,0.2915]	[0.0638,0.2573]	[0.0860,0.2871]
β	0.8183	0.7796	0.8336	0.7899
	[0.6899,0.9508]	[0.6479,0.9155]	[0.7197,0.9509]	[0.6689,0.9108]
γ	0.0005	0.0004	0.0867	0.0495
	[0.0000,0.0009]	[-0.0002,0.0010]	[0.0423,0.1311]	[-0.0375,0.1345]
μ	-0.0057	-0.0015	-0.1709	-0.0357
	[-0.2549,0.2418]	[-0.2411,0.2364]	[-0.4080,0.0646]	[-0.2722,0.2032]
$\|\sigma_\eta\|$	-	0.0032	-	0.0035
	[-,-]	[0.0016,0.0053]	[-,-]	[0.0020,0.0055]
σ_e^2	0.0023	0.0021	0.0024	0.0021
	[0.0019,0.0027]	[0.0018,0.0025]	[0.0020,0.0028]	[0.0018,0.0025]

Notes: A linear deterministic trend (columns 1 and 2) or the household debt to income ratio (columns 3 and 4) is used for fl_t. Reported are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Estimations are conducted over the period $1966Q3 - 2016Q4$ while the effective sample period is $1968Q2 - 2015Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

3.4.3 Causality

As the framework presented in Section 2 suggests that there is a causal effect of financial liberalization on the consumption-wealth ratio, we provide more evidence to support this causality in this section. First, we estimate our long-run regression using a more exogenous measure of liberalization. Second, we look at the short-run dynamics between the consumption-wealth ratio and our baseline CEA index. Finally, we investigate the impact of exogenous credit shocks on the consumption-wealth ratio.

A more exogenous financial liberalization indicator

As argued in Section 3.2 above, Abiad et al. (2008)'s indicator of financial reform, while less appealing in other respects, can be considered a more exogenous measure of liberalization compared to our baseline CEA index. Table 2 above suggests that this index also adequately captures the non-stationarity in the consumption-wealth ratio as the posterior probability that a stochastic trend is present in the error term of the long-run regression between consumption, wealth and liberalization is very close to zero when this

Table 7: Model with CEA index for fl_t^1 and alternative trended variable for fl_t^2: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma^1 fl_t^1 + \gamma^2 fl_t^2 + \mu_t + v_t$

	(1) CEA index + linear deterministic trend	(2) CEA index + household debt to income ratio
α	0.2554	0.2555
	[0.0705,0.4347]	[0.0775,0.4281]
β	0.7551	0.7556
	[0.5763,0.9387]	[0.5832,0.9338]
γ^1	0.1876	0.1314
	[0.0867,0.2893]	[0.0814,0.1818]
γ^2	-0.0004	-0.0167
	[-0.0010,0.0003]	[-0.0806,0.0458]
μ	0.0019	0.0196
	[-0.2445,0.2467]	[-0.2216,0.2593]
σ_e^2	0.0022	0.0022
	[0.0019,0.0026]	[0.0019,0.0026]

Notes: The CEA index is used for fl_t^1 while a linear deterministic trend (column 1) or the household debt to income ratio (column 2) are used for fl_t^2. Reported are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$ and with reported estimates obtained under the restriction $\iota = 0$, i.e., no unobserved stochastic trend is included in the regression. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t^1 & fl_t^2 \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Data are available over the period $1966Q3 - 2016Q4$ while the effective sample period is $1968Q2 - 2015Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

index is used as the liberalization measure. From Table 8, we further note that the parameter of interest γ, i.e., the impact of Abiad et al. (2008)'s measure on the consumption-wealth ratio, is positive while, for the relevant $\iota = 0$ case, its HPD interval is sufficiently narrow to not include zero. The results obtained with this more exogenous variable therefore confirm the earlier findings obtained with the CEA index.

The CEA index and the consumption-wealth ratio in the short run

The static long-run trend relationship that we estimate in Section 3.4.1 between the log consumption-wealth ratio $c_t - w_t$ and the CEA index as our baseline measure of financial liberalization fl_t does not allow us to determine the direction of causality between these variables. Investigating the short-run dynamics between both variables can shed some light on this issue. To this end, we estimate an error correction model for each variable. In particular, we regress the first-differences $\Delta(fl_t)$ and $\Delta(c_t - w_t)$ on a constant, a one-quarter lagged error correction term ect_{t-1} and two of their own lags.[9] The error correction term

[9]The number of lags included is deemed sufficient based on inspection of the (partial) autocorrelation functions of the residuals.

Table 8: Model with the Abiad et al. (2008) index for fl_t: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$

	(1)	(2)
	$\iota = 0$	$\iota = 1$
α	0.2405	0.2322
	[0.1124,0.3638]	[0.1007,0.3599]
β	0.7251	0.7356
	[0.5773,0.8766]	[0.5837,0.8916]
γ	0.1362	0.0966
	[0.0514,0.2193]	[-0.0388,0.2086]
μ	-0.0603	-0.0433
	[-0.2924,0.1709]	[-0.2789,0.1938]
$\lvert\sigma_\eta\rvert$	-	0.0022
	[-,-]	[0.0002,0.0054]
σ_e^2	0.0022	0.0022
	[0.0018,0.0027]	[0.0017,0.0026]

Notes: The Abiad et al. (2008) index of financial reform is used as a measure of financial liberalization. Reported are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Data are available over the period $1973Q1 - 2005Q4$ while the effective sample period is $1974Q4 - 2003Q2$ with effective sample size $T = 119$, i.e., 132 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

is the deviation of $c_t - w_t$ from its trend value implied by fl_t, i.e., we calculate $ect_t = c_t - w_t - \gamma fl_t$.

The results are presented in Table 9. We note, first, that the lagged error correction term has no impact on $\Delta(fl_t)$ but has a negative impact on $\Delta(c_t - w_t)$. This implies that it is $c_t - w_t$ and not fl_t that adjusts towards the long-run equilibrium that exists between both variables. Second, the lags of $\Delta(c_t - w_t)$ have no impact on $\Delta(fl_t)$ while the lags of $\Delta(fl_t)$ *do* have a positive impact on $\Delta(c_t - w_t)$. The effects of the lags are summarized in the bottom panel of the table where we report the sums of the coefficients on the lagged first-differences. Jointly, these findings imply that fl_t Granger causes $c_t - w_t$ but $c_t - w_t$ does not Granger cause fl_t (see e.g., Enders, 2004, for the terminoloy).

Credit shocks and the consumption-wealth ratio

As a final approach that we consider to shed light on the causality between financial liberalization and the consumption-wealth ratio, we look at exogenous credit shocks. Figure 4 shows Gambetti and Musso

Table 9: Short-run dynamics between financial liberalization fl_t and the log consumption-wealth ratio $c_t - w_t$: posterior distributions parameters of an error correction model

	Dependent variable	
Regressor	$\Delta(fl_t)$	$\Delta(c_t - w_t)$
constant	0.0018	-0.0006
	[0.0008,0.0027]	[-0.0016,0.0004]
ect_{t-1}	-0.0163	-0.0704
	[-0.0677,0.0357]	[-0.1248,-0.0166]
$\Delta(fl_{t-1})$	0.4420	0.1161
	[0.3462,0.5381]	[0.0137,0.2175]
$\Delta(fl_{t-2})$	0.2020	0.1247
	[0.1041,0.2997]	[0.0214,0.2278]
$\Delta(c_{t-1} - w_{t-1})$	-0.0685	-0.2478
	[-0.1643,0.0273]	[-0.3496,-0.1470]
$\Delta(c_{t-2} - w_{t-2})$	-0.0040	-0.0341
	[-0.0976,0.0892]	[-0.1328,0.0652]
$\sum_{i=1}^{2} \Delta(fl_{t-i})$	0.6440	0.2409
	[0.5518,0.7369]	[0.1407,0.3411]
$\sum_{i=1}^{2} \Delta(c_{t-i} - w_{t-i})$	-0.0725	-0.2818
	[-0.2229,0.0774]	[-0.4409,-0.1228]
R^2_{adj}	0.4784	0.1658
	[0.4466,0.5029]	[0.1279,0.1939]

Notes: The estimations are conducted per equation using Bayesian OLS with uninformative priors, i.e., the prior distribution of the slope coefficients is standard Gaussian while that of the error variance is inverse gamma with low prior belief strength. $\sum_{i=1}^{2} \Delta(fl_{t-i})$ and $\sum_{i=1}^{2} \Delta(c_{t-i} - w_{t-i})$ denote the sum of the coefficients on the lags of $\Delta(fl_t)$, respectively $\Delta(c_t - w_t)$. $R^2_{adj.}$ denotes the adjusted R-squared of the regression. Reported are the posterior means with 90% HPD intervals (in square brackets). The log consumption-wealth ratio $c_t - w_t$ is from the baseline estimation reported in Table 4 (column $\iota = 0$) and depicted in Figure 3 (right panel, blue graph). The CEA index is used for fl_t. The variable ect_{t-1} is the one-quarter lagged error correction term where ect_t equals $c_t - w_t - \gamma fl_t$ where, from Table 4 (column $\iota = 0$), we set $\gamma = 0.1014$. The sample period equals $1968Q2 - 2015Q2$ with the effective sample period reduced to $1968Q4 - 2015Q2$ due to the use of lags.

(2017)'s loan supply shock for the US estimated from a VAR with sign restrictions as well as Ciccarelli et al. (2015)'s lending standard shock for the US. For the former, a decrease signals a tightening of credit, i.e., less loans supplied. For the latter, an increase signals a tightening of credit, i.e., an increase in banks' overall lending standards.

We then estimate autoregressive distributed lag (ADL) regressions consisting of the log consumption-wealth ratio obtained from the baseline estimations reported above and both exogenous credit shocks. In particular, the log consumption-wealth ratio is regressed on two lags of itself and on the current and two lagged values of either the loan supply or the lending standard shock.[10] The results are reported in Table 10. From the table, we note that the current value of the loan supply shock of Gambetti and Musso (2017) has the expected positive impact while only the first lag of the lending standard shock of Ciccarelli et al. (2015) has the expected negative impact on the consumption-wealth ratio. When looking at the total impact of each shock, i.e., the estimated sum of the coefficients on the current and lagged values of the shock as reported in the bottom panel of the table, we find that both shocks have the expected total effect on the consumption-wealth ratio. Summarizing, the results of estimating ADL regressions that include exogenous credit shocks are again supportive of a positive causal effect of credit expansion on the consumption-wealth ratio.

3.4.4 Other theories

As the possibility exists that the trend in the consumption-wealth ratio is related to some other structural change, this section considers two alternative theories that could potentially explain the stochastic trend in this ratio.

First, given the literature on precautionary saving, we investigate whether uncertainty can explain the trend in the consumption-wealth ratio. To this end, we investigate whether Carroll et al. (2019)'s unemployment risk measure, which serves as a proxy for uncertainty, has a long-run impact on the consumption-wealth ratio. While this measure is stochastically trended (i.e., it has a unit root), Figure 5 shows that there is no clear upward or downward trend in this variable, however.[11] Moreover, to explain the upward trend in the log consumption-wealth ratio, we would expect this variable to show a clear downward trend as the theory of precautionary saving implies that uncertainty reduces consumption. Hence, it is doubtful that this variable can capture the trend in the consumption-wealth ratio. This doubt is confirmed by our testing methodology. The results reported in Table 2 above show that the posterior probability that there an unobserved stochastic trend in the regression model consisting of consumption, asset wealth, labor income *and* unemployment risk still equals one.

Second, as noted by Carroll et al. (2019, page 19), aside from demographics there are no other core variables of standard consumption and saving models that have had strong trends like financial liberalization. Hence, we investigate whether the old-age dependency ratio reflecting the trend in demographics has an impact on the consumption-wealth ratio. Like the uncertainty channel, however, the demographics channel can be ruled out a priori. The increase in the old-age dependency ratio observed over the sample

[10] The number of lags included is deemed sufficient based on inspection of the (partial) autocorrelation functions of the residuals.

[11] Other uncertainty measures were considered, but these were found to be stationary. This a priori implies that they cannot account for the stochastic trend in the consumption-wealth ratio.

Table 10: Credit shocks and the log consumption-wealth ratio $c_t - w_t$: posterior distributions parameters of an autoregressive distributed lag model for $c_t - w_t$

	Credit shock	
	Gambetti and Musso (2017)	Ciccarelli et al. (2015)
constant	0.0077	0.0131
	[0.0037,0.0118]	[0.0043,0.0218]
$(c_{t-1} - w_{t-1})$	0.6251	0.5135
	[0.4847,0.7680]	[0.3453,0.6829]
$(c_{t-2} - w_{t-2})$	0.2726	0.3148
	[0.1357,0.4089]	[0.1505,0.4774]
$shock_t$	0.0034	0.0106
	[0.0017,0.0051]	[-0.0019,0.0232]
$shock_{t-1}$	0.0014	-0.0177
	[-0.0004,0.0031]	[-0.0346,-0.0007]
$shock_{t-2}$	0.0023	0.0002
	[0.0006,0.0040]	[-0.0118,0.0122]
$\sum_{i=0}^{2} shock_{t-i}$	0.0070	-0.0069
	[0.0036,0.0105]	[-0.0122,-0.0016]
R^2_{adj}	0.8371	0.6142
	[0.8282,0.8429]	[0.5876,0.6313]

Notes: The dependent variable is $c_t - w_t$. The estimations are conducted using Bayesian OLS with uninformative priors, i.e., the prior distribution of the slope coefficients is standard Gaussian while that of the error variance is inverse gamma with low prior belief strength. $\sum_{i=0}^{2} shock_{t-i}$ denotes the sum of the coefficients on the current and lagged shocks. $R^2_{adj.}$ denotes the adjusted R-squared of the regression. Reported are the posterior means with 90% HPD intervals (in square brackets). The log consumption-wealth ratio is from the baseline estimation reported in Table 4 (column $\iota = 0$) and depicted in Figure 3 (right panel, blue graph). The credit shock is either Gambetti and Musso (2017)'s loan supply shock or Ciccarelli et al. (2015)'s lending standard shock. The sample period is determined by the availability of data for the credit shock and for the log consumption-wealth ratio. It equals $1980Q4 - 2011Q4$ when using the loan supply shock and $1990Q1 - 2015Q2$ when using the lending standard shock. The effective sample period is reduced to $1981Q2 - 2011Q4$, respectively $1990Q3 - 2015Q2$, due to the use of lags.

period and depicted in Figure 5 would presumably have decreased the consumption-wealth ratio. This is the opposite of what we observe. The results in Table 2 again confirm that this alternative explanation is not valid, i.e., the posterior probability that there is an unobserved stochastic trend in the regression model consisting of consumption, asset wealth, labor income *and* demographics still equals one.

In Appendix E.1, we further report the estimated coefficients of the long-run regressions between consumption, asset wealth, labor income and either uncertainty or demographics. As expected, we do not find evidence of a long-run impact of either unemployment risk or the old-age dependency ratio on the consumption-wealth ratio.

3.4.5 Further robustness checks

A number of additional robustness checks for the long-run relationship between consumption, wealth and financial liberalization are presented in Appendix E. First, in Appendix E.2, we consider different lag/lead lengths p for the first-differences of the regressors included in the stationary component v_t of the regression's error term (see eqs.(10), (11) and (14)). In this appendix, we also look at the effect of imposing alternative priors for the parameters of the regression equation. Second, in Appendix E.3, we look at alternative data for, in particular, consumption and asset wealth that can be used to estimate this relationship. Finally, in Appendix E.4, we provide some results based on international data, i.e., we check whether the positive impact of liberalization on the consumption-wealth ratio can also be observed in countries other than the US. Generally, all these robustness checks are supportive of the conclusions presented in this section, i.e., we find a positive long-run impact of financial liberalization on the consumption-wealth ratio. In the next section, we take a closer look at the channels that could be responsible for this relationship.

4 Investigating the channel: financial liberalization, expected returns and expected consumption growth

In the previous section, we report evidence that financial liberalization has a positive long-run impact on the consumption to wealth ratio. From the intertemporal budget constraint framework presented in Section 2, this implies that financial liberalization either has a positive impact on expected future returns on wealth or a negative impact on expected future consumption growth rates or both. This section investigates these channels. First, the predictive equations (2) and (3) are estimated, from which we conclude that financial liberalization affects the consumption-wealth ratio via the consumption growth channel rather than the returns channel. Second, we provide a theoretical interpretation to the reported results, i.e., we argue in favor of an incomplete markets channel to explain the positive impact of liberalization on the consumption-wealth ratio.

4.1 The predictive impact of liberalization for returns and consumption growth

4.1.1 Specification, data and methodology

To investigate through which channels financial liberalization affects the consumption-wealth ratio, we estimate the equations (2)-(3) which we rewrite here in the following generalized form,

$$z_{t+1} = \psi_0^z + \psi_1^z fl_t + \chi_{t+1}^z \tag{16}$$

where the predicted variable z_{t+1} is either the real return on wealth r_{t+1} or aggregate consumption growth Δc_{t+1} and where the predictor variable is the financial liberalization indicator fl_t. The unobserved component χ_{t+1}^z captures all other factors affecting z_{t+1} and is assumed to follow an $AR(1)$ process given by

$$\chi_{t+1}^z = \pi^z \chi_t^z + o_{t+1}^z \tag{17}$$

with the error term o_{t+1}^z given by $o_{t+1}^z \sim iid\mathcal{N}\left(0, \sigma_{o^z}^2\right)$.[12] The parameter of interest is ψ_1^z since it tells us what the predictive impact is of financial liberalization for returns and consumption growth.

As far as the data are concerned, for the financial liberalization variable fl_t we use, as before, our baseline CEA index. For per capita real aggregate consumption c_{t+1}, we use two measures. First, as before, we use per capita real total personal consumption expenditures. Second, we also use per capita real expenditures on nondurable goods and services as a measure for consumption. Since we are looking at an expression for the growth rate of consumption, we are implicitly looking at a model of consumer behavior, i.e., at a consumer first-order condition or Euler equation.[13] When estimating consumer Euler equations, the tradition in the literature is to use nondurable and services expenditures as the measure of consumption.[14] We refer to Rudd and Whelan (2006, page 39) for a discussion of this for the 'cay' literature and, more generally, to Deaton (1992, and references therein). Finally, to proxy real returns on wealth r_{t+1}, we use three different return series. First, we use real stock returns which constitute the series that are conventionally used to proxy returns on wealth. Second, as Lustig et al. (2013) argue that returns on wealth may be better approximated by bond returns, we also estimate the regression using real returns on 10-year government bonds. Third, we also consider real returns on housing wealth. Housing is relevant in this context both because financial liberalization over the past decades can be linked to developments on the mortgage market and because housing is the main asset for a majority of households. We refer to Appendix B for details on the sources and the construction of all data used.

We estimate the regression eqs.(16)-(17) using Gibbs sampling with the general outline and technical details of the sampler provided in Appendix F. In Table 6, we report the prior distributions assumed for the regression parameters. The prior distributions of the parameters ψ_0^z, ψ_1^z and π^z are assumed to be standard Gaussian while that of the variance parameter $\sigma_{o^z}^2$ is inverse gamma (IG). The numbers

[12]Higher-order AR processes were also considered, but the additional lags were found to be close to zero.

[13]The relevant model of consumer behavior is made explicit in the next section.

[14]This is the case because the utility function depends on the flow of consumption. It does not depend on total consumer expenditures as expenditures on durable goods are not a part of the flow but add to or replace the existing stock of durable goods. Rather, utility depends on expenditures on nondurables and services and on a service flow from the existing stock of durable goods. The latter is unobserved, but we implicitly control for it in our estimations through the inclusion of the unobserved AR component χ^z (which, among other things, controls for all variables that affect utility other than nondurable and services consumption).

reported in the table imply relatively flat priors for all parameters.

Table 11: Prior distributions of parameters regression equation $z_{t+1} = \psi_0^z + \psi_1^z fl_t + \chi_{t+1}^z$

Gaussian priors $\mathcal{N}(b_0, V_0)$				Percentiles	
		mean (b_0)	variance (V_0)	5%	95%
Intercept	ψ_0^z	0.00	1.00	−1.64	1.64
Coefficient on CEA index	ψ_1^z	0.00	1.00	−1.64	1.64
AR coefficient regression error	π^z	0.00	1.00	−1.64	1.64
Inverse Gamma prior $IG(\nu_0 T, \nu_0 T\sigma_0^2)$				Percentiles	
		belief (σ_0^2)	strength (ν_0)	5%	95%
Variance error term o_t^z	$\sigma_{o^z}^2$	.0001	0.01	.0000	.0019

Notes: The regression equation is $z_{t+1} = \psi_0^z + \psi_1^z fl_t + \chi_{t+1}^z$ where either $z_{t+1} = r_{t+1}$ or $z_{t+1} = \Delta c_{t+1}$. The error term $\chi_{t+1}^z = \pi^z \chi_t^z + o_{t+1}^z$ follows an $AR(1)$ process with AR parameter π^z and innovation variance $\sigma_{o^z}^2$.

4.1.2 Results

The estimation results are reported in Table 12. From the table, we note that the predictive impact of financial liberalization on all considered returns is not different from zero, i.e., the HPD intervals for the parameter ψ_1^z (with $z = r$) are rather wide with the value of zero contained well within these intervals. The impact of fl_t on future aggregate consumption growth, however, is more substantial. The parameter ψ_1^z (with $z = \Delta c$) has the expected negative sign while the value of zero lies just inside the HPD interval when we use total personal consumer expenditures and lies just outside the HPD interval when we use expenditures on nondurables and services. Hence, the results are more conclusive when we use the more appropriate expenditures on nondurables and services series as a measure of consumption.[15]

We emphasize that the regressions that we estimate in this section consist of highly volatile dependent variables (i.e., returns and consumption growth rates) and a slow moving and persistent low frequency regressor (i.e., the CEA index). Regressions like these are typically hard to estimate given the low signal-to-noise ratio involved. Considering this, we believe that the results reported here provide reasonable evidence to support the expected consumption growth channel as an explanation for the positive impact of financial liberalization on the consumption-wealth ratio documented in Section 3 above, i.e., liberalization reduces expected future consumption growth rates which, through the intertemporal budget constraint,

[15] We note that the estimates obtained in Section 3 for γ, i.e., the impact of financial liberalization fl_t on the consumption-wealth ratio $c_t - w_t$, are consistent with the estimates obtained in this section for ψ_1^r and $\psi_1^{\Delta c}$, i.e., the predictive impact of fl_t for returns r_{t+1} and consumption growth Δc_{t+1}. To see this, note that from Section 2 we have $\gamma = \frac{\rho}{1-\rho}(\psi_1^r - \psi_1^{\Delta c})$ with ρ the discount factor which is theoretically expected to be slightly smaller than one. As estimates for γ, ψ_1^r and $\psi_1^{\Delta c}$ imply values for the parameter ρ, i.e., we have $\rho = \frac{\gamma}{\gamma + \psi_1^r - \psi_1^{\Delta c}}$, we calculate the posterior distribution of ρ from the posterior distributions of γ, ψ_1^r and $\psi_1^{\Delta c}$. We find that the posterior mean of ρ indeed is slightly smaller than one, i.e., it equals 0.97 on average across our estimations. This theoretically sound value confirms that the estimates obtained in Sections 3 and in this section are consistent with each other.

Table 12: Predictive impact of financial liberalization on returns and aggregate consumption growth: posterior distributions parameters of equation $z_{t+1} = \psi_0^z + \psi_1^z fl_t + \chi_{t+1}^z$

	(a) $z_{t+1} = r_{t+1}$			(b) $z_{t+1} = \Delta c_{t+1}$	
	(1) stocks	(2) bonds	(3) housing	(4) pce	(5) nds
ψ_0^z	0.0002	0.0055	0.0340	0.0066	0.0060
	[-0.0211,0.0211]	[-0.0047,0.0156]	[-0.8902,0.8649]	[0.0044,0.0087]	[0.0042,0.0077]
ψ_1^z	0.0157	0.0075	0.0421	-0.0029	-0.0034
	[-0.0215,0.0527]	[-0.0104,0.0253]	[-0.1081,0.2228]	[-0.0067,0.0008]	[-0.0064,-0.0003]
π^z	0.0743	0.0244	0.8680	0.3386	0.4897
	[-0.0410,0.1896]	[-0.0918,0.1408]	[0.6460,1.0075]	[0.2269,0.4506]	[0.3819,0.5980]
$\sigma_{o^z}^2$	0.0075	0.0019	0.0007	.00004	.00001
	[0.0064,0.0088]	[0.0016,0.0023]	[0.0005,0.0010]	[.00003,.00005]	[.00000,.00002]

Notes: The CEA index is used as a measure of financial liberalization fl_t. Reported are the posterior means with 90% HPD intervals (in square brackets). Per capita real total personal consumer expenditures are used for c_t in the 'pce' results while per capita real expenditures on nondurables and services are used for c_t in the 'nds' results. Details on these data and on the returns data are provided in Appendix B. The error term $\chi_{t+1}^z = \pi^z \chi_t^z + o_{t+1}^z$ follows an $AR(1)$ process with AR parameter π^z and innovation variance $\sigma_{o^z}^2$. The estimations reported in columns 1, 2, 4 and 5 are based on quarterly data with data available over the period $1966Q3 - 2016Q4$ and effective sample period $1966Q4 - 2016Q4$ (i.e., $T = 201$). The estimation reported in column 3 is based on annual data with data available over the period $1967 - 2015$ and effective sample period $1968 - 2015$ (i.e., $T = 48$).

increases the current consumption to wealth ratio.

Figure 6 presents the fit of the regressions conducted for aggregate consumption growth using both measures of consumption. From the figure, we note that a low frequency downward evolution is present in these growth rates, in particular when expenditures on nondurables and services are used for consumption. This trend can be captured by our preferred baseline financial liberalization measure, i.e., the CEA index. The result that financial liberalization captures the structural decline in expected consumption growth over the sample period is in line with the findings of Carroll et al. (2019) who argue that liberalization explains the structural decline in the US saving rate. This is not surprising because looking at consumption growth is essentially another way of looking at saving, i.e., shifting consumption from today to tomorrow implies both higher saving and higher consumption growth (and vice versa).

To conclude, the evidence presented in this section suggests that financial liberalization negatively affects expected consumption growth. Since we find no evidence that liberalization exerts its influence through the expected returns on wealth, in the next section we argue in favor of an incomplete markets interpretation for the estimated positive impact of financial liberalization on the consumption-wealth ratio.

4.2 Interpretation of the channel

From the previous sections, we conclude that financial liberalization reduces expected future consumption growth, which, through the intertemporal budget constraint, has a positive impact on the current consumption-wealth ratio. The question remains as to how we can interpret the impact of liberalization on expected consumption growth. To answer this question, we decompose aggregate consumption growth into its distinct components. We argue that our results support an incomplete markets interpretation, i.e., liberalization reduces expected consumption growth because it increases market completeness.

Consider the following first-order condition for a utility-maximizing consumer who faces uncertainty about future labor income and returns as well as a potentially binding liquidity constraint, i.e.,

$$E_t\left(\delta(1+r_{t+1})\frac{U'(C_{t+1})}{U'(C_t)}\right)+\lambda_t=1 \tag{18}$$

where (as before) r_t denotes the real return on wealth and E_t is the expectations operator conditional on period t information and where $U(C_t)$ denotes utility as a function of the level of real consumption C_t, where δ reflects time preference, and where $\lambda_t \geq 0$ is the (normalized) Langrange multiplier associated with the liquidity constraint which is positive when the constraint is binding and zero when the constraint is not binding (see e.g., Zeldes, 1989). This equation can also be written as,

$$\left(\delta(1+r_{t+1})\frac{U'(C_{t+1})}{U'(C_t)}\right)=1-\lambda_t+\varepsilon_{t+1} \tag{19}$$

where ε_{t+1} is an expectation error uncorrelated with period t information, i.e., we have $E_t\varepsilon_{t+1}=0$. Using the isoelastic utility function $U(C)=\frac{C^{1-\theta}}{1-\theta}$ with coefficient of relative risk aversion $\theta>0$, we can rewrite eq.(19) as,

$$\left(\delta(1+r_{t+1})\frac{C_{t+1}^{-\theta}}{C_t^{-\theta}}\right)=1-\lambda_t+\varepsilon_{t+1} \tag{20}$$

After taking logs of both sides of this expression and solving for the growth rate in consumption Δc_{t+1}, we obtain,

$$\Delta c_{t+1}=\frac{1}{\theta}\ln\delta+\frac{1}{\theta}r_{t+1}+\frac{1}{\theta}\nu_{t+1} \tag{21}$$

where $\nu_{t+1}\equiv -\ln(1-\lambda_t+\varepsilon_{t+1})$. This term can be decomposed into an expected part $E_t\nu_{t+1}$ and an unexpected part $(\nu_{t+1}-E_t\nu_{t+1})$, after which we obtain,

$$\Delta c_{t+1}=\underbrace{\frac{1}{\theta}\ln\delta}_{\Delta c_{t+1}^{TP}}+\underbrace{\frac{1}{\theta}r_{t+1}}_{\Delta c_{t+1}^{IS}}+\underbrace{\frac{1}{\theta}E_t\nu_{t+1}}_{\Delta c_{t+1}^{IM}}+\underbrace{\frac{1}{\theta}[\nu_{t+1}-E_t\nu_{t+1}]}_{\Delta c_{t+1}^{NI}} \tag{22}$$

where Δc_{t+1}^{TP} denotes the consumption growth component related to time preference (TP) or impatience, Δc_{t+1}^{IS} denotes the consumption growth component related to intertemporal substitution (IS) in consumption with respect to changes in the rate of return on wealth, Δc_{t+1}^{IM} denotes the consumption growth component related to incomplete markets (IM), and Δc_{t+1}^{NI} denotes the consumption growth component related to the arrival of new information (NI).[16]

The incomplete markets component of consumption growth, i.e., the term $\Delta c_{t+1}^{IM} = E_t \nu_{t+1} = -E_t \ln(1-\lambda_t + \varepsilon_{t+1})$, is due to the presence of a precautionary saving motive and a liquidity constraint. These reduce period t consumption and augment period $t+1$ consumption, thereby raising consumption growth from t to $t+1$, i.e., we have $E_t \nu_{t+1} > 0$.[17]

Since Δc_{t+1}^{TP} is constant and Δc_{t+1}^{NI} is unpredictable, if financial liberalization has an impact on expected consumption growth, this impact must occur either through the intertemporal substitution component Δc_{t+1}^{IS} or through the incomplete markets component Δc_{t+1}^{IM}. In Section 4.1, we document that while financial liberalization has a negative impact on expected consumption growth, it does not have predictive power for returns over the sample period. It is therefore likely that the negative impact of financial liberalization on expected consumption growth occurs through the component Δc_{t+1}^{IM} rather than through the component Δc_{t+1}^{IS} which depends on returns. As liberalization lifts the restrictions that consumers face to transfer resources across time or across uncertain states of the world, the incomplete markets component $\Delta c_{t+1}^{IM} = E_t \nu_{t+1}$ falls which, in turn, reduces aggregate consumption growth Δc_{t+1}.[18]

5 Conclusions

Recent empirical evidence suggests that the consumption to total wealth ratio in the US is non-stationary. At the same time, findings in the literature indicate that the structural decline in the US saving rate, another important macroeconomic ratio, can be attributed to financial liberalization. Motivated by these results, we investigate the potential impact of liberalization on the trend in the consumption-wealth ratio. Financial liberalization is persistent and may signal changes in expected future consumption growth rates and/or in expected future rates of return on wealth that, through the intertemporal budget constraint, affect the current consumption-wealth ratio. We derive an estimable aggregate long-run relationship between consumption, total wealth and financial liberalization. Estimation using quarterly US data is conducted within a state space framework which allows us to reliably estimate the long-run relationship between the stochastically trended variables in the regression even in the presence of a

[16] See Parker and Preston (2005) for a similar decomposition of aggregate consumption growth in a heterogeneous agent setting.

[17] To see this, we suppress subscripts and note that $\ln(E(1-\lambda+\varepsilon)) = \ln(1-\lambda) \leq 0$ (this follows from $E(\varepsilon) = 0$, $E(\lambda) = \lambda$ and $\lambda \geq 0$). For the concave log function, we have that $\ln(E(.)) > E(\ln(.))$ so that $E(\ln(1-\lambda+\varepsilon)) < 0$ and $-E(\ln(1-\lambda+\varepsilon)) > 0$.

[18] To see, for example, how the relaxation of the liquidity constraint due to liberalization improves market completeness, note that the derivative of Δc_{t+1}^{IM} with respect to λ_t (where $\lambda_t \geq 0$ is the Langrange multiplier associated with the liquidity constraint) is positive, i.e., a decrease in λ_t - a less binding constraint - implies a decrease in Δc_{t+1}^{IM} and therefore in Δc_{t+1}.

non-stationary error term. We find that our baseline financial liberalization indicator, i.e., the 'credit easing accumulated' (CEA) index, adequately captures the trend in the estimated consumption-wealth ratio. Moreover, we find that the increase in this indicator over the sample period has increased the consumption-wealth ratio with about ten percent. These findings survive several robustness checks. We attribute the positive impact of financial liberalization on the consumption-wealth ratio to the negative effect of liberalization on expected future consumption growth. In particular, our estimates point towards an incomplete markets interpretation of the link between liberalization and the consumption-wealth ratio, i.e., liberalization signals improved possibilities to smooth consumption over time and across states of the world and therefore reduces the incomplete markets component in expected consumption growth. Through the intertemporal budget constraint, this reduction in expected future consumption growth increases the current consumption-wealth ratio.

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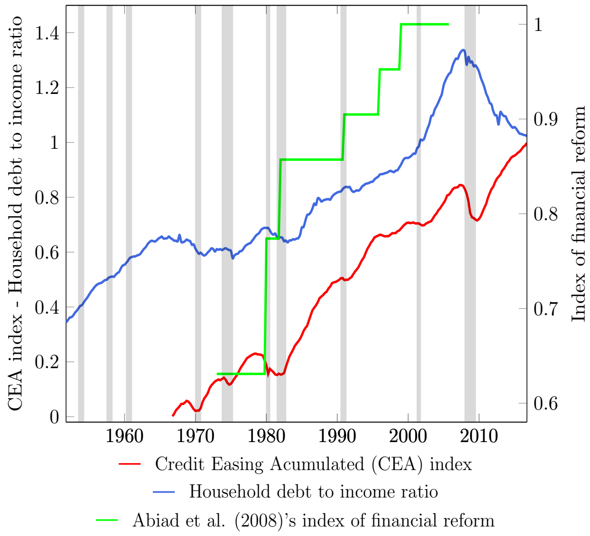
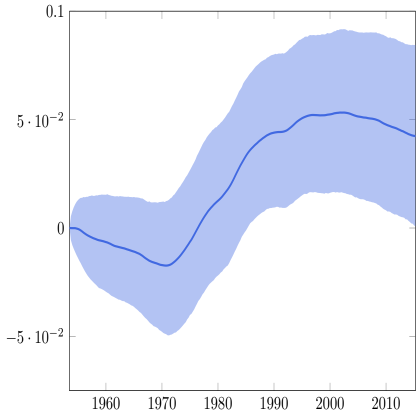
Figure 1: Indices of financial liberalization



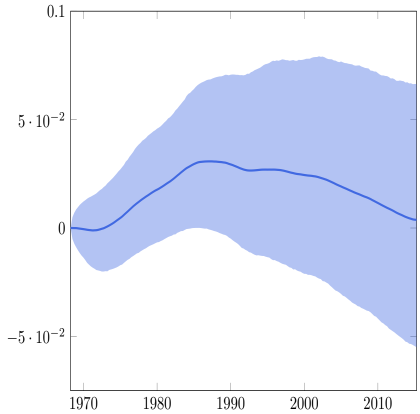
Notes: Depicted are the CEA index (period $1966Q3 - 2016Q4$), the household debt to income ratio (period $1951Q4 - 2016Q4$) and Abiad et al. (2008)'s index of financial reform (period $1973Q1 - 2005Q4$). The grey shaded areas are the NBER recessions. Details on the construction of these indices are provided in Appendix B.

Figure 2: The unobserved stochastic trend in the model without and with financial liberalization

(a) Without financial liberalization



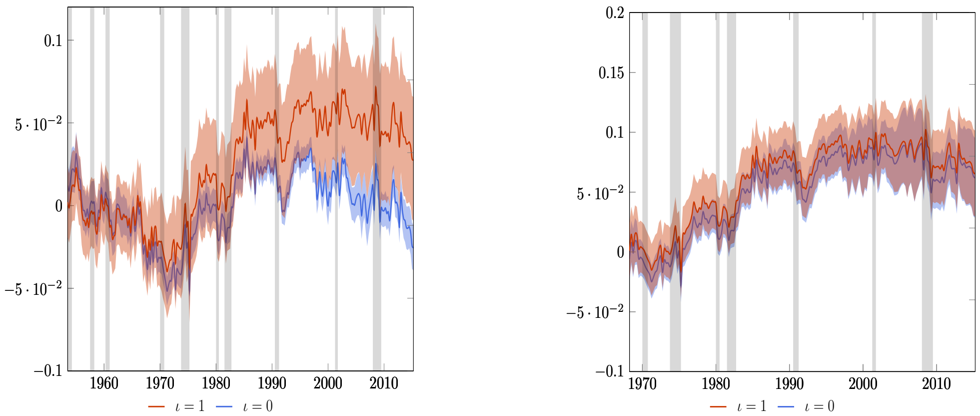
(b) With financial liberalization



Note: Depicted is the posterior mean and the 90% HPD interval (shaded area) of the estimated component $\sigma_\eta \mu_t^*$. This is obtained from the estimation of equation $c_t = \alpha a_t + \beta y_t + \gamma f l_t + \mu + \iota \sigma_\eta \mu_t^* + v_t$ where the case without financial liberalization is obtained under the restriction $\gamma = 0$ and where the case with financial liberalization uses the CEA index for fl_t. Estimation in both instances occurs under the restriction $\iota = 1$. As $\mu_t^* = \mu_{t-1}^* + \eta_t^*$ and $\mu_0^* = 0$, $\sigma_\eta \mu_t^*$ is initialized at zero. The corresponding parameter estimates are reported in Table 3 (column 2) for the case without financial liberalization and in Table 4 (column 2) for the case with financial liberalization. The effective sample periods are $1953Q3 - 2015Q2$ (case without liberalization) and $1968Q2 - 2015Q2$ (case with liberalization).

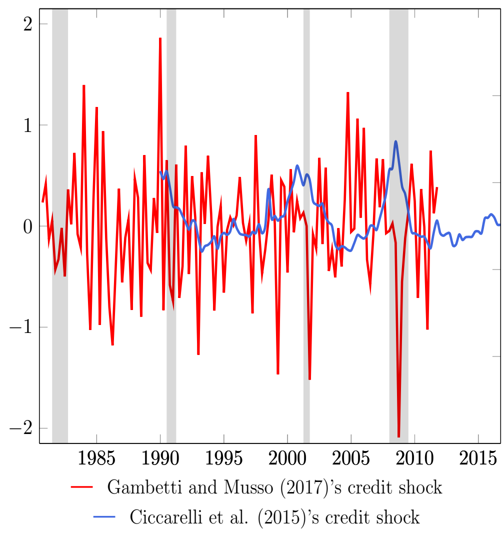
Figure 3: The log consumption-wealth ratio in the model without and with financial liberalization

(a) Without financial liberalization **(b)** With financial liberalization



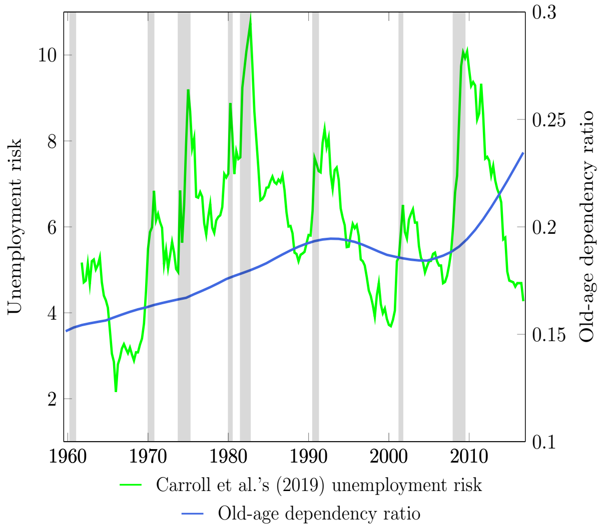
Note: Depicted is the posterior mean and the 90% HPD interval (shaded area) of the calculated log consumption-wealth ratio $c_t - \mu - \alpha a_t - \beta y_t$. This is obtained from the estimation of equation $c_t = \alpha a_t + \beta y_t + \gamma f l_t + \mu + \iota \sigma_\eta \mu_t^* + v_t$ where the case without financial liberalization is obtained under the restriction $\gamma = 0$ and where the case with financial liberalization uses the CEA index for fl_t. For the model with an unobserved stochastic trend included ($\iota = 1$), the ratio is printed in red, while for the model without an unobserved stochastic trend included ($\iota = 0$), the ratio is printed in blue. The corresponding parameter estimates are reported in Table 3 (columns 1 and 2) for the case without financial liberalization and in Table 4 (columns 1 and 2) for the case with financial liberalization. The grey shaded areas are the NBER recessions. The effective sample periods are $1953Q3 - 2015Q2$ (case without liberalization) and $1968Q2 - 2015Q2$ (case with liberalization).

Figure 4: Credit shocks



Notes: Depicted are Gambetti and Musso (2017)'s loan supply shock (period $1980Q4 - 2011Q4$) and Ciccarelli et al. (2015)'s lending standard shock for the broad credit channel (period $1990Q1 - 2016Q4$). The latter is the reported one divided by 100. The grey shaded areas are the NBER recessions. Details on these shocks are provided in Appendix B.

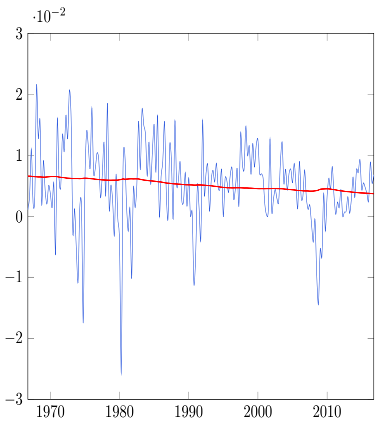
Figure 5: Alternative theories: unemployment risk and demographics



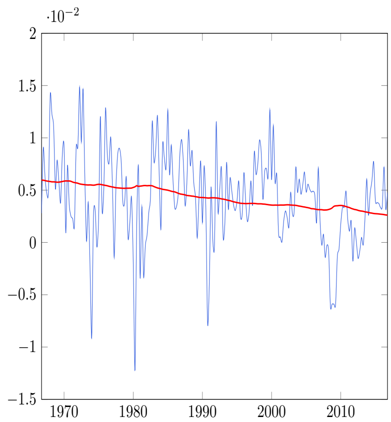
Notes: Depicted are Carroll et al. (2019)'s unemployment risk indicator (period $1961Q4 - 2016Q4$) and the old-age dependency ratio measured as the share of total population above 65 years (period $1959Q4 - 2016Q4$). The grey shaded areas are the NBER recessions. Details on these variables are provided in Appendix B.

Figure 6: Fit regression of aggregate consumption growth on the lagged CEA index of financial liberalization

(a) Per capita real personal consumer expenditures for c_t



(b) Per capita real expenditures on nondurables and services for c_t



Note: Depicted is actual aggregate consumption growth Δc_{t+1} (blue line) and the fitted value of the regression $\psi_0^{\Delta c} + \psi_1^{\Delta c} fl_t$ (red line) where the CEA index is used as a measure of financial liberalization. Details on the consumption data (total personal consumer expenditures and expenditures on nondurables and services) are provided in Appendix B. The effective sample period is $1966Q4 - 2016Q4$.

Online Appendix

"Aggregate consumption and wealth in the long run: the impact of financial liberalization"

by Malin Gardberg and Lorenzo Pozzi

Appendix A Derivation of equation (1)

This appendix briefly describes the steps in the derivation of eq.(1) in Section 2. For more details, we refer to Campbell and Mankiw (1989). We can write the per period constraint $W_{t+1} = (1+r_{t+1})(W_t - C_t)$ as $\frac{W_{t+1}}{W_t} = (1+r_{t+1})\left(1 - \frac{C_t}{W_t}\right)$. After taking logs, this gives $\Delta w_{t+1} = r_{t+1} + \ln\left(1 - \exp(c_t - w_t)\right)$ with $w_t = \ln W_t$ and $c_t = \ln C_t$. We linearize this equation through a first-order Taylor approximation which gives,

$$\Delta w_{t+1} = r_{t+1} + \left(1 - \frac{1}{\rho}\right)(c_t - w_t) \tag{A-1}$$

where we ignore the unimportant linearization constant and where $\rho = \frac{W-C}{W}$ with $0 < \rho < 1$ and with W and C the steady state values of W_t and C_t.[1] We note that ρ is expected to be close to one. Further, we can write Δw_{t+1} as $\Delta w_{t+1} = \Delta c_{t+1} + (c_t - w_t) - (c_{t+1} - w_{t+1})$. Upon combining this result with equation (A-1) and rearranging terms, we obtain,

$$c_t - w_t = \rho(r_{t+1} - \Delta c_{t+1}) + \rho(c_{t+1} - w_{t+1}) \tag{A-2}$$

Solving equation (A-2) forward ad infinitum, taking expectations at period t, and imposing the transversality condition $\rho^{\infty} E_t(c_{t+\infty} - w_{t+\infty}) = 0$ then gives eq.(1) in the text.

Appendix B Data

B.1 Data for the consumption, labor income and asset variables c_t, y_t and a_t

We collect data for the period $1951Q4 - 2016Q4$. Quarterly seasonally adjusted data for consumption, disposable labor income, population and the price deflator are collected from the National Income and Product Accounts (NIPA) from the Bureau of Economic Analysis (BEA) at the US Department of Commerce. The assets (financial wealth) data are collected from the Flow of Funds Accounts of the Board of Governors of the Federal Reserve System.

Consumption is measured as total personal consumption expenditures (line 1 of NIPA Table 2.3.5). Consumption on nondurable goods and services is defined as nondurable goods expenditure (line 8 of

[1] The linearization occurs around the point $c_t - w_t = c - w$ with $c - w = \ln\left(\frac{C}{W}\right)$.

NIPA Table 2.3.5) minus clothing and footwear (line 10 of NIPA Table 2.3.5) plus services expenditures (line 13 of NIPA Table 2.3.5), with the sampling mean matching the sampling mean of total personal consumption expenditures.

Disposable labor income is calculated as the sum of compensation for employees (line 2 of NIPA Table 2.1) plus personal current transfer receipts (line 16) minus contributions for domestic government social insurance (line 25) and minus personal labor taxes. Personal labor taxes are derived by first calculating the labor income fraction of total income, and subsequently using this ratio to back out the share of labor taxes from the total personal current taxes (line 26). The labor income to total income ratio is defined as the ratio of wages and salaries (line 3) to the sum of wages and salaries (line 3), proprietors' income (line 9), rental income (line 12) and personal income receipts on assets (line 13).

Asset wealth is calculated as the net worth of households and nonprofit organizations (including consumer durables).

All calculated series except the nondurable goods and services consumption are deflated with the price index for total personal consumption expenditures (line 1 of NIPA Table 2.3.4). The price index used to deflate the nondurable goods and services consumption measure is based on the price developments of the nondurable goods (excl. clothing and footwear) and services (i.e., the ratio of nominal to real nondurable goods and services). The base year is 2009 = 100 for both deflators. The variables are further expressed in per capita terms using population data collected from the NIPA (line 40 of Table 2.1).

B.2 Data for the financial liberalization variable fl_t

The baseline indicator used for the financial liberalization variable is the 'credit easing accumulated' or CEA index (see Carroll et al., 2019). This index can be calculated over the period $1966Q3 - 2016Q4$. It is based on the question from the Senior Loan Officer Opinion Survey (SLOOS) on bank lending practices, i.e., it asks whether domestic US banks are more willing to make consumer installment loans now as opposed to three months ago. The survey scores are accumulated after being weighted using the household debt to personal disposable income ratio (see below for its construction) and then normalized to lie between zero and one.

A second variable used to measure financial liberalization is the household debt to personal disposable income ratio. This ratio can be calculated for the period $1951Q4 - 2016Q4$. Quarterly seasonally adjusted nominal personal disposable income is taken from the NIPA (line 27 of NIPA Table 2.1). Quarterly seasonally adjusted nominal liabilities of households and nonprofit organizations are taken from the FRED database (Federal Reserve Bank of St.Louis).

A third proxy for financial liberalization is Abiad et al. (2008)'s index of financial reform. This index covers the period $1973Q1 - 2005Q4$. It is available at the annual frequency but we construct a quarterly series by allocating the value for a given year to every quarter in that year. It includes seven different dimensions of financial sector policy: credit controls and reserve requirements, interest rate controls, entry barriers, state ownership, policies on securities markets, banking regulations and restrictions on the capital account. Liberalization scores for each category are combined in a graded index which lies between zero and one.

B.3 Data for returns r_t

Stock and bond returns data are taken from the Center for Research in Security Prices (CRSP) collected via Wharton Research Data Services (WRDS). Stock returns are calculated from the value-weighted CRSP index. Government bond returns are calculated from the 10-year government bond index. Housing returns are taken from Jordà et al. (2019) and are available only at an annual frequency. Housing returns are defined as housing capital gains plus imputed rents to owners and renters. All returns are deflated using the inflation rate as calculated from the price index for total personal consumption expenditures (line 1 of NIPA Table 2.3.4).

B.4 Other data

Loan supply shocks for the US are estimated by Gambetti and Musso (2017)[2], who apply a time-varying parameter VAR model with stochastic volatility and identify the loan supply shocks with sign restrictions. The measure is available over the period $1980Q4 - 2011Q4$.

The lending standard shock for the US is calculated as the broad credit channel measure in Ciccarelli et al. (2015). The measure is based on the question from the Senior Loan Officer Opinion Survey (SLOOS) on bank lending practices, and is the net percentage of domestic banks tightening standards for commercial and industrial (C&I) loans to large and middle-market firms. The lending standard shock is available over the period $1990Q1 - 2016Q4$.

The measure for unemployment risk is calculated as in Carroll et al. (2019) and is available for the period $1961Q4 - 2016Q4$. The unemployment risk measure, i.e., the expected change in unemployment four quarters ahead, is based on re-scaled answers to the question regarding the expected change in unemployment during the next year in the University of Michigan Surveys of Consumers. More precisely, the expected change in unemployment four quarters ahead, $E_t u_{t+4}$, is estimated using fitted values of the unemployment change from the regression of the change in unemployment four quarters ahead ($\Delta_4 u_{t+4}$) on the survey answers on unemployment expectations ($UExp_t$). Thus, $\Delta_4 u_{t+4} = \alpha_0 + \alpha_1 UExp_t + \varepsilon_{t+4}$

[2]We thank Alberto Musso for providing the series to us.

and $E_t u_{t+4} = u_t + \Delta_4 \hat{u}_{t+4}$, where $\Delta_4 u_{t+4} = u_{t+4} - u_t$.

The old-age dependency ratio is defined as the older dependents in the US in percent of the US working-age population. The data are available at the annual frequency, and have been linearly interpolated to quarterly observations. The data are taken from the FRED database (Federal Reserve Bank of St.Louis) and are available over the period $1959Q4 - 2016Q4$.

Appendix C Frequentist unit root test on 'cay'

This appendix reports the results of a frequentist augmented Dickey-Fuller unit root test applied to the 'cay' variable. This variable is considered both over the sample period $1951Q4 - 2016Q4$ and over the shorter period $1966Q3 - 2016Q4$ over which our baseline financial liberalization indicator, i.e., the CEA index, is also available. The 'cay' variable is taken from Martin Lettau's website.[3] It is calculated according to the methodology described in Lettau and Ludvigson (2001) with an update on the data used in its construction detailed in Lettau and Ludvigson (2015), i.e., for consumption, total personal consumption expenditures are used instead of expenditures on nondurables and services. These data correspond fully with the consumption data that we use in the estimations reported in Section 3 in the main text. Table C-1 reports the Dickey-Fuller t-statistics for different lags included in the augmented Dickey-Fuller regression - with the case for which the number of lags is optimal denoted by an asterisk - along with the appropriate 5% and 10% critical values. In none of the reported cases, the null hypothesis of a unit root in the 'cay' variable can be rejected. This is in line with results reported previously in the literature (see Bianchi et al., 2018) and with the results from our Bayesian model selection approach that suggest that the posterior probability that there is an unobserved random walk component in the standard regression of consumption on asset wealth and labor income (i.e., in the model without financial liberalization) equals one (see Table 2 in the main text).

[3]See https://sites.google.com/view/martinlettau/data.

Table C-1: Augmented Dickey-Fuller test on 'cay'

	Dickey-Fuller t-statistic					Critical values	
	Lag=0	Lag=1	Lag=2	Lag=3	Lag=4	5%	10%
Period $1951Q4 - 2016Q4$	-3.35	-2.58*	-2.42	-2.37	-2.18	-3.77	-3.48
Period $1966Q3 - 2016Q4$	-2.80	-2.00*	-1.93	-1.78	-1.72	-3.78	-3.48

Notes: The augmented Dickey-Fuller statistic tests the null hypothesis of a unit root. The Dickey-Fuller t-statistic is obtained from an augmented Dickey Fuller regression applied to cay with the number of lagged first differences included in the regression going from 0 to 4. * denotes the t-statistic obtained for the optimal number of lags based on the Bayesian information criterion. The 5% and 10% critical values are taken from MacKinnon (2010), i.e., Table 2 in the Appendix (2010 version) for N=3 as 'cay' is calculated from a cointegrating regression involving three integrated variables. The 'cay' variable is taken from Martin Lettau's website https://sites.google.com/view/martinlettau/data and calculated according to the methodology described in Lettau and Ludvigson (2001) with an update on the data used in its construction detailed in Lettau and Ludvigson (2015) (i.e., the use of personal consumption expenditures instead of nondurables and services). The $1966Q3 - 2016Q4$ period is the period over which the CEA indicator of financial liberalization is available. The effective sample periods are reduced due to the use of first differences and lags.

Appendix D Estimation details state space model of Section 3

This appendix discusses the estimation of the state space system given by eqs.(10)-(15). First, we present the general outline of the Gibbs sampler in Section D.1. Then, the technical details about the different steps of the sampler are discussed in Section D.2. Finally, a convergence analysis is provided in Section D.3.

D.1 General outline

We collect the constant parameters in a vector Γ, i.e., $\Gamma = (\iota, \phi, \kappa, \mu, \sigma_\eta, \sigma_e^2)$. The Gibbs approach allows us to simulate draws from the intractable joint posterior distribution of parameters Γ and state μ^*, i.e., $f(\Gamma, \mu^*|data)$, using only tractable conditional distributions. In particular, given the prior distribution of the parameter vector $f(\Gamma)$ and an initial draw for μ^* taken from its prior distribution, the following steps are implemented:

1. Sample the constant parameters Γ conditional on the unobserved state μ^* and the data
   (a) Sample the binary indicator ι marginalizing over the parameter σ_η for which variable selection is carried out (see Frühwirth-Schnatter and Wagner, 2010).
   (b) If $\iota = 1$, sample the parameters ϕ, κ, μ, σ_η, σ_e^2. If $\iota = 0$, sample the parameters ϕ, κ, μ and σ_e^2. In the latter case, we set $\sigma_\eta = 0$.
2. Sample the unobserved state μ^* conditional on the constant parameters Γ and the data. To this

end, if $\iota = 1$, we use the multimove sampler for state space models of Carter and Kohn (1994)(see also Kim and Nelson, 1999). If $\iota = 0$, we draw μ^* from its prior distribution.

These steps are iterated 30.000 times and in each iteration Γ and μ^* are sampled. Given 10.000 burn-in draws, the reported results are all based on posterior distributions constructed from 20.000 retained draws. From the distribution of the binary indicator ι, we calculate the posterior probability that there is an unobserved stochastic trend in regression eq.(10) as the fraction of ι's that are equal to 1 over the 20.000 retained draws of the Gibbs sampler.

D.2 Details on the steps of the sampler

D.2.1 Regression framework

The parameters contained in Γ can be sampled from a standard regression model,

$$Z = X^r \zeta^r + \varphi \tag{D-1}$$

where Z is a $T \times 1$ vector containing T observations on the dependent variable, X is a $T \times M$ matrix containing T observations of M predictor variables, ζ is the $M \times 1$ parameter vector and φ is the $T \times 1$ vector of error terms for which $\varphi \sim iid\mathcal{N}\left(0, \sigma_\varphi^2 I_T\right)$. If the binary indicators ι equal 1, then the parameter vector ζ^r and the corresponding predictor matrix X^r are equal to the unrestricted ζ, respectively X. Otherwise, the restricted ζ^r and X^r exclude those elements in X and ζ for which the corresponding binary indicators ι equal 0. The prior distribution of ζ^r is given by $\zeta^r \sim \mathcal{N}\left(b_0^r, B_0^r \sigma_\varphi^2\right)$ with b_0^r a $M^r \times 1$ vector and B_0^r a $M^r \times M^r$ matrix. The prior distribution of σ_φ^2 is given by $\sigma_\varphi^2 \sim \mathcal{IG}\left(s_0, S_0\right)$ with scalars s_0 (shape) and S_0 (scale). The posterior distributions (conditional on Z, X^r, and ι) of ζ^r and σ_φ^2 are then given by $\zeta^r \sim \mathcal{N}\left(b^r, B^r \sigma_\varphi^2\right)$ and $\sigma_\varphi^2 \sim \mathcal{IG}\left(s, S^r\right)$ with,

$$\begin{aligned}
B^r &= \left[(X^r)' X^r + (B_0^r)^{-1}\right]^{-1} \\
b^r &= B^r \left[(X^r)' Z + (B_0^r)^{-1} b_0^r\right] \\
s &= s_0 + T/2 \\
S^r &= S_0 + \frac{1}{2}\left[Z'Z + (b_0^r)'(B_0^r)^{-1} b_0^r - (b^r)'(B^r)^{-1} b^r\right]
\end{aligned} \tag{D-2}$$

The posterior distribution of the binary indicators ι is obtained from Bayes' theorem as,

$$p(\iota | Z, X, \sigma_\varphi^2) \propto p(Z | \iota, X, \sigma_\varphi^2) p(\iota) \tag{D-3}$$

where $p(\iota)$ is the prior distribution of ι and $p(Z|\iota, X, \sigma_\varphi^2)$ is the marginal likelihood of regression eq.(D-1) where the effect of the parameters ζ has been integrated out. We refer to Frühwirth-Schnatter and Wagner (2010) (their eq.(25)) for the closed-form expression of the marginal likelihood for the regression model of eq.(D-1).

Sample the binary indicator ι

There is one binary indicator ι in our model which we sample by calculating the marginal likelihoods $p(Z|\iota = 1, X, \sigma_\varphi^2)$ and $p(Z|\iota = 0, X, \sigma_\varphi^2)$ (see Frühwirth-Schnatter and Wagner, 2010, for the correct expressions). Upon combining the marginal likelihoods with the Bernoulli prior distributions of the binary indicators $p(\iota = 1) = p_0$ and $p(\iota = 0) = 1 - p_0$, the posterior distributions $p(\iota = 1|Z, X, \sigma_\varphi^2)$ and $p(\iota = 0|Z, X, \sigma_\varphi^2)$ are obtained from which the probability $prob(\iota = 1|Z, X, \sigma_\varphi^2) = \frac{p(\iota=1|Z,X,\sigma_\varphi^2)}{p(\iota=1|Z,X,\sigma_\varphi^2)+p(\iota=0|Z,X,\sigma_\varphi^2)}$ is calculated which is used to sample ι, i.e., draw a random number r from a uniform distribution with support between 0 and 1 and set $\iota = 1$ if $r < prob(.)$ and $\iota = 0$ if $r > prob(.)$.

Sample the other parameters in Γ

We then sample the regression coefficients ϕ, κ, μ and σ_η and the regression error variance σ_e^2 conditional on ι, the data and the unobserved component μ_t^*. The dependent variable is $Z = c$ where c is the $T \times 1$ vector containing consumption c_t stacked over time while the error term is $\varphi = e$ with e containing e_t stacked over time and where the variance is given by $\sigma_\varphi^2 = \sigma_e^2$. When $\iota = 1$, we have $X^r = X = \begin{bmatrix} x & \Delta x_{-p} & ... & \Delta x_{+p} & \varrho & \mu^* \end{bmatrix}$ and $\zeta^r = \zeta = \begin{bmatrix} \phi' & \kappa'_{-p} & ... & \kappa'_{+p} & \mu & \sigma_\eta \end{bmatrix}'$ where ϱ is a $T \times 1$ vector of ones and μ^* is a $T \times 1$ vector containing μ_t^* stacked over time. We note that x and every Δx_j (for $j = -p ... + p$) are $T \times k$ matrices where either $k = 2$ (model without financial liberalization), $k = 3$ (model with financial liberalization or model based on another theory as discussed in Section 3.4.4) or $k = 4$ (model with financial liberalization and another trended variable as discussed in Section 3.4.2). Then, ϕ and every κ_j are $k \times 1$ vectors and we have $M = k(2p + 2) + 2$. When $\iota = 0$, we have $X^r = \begin{bmatrix} x & \Delta x_{-p} & ... & \Delta x_{+p} & \varrho \end{bmatrix}$ and $\zeta^r = \begin{bmatrix} \phi' & \kappa'_{-p} & ... & \kappa'_{+p} & \mu \end{bmatrix}'$ (and σ_η is set to zero). In this case, we have $M^r = k(2p + 2) + 1$. Once the matrices of eq.(D-1) are determined, the parameters ζ^r and σ_φ^2 can be sampled from the posterior distributions given above with the prior distributions as specified in Table 1 in the text.[4]

D.2.2 State space framework

If $\iota = 0$, the unobserved component is drawn from its prior distribution. In particular, μ_t^* is drawn from eq.(13), i.e., as a cumulative sum of standard normally distributed shocks η_t^* so $\mu_t^* = \sum_{s=1}^{t} \eta_s^*$. If $\iota = 1$, the unobserved component μ_t^* is sampled conditional on the constant parameters and on the data using a state space approach. In particular, we use the forward-filtering backward-sampling approach discussed in detail in Kim and Nelson (1999) to sample the unobserved state. The general form of the state space

[4] We note that $s_0 = \nu_0 T$ and $S_0 = \nu_0 T \sigma_0^2$ with the values for ν_0 and σ_0^2 given in Table 1. We note that b_0^r is a $M^r \times 1$ vector containing the values of b_0 given in Table 1. Further, B_0^r is an $M^r \times M^r$ diagonal matrix containing as elements the variances 1 - i.e., the variable V_0 in Table 1 - divided by the prior belief for σ_e^2 - i.e., the variable σ_0^2 in Table 1.

model is given by,

$$Y_t = AS_t + V_t, \qquad V_t \sim iid\mathcal{N}(0, H), \tag{D-4}$$

$$S_t = BS_{t-1} + KE_t, \qquad E_t \sim iid\mathcal{N}(0, Q), \tag{D-5}$$

$$S_0 \sim iid\mathcal{N}(s_0, P_0), \tag{D-6}$$

(where $t = 1, ..., T$) with observation vector Y_t $(n \times 1)$, state vector S_t $(n^s \times 1)$, error vectors V_t $(n \times 1)$ and E_t $(n^{ss} \times 1$ with $n^{ss} \leq n^s)$ that are assumed to be serially uncorrelated and independent of each other, and with the system matrices that are assumed to be known (conditioned upon) namely A $(n \times n^s)$, B $(n^s \times n^s)$, K $(n^s \times n^{ss})$, H $(n \times n)$, Q $(n^{ss} \times n^{ss})$ and the mean s_0 $(n^s \times 1)$ and variance P_0 $(n^s \times n^s)$ of the initial state vector S_0. As eqs. (D-4)-(D-6) constitute a linear Gaussian state space model, the unknown state variables in S_t can be filtered using the standard Kalman filter. Sampling $S = [S_1, \ldots, S_T]$ from its conditional distribution can then be done using the multimove Gibbs sampler of Carter and Kohn (1994). Given our state space system presented in eqs.(10)-(15), we have $n = n^s = n^{ss} = 1$. The matrices are then given by $Y_t = c_t - x_t\phi - \mu - \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j$, $A = \sigma_\eta$, $S_t = \mu_t^*$, $V_t = e_t$, $H = \sigma_e^2$, $B = 1$, $K = 1$, $E_t = \eta_t^*$, $Q = 1$. Moreover, we have $s_0 = \mu_0^* = 0$ and $P_0 = 10^{-6}$, i.e., the initial state is fixed at zero.

D.3 Convergence analysis

We analyse the convergence of the MCMC sampler using the simulation inefficiency factors as proposed by Kim et al. (1998) and the convergence diagnostic of Geweke (1992) for equality of means across subsamples of draws from the Markov chain (see Groen et al., 2013, for a similar convergence analysis).

For each fixed parameter and for every point-in-time estimate of the unobserved component, we calculate the inefficiency factor as $IF = 1 + 2\sum_{l=1}^{m} \kappa(l, m)\widehat{\theta}(l)$ where $\widehat{\theta}(l)$ is the estimated the l-th order autocorrelation of the chain of retained draws and $\kappa(l, m)$ is the kernel used to weigh the autocorrelations. We use a Bartlett kernel with bandwidth m, i.e., $\kappa(l, m) = 1 - \frac{l}{m+1}$, where we set m equal to 4% of the 20.000 retained sampler draws (see Section D.1 above). If we assume that d draws are sufficient to cover the posterior distribution in the ideal case where draws from the Markov chain are fully independent, then $d \times IF$ provides an indication of the minimum number of draws that are necessary to cover the posterior distribution when the draws are not independent. Usually, d is set to 100. Then, for example, an inefficiency factor equal to 20 suggests that we need at least 2.000 draws from the sampler for a reasonably accurate analysis of the parameter of interest. Additionally, we also compute the p-values of the Geweke (1992) test which tests the null hypothesis of equality of the means of the first 40% and last 40% of the retained draws obtained from the sampler for each fixed parameter and for every point-in-time estimate of the unobserved component. The variances of the respective means are calculated using the

Newey and West (1987) robust variance estimator using a Bartlett kernel with bandwidth equal to 4% of the respective sample sizes (i.e., the first 40% and the last 40%).

In Table D-1, we present the convergence analysis corresponding to the results reported in the first two columns of Table 3 and in Table 4. The convergence results are reported for individual parameters or for groups of parameters. Groups are considered when the parameters can be meaningfully grouped which is the case for the k parameters in ϕ (with $k = 2$ or $k = 3$ depending on whether $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ or $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$), for the $k \times (p+1)$ parameters κ of the DOLS specification of the stationary component v_t (where, given $p = 6$, we have 26 or 39 parameters depending again on whether $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ or $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$), and for the unobserved component μ which is a constant when $\iota = 0$ or a state when $\iota = 1$. In the latter case, it is a time series of either length $T = 189$ (model with liberalization estimated over the period $1966Q3 - 2016Q4$) or $T = 248$ (model without liberalization estimated over the period $1951Q4 - 2016Q4$). We report statistics of the distributions of the inefficiency factors for every parameter or parameter group, i.e., median, minimum, maximum, and - for μ when it is a state - the 5% and 10% quantiles. Obviously, these statistics are identical for the non-grouped parameters. The tables also report the rejection rates of the Geweke tests conducted both at the 5% and 10% levels of significance. These rates are equal to the number of rejections of the null hypothesis of the test per parameter group divided by the number of parameters in a parameter group. These rates can only be zero or one for individual (non-grouped) parameters but can lie between zero and one for the grouped parameters.

Table D-1: Inefficiency factors and convergence diagnostics for the results of Table 3 (first two columns) and Table 4

				Inefficiency factors (Stats distribution)					Convergence (Rejection rates)	
Model	Trend	Parameters	Number	Median	Min	Max	5%	10%	5%	10%
Without fl_t ($\gamma = 0$)	$\iota = 0$	ϕ	2	1.26	1.23	1.28	-	-	0.00	0.00
		σ_e^2	1	1.02	1.02	1.02	-	-	0.00	0.00
		κ	26	0.97	0.81	1.10	-	-	0.00	0.08
		μ	1	1.10	1.10	1.10	-	-	0.00	0.00
	$\iota = 1$	ϕ	2	10.32	8.52	12.13	-	-	0.00	0.00
		σ_e^2	1	1.11	1.11	1.11	-	-	0.00	0.00
		κ	26	1.04	0.80	1.21	-	-	0.04	0.11
		μ	248	10.89	8.32	11.51	9.21	11.41	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	6.34	6.34	6.34	-	-	0.00	0.00
With fl_t ($\gamma \neq 0$)	$\iota = 0$	ϕ	3	1.32	1.13	1.36	-	-	0.00	0.00
		σ_e^2	1	1.01	1.01	1.01	-	-	0.00	0.00
		κ	39	0.96	0.75	1.16	-	-	0.02	0.08
		μ	1	1.10	1.10	1.10	-	-	0.00	0.00
	$\iota = 1$	ϕ	3	1.77	1.68	14.99	-	-	0.00	0.00
		σ_e^2	1	1.05	1.05	1.05	-	-	0.00	0.00
		κ	39	0.98	0.76	1.16	-	-	0.00	0.10
		μ	189	1.84	1.12	2.61	1.19	2.59	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	1.41	1.41	1.41	-	-	0.00	0.00

Notes: The convergence analysis in the upper half of the table corresponds to the results reported in the first two columns of Table 3 while the analysis in the lower half of the table corresponds to the results reported in Table 4. The statistics of the distribution of the inefficiency factors are presented in columns 5 to 9 for every parameter or group of parameters. These statistics are identical when parameters are considered individually as only one inefficiency factor is calculated in these cases. The inefficiency factors are calculated for every fixed parameter and for every point-in-time estimate of the unobserved component using a Bartlett kernel with bandwidth equal to 4% of the 20.000 retained sampler draws. The rejection rates of the Geweke (1992) test conducted at the 5% and 10% levels of significance are reported in columns 10 and 11. These rates are equal to the number of rejections of the null hypothesis of the test per parameter group divided by the number of parameters in a parameter group. These rates are either zero or one for parameters that are considered individually. They are based on the p-value of the Geweke test of the hypothesis of equal means across the first 40% and last 40% of the 20.000 retained draws which is calculated for every fixed parameter and for every point-in-time estimate of the unobserved component. The variances of the respective means in the Geweke (1992) test are calculated with the Newey and West (1987) robust variance estimator using a Bartlett kernel with bandwidth equal to 4% of the respective sample sizes (i.e., the first 40% and the last 40%).

The calculated inefficiency factors suggest that the MCMC sampler performs well and that all parameters have well converged using our retained 20.000 draws. In fact, an accurate analysis using inefficiency factors could have been conducted with far less than 20.000 draws. From Table D-1, we note that more draws of the parameters/states ϕ and μ are required when the unobserved random walk component is included in the model and estimated, i.e., when $\iota = 1$ as compared to $\iota = 0$. This is especially the case in the model without financial liberalization (i.e., when $\gamma = 0$). From the text above, we know that the unobserved stochastic trend is much more relevant in this case. Our findings for the inefficiency factors are corroborated by the results for the Geweke (1992) test for equality of means across subsamples of the retained draws. The rejection rates reported in the tables are, with few exceptions, very close to or equal to zero and therefore strongly suggest that the means of the first 40% and last 40% of the retained draws are equal. Hence, in general, we can conclude that the convergence of the sampler for the retained number of draws is satisfactory.

Appendix E Additional results and robustness checks

E.1 Other theories: uncertainty and demographics

In this appendix, we investigate whether alternative trended variables such as uncertainty or demographics have an impact on the consumption-wealth ratio. We use Carroll et al. (2019)'s unemployment risk measure to proxy for uncertainty, and the old-age dependency ratio to reflect the trend in demographics. As discussed in Section 3.4.4 in the main text, based both on a priori considerations and on explicit testing, we find that these variables cannot explain the stochastic trend in the consumption-wealth ratio.

In Table E-1, we present the estimated coefficients of the long-run regressions between consumption, asset wealth, labor income and either Carroll et al. (2019)'s unemployment risk measure or the old-age dependency ratio. The table reports both the case without and with a stochastic trend included in the regression error, i.e., for $\iota = 0$ and for $\iota = 1$. As the posterior inclusion probabilities of an unobserved stochastic trend in the regression error are equal to one for both models (see Table 2 in the main text), the preferred models are those with an unobserved component, i.e., where $\iota = 1$. The HPD intervals for γ, which captures the impact of unemployment risk or the old-age dependency ratio on the consumption-wealth ratio, include zero in both models. Thus, we do not find evidence of a long-run impact of either uncertainty or demographics on the consumption-wealth ratio.

Table E-1: Model with unemployment risk and the old-age dependency ratio to capture the trend in $c_t - w_t$: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma trend_t + \mu_t + v_t$

	Unemployment risk		Old-age dependency ratio	
	(1)	(2)	(3)	(4)
	$\iota = 0$	$\iota = 1$	$\iota = 0$	$\iota = 1$
α	0.2338	0.1972	0.2218	0.2109
	[0.1337,0.3311]	[0.0881,0.3046]	[0.1509,0.2902]	[0.1199,0.3003]
β	0.7899	0.7832	0.8017	0.7667
	[0.6661,0.9160]	[0.6518,0.9166]	[0.7185,0.8877]	[0.6582,0.8772]
γ	0.0017	-0.0007	0.1677	0.0183
	[-0.0046,0.0079]	[-0.0086,0.0070]	[-0.0780,0.4057]	[-0.2193,0.2512]
μ	-0.5183	-0.0479	-0.5144	-0.0544
	[-0.6794,-0.3583]	[-0.2825,0.1876]	[-0.6674,-0.3623]	[-0.2845,0.1770]
$\|\sigma_\eta\|$	-	0.0036	-	0.0035
	[-,-]	[0.0022,0.0055]	[-,-]	[0.0022,0.0053]
σ_e^2	0.0025	0.0021	0.0025	0.0021
	[0.0021,0.0029]	[0.0018,0.0025]	[0.0021,0.0029]	[0.0018,0.0025]

Notes: Carroll et al. (2019)'s unemployment risk (columns 1 and 2) or the old-age dependency ratio (columns 3 and 4) is used for $trend_t$. Reported are the posterior means with 90% HPD intervals (in square brackets). The random walk component is $\mu_t = \mu + \iota\sigma_\eta\mu_t^*$ with $\mu_t^* = \mu_{t-1}^* + \eta_t^*$. The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & trend_t \end{bmatrix}$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Estimations using unemployment risk are conducted over the period $1961Q4 - 2016Q4$ with effective sample size diminished due to the use of first differences and lags/leads. Estimations using the old-age dependency ratio are conducted over the period $1959Q4 - 2016Q4$ with effective sample size diminished due to the use of first differences and lags/leads.

E.2 Different lag/lead lengths and different priors

In this appendix, we present checks conducted to ensure that the results obtained when estimating the baseline model with the CEA index as a measure of financial liberalization are robust to imposing different estimation settings.

First, we consider different lag/lead lengths for the first-differences of the regressors included in the long-run regressions. Following Bianchi et al. (2018), the long-run estimations reported in the main text are based on dynamic OLS specifications that include $p = 6$ lags and leads of the first differences of the included regressors. These lags and leads are included to make the error term in the regression equation orthogonal to the past and future history of stochastic regressor innovations. To verify that our main results are not affected by the choice of p, we provide the results of estimating our baseline model with the CEA index for financial liberalization using different values for p, i.e., for $p = 1, 2, 4, 8$. The results presented in Table E-2 are for regression equations without an unobserved stochastic trend included (i.e., for $\iota = 0$), as the posterior probabilities of an there being an unobserved stochastic trend in these regressions are well below the prior probability of 50% in all cases. As can be seen from the table, the estimates are hardly affected by the choice of p as all are very similar to the ones reported in Table 4 in the main text. The results thus confirm that our results regarding the impact of liberalization on the consumption-wealth ratio are robust to the use of different lag/lead lengths for the first-differences of the regressors included in the long-run regressions.

Table E-2: Model with CEA index for fl_t and different lags/leads p for the stationary component v_t: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + v_t$

	(1) $p = 1$	(2) $p = 2$	(3) $p = 4$	(4) $p = 8$
α	0.1228	0.1243	0.1268	0.1397
	[0.0423,0.2007]	[0.0413,0.2046]	[0.0378,0.2130]	[0.0395,0.2366]
β	0.8635	0.8618	0.8589	0.8439
	[0.7701,0.9597]	[0.7656,0.9611]	[0.7554,0.9657]	[0.7277,0.9641]
γ	0.0986	0.0993	0.1009	0.1022
	[0.0654,0.1318]	[0.0660,0.1328]	[0.0671,0.1350]	[0.0673,0.1375]
μ	0.0284	0.0269	0.0245	0.0186
	[-0.2148,0.2699]	[-0.2159,0.2682]	[-0.2179,0.2653]	[-0.2228,0.2584]
σ_e^2	0.0023	0.0023	0.0023	0.0022
	[0.0019,0.0027]	[0.0019,0.0027]	[0.0019,0.0027]	[0.0019,0.0026]

Notes: The CEA index is used as a measure of financial liberalization fl_t. Reported are the posterior means with 90% HPD intervals (in square brackets). The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ with different values considered for p and where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. There is no unobserved random walk component in the model, i.e., $\mu_t = \mu$ $(\forall t)$. The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Estimations are conducted over the period $1966Q3 - 2016Q4$ with effective sample size diminished according to the value of p.

Second, we consider alternative parameter prior settings. In our analysis, we have chosen relatively flat priors to allow the data to speak fully with respect to the relationship between financial liberalization and the log consumption-wealth ratio. To confirm that our results are not driven by this choice of priors, in Table E-3 we report the results with somewhat more informative parameter prior configurations. The reported results are for regression equations without an unobserved stochastic trend included (i.e., for $\iota = 0$). First, in column (1) we report the results of tightening the prior variances of all slope coefficients of this regression equation from 1 to 0.1. Second, in column (2) we report the results of using different prior means for the parameters of interest α, β and γ. These are obtained from a preliminary OLS regression of consumption on asset wealth, labor income and the CEA index using as training sample the period

1966$Q3$ − 1973$Q4$ (i.e., with 30 observations) and are equal to respectively 0.15, 0.70 and 0.15. Finally, in column (3) we implement both previous configurations jointly. We note that the other parameter prior settings are as reported in Table 1 in the main text. The posterior means for the coefficient on financial liberalization, γ, vary somewhat with the different prior specifications, but the impact is still centered around 10%. The results thus confirm that our results regarding the impact of liberalization on the consumption-wealth ratio are quite robust to the use of different parameter prior configurations.[5]

Table E-3: Model with CEA index for fl_t and alternative parameter priors: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + v_t$

	(1) Alt. priors 1	(2) Alt. priors 2	(3) Alt. priors 3
α	0.1243	0.2085	0.1880
	[0.0288,0.2165]	[0.1620,0.2535]	[0.1415,0.2330]
β	0.8598	0.7650	0.7868
	[0.7491,0.9742]	[0.7114,0.8204]	[0.7331,0.8422]
γ	0.1057	0.0833	0.0983
	[0.0713,0.1404]	[0.0604,0.1062]	[0.0753,0.1212]
μ	0.0426	-0.0049	0.0158
	[-0.1990,0.2826]	[-0.0841,0.0738]	[-0.0635,0.0945]
σ_e^2	0.0022	0.0023	0.0023
	[0.0019,0.0026]	[0.0020,0.0027]	[0.0020,0.0027]

Notes: The CEA index is used as a measure of financial liberalization fl_t. 'Alt. priors 1' refers to the estimation where all slope coefficients have prior variances of 0.1. 'Alt. priors 2' refers to the estimation where the prior means for α, β and γ are obtained from a preliminary OLS regression of consumption on asset wealth, labor income and the CEA index using as a training sample the period 1966$Q3$ − 1973$Q4$. 'Alt. priors 3' refers to the estimation where the configurations of 'Alt. priors 1' and 'Alt. priors 2' are combined. Reported are the posterior means with 90% HPD intervals (in square brackets). The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j} \kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. There is no unobserved random walk component in the model, i.e., $\mu_t = \mu$ ($\forall t$). The coefficients κ_j are excluded from the table due to space constraints. Details on the data are provided in Section 3.2 and Appendix B. Data are available over the period 1966$Q3$ − 2016$Q4$ while the effective sample period is 1968$Q2$ − 2015$Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

E.3 Alternative data

In the main text, we follow Lettau and Ludvigson (2015) and Bianchi et al. (2018) when it comes to our choice of data used for the calculation of the variables c_t, a_t and y_t. In this appendix we consider

[5] The same conclusion applies to the posterior inclusion probabilities for the unobserved stochastic trend. These results are not reported, but are available upon request.

two alternative datasets. We refer to Rudd and Whelan (2006) for a discussion on the theoretical validity of using these alternative data when estimating 'cay' regressions. First, in 'Alt. dataset 1', the variables c_t and y_t are as in our baseline dataset but asset wealth a_t is now calculated from household net worth *excluding* consumer durables. A motivation for this is that expenditures on consumer durables are included in the consumption variable which here is calculated based on total personal consumption expenditures. Second, in 'Alt. dataset 2', we use expenditures on nondurable goods and services (minus clothing and footwear) as a measure for consumption. Labor income and asset wealth are calculated as in our baseline dataset (with asset wealth consisting of total household net worth *including* consumer durables). To calculate c_t, a_t and y_t for this dataset, consumption, disposable labor income and assets are all deflated by the price deflator for nondurables (excluding clothing and footwear) and services.

In Table E-4, we report the results of estimating our baseline model with these alternative datsets and with the baseline CEA index as a measure of financial liberalization. The results presented are for regression equations without an unobserved stochastic trend included (i.e., for $\iota = 0$) as (unreported) preliminary estimations suggest that the posterior probabilities of such a trend being present are well below the prior probability of 50%. The results for 'Alt. dataset 1', which is very close to the main dataset used in the text, are very similar to the baseline results presented in Section 3.4.1, i.e., we find a value for the impact γ of financial liberalization on the consumption-wealth ratio of about 0.10. The results for 'Alt. dataset 2' provide even stronger support for a positive impact of liberalization on the consumption-wealth ratio as the value for γ equals 0.16 in this case.

Table E-4: Model with CEA index for fl_t and alternative datasets: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + v_t$

	(1) Alt. dataset 1	(2) Alt. dataset 2
α	0.1144	0.1250
	[0.0236,0.2024]	[0.0315,0.2154]
β	0.8744	0.8540
	[0.7695,0.9825]	[0.7456,0.9657]
γ	0.0993	0.1608
	[0.0633,0.1355]	[0.1287,0.1931]
μ	0.0289	-0.0189
	[-0.2135,0.2695]	[-0.2601,0.2207]
σ_e^2	0.0023	0.0022
	[0.0019,0.0027]	[0.0018,0.0026]

Notes: The CEA index is used as a measure of financial liberalization fl_t. The variables used for c_t, a_t and y_t in the alternative datasets 'Alt. dataset 1' and 'Alt. dataset 2' are discussed in the text of this appendix. Reported are the posterior means with 90% HPD intervals (in square brackets). The stationary component is $v_t = \sum_{j=-p}^{p} \Delta x_{t+j}\kappa_j + e_t$ where $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$. There is no unobserved random walk component in the model, i.e., $\mu_t = \mu$ $(\forall t)$. The coefficients κ_j are excluded from the table due to space constraints. Data are available over the period $1966Q3 - 2016Q4$ while the effective sample period is $1968Q2 - 2015Q2$ with effective sample size $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

E.4 International evidence

In this appendix, we briefly explore whether the positive impact of liberalization on the consumption-wealth ratio can also be observed in countries other than the US. To this end, we present some results based on annual international data for Canada, France, Japan, the UK and the US (i.e., the G7 countries minus Italy and Germany). For these countries, internationally comparable historical data for consumption, asset wealth and labor income are available over the full period $1973 - 2005$ which is the period over which Abiad et al. (2008)'s internationally constructed indicator of financial reform is also available.

We measure consumption as private final consumption expenditures, labor income as the compensation of employees and asset wealth as net personal wealth for Canada, France, Japan and the US, and as net private wealth for the UK. All series are deflated using the inflation rate as calculated from the price index for the private final consumption expenditures, and the series are scaled by total population.[6]

[6] The consumption, price index and population series are from the World Bank's World Development Indicators (WDI), the net personal and private asset wealth series are from the World Inequality Database (WID), and the compensation of employees series are from the OECD for Canada, France and the UK, from the BEA for the US, and from WID for Japan.

A thorough analysis that involves testing for and incorporating unobserved stochastic trends is difficult given the low number of degrees of freedom. We therefore estimate a simple long-run regression of log consumption on a constant, log asset wealth, log labor income and Abiad et al. (2008)'s financial liberalization index for these five economies. We estimate this specification using Bayesian OLS with the same priors used in our more elaborate estimations which are reported in Table 1 in the main text.[7] As can be seen from the results reported in Table E-5, we find a positive impact of the liberalization measure - which shows a substantial upward trend over the sample period for all considered economies - on the consumption-wealth ratio for France, Japan, and the UK. For these countries, the estimates suggest that financial liberalization has increased the consumption-wealth ratio by 10 to 15%. The estimate for the coefficient on financial liberalization for the US is close to the one obtained using quarterly data and reported Section 3.4.3 of the main text, although the HPD interval for the posterior is somewhat wider here and (narrowly) contains the value of zero. Summarizing, the structural increase in the consumption-wealth ratio observed in the US can be observed in other countries as well, and the data seem to support a financial liberalization interpretation of this increase.

Table E-5: Estimation with annual international data: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + v_t$

	(1) Canada	(2) France	(3) Japan	(4) UK	(5) US
α	0.1905	-0.0282	0.0316	0.2426	0.1963
	[0.0939,0.2873]	[-0.1197,0.0611]	[-0.0573,0.1183]	[0.1399,0.3437]	[0.0856,0.3047]
β	0.7840	0.9986	0.9457	0.6737	0.7790
	[0.6779,0.8871]	[0.8787,1.1199]	[0.8346,1.0584]	[0.5293,0.8199]	[0.6438,0.9161]
γ	0.0129	0.0998	0.1546	0.1529	0.1015
	[-0.1434,0.1655]	[0.0656,0.1341]	[0.0693,0.2387]	[0.0422,0.2650]	[-0.0127,0.2172]
μ	0.0010	0.3082	0.2153	0.4461	-0.0368
	[-0.2853,0.2792]	[-0.0774,0.6956]	[-0.3656,0.7989]	[-0.0064,0.9007]	[-0.3870,0.3150]
σ_e^2	0.0004	0.0007	0.0013	0.0011	0.0005
	[0.0002,0.0005]	[0.0004,0.0010]	[0.0009,0.0019]	[0.0007,0.0016]	[0.0003,0.0008]

Notes: Reported are the posterior means with 90% HPD intervals (in square brackets). The long-run regression $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + v_t$ does not include an unobserved random walk component, i.e., $\mu_t = \mu$ $(\forall t)$. Neither does it contain DOLS terms, i.e., the stationary component is $v_t = e_t$ $(\forall t)$. The Abiad et al. (2008) index of financial reform is used as a measure of financial liberalization fl_t. Details on the other data used are provided in the text of this appendix. All results are based on annual data with sample period equal to $1973 - 2005$, i.e., $T = 33$.

[7] The only difference is the lower prior belief for the variance of the regression error term which, taking into account the lower volatility of annual data, is set to 0.01 instead of 0.1.

Appendix F Estimation details regression model of Section 4

This appendix discusses the estimation of the regression eqs.(16)-(17) through Gibbs sampling. First, we present the general outline of the Gibbs sampler in Section F.1. Then, the technical details about the different steps of the sampler are discussed in Section F.2. We do not report the convergence analysis, but it is available from the authors upon request.

F.1 General outline

We collect the parameters in a vector Γ, i.e., $\Gamma = (\pi^z, \psi_0^z, \psi_1^z, \sigma_{o^z}^2)$. The Gibbs approach allows us to simulate draws from the intractable joint posterior distribution of the parameters in Γ, i.e., $f(\Gamma|data)$, using tractable conditional distributions. In particular, given the prior distribution of the parameter vector $f(\Gamma)$, the following steps are implemented:

1. Sample the AR parameter π^z conditional on the parameters ψ_0^z, ψ_1^z, $\sigma_{o^z}^2$ and the data
2. Sample the regression coefficients ψ_0^z and ψ_1^z and innovation variance $\sigma_{o^z}^2$ conditional on π^z and the data

These steps are iterated 30.000 times and in each iteration the parameters in Γ are sampled. Given 10.000 burn-in draws, the reported results are all based on posterior distributions constructed from 20.000 retained draws.

F.2 Details on the steps of the sampler

F.2.1 Regression framework

The parameters contained in Γ can be sampled from a standard regression model,

$$Z = X\zeta + \varphi \tag{F-1}$$

where Z is a $T \times 1$ vector containing T observations on the dependent variable, X is a $T \times M$ matrix containing T observations of M predictor variables, ζ is the $M \times 1$ parameter vector and φ is the $T \times 1$ vector of error terms for which $\varphi \sim iid\mathcal{N}\left(0, \sigma_\varphi^2 I_T\right)$. The prior distribution of ζ is given by $\zeta \sim \mathcal{N}\left(b_0, B_0\sigma_\varphi^2\right)$ with b_0 a $M \times 1$ vector and B_0 a $M \times M$ matrix. The prior distribution of σ_φ^2 is given by $\sigma_\varphi^2 \sim \mathcal{IG}\left(s_0, S_0\right)$ with scalars s_0 (shape) and S_0 (scale). The posterior distributions (conditional on Z and X) of ζ and σ_φ^2 are then given by $\zeta \sim \mathcal{N}\left(b, B\sigma_\varphi^2\right)$ and $\sigma_\varphi^2 \sim \mathcal{IG}\left(s, S\right)$ with,

$$B = \left[X'X + B_0^{-1}\right]^{-1}$$

$$b = B\left[X'Z + B_0^{-1}b_0\right] \tag{F-2}$$

$$s = s_0 + T/2$$

$$S = S_0 + \frac{1}{2}\left[Z'Z + b_0'B_0^{-1}b_0 - b'B^{-1}b\right]$$

F.2.2 Sample π^z

To sample π^z conditional on the parameters ψ_0^z, ψ_1^z, $\sigma^2_{o^z}$ and the data, we note that eq.(17) in the text can be cast in the framework of eq.(F-1). We calculate $\chi^z_{t+1} \equiv z_{t+1} - \psi_0^z - \psi_1^z fl_t$ so that the dependent variable is $Z = \chi^z_{+1}$ where χ^z_{+1} is the $T \times 1$ vector containing χ^z_{t+1} stacked over time. The regressor is $X = \chi^z$ where χ^z contains χ^z_t stacked over time. The regression coefficient is $\zeta = \pi^z$. The error term is $\varphi = o^z_{+1}$ where o^z_{+1} contains o^z_{t+1} stacked over time. The variance $\sigma^2_\varphi = \sigma^2_{o^z}$ is assumed to be given in this step (it is sampled in the next step). Once the matrices of eq.(F-1) are determined, the parameter ζ can be sampled from the Gaussian posterior distribution given above with the prior distribution as specified in Table 11 in the text.[8]

F.2.3 Sample ψ_0^z, ψ_1^z and $\sigma^2_{o^z}$

To sample the parameters ψ_0^z, ψ_1^z and $\sigma^2_{o^z}$ conditional on the parameter π^z and the data, we first transform eq.(16) in the text so that it can be cast in the framework of eq.(F-1). First, we write eq.(16) as $z_{t+1} = x_t\psi^z + \chi^z_{t+1}$ where $x_t = \begin{bmatrix} \varrho & fl_t \end{bmatrix}$ (with ϱ a vector of ones) and where $\psi^z = \begin{bmatrix} \psi_0^z & \psi_1^z \end{bmatrix}'$. Second, we premultiply both sides of $z_{t+1} = x_t\psi^z + \chi^z_{t+1}$ by $(1 - \pi^z L)$ (with L the lag operator) to obtain $\tilde{z}_{t+1} = \tilde{x}_t\psi^z + o^z_{t+1}$ where $\tilde{z}_{t+1} = (1 - \pi^z L)z_{t+1}$ and $\tilde{x}_t = (1 - \pi^z L)x_t$. Equation $\tilde{z}_{t+1} = \tilde{x}_t\psi^z + o^z_{t+1}$ is in accordance with eq.(F-1). The dependent variable is $Z = \tilde{z}_{+1}$ where $\tilde{z}_{+1}$ is the $T \times 1$ vector containing $\tilde{z}_{t+1}$ stacked over time. The regressor is $X = \tilde{x}$ where $\tilde{x}$ contains $\tilde{x}_t$ stacked over time. The regression coefficient is $\zeta = \psi^z$. The error term is $\varphi = o^z_{+1}$ where o^z_{+1} contains o^z_{t+1} stacked over time. The variance $\sigma^2_\varphi = \sigma^2_{o^z}$. Once the matrices of eq.(F-1) are determined, the parameters ζ and σ^2_φ can be sampled from the posterior distributions given above with the prior distributions as specified in Table 11 in the text.[9]

[8]The prior distribution depends on b_0 and $B_0 = V_0/\sigma_0^2$ with the values for b_0, V_0 and σ_0^2 given in Table 11.

[9]We note that $s_0 = \nu_0 T$ and $S_0 = \nu_0 T\sigma_0^2$ with the values for ν_0 and σ_0^2 given in Table 11. Note that b_0 is a 2×1 vector containing the values of b_0 for ψ_0^z and ψ_1^z given in Table 11. Further, B_0 is an 2×2 diagonal matrix containing as elements the variances 1 - i.e., the variable V_0 in Table 11 - divided by the prior belief for $\sigma^2_{o^z}$ - i.e., the variable σ_0^2 in Table 11.