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Aggregate Consumption and Wealth in the Long Run: The Impact of Financial Liberalization

Malin Gardberg and Lorenzo Pozzi

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

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

Malin Gardberg[1] and Lorenzo Pozzi[†2]

[1] *Research Institute of Industrial Economics*

[2] *Erasmus University Rotterdam & Tinbergen Institute*

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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). We propose a heterogeneous agent framework with incomplete markets where financial liberalization, by signalling a future reduction in the incomplete markets component of consumption growth, increases the current consumption-wealth ratio. From the model, an aggregate long-run relationship is derived between consumption, total wealth and financial liberalization which is estimated 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 to sixteen percent. Additional estimations suggest that financial liberalization has predictive power for aggregate consumption growth, a result that provides support for the incomplete markets channel put forward in the paper.

JEL Classification: E21, C32, C11

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

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†Corresponding author at Department of Economics, P.O. Box 1738, 3000 DR Rotterdam, the Netherlands. Email: pozzi@ese.eur.nl. Website: http://people.few.eur.nl/pozzi.

1 Introduction

In a recent paper, Carroll et al. (2019) attribute the structural decline observed in the US saving rate from the late 1970's until the Great Recession to financial liberalization, i.e., over this period the expanding credit supply has decreased the fraction of disposable income that households save by about eight percentage points. Additionally, the time series behavior of another important US macroeconomic ratio, the ratio between consumption and total wealth (the sum of asset and human wealth), has recently received renewed scrutiny. Bianchi et al. (2017) argue that the commonly used proxy 'cay' for this unobserved ratio is non-stationary, which they attribute to regime shifts caused by monetary policy changes.[1,2] Given the importance of financial deregulation to explain the structural trend in the US saving rate, however, the question remains whether the non-stationarity in 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.

This paper therefore investigates the impact of financial liberalization on the relationship between consumption and total wealth, i.e., on the consumption-wealth ratio. To this end, we use a heterogeneous agent framework with incomplete markets stemming from the presence of a precautionary saving motive and a potentially binding liquidity constraint. This setting implies the existence of an incomplete markets component in the growth rate of an individual agent's consumption (see e.g., Parker and Preston, 2005). As the economy-wide financial liberalization process is persistent, it signals a future reduction in the incomplete markets components of consumers and therefore a reduction in their expected future consumption growth rates which, through their intertemporal budget constraints, increases their current consumption to wealth ratios. From this model, we derive a long-run relationship between consumption, total wealth and financial liberalization at the aggregate level. We then estimate this relationship using quarterly US data. With respect to the data, the estimations are conducted with two different measures of consumption - total personal consumption expenditures and expenditures on nondurables and services - which, as noted by Rudd and Whelan (2006), are both valid from a theoretical perspective. Following Lettau and Ludvigson (2001), we use labor income to proxy unobserved human wealth. To measure financial liberalization, we use the so-called 'credit easing accumulated' (CEA) index as our baseline indicator (see e.g., Carroll et al., 2019, and references therein) as well as two alternative liberalization indicators, namely the household debt to disposable income ratio and Abiad et al. (2008)'s index of financial re-

[1] The proxy 'cay' is constructed as the residual from a time series regression of log consumption on a constant, on log assets and on log labor income where the latter serves as a proxy for log human wealth (see Lettau and Ludvigson, 2001).

[2] While other authors have argued that 'cay' is non-stationary, they attribute this to data issues and methodological issues and do not give an economic interpretation to the non-stationarity (see e.g., Rudd and Whelan, 2006).

form. With respect to the estimation method, we note that the long-run regression equation implied by the model 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 incomplete markets channel through which, according to our model, financial liberalization affects the consumption-wealth ratio by investigating whether, as our model suggests, financial liberalization has predictive power for aggregate consumption growth. We check whether the estimates obtained from these predictive regressions are consistent with the estimates obtained from the long-run regressions between consumption, wealth and liberalization. Finally, we also investigate an alternative cost of capital channel, not incorporated in the model, whereby financial liberalization could affect the consumption-wealth ratio through its impact on expected 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 recent evidence reported by Bianchi et al. (2017) on the non-stationarity of the traditional 'cay' variable as a proxy for the consumption to wealth ratio. 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 to sixteen percent. The model with financial liberalization further provides estimates for the ratio of human wealth over total wealth that are considerably higher than those typically reported in papers that use 'cay' as a proxy for total wealth and in line with the recent findings that report estimates for this ratio as high as 90% (see Lustig et al., 2013, and references therein). Finally, we find that financial liberalization has predictive power for aggregate consumption growth, i.e., it reduces expected future consumption growth. This evidence, combined with the finding that liberalization has no predictive ability for returns on wealth over the sample period, supports the incomplete markets channel put forward in this paper to explain the relationship between liberalization and the consumption-wealth ratio.

The structure of the paper is as follows. Section 2 presents and discusses the theoretical framework that forms the basis of the empirical sections. Section 3 deals with the estimation of the long-run relationship between consumption, total wealth and financial liberalization that is implied by the model. Section 4 investigates the incomplete markets channel that is put forward in this paper to explain the impact of financial liberalization on the consumption-wealth ratio. Section 5 concludes.

2 Theoretical framework

This section presents the theoretical framework used to investigate the impact of financial liberalization on the long-run relationship between aggregate consumption and total wealth. First, we consider a simple heterogeneous agent consumption model with incomplete markets for consumption insurance caused by the existence of a precautionary saving motive and the presence of a liquidity constraint. Second, we use the model to argue that financial liberalization can - by reducing the incomplete markets component in expected future consumption growth - increase the current consumption to total wealth ratio. Third, since our focus lies on the long-run aggregate time series relationship between the considered variables, we aggregate the derived relationship and implement steps to obtain an estimable regression equation.

2.1 Incomplete markets and the consumption-wealth ratio

2.1.1 Set-up

Each consumer faces uncertain future labor income and chooses consumption by maximizing expected utility given by,

$$E_{it} \sum_{j=0}^{\infty} \delta^j U(C_{i,t+j}) \tag{1}$$

where E_{it} is the rational expectations operator conditional on consumer i's period t information set, where $0 < \delta \leq 1$ is the discount factor that reflects the rate of time preference, where $U(.)$ is an isoelastic contemporaneous utility function and where C_{it} is consumer i's real consumption in period t. Maximization occurs subject to the budget constraint,

$$A_{i,t+1} = (1 + r_{i,t+1})(A_{it} + Y_{it} - C_{it}) \tag{2}$$

and the liquidity constraint,

$$A_{i,t+1} \geq 0 \tag{3}$$

where A_{it} denotes real asset (or financial) wealth at the beginning of period t, where Y_{it} denotes real disposable labor income in period t and where r_{it} is the period t real rate of return.[3] Consumer i's total real wealth W_{it} at the beginning of period t consists of asset wealth A_{it} and human wealth H_{it}, i.e.,

$$W_{it} \equiv A_{it} + H_{it} \tag{4}$$

[3] We note that our framework makes no distinction between the real return on asset wealth and the return on human wealth, i.e., r_{it} denotes the real return on A_{it} and H_{it} and therefore also on total wealth W_{it}. The framework can easily be extended to incorporate a distinction between the returns on A_{it} and H_{it} but this offers no additional insight.

where human wealth is defined as the present discounted value of future real disposable labor income, i.e.,

$$H_{it} \equiv Y_{it} + E_{it} \sum_{j=1}^{\infty} \frac{Y_{i,t+j}}{\prod_{k=1}^{j}(1 + r_{i,t+k})} \tag{5}$$

2.1.2 Intertemporal budget constraint and the consumption-wealth ratio

We now use the log-linearized intertemporal budget constraint of each consumer i to obtain an expression for the log of the consumption to total wealth ratio. Eq.(5) can be written as $H_{it} = Y_{it} + \frac{H_{i,t+1}}{1+r_{i,t+1}}$ in ex-post terms. After substituting this into eq.(2) and using eq.(4), we obtain the budget constraint for total wealth, i.e., $\frac{W_{i,t+1}}{1+r_{i,t+1}} = W_{it} - C_{it}$. After log-linearizing and solving forward this constraint, imposing a transversality condition and taking expectations at t of the resulting expression, we obtain,

$$c_{it} - w_{it} = E_{it} \sum_{j=1}^{\infty} (\rho^c)^j \left(r_{i,t+j} - \Delta c_{i,t+j}\right) \tag{6}$$

where $c_{it} = \ln C_{it}$, $w_{it} = \ln W_{it}$, where $0 < \rho^c < 1$ is a discount factor which equals $\frac{W-C}{W}$ with C and W the steady state values of consumption and total wealth and which is expected to be close to one. Note that the unimportant linearization constant is omitted. We refer to Appendix A for the derivation. Eq.(6) states that if consumer i's consumption-wealth ratio is high in period t, subsequent rate of return increases or lower growth rates of consumption are necessary for this consumer's budget constraint to hold intertemporally.

By applying the same steps to the equation $H_{it} = Y_{it} + \frac{H_{i,t+1}}{1+r_{i,t+1}}$, we obtain a log-linear relationship between human wealth and labor income which is given by,

$$h_{it} - y_{it} = E_{it} \sum_{j=1}^{\infty} (\rho^y)^j \left(\Delta y_{i,t+j} - r_{i,t+j}\right) \tag{7}$$

where $h_{it} = \ln H_{it}$, $y_{it} = \ln Y_{it}$, where $0 < \rho^y < 1$ is a discount factor which equals $\frac{H-Y}{H}$ with Y and H the steady state values of labor income and human wealth and which is expected to be close to one. Again, the unimportant linearization constant is omitted.

2.1.3 First-order condition

The maximization problem given by eqs.(1)-(3) implies the following first-order condition,

$$E_{it}\left(\delta(1 + r_{i,t+1})\frac{U'(C_{i,t+1})}{U'(C_{it})}\right) + \lambda_{it} = 1 \tag{8}$$

where $\lambda_{it} \geq 0$ 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). Eq.(8) can also be written as,

$$\left(\delta(1+r_{i,t+1})\frac{U'(C_{i,t+1})}{U'(C_{it})}\right) = 1 - \lambda_{it} + \varepsilon_{i,t+1} \tag{9}$$

where $\varepsilon_{i,t+1}$ is an expectation error uncorrelated with period t information, i.e., we have $E_{it}\varepsilon_{i,t+1} = 0$. 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.(9) as,

$$\left(\delta(1+r_{i,t+1})\frac{C_{i,t+1}^{-\theta}}{C_{it}^{-\theta}}\right) = 1 - \lambda_{it} + \varepsilon_{i,t+1} \tag{10}$$

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

$$\Delta c_{i,t+1} = \frac{1}{\theta}\ln\delta + \frac{1}{\theta}r_{i,t+1} + \frac{1}{\theta}\nu_{i,t+1} \tag{11}$$

where $\nu_{i,t+1} \equiv -\ln(1 - \lambda_{it} + \varepsilon_{i,t+1})$.

The term $\frac{1}{\theta}r_{i,t+1}$ captures intertemporal substitution in consumption with respect to changes in the rate of return on wealth. The unexpected part of $\nu_{i,t+1}$ reflects new information available to the consumer while the expected part of $\nu_{i,t+1}$, i.e., the term $E_{it}\nu_{i,t+1} = -E_{it}\ln(1-\lambda_{it}+\varepsilon_{i,t+1})$, reflects the incomplete markets component of consumption growth which is due to the presence of a precautionary saving motive and a liquidity constraint (see Parker and Preston, 2005). These reduce period t consumption and augment period $t+1$ consumption thereby raising consumption growth from t to $t+1$, i.e., we have $E_{it}\nu_{i,t+1} > 0$.[4] It is straightforward to see, upon combining eqs.(6) and (11), that when the incomplete markets term in consumption growth is expected to fall, the current consumption to wealth ratio $c_{it} - w_{it}$ may go up. In the next section, we link the incomplete markets term in consumption growth to the process of financial liberalization to obtain an expression for $c_{it} - w_{it}$ as a function of liberalization.

2.2 Financial liberalization and the consumption-wealth ratio

Financial liberalization is expected to lift the restrictions that consumers face to transfer resources across time or across uncertain states of the world and therefore to improve consumption smoothing opportunities. Hence, we expect financial liberalization to reduce the incomplete markets component $E_{it}\nu_{i,t+1}$ in consumer i's first-order condition. To capture this, we write,

$$\nu_{i,t+1} = a_i + b_i fl_t + \varpi_{i,t+1} \tag{12}$$

[4] 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 $-E(\ln(1-\lambda+\varepsilon)) > 0$.

where fl_t denotes the economy-wide financial liberalization process and where $\varpi_{i,t+1}$ is an unobserved component that captures all other factors affecting $\nu_{i,t+1}$. We expect $b_i \leq 0$, i.e., liberalization increases market completeness. 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,

$$fl_{t+1} = fl_t + \xi_{t+1} \tag{13}$$

where $E_{it}\xi_{t+1} = 0$.

By inserting eqs.(11), (12) and (13) into eq.(6), we can write the log consumption-wealth ratio of consumer i as,

$$c_{it} - w_{it} = \gamma_i fl_t + \epsilon_{it}^c \tag{14}$$

where $\epsilon_{it}^c = E_{it} \sum_{j=1}^{\infty} (\rho^c)^j \left[(1 - \frac{1}{\theta}) r_{i,t+j} - \frac{1}{\theta}\varpi_{i,t+j}\right]$ is an unobserved component. We note that we omit the constants in the equation, the derivation of which is provided in Appendix A. The parameter $\gamma_i = -\frac{b_i}{\theta}\frac{\rho^c}{1-\rho^c}$ captures the impact of financial liberalization on consumer i's consumption to total wealth ratio. Since $\theta > 0$, $0 < \rho^c < 1$ and $b_i \leq 0$, we have $\gamma_i \geq 0$, i.e., financial liberalization increases the consumption-to-wealth ratio over time. As the liberalization process is persistent, it signals a future reduction in the incomplete markets component of consumption growth and therefore a reduction in expected future consumption growth which, through the intertemporal budget constraint, increases the current consumption to wealth ratio.

2.3 Aggregation

2.3.1 Long-run relationships

We denote by $N(t)$ the number of people alive in periods t and $t+1$. Averaging eq.(14) over $N(t)$ consumers gives,

$$c_t - w_t = \gamma fl_t + \epsilon_t^c \tag{15}$$

where $\gamma = \frac{1}{N(t)}\sum_i \gamma_i$, $c_t = \frac{1}{N(t)}\sum_i c_{it} - \tau_t^c$, $w_t = \frac{1}{N(t)}\sum_i w_{it} - \tau_t^w$ and $\epsilon_t^c = \frac{1}{N(t)}\sum_i \epsilon_{it}^c - \tau_t^c + \tau_t^w$ with τ_t^c and τ_t^w denoting Theil's entropy measures (see e.g., Attanasio and Weber, 1993).

The entropy measures are introduced to capture the discrepancy between how the model variables are expressed starting from the level of the individual consumer, i.e., as averages of logs, and how the model variables are expressed in the aggregate, i.e., as logs of averages. The latter are in accordance with how the aggregate data used in estimation are constructed.[5,6]

We also aggregate the relationship between human wealth and labor income given by eq.(7), i.e., $h_{it} - y_{it} = \epsilon_{it}^{y}$ where $\epsilon_{it}^{y} = E_{it} \sum_{j=1}^{\infty} (\rho^{y})^{j} (\Delta y_{i,t+j} - r_{i,t+j})$ is an unobserved component. Aggregation gives,

$$h_t - y_t = \epsilon_t^{y} \tag{16}$$

where $h_t = \frac{1}{N(t)} \sum_i h_{it} - \tau_t^h$, $y_t = \frac{1}{N(t)} \sum_i y_{it} - \tau_t^y$ and $\epsilon_t^y = \frac{1}{N(t)} \sum_i \epsilon_{it}^y - \tau_t^h + \tau_t^y$ with τ_t^h and τ_t^y denoting Theil's entropy measures.

2.3.2 First-order condition

We also aggregate the first-order condition. After substituting eq.(12) into eq.(11) and then averaging, we obtain,

$$\Delta c_{t+1} = \frac{1}{\theta} \ln \delta + \frac{1}{\theta} r_{t+1} + \frac{1}{\theta} a + \frac{1}{\theta} b f l_t + \frac{1}{\theta} \varpi_{t+1} \tag{17}$$

where $\Delta c_{t+1} = \frac{1}{N(t)} \sum_i \Delta c_{i,t+1} - \Delta \tau_{t+1}^c$ with τ_{t+1}^c being Theil's entropy measure, $r_{t+1} = \frac{1}{N(t)} \sum_i r_{i,t+1}$, $\varpi_{t+1} = \frac{1}{N(t)} \sum_i \varpi_{i,t+1} - \theta \Delta \tau_{t+1}^c$, $a = \frac{1}{N(t)} \sum_i a_i$ and $b = \frac{1}{N(t)} \sum_i b_i$. We note that $\frac{1}{\theta} b \leq 0$ since $\theta > 0$ and $b_i \leq 0$ $(\forall i)$.

Eq.(17) thus shows that the model implies that financial liberalization has predictive power for aggregate consumption growth. Financial liberalization - by increasing market completeness through the relaxation of liquidity constraints of consumers and through the reduction of the precautionary saving motive of consumers - is expected to reduce future aggregate consumption growth. This channel, through which financial liberalization affects the consumption to wealth ratio, is investigated in Section 4.

2.4 Deriving an estimable relationship between consumption, wealth and financial liberalization

Eq.(15) cannot be estimated since log total wealth w_t is unobservable. After aggregating eq.(4), we have $W_t = A_t + H_t$ where $W_t = \frac{1}{N(t)} \sum_i W_{it}$, $A_t = \frac{1}{N(t)} \sum_i A_{it}$ and $H_t = \frac{1}{N(t)} \sum_i H_{it}$. Hence, aggregate total wealth equals the sum of aggregate asset wealth and aggregate human wealth where the former is observed but the latter is not. Log-linearizing this sum, we write,

$$w_t = \alpha a_t + \beta h_t \tag{18}$$

[5] In particular, for any variable $z_i = \ln Z_i$, Theil's entropy measure is given by $\tau^z = \left(\frac{1}{N} \sum_i z_i\right) - \ln\left(\frac{1}{N} \sum_i Z_i\right)$ which also equals $\ln\left((\prod_i Z_i)^{1/N}\right) - \ln\left(\frac{1}{N} \sum_i Z_i\right)$, i.e., the difference between the log of the geometric mean of Z_i and the log of the arithmetic mean of Z_i. Defining $z \equiv \ln\left(\frac{1}{N} \sum_i Z_i\right)$, we then have $z = \left(\frac{1}{N} \sum_i z_i\right) - \tau^z$.

[6] The entropy measures are relegated to the error term in estimation as they cannot be constructed for all variables over the desired period and at the desired frequency.

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 aggregate asset wealth and aggregate human wealth. Substituting eq.(18) into eq.(15), we obtain,

$$c_t = \alpha a_t + \beta h_t + \gamma fl_t + \epsilon_t^c \tag{19}$$

Then, following Lettau and Ludvigson (2001, 2004), we use eq.(16) to replace the unobserved log human capital variable h_t with the observed log labor income variable y_t to obtain,

$$c_t = \alpha a_t + \beta y_t + \gamma fl_t + \epsilon_t \tag{20}$$

where $\epsilon_t = \epsilon_t^c + \beta \epsilon_t^y$ is the error term. In the next section, we discuss the estimation of this equation 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.(20) do not necessarily have a stationary error term. 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. Finally, even if the model is complete and its assumptions are valid, the error term ϵ_t of eq.(20) may be non-stationary if one or more variables and components that constitute this error term are non-stationary. For example, a non-stationary error term may be the result of the presence of the entropy measures that result from aggregation as discussed in Section 2.3.[7]

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.(20) 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.,

[7]Suppose that we model the entropy measures τ_t^j (with $j = j = c, w, y, h$) in Section 2.3 as simple random walks, i.e., $\tau_t^j = \tau_{t-1}^j + \varsigma_t^j$ with innovation variances $\sigma^2_{\varsigma^j}$. Provided the components ϵ_{it}^c and ϵ_{it}^y are stationary for all i, then the aggregate terms ϵ_t^c and ϵ_t^y and therefore also ϵ_t are stationary only if $\sigma^2_{\varsigma^j} \approx 0$.

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.(20), 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.(20) in general form as,

$$c_t = x_t \phi + \epsilon_t \tag{21}$$

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,

$$\epsilon_t = \mu_t + v_t \tag{22}$$

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,

$$\mu_t = \mu + \sigma_\eta \mu_t^* \tag{23}$$

$$\mu_t^* = \mu_{t-1}^* + \eta_t^* \tag{24}$$

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.,

$$v_t = \sum_{j=-p}^{p} \Delta x_{t+j} \kappa_j + e_t \tag{25}$$

where $e_t \sim iid\mathcal{N}\left(0, \sigma_e^2\right)$. This specification follows the literature where dynamic OLS is typically applied to the estimation of regression equations between consumption, earnings and assets (see e.g., Bianchi et al., 2017). For all the estimations conducted in the paper, we set $p = 6$. The main conclusions presented in the paper are not affected however when using alternative values for p.

3.2 Data

We estimate eq.(21) using quarterly US data. Full details on the sources and the exact construction of the data are provided in Appendix B.

We consider two datasets for the variables c_t, a_t and y_t. We refer to Rudd and Whelan (2006) for a discussion on why both these datasets are valid when estimating long-run regressions containing consumption, labor income and asset wealth. The first dataset, which we denote by PCE, uses total personal consumption expenditures as a measure for consumption while the second dataset, which we denote by NDS, uses expenditures on nondurable goods and services (minus clothing and footwear) as a measure for consumption. In the PCE dataset, asset wealth consists of household net worth excluding consumer durables (as durables are included in the consumption measure) while consumption, disposable labor income and assets are all deflated by the price deflator for total personal consumption expenditures.[8] In the NDS dataset, asset wealth consists of total household net worth (which includes consumer durables) while consumption, disposable labor income and assets are all deflated by the price deflator for nondurables (excluding clothing and footwear) and services. Once expressed in real terms, consumption, disposable labor income and asset wealth are 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. Both datasets are calculated over the period $1951Q4 - 2016Q4$.

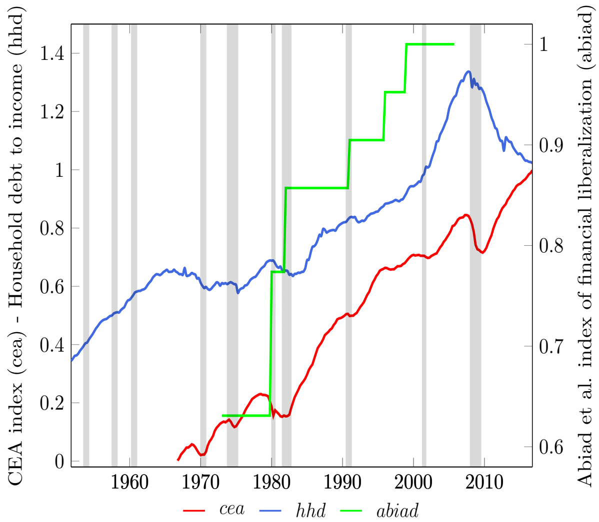
To measure financial liberalization fl_t, our main baseline indicator is the 'credit easing accumulated' (CEA) index considered also by Carroll et al. (2019). It is constructed from a survey that inquires on the willingness of US banks to make consumer installment loans. This measure is advantageous 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, i.e., the household debt to disposable income ratio, has even better availability - i.e., from 1951 onward - but it is conceptually less appealing as a measure of liberalization and expanding credit supply as it is determined by both supply and demand.[9] The third considered measure for fl_t is the index of financial liberalization of Abiad et al. (2008) which is a mixture of financial development indicators and hence reflects credit supply conditions. 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

[8] Our PCE dataset does not correspond completely with the dataset based on personal consumption expenditures used recently by Lettau and Ludvigson (2015) and Bianchi et al. (2017) who conduct regressions of consumption on assets and labor income. In these studies, the asset variable *does* include consumer durables. We find that using this alternative asset variable in our PCE dataset has a negligible impact on our conclusions.

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

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. Our preferred CEA indicator - and, to a lesser extent, also the household debt to income ratio - also reveals a clear cyclical pattern, i.e., during recessions, credit availability diminishes.

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 liberalization (period $1973Q1 - 2005Q4$). The grey shaded areas are the NBER recessions. Details on the construction of these indices are provided in Appendix B.

3.3 Methodology

Eqs.(21)-(25) 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 C. 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.(21) 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.(23) 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.(23) 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.(23) as,

$$\mu_t = \mu + \iota\sigma_\eta\mu_t^* \tag{26}$$

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. 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.[10] 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

[10] Results unreported but available upon request.

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 2.4, we know that, theoretically, the coefficients α and β reflect the weight in steady state of respectively financial 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.[11] As noted by Frühwirth-Schnatter and Wagner (2010), this approach 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.[12] We again impose a unit variance so that the prior distribution has support over a wide range of parameter values.

[11] 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 $\pm|\sigma_\eta|$.

[12] 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 $\sigma_\eta^2 = 0$.

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 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). 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 either $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ or $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$.

3.4 Results

In this section we first discuss the calculated probabilities that there is an unobserved stochastic trend in the regression error for all considered regression models. Then, we present the estimation results for the model without financial liberalization. Next, we report the baseline results for the regression equation with the CEA index used as an indicator for financial liberalization. Finally, we discuss the findings obtained with two alternative measures of financial liberalization.

3.4.1 Results of the test for a stochastic trend in the regression error

As noted above, the presence of a non-stationary error term in our long-run regression equation may reflect model misspecification due to one or more variables that are missing from the model or because one or more imposed model assumptions are violated. Table 2 therefore 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 prior probability is set to 50% in all cases. We consider both the estimation of eq.(21) without financial liberalization in which case we have $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta \end{bmatrix}'$ and with financial liberalization in which case we have $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix}'$. In the latter case, three different variables are used as indicators for financial liberalization, i.e., our baseline 'credit easing accumulated' (CEA) index, the household debt to disposable income ratio and Abiad et al. (2008)'s indicator of financial reform. We refer to Section 3.2 above for a discussion of these indicators.

Results are reported for both datasets which are also detailed in Section 3.2, i.e., the PCE dataset (with consumption measured through total personal consumer expenditures) and the NDS dataset (with consumption measured through expenditures on nondurables and services).

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

	(a) PCE dataset	(b) NDS dataset
Model without financial liberalization ($\gamma = 0$)	0.99	1.00
Model with financial liberalization ($\gamma \neq 0$)		
1) Baseline CEA index for fl_t	0.33	0.03
2) Household debt to income ratio for fl_t	0.97	1.00
3) Abiad et al. index for fl_t	0.02	0.02

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). 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 of the 10.000 binary indicators ι with each ι sampled in a Gibbs iteration. The prior distribution of ι is Bernoulli with probability $p_0 = 0.5$. Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. For the model without financial liberalization or for the model with household debt to income used for fl_t, data are available over the period $1951Q4 - 2016Q4$. The effective sample period is $1953Q3 - 2015Q2$ and the effective sample size is $T = 248$, i.e., 261 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$. For the model with the CEA index used for fl_t, data are available over the period $1966Q3 - 2016Q4$ (with effective sample period $1968Q2 - 2015Q2$ and effective sample size equal to $T = 189$). For the model with the Abiad et al. index used for fl_t, data are available over the period $1973Q1 - 2005Q4$ (with effective sample period $1974Q4 - 2003Q2$ and effective sample size equal to $T = 119$).

From the posterior probabilities reported in Table 2, we conclude that, irrespective of the considered dataset, 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 result supports the recent evidence reported in the literature on the non-stationarity of the traditional 'cay' variable as a proxy for the consumption to wealth ratio (see e.g., Bianchi et al., 2017). The CEA and Abiad indices of liberalization seem to provide an adequate characterization of the non-stationarity of the regression error as the posterior probabilities that a stochastic trend is present in the error term are well below 0.5 and sometimes close to zero when these indicators of financial liberalization are included in the regression. The probabilities close to one obtained for the model with the household debt to income ratio used as an indicator for liberalization, on the other hand, suggest that this variable does not capture the non-stationarity of the regression error term. This shows that not just any proxy of liberalization or, more generally, not just any upwardly trended variable is capable of capturing the non-stationarity that is present in the consumption-wealth ratio.

3.4.2 Results without financial liberalization

The results obtained when estimating the model without the financial liberalization variable fl_t included - i.e., when in eq.(21), we have $x_t = \begin{bmatrix} a_t & y_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta \end{bmatrix}'$ - are presented in Table 3. In particular, we report the means and 90% highest posterior density (HPD) intervals of the posterior distributions of the fixed regression parameters of eqs.(21), (22), (25) and (26) with the exception of the coefficients κ_j which are excluded due to space constraints. Results are reported for both datasets detailed in Section 3.2, i.e., the PCE dataset (with consumption measured through total personal consumer expenditures) and the NDS dataset (with consumption measured through expenditures on nondurables and services). Furthermore, we present results both with the binary indicator of the random walk component in eq.(26) set to one and with the binary indicator set to zero. Setting $\iota = 1$ is in line with posterior inclusion probabilities for the unobserved random walk component that are close to one as reported in Table 2, i.e., the stochastic trend is found to be relevant so it is included in the model and estimated. 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 eq.(21) is typically not accounted for.

From the table, 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 according to whether or not the unobserved stochastic trend is included in estimation. When excluding the stochastic trend by setting $\iota = 0$ (although the posterior inclusion probability is very close to one), the impact of log assets a_t on log consumption c_t is overestimated, in particular when we make use of the NDS dataset. Further, when estimating the regression model under the restriction $\iota = 1$, we include and estimate an unobserved random walk component in the regression error term with the innovation standard deviation $|\sigma_\eta|$ reported in Table 3. We find that it is larger than zero which reflects the presence of time-variation in μ_t. This is in line with the finding of a posterior inclusion probability $p(\iota = 1)$ close to one for the unobserved stochastic trend in the regression error as reported in Table 2.

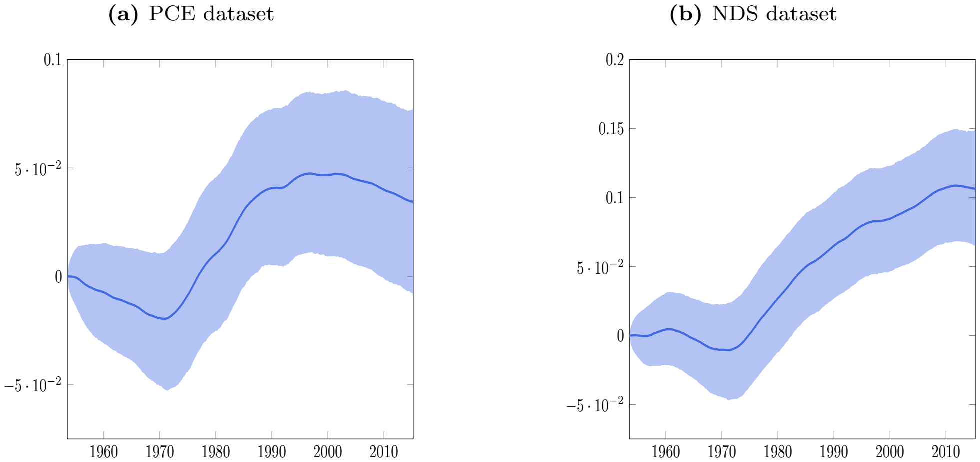
Table 3: Model without financial liberalization: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \mu_t + v_t$

	(a) PCE dataset		(b) NDS dataset	
	(1)	(2)	(3)	(4)
	$\iota = 0$	$\iota = 1$	$\iota = 0$	$\iota = 1$
α	0.2241	0.2065	0.3089	0.2141
	[0.1692,0.2790]	[0.1239,0.2906]	[0.2473,0.3706]	[0.1230,0.3052]
β	0.7972	0.7737	0.7313	0.7511
	[0.7344,0.8610]	[0.6722,0.8740]	[0.6608,0.8031]	[0.6411,0.8619]
μ	-0.4472	-0.0345	-0.9103	-0.0382
	[-0.5706,-0.3235]	[-0.2595,0.1893]	[-1.0676,-0.7523]	[-0.2690,0.1959]
$\|\sigma_\eta\|$	-	0.0033	-	0.0039
	[-,-]	[0.0020,0.0049]	[-,-]	[0.0026,0.0055]
σ_e^2	0.0024	0.0021	0.0028	0.0021
	[0.0021,0.0028]	[0.0018,0.0024]	[0.0024,0.0033]	[0.0018,0.0024]

Notes: Reported are the posterior mean with 90% HPD interval (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 datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. Data are available over the period $1951Q4 - 2016Q4$ while the effective sample period is $1953Q3 - 2015Q2$ and the effective sample size is $T = 248$, i.e., 261 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

Figure 2 then presents the time-varying part of the random walk component that we estimate when setting $\iota = 1$, i.e., the term $\sigma_\eta\mu_t^*$ which, given $\mu_0^* = 0$, is initialized at zero. We note from the figure that this component shows a clear upward evolution. While this holds for both datasets, the evolution is more outspoken for the NDS dataset. The presence of an unobserved upward stochastic trend in the regression error suggests that the model that we consider in this section is not fully specified and therefore incomplete.

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



Note: Depicted is the mean and the 90% HPD interval (shaded area) of the estimated component $\sigma_\eta \mu_t^*$. This is obtained from the estimation of equation $c_t = \alpha a_t + \beta y_t + \mu + \iota \sigma_\eta \mu_t^* + v_t$ under the restriction $\iota = 1$, the results of which are reported in Table 3, columns (2) and (4). Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. The effective sample period is $1953Q3 - 2015Q2$.

We can proxy the evolution of the log consumption to total wealth ratio $c_t - w_t$ in the model without financial liberalization by calculating $c_t - \mu - \alpha a_t - \beta y_t$.[13] We calculate this proxy for both datasets and for the model with and without the unobserved stochastic trend included in the error term. Figure 3 shows the posterior means and 90% HPD intervals. The blue graphs depict the proxied log consumption-wealth ratio obtained from the model without an unobserved stochastic trend ($\iota = 0$). For the PCE dataset, this almost completely corresponds to the standard 'cay' variable reported recently by Bianchi et al. (2017).[14] The red graphs depict the proxied log consumption-wealth ratio obtained from the model with an unobserved stochastic trend ($\iota = 1$). These ratios show, as expected, a clearer upward trend as they are not restricted to be stationary.[15] Hence, a rather large discrepancy can be observed between the consumption-wealth ratios calculated from regression equations with and without a trend in the error term. For the NDS dataset, this discrepancy is even larger which is in line with the more outspoken upward trend estimated when using this dataset as shown in Figure 2 above. These results suggest that not dealing with the unobserved trend in the regression error term has important consequences for the

[13]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 proxy for log consumption-wealth ratio. It implies that our proxy is initialized around zero when $\iota = 1$ or averages to zero when $\iota = 0$.

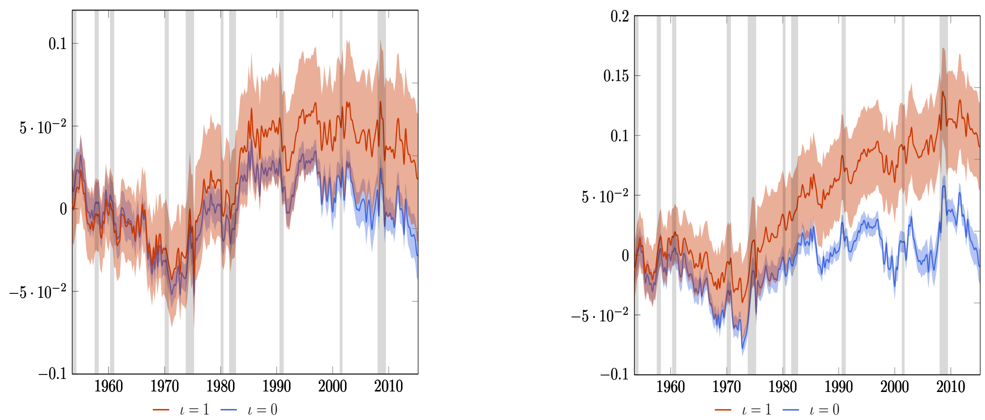
[14]The main difference being that our PCE dataset excludes durable goods from the asset variable a_t, whereas in Bianchi et al. (2017) these are included in a_t. We refer to Section 3.2 and Appendix B for details.

[15]From the figure, we note that the HPD interval for the log consumption-wealth proxy obtained under $\iota = 1$ (red) is wider than that 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 estimation of the latter entails only the estimation of fixed parameters.

estimation of the evolution of the consumption to total wealth ratio.

Figure 3: The log consumption-wealth ratio in the model without financial liberalization: model with ($\iota = 1$) and without ($\iota = 0$) unobserved stochastic trend

(a) PCE dataset **(b)** NDS dataset



Note: Depicted is the mean and the 90% HPD interval (shaded area) of the calculated log consumption-wealth ratio $c_t - \mu - \alpha a_t - \beta y_t$ for every case reported in Table 3. For the model with an unobserved random walk included ($\iota = 1$), the ratio is printed in red while for the model without an unobserved random walk included ($\iota = 0$), the ratio is printed in blue. The grey shaded areas are the NBER recessions. Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. The effective sample period is $1953Q3 - 2015Q2$.

3.4.3 Baseline case: CEA index for financial liberalization

The results obtained when estimating the model with the 'credit easing accumulated' (CEA) index used as our baseline financial liberalization indicator fl_t are presented in Table 4. In the table, we report the means and 90% highest posterior density (HPD) intervals of the posterior distributions of the fixed regression parameters of eq.(21) - now with $x_t = \begin{bmatrix} a_t & y_t & fl_t \end{bmatrix}$ and $\phi = \begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix}'$ - and eqs.(22), (25) and (26) with the exception of the coefficients κ_j which are excluded due to space constraints. Again, results are reported for both datasets detailed in Section 3.2, i.e., the PCE dataset (with consumption measured through total personal consumer expenditures) and the NDS dataset (with consumption measured through expenditures on nondurables and services). And again, results are reported for both the case with and without a stochastic trend included in the regression error. Setting $\iota = 0$ is in line with the posterior inclusion probabilities that we report in Table 2 for the model which uses the CEA index as a measure of liberalization, which are well below 50%.

Table 4: Model with financial liberalization: posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$

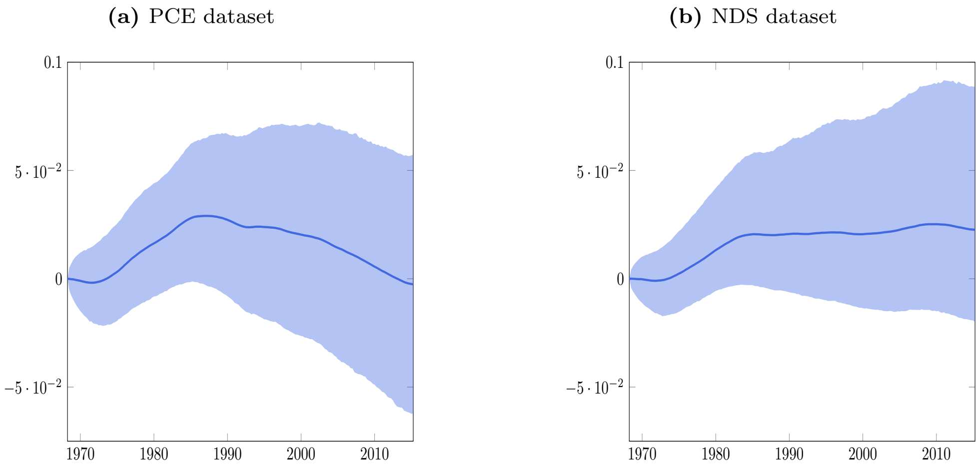
	(a) PCE dataset		(b) NDS dataset	
	(1) $\iota = 0$	(2) $\iota = 1$	(3) $\iota = 0$	(4) $\iota = 1$
α	0.1147	0.1556	0.1252	0.1448
	[0.0260,0.2040]	[0.0597,0.2521]	[0.0340,0.2171]	[0.0479,0.2432]
β	0.8739	0.8268	0.8535	0.8289
	[0.7683,0.9794]	[0.7123,0.9419]	[0.7446,0.9619]	[0.7110,0.9462]
γ	0.0993	0.0879	0.1608	0.1330
	[0.0630,0.1355]	[0.0131,0.1600]	[0.1286,0.1930]	[0.0504,0.1920]
μ	0.0307	0.0081	-0.0170	-0.0086
	[-0.2116,0.2741]	[-0.2212,0.2443]	[-0.2583,0.2252]	[-0.2393,0.2283]
$\|\sigma_\eta\|$	-	0.0030	-	0.0022
	[-,-]	[0.0014,0.0050]	[-,-]	[.0003,0.0045]
σ_e^2	0.0023	0.0021	0.0022	0.0021
	[0.0019,0.0027]	[0.0018,0.0025]	[0.0018,0.0026]	[0.0018,0.0025]

Notes: The CEA index is used as a measure of financial liberalization. Reported are the posterior mean with 90% HPD interval (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 datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. Data are available over the period $1966Q3 - 2016Q4$ while the effective sample period is $1968Q2 - 2015Q2$ and the effective sample size is $T = 189$, i.e., 202 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$.

From the table, we note that our main parameter of interest γ, which captures the impact of financial liberalization on the consumption-wealth ratio, is positive in all instances. Hence, we find that financial liberalization, as measured through the CEA index, increases the consumption to wealth ratio. In particular, for the regressions 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 10% when we consider the PCE dataset and with 16% when we consider the NDS dataset. We further note that the elasticities α and β are of different magnitude as compared to those obtained from the model without financial liberalization which are reported in Table 3 above. 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 wealth ratio estimates of about 90% and more reported recently in the literature (see e.g., Lustig et al., 2013, and references therein).

Figure 4 presents the estimated time-varying part $\sigma_\eta \mu_t^*$ of the unobserved random walk component in the model that uses the CEA index as an indicator of financial liberalization, both with the PCE dataset and with the NDS dataset. Although the posterior inclusion probabilities reported in Table 2 above suggest 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 probabilities are 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 which is presented in Figure 2 above. From the figure, we note that for the NDS dataset, the unobserved random walk component is almost constant. For the PCE dataset, there is still some time-variation in this component in the model with financial liberalization. These findings are in line with the posterior inclusion probabilities reported in Table 2 above for the model with the CEA index used for fl_t, i.e., the probability equals only 3% for the NDS dataset but it is still substantial at 33% when the PCE dataset is used. These findings are also in line with the estimated standard deviations $|\sigma_\eta|$ of the error term of the random walk component μ_t reported in Table 4. While still larger than zero, they are smaller - substantially so, for the NDS dataset - than those reported in Table 3 above for the model without liberalization. Importantly, for both datasets, the upward trend observed in Figure 2 in the random walk component of the model without liberalization is no longer visible in Figure 4 and therefore seems to have been well-captured by the inclusion of the CEA index to the regression model.

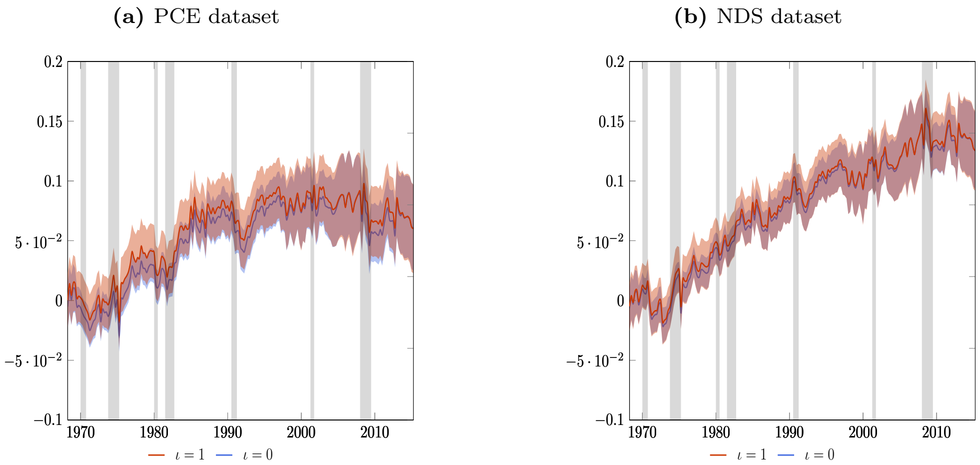
Figure 4: The unobserved stochastic trend in the model with financial liberalization



Note: Depicted is the mean and the 90% HPD interval (shaded area) of the estimated component $\sigma_\eta \mu_t^*$. This is obtained from the estimation of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu + \iota \sigma_\eta \mu_t^* + v_t$ under the restriction $\iota = 1$, the results of which are reported in Table 4, columns (2) and (4). Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. The effective sample period is $1968Q2 - 2015Q2$.

Again, we can proxy the evolution of the log consumption to total wealth ratio $c_t - w_t$ by calculating $c_t - \mu - \alpha a_t - \beta y_t$ for both datasets and for the model with and without the unobserved stochastic trend included in the error term. Figure 5 shows the posterior means and 90% HPD intervals. As before, the blue graphs depict the proxied log consumption-wealth ratio obtained from the model without an unobserved stochastic trend ($\iota = 0$) while the red graphs depict the proxied log consumption-wealth ratio obtained from the model with an unobserved stochastic trend ($\iota = 1$). The discrepancy observed between both is very 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 proxied consumption to total wealth ratio. Figure 5 also depicts the US recessions as determined by the NBER (grey shaded areas). From these, we can further observe that the calculated consumption-wealth ratios are cyclical, i.e., the consumption-wealth ratio tends to falls 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).

Figure 5: The log consumption-wealth ratio in the model with financial liberalization: model with ($\iota = 1$) and without ($\iota = 0$) unobserved stochastic trend



Note: Depicted is the mean and the 90% HPD interval (shaded area) of the calculated log consumption-wealth ratio $c_t - \mu - \alpha a_t - \beta y_t$ for every case reported in Table 4. For the model with an unobserved random walk included ($\iota = 1$), the ratio is printed in red, while for the model without an unobserved random walk included ($\iota = 0$), the ratio is printed in blue. The grey shaded areas are the NBER recessions. Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. The effective sample period is $1968Q2 - 2015Q2$.

3.4.4 Alternative financial liberalization measures

In Section 3.2, we also discussed alternative proxies of financial liberalization, namely the household debt to disposable income ratio (hhd) and the Abiad et al. index of financial reform (abiad). While the CEA index is our preferred indicator, it is nonetheless interesting to investigate to what extent these alternative measures have an impact on the relationship between consumption and wealth. Table 5 presents the results obtained when estimating eq.(21) with the variables hhd and abiad used as proxies for fl_t. To save space, in line with the posterior probabilities reported in Table 2 above, the hhd results are based on a regression that includes an unobserved stochastic trend ($\iota = 1$) while the abiad results are based on a regression that does not include an unobserved stochastic trend ($\iota = 0$). As before, results are reported for both datasets detailed in Section 3.2, i.e., the PCE dataset (with consumption measured through total personal consumer expenditures) and the NDS dataset (with consumption measured through expenditures on nondurables and services). From the table, we note that the parameter of interest γ is positive in all instances. Only for the abiad indicator of liberalization, however, do we find that the highest posterior density interval (HPD) for γ does not contain the value of zero. The results obtained with the abiad measure therefore confirm the earlier findings obtained with the CEA index. Results obtained with the hhd variable do not point towards an important impact of liberalization on the consumption-wealth ratio. To put this result in perspective, we reiterate that while the hhd variable has the advantage of being available over a long period, it is not a conceptually appealing measure of liberalization as it is affected by both credit supply and demand, as well as variations in collateral values.

Table 5: Model with financial liberalization (alternative measures): posterior distributions parameters of equation $c_t = \alpha a_t + \beta y_t + \gamma fl_t + \mu_t + v_t$

	(a) PCE dataset		(b) NDS dataset	
	(1) hhd	(2) abiad	(3) hhd	(4) abiad
α	0.1936	0.2327	0.2052	0.2309
	[0.1087,0.2778]	[0.1134,0.3562]	[0.1160,0.2927]	[0.1088,0.3565]
β	0.7840	0.7371	0.7543	0.7218
	[0.6839,0.8848]	[0.5936,0.8784]	[0.6500,0.8604]	[0.5752,0.8657]
γ	0.0307	0.1213	0.0768	0.1984
	[-0.0458,0.1047]	[0.0318,0.2100]	[-0.0050,0.1540]	[0.1126,0.2819]
μ	-0.0052	-0.0506	-0.0053	-0.0578
	[-0.2342,0.2229]	[-0.2782,0.1779]	[-0.2325,0.2260]	[-0.2884,0.1737]
$\lvert\sigma_\eta\rvert$	0.0032	-	0.0035	-
	[0.0018,0.0048]	[-,-]	[0.0021,0.0052]	[-,-]
σ_e^2	0.0021	0.0022	0.0021	0.0022
	[0.0018,0.0024]	[0.0018,0.0027]	[0.0018,0.0024]	[0.0017,0.0027]

Notes: The household debt to income ratio (hhd) and the Abiad et al. index of financial liberalization (abiad) are used as measures of financial liberalization. Given the results reported in Table 2, the reported estimations using the measure hhd are for $\iota = 1$ while those using the measure abiad are for $\iota = 0$. Reported are the posterior mean with 90% HPD interval (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 datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. For estimations using hhd for fl_t, data are available over the period $1951Q4 - 2016Q4$ while the effective sample period is $1953Q3 - 2015Q2$ and the effective sample size is $T = 248$, i.e., 261 observations minus 1 for first-differencing and minus 12 for constructing leads and lags since $p = 6$. For estimations using abiad for fl_t, data are available over the period $1973Q1 - 2005Q4$ (with effective sample period $1974Q4 - 2003Q2$ and effective sample size equal to $T = 119$).

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

The model presented in Section 2 implies that financial liberalization affects the consumption to wealth ratio via an incomplete markets channel, i.e., financial liberalization reduces the incomplete markets component of expected future consumption growth which, through the intertemporal budget constraint, increases the current consumption-wealth ratio. An alternative channel, not incorporated in the model above, would be the possibility that financial liberalization affects the consumption-wealth ratio through its impact on expected returns, i.e., financial liberalization reduces expected returns because it reduces the cost of capital (see e.g., Arouri et al., 2010, pages 45-47 and references therein). The impact of financial liberalization on the consumption-wealth ratio via expected returns could be direct, i.e., through the intertemporal budget constraint as can be seen from eq.(6), or could be indirect, i.e., through the impact of returns on consumption growth as can be seen from eqs.(11) and (17). This section presents empirical evidence that supports the incomplete markets channel and refutes the expected returns channel, hence providing further support for the model presented above. First, reduced form regressions are estimated that investigate the impact of financial liberalization on expected returns and on expected aggregate consumption growth. Next, we use the structural model of Section 2 to check whether the estimates obtained in this section are consistent with the long-run regression estimates reported above in Section 3.

4.1 Estimating reduced form regressions for returns and consumption growth

4.1.1 Specification, data and methodology

If financial liberalization affects the consumption-wealth ratio through the incomplete markets channel put forward in the model of Section 2 rather than through an alternative cost of capital channel, we should find that, at least over the sample period, financial liberalization has predictive power for aggregate consumption growth but that it does not have predictive ability for returns on wealth. To investigate this, we estimate reduced form predictive regressions of the following form,

$$z_{t+1} = \Psi_0^z + \Psi_1^z fl_t + \chi_{t+1}^z \tag{27}$$

where the predicted variable z_{t+1} is either aggregate returns 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

$$\chi_{t+1}^z = \pi^z \chi_t^z + o_{t+1}^z \tag{28}$$

with the error term o_{t+1}^z given by $o_{t+1}^z \sim iid\mathcal{N}\left(0, \sigma_{o^z}^2\right)$.[16] The parameter of interest is Ψ_1^z. We expect this parameter to be zero when $z_{t+1} = r_{t+1}$, i.e., we expect $\Psi_1^r = 0$ which suggests the absence of a cost

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

of capital channel. We expect this parameter to be negative if $z_{t+1} = \Delta c_{t+1}$, i.e., we expect $\Psi_1^{\Delta c} < 0$ which suggests the presence of an incomplete markets channel. From the structural equation, eq.(17), derived for aggregate consumption growth Δc_{t+1} in the model of Section 2, we note that, provided that the impact of fl_t on r_{t+1} is zero, the overall impact of fl_t on Δc_{t+1} stems from the unobserved incomplete markets component. This impact is negative as financial liberalization increases market completeness and therefore reduces expected aggregate consumption growth.[17]

As far as the data are concerned, for the financial liberalization variable fl_t we use, as before, the CEA index which is detailed in Section 3.2 and Appendix B. For real per capita aggregate consumption growth Δc_{t+1}, we use both total personal consumption expenditures (PCE) and expenditures on nondurable goods and services (NDS) as measures for consumption. We again refer to Section 3.2 and Appendix B for details. Finally, to proxy real returns on wealth r_{t+1}, we use real stock returns which constitute the data that are conventionally used to proxy returns on wealth. 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. We refer to Appendix B for more details on the construction of both returns series.

We estimate the regression eqs.(27)-(28) using Gibbs sampling with the general outline and technical details of the sampler provided in Appendix D. 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 $\sigma^2_{o^z}$ is inverse gamma (IG). The numbers reported in the table imply relatively flat priors for all parameters.

Table 6: 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	$\sigma^2_{o^z}$	.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 $\sigma^2_{o^z}$.

[17] By estimating reduced-form regressions instead of estimating the first-order condition eq.(17) directly, we avoid the complications related to the estimation of the intertemporal elasticity of substitution parameter (see Havranek et al., 2015, and references therein).

4.1.2 Results

The estimation results are reported in Table 7. From the table, we note that the impact of financial liberalization on future returns is not different from zero, i.e., the HPD interval for the parameter Ψ_1^z (with $z = r$) contains the value of zero. The impact of fl_t on future aggregate consumption growth is, as expected, different from zero and negative. This is particularly the case for the NDS dataset. From the structural model eq.(17), we note that these results suggest that financial liberalization has an impact on expected consumption growth that is not related to its impact on expected returns but rather stems from its impact on the (unobserved) incomplete markets term in aggregate consumption growth. In particular, financial liberalization reduces expected aggregate consumption growth because it decreases the incomplete markets component in consumption growth.

Table 7: 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) PCE	(4) NDS
Ψ_0^z	0.0003	0.0055	0.0066	0.0060
	[-0.0207,0.0215]	[-0.0045,0.0158]	[0.0044,0.0088]	[0.0042,0.0077]
Ψ_1^z	0.0154	0.0074	-0.0029	-0.0034
	[-0.0217,0.0524]	[-0.0105,0.0251]	[-0.0067,0.0008]	[-0.0065,-0.0003]
π^z	0.0734	0.0234	0.3377	0.4888
	[-0.0429,0.1902]	[-0.0937,0.1411]	[0.2248,0.4515]	[0.3790,0.5990]
$\sigma_{o^z}^2$	0.0075	0.0019	.00004	.00001
	[0.0064,0.0088]	[0.0016,0.0023]	[.00003,.00005]	[.00000,.00002]

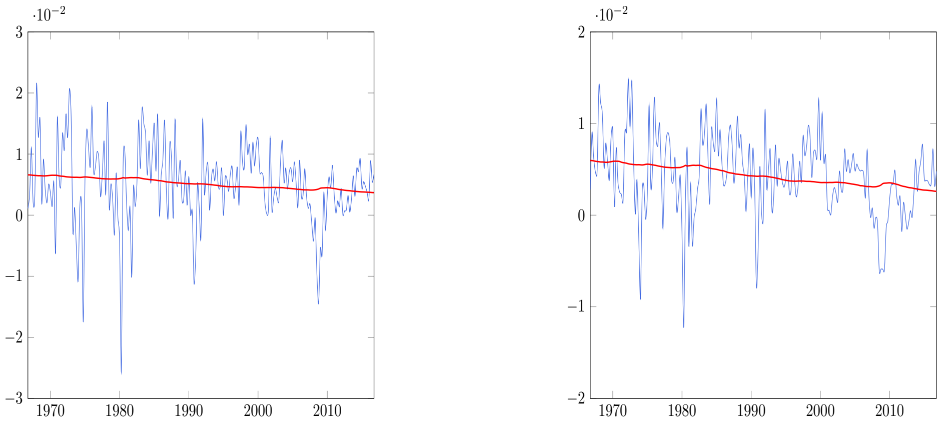
Notes: The CEA index (cea) is used as a measure of financial liberalization fl_t. Reported are the posterior mean with 90% HPD interval (in square brackets). The error term $\chi_{t+1}^z = \pi^z \chi_t^z + o_{t+1}^z$ follows an $AR(1)$ process with AR parameter π^z and innovation variance $\sigma_{o^z}^2$. Details on the data used for stock and bond returns as well as details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2 and in Appendix D. Data are available over the period $1966Q3 - 2016Q4$ with the effective sample period being $1966Q4 - 2016Q4$ (i.e., $T = 201$).

Figure 6 presents the fit of both regressions conducted for aggregate consumption growth, i.e., for the PCE and NDS datasets. From the figure, we note that a low frequency downward evolution is present in aggregate consumption growth which can be captured by our preferred baseline financial liberalization measure, i.e., the CEA index.

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, this finding supports the incomplete markets channel that we put forward in this paper to explain the impact of liberalization on the consumption-wealth ratio. In the next section, we check whether the estimates obtained from estimating the reduced form eq.(27) and those obtained from estimating the long-run regression eq.(21) of the previous section are consistent with each other.

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

(a) PCE dataset **(b)** NDS dataset



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 (cea) is used as a measure of financial liberalization. Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2. The effective sample period is $1966Q4 - 2016Q4$.

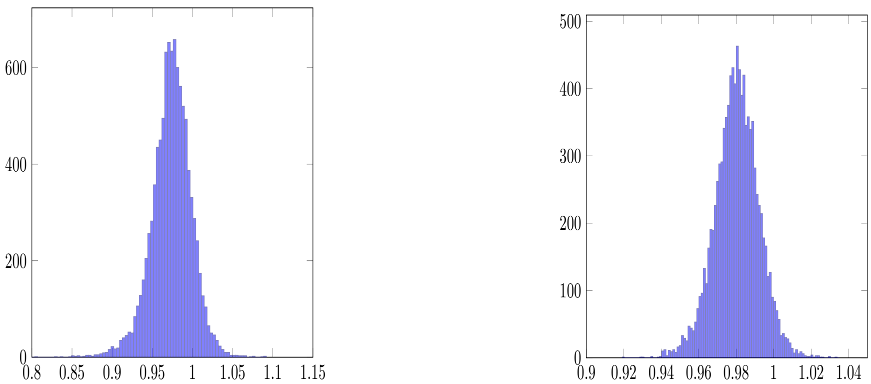
4.2 Link with the structural model

In this section, we check the consistency of the estimates obtained in Section 3 for γ, i.e., the impact of financial liberalization fl_t on the consumption-wealth ratio $c_t - w_t$ (see eq.(15) above), and the estimates obtained in Section 4.1 for $\Psi_1^{\Delta c}$, i.e., the total impact of fl_t on aggregate consumption growth Δc_{t+1}. Since the estimations conducted in the previous subsection imply that fl_t affects Δc_{t+1} directly through the incomplete markets component of Δc_{t+1} rather than through returns, we can write, using the structural model eq.(17) above, that $\Psi_1^{\Delta c} = \frac{1}{\theta} b$ with $\theta > 0$ the coefficient of relative risk aversion and $b \leq 0$ the aggregate impact of financial liberalization on the incomplete markets component of consumption growth. Similarly, we can write γ as a function of the model parameters since from the model in Section 2, we have $\gamma = -\frac{b}{\theta} \frac{\rho^c}{1-\rho^c}$ with ρ^c the discount factor which reflects the relative steady states values of total wealth and consumption. As such, the estimates obtained for γ and $\Psi_1^{\Delta c}$ imply values for the structural parameter

ρ^c, i.e., we have $\rho^c = \frac{\gamma}{\gamma - \Psi_1^{\Delta c}}$. As noted in Section 2 above, this discount factor is theoretically expected to be slightly smaller than one. This is confirmed by Figure 7 which reports the posterior distribution of ρ^c calculated as implied from the posterior distributions of γ and $\Psi_1^{\Delta c}$. For both considered datasets (PCE and NDS), the posterior mean of ρ^c lies slightly below one, i.e., it equals 0.97 for the PCE dataset and it equals 0.98 for the NDS dataset. These are theoretically sound values that confirm that the estimates obtained in Sections 3 and 4 of the paper are consistent with each other. This result provides further support for the incomplete markets channel put forward in the paper as an explanation for the estimated impact of financial liberalization on the long-run relationship between consumption and wealth.

Figure 7: Posterior distribution of the discount factor ρ^c

(a) PCE dataset **(b)** NDS dataset



Note: Depicted is the posterior distribution of the discount factor ρ^c. For the PCE dataset, the mean equals 0.9702 with 90% HPD interval $[0.9289, 1.0080]$ while for the NDS dataset, the mean equals 0.9791 with 90% HPD interval $[0.9596, 0.9979]$. The discount factor ρ^c is calculated from the distributions of the parameters γ and $\Psi_1^{\Delta c}$ (see Tables 4 and 7) as $\rho^c = \frac{\gamma}{\gamma - \Psi_1^{\Delta c}}$. Details on the datasets PCE (with consumption measured through total personal consumer expenditures) and NDS (with consumption measured through expenditures on nondurables and services) are provided in Section 3.2.

5 Conclusions

We investigate the impact of financial liberalization on the relationship between consumption and total wealth, i.e., on the consumption-wealth ratio. The theoretical framework consists of a heterogeneous agent model in which the presence of a precautionary saving motive and a liquidity constraint imply the existence of an incomplete markets component in consumption growth. Financial liberalization is persistent and signals a future reduction in this incomplete markets component. This implies a reduction in expected future consumption growth which, through the consumer's intertemporal budget constraint, increases the current consumption to wealth ratio. From the model, an estimable aggregate long-run relationship is derived between consumption, total wealth and financial liberalization. Estimation using quarterly US data is conducted within a state space framework which allows to reliably estimate the long-run relationship between the stochastically trended variables in the regression even in the presence of a 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 to sixteen percent. We then check the incomplete markets channel through which financial liberalization affects the consumption-wealth ratio according to our model by testing whether, as our model suggests, financial liberalization has predictive power for aggregate consumption growth. Our estimates confirm that this is the case.

References

Abiad, A., E. Detragiache, and T. Tressel (2008). A new database of financial reforms. Working paper 266, International Monetary Fund.

Arouri, M., F. Jawadi, and D. Nguyen (2010). *The dynamics of emerging stockmarkets*. Springer-Verlag Berlin.

Attanasio, O. and G. Weber (1993). Consumption growth, the interest rate and aggregation. *Review of Economic Studies 60*, 631–649.

Bauwens, L., M. Lubrano, and J.-F. Richard (2000). *Bayesian inference in dynamic econometric models*. Oxford University Press.

Bianchi, F., M. Lettau, and S. Ludvigson (2017). Monetary policy and asset valuation. *Unpublished manuscript*.

Canarella, G., S. Pollard, and K. Lai (1990). Cointegration between exchange rates and relative prices: another view. *European Economic Review 34*(7), 1303–1322.

Carroll, C. D., J. Slacalek, and M. Sommer (2019). Dissecting saving dynamics: measuring wealth, precautionary, and credit effects. *NBER Working Paper 26131*.

Carter, C. and R. Kohn (1994). On Gibbs sampling for state space models. *Biometrika 81*, 541–53.

Durbin, J. and S. Koopman (2001). *Time series analysis by state space methods*. Oxford University Press.

Everaert, G. (2010). Estimation and inference in time series with omitted $I(1)$ variables. *Journal of Time Series Econometrics 2*(2), 1–25.

Frühwirth-Schnatter, S. and H. Wagner (2010). Stochastic model specification search for Gaussian and partial non-Gaussian state space models. *Journal of Econometrics 154*(1), 85–100.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In J. Berger, J. Bernardo, A. Dawid, and A. Smith (Eds.), *Bayesian statistics*. Oxford University Press.

Groen, J., R. Paap, and F. Ravazzolo (2013). Real-time inflation forecasting in a changing world. *Journal of Business and Economic Statistics 31*(1), 29–44.

Harvey, A. (1989). *Forecasting structural time series models and the Kalman filter*. Cambridge University Press.

Harvey, A., S. Henry, S. Peters, and S. Wren-Lewis (1986). Stochastic trends in dynamic regression models: an application to the employment-output equation. *Economic Journal 96*, 975–985.

Havranek, T., R. Horvath, Z. Irsova, and M. Rusnak (2015). Cross-country heterogeneity in intertemporal substitution. *Journal of International Economics 96*, 100–118.

Justiniano, A., G. Primiceri, and A. Tambalotti (2015). Household leveraging and deleveraging. *Review of Economic Dynamics 18*(1), 3–20.

Kim, C.-J. and C. Nelson (1999). *State-space models with regime switching. Classical and Gibbs-sampling approaches with applications*. Cambridge: MIT Press.

Kim, S., N. Shephard, and S. Chib (1998, July). Stochastic volatility: likelihood inference and comparison with ARCH Models. *Review of Economic Studies 65*(3), 361–93.

Lettau, M. and S. Ludvigson (2001). Consumption, aggregate wealth, and expected stock returns. *Journal of Finance LVI*(3), 815–849.

Lettau, M. and S. Ludvigson (2004). Understanding trend and cycle in asset values: re-evaluating the wealth effect on consumption. *American Economic Review 94*(1), 276–299.

Lettau, M. and S. Ludvigson (2005). Expected returns and expected dividend growth. *Journal of Financial Economics 76*(3), 583–626.

Lettau, M. and S. Ludvigson (2015). Changes in the measurement of consumption in cay. *Report*.

Lustig, H., S. Van Nieuwerburgh, and A. Verdelhan (2013). The wealth-consumption ratio. *Review of Asset Pricing Studies 3*(1), 38–94.

Newey, W. and K. West (1987). A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*, 703–708.

Parker, J. and B. Preston (2005). Precautionary savings and consumption fluctuations. *American Economic Review 95*(4), 1119–1143.

Planas, C., W. Roeger, and A. Rossi (2007). How much has labor taxation contributed to European structural unemployment? *Journal of Economic Dynamics and Control 31*(4).

Rudd, J. and K. Whelan (2006). Empirical proxies for the consumption-wealth ratio. *Review of Economic Dynamics 9*, 34–51.

Zeldes, S. (1989). Consumption and liquidity constraints: an empirical investigation. *Journal of Political Economy 97*(2), 305–346.

Appendices

Appendix A Derivations theoretical framework of Section 2

A.1 Derivation of eq.(6)

This appendix briefly describes the steps in the derivation of eq.(6) in Section 2 (see e.g., Lettau and Ludvigson, 2005). We can write the per period constraint $W_{i,t+1} = (1+r_{i,t+1})(W_{it}-C_{it})$ as $\frac{W_{i,t+1}}{W_{it}} = (1+r_{i,t+1})\left(1-\frac{C_{it}}{W_{it}}\right)$. After taking logs, this gives $\Delta w_{i,t+1} = r_{i,t+1} + \ln(1-\exp(c_{it}-w_{it}))$ with $w_{it} = \ln W_{it}$ and $c_{it} = \ln C_{it}$. We linearize this equation through a first-order Taylor approximation which gives,

$$\Delta w_{i,t+1} = r_{i,t+1} + \left(1 - \frac{1}{\rho^c}\right)(c_{it} - w_{it}) \tag{A-1}$$

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

$$c_{it} - w_{it} = \rho^c(r_{i,t+1} - \Delta c_{i,t+1}) + \rho^c(c_{i,t+1} - w_{i,t+1}) \tag{A-2}$$

Solving equation (A-2) forward ad infinitum, imposing the transversality condition $(\rho^c)^\infty(c_{i,t+\infty} - w_{i,t+\infty}) = 0$ and taking expectations at period t then gives eq.(6) in the text.

A.2 Derivation of eq.(14)

This appendix briefly describes the steps in the derivation of eq.(14) in Section 2. Substituting eq.(12) into eq.(11) and writing down the resulting expression for period $t+j$, we obtain,

$$\Delta c_{i,t+j} = \frac{1}{\theta}\ln\delta + \frac{1}{\theta}r_{i,t+j} + \frac{1}{\theta}a_i + \frac{1}{\theta}b_i fl_{t+j-1} + \frac{1}{\theta}\varpi_{i,t+j} \tag{A-3}$$

Taking expectations at time t of eq.(A-3) and using the result $E_{it} fl_{t+j-1} = fl_t$ which follows from the random walk process assumed for fl_{t+1} in eq.(13), we obtain,

$$E_{it}\Delta c_{i,t+j} = \frac{1}{\theta}\ln\delta + \frac{1}{\theta}E_{it}r_{i,t+j} + \frac{1}{\theta}a_i + \frac{1}{\theta}b_i fl_t + \frac{1}{\theta}E_{it}\varpi_{i,t+j} \tag{A-4}$$

Substituting eq.(A-4) - where we leave out the constants $\frac{1}{\theta}\ln\delta$ and $\frac{1}{\theta}a_i$ for simplicity - into eq.(6) gives,

$$c_{it} - w_{it} = -\frac{1}{\theta}b_i fl_t \sum_{j=1}^{\infty}(\rho^c)^j + E_{it}\sum_{j=1}^{\infty}(\rho^c)^j\left[(1-\frac{1}{\theta})r_{i,t+j} - \frac{1}{\theta}\varpi_{i,t+j}\right] \tag{A-5}$$

Upon noting that $\sum_{j=1}^{\infty}(\rho^c)^j = \frac{\rho^c}{1-\rho^c}$ and using this in eq.(A-5), we obtain eq.(14) in the text.

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

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.

For the PCE dataset, consumption is measured as total personal consumption expenditures (line 1 of NIPA Table 2.3.5). For the NDS dataset, consumption equals nondurable goods expenditure (line 8 of 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.

For both datasets, 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).

For the PCE dataset, asset wealth is calculated as the net worth of households and nonprofit organizations minus the households' and nonprofit organizations' holdings of consumer durable goods as durable goods in the PCE dataset are already accounted for in the consumption measure. For the NDS dataset, asset wealth is calculated as the net worth of households and nonprofit organizations which includes households' and nonprofit organizations' holdings of consumer durable goods.

For the PCE dataset, all calculated series are deflated with the price index for total personal consumption expenditures (line 1 of NIPA Table 2.3.4). For the NDS dataset, the price index used to deflate all series 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 $2009 = 100$. 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 is 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

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. 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).

Appendix C Estimation details state space model of Section 3

This appendix discusses the estimation of the state space system given by eqs.(21)-(26). First, we present the general outline of the Gibbs sampler in Section C.1. Then, the technical details about the different steps of the sampler are discussed in Section C.2. Finally, a convergence analysis is provided in Section

C.3.

C.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 20.000 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 10.000 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.(21) as the fraction of ι's that are equal to 1 over the 10.000 retained draws of the Gibbs sampler.

C.2 Details on the steps of the sampler

C.2.1 Regression framework

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

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

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,

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

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

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

where $p(\iota)$ is the prior distribution of ι and $p(Z|\iota, X, \sigma_\varphi^2)$ is the marginal likelihood of regression eq.(C-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.(C-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 $X^r = X = \left[\begin{array}{cccccc} x & \Delta x_{-p} & ... & \Delta x_{+p} & \varrho & \mu^* \end{array}\right]$ and $\zeta^r = \zeta = \left[\begin{array}{cccccc} \phi' & \kappa'_{-p} & ... & \kappa'_{+p} & \mu & \sigma_\eta \end{array}\right]'$ 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 variable included) or $k = 3$ (model with financial liberalization variable included). 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.(C-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.[2]

C.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.(24), 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 model is given by,

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

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

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

(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. (C-4)-(C-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.(21)-(26), 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.

[2] 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.

C.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 10.000 retained sampler draws (see Section C.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 20% 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 20% and the last 40%).

In Tables C-1 and C-2, we present the convergence analysis corresponding to the results reported in Tables 3 and 4 in the text. 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 state, i.e., a time series of length $T = 248$ (Table C-1) or $T = 189$ (Table C-2). In both tables, we report statistics of the distributions of the inefficiency factors for every parameter or parameter group, i.e., median, minimum, maximum, and - for the state μ^* - 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 C-1: Inefficiency factors and convergence diagnostics (results Table 3)

				Inefficiency factors (Stats distribution)					Convergence (Rejection rates)	
Dataset	Trend	Parameters	Number	Median	Min	Max	5%	10%	5%	10%
PCE	$\iota = 0$	ϕ	2	0.83	0.83	0.83	-	-	0.00	0.00
		μ	1	0.78	0.78	0.78	-	-	0.00	0.00
		σ_e^2	1	1.03	1.03	1.03	-	-	0.00	0.00
		κ	26	0.95	0.84	1.20	-	-	0.08	0.11
	$\iota = 1$	ϕ	2	6.72	5.08	8.36	-	-	0.00	0.00
		μ	1	9.06	9.06	9.06	-	-	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	8.48	8.48	8.48	-	-	0.00	0.00
		σ_e^2	1	1.06	1.06	1.06	-	-	0.00	0.00
		κ	26	1.01	0.84	1.27	-	-	0.08	0.11
		μ^*	248	0.94	0.81	1.19	0.90	1.14	0.00	0.01
NDS	$\iota = 0$	ϕ	2	0.83	0.83	0.83	-	-	0.00	0.00
		μ	1	0.78	0.78	0.78	-	-	0.00	0.00
		σ_e^2	1	1.03	1.03	1.03	-	-	0.00	0.00
		κ	26	0.95	0.84	1.20	-	-	0.04	0.08
	$\iota = 1$	ϕ	2	8.92	7.35	10.50	-	-	0.00	0.00
		μ	1	5.89	5.89	5.89	-	-	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	19.14	19.14	19.14	-	-	0.00	0.00
		σ_e^2	1	1.01	1.01	1.01	-	-	0.00	0.00
		κ	26	1.02	0.83	1.41	-	-	0.04	0.11
		μ^*	248	0.98	0.80	1.17	0.90	1.12	0.00	0.00

Notes: The convergence analysis corresponds to the results reported in Table 3 and 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 10.000 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 20% and last 40% of the 10.000 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 20% and the last 40%).

Table C-2: Inefficiency factors and convergence diagnostics (results Table 4)

				Inefficiency factors (Stats distribution)					Convergence (Rejection rates)	
Dataset	Trend	Parameters	Number	Median	Min	Max	5%	10%	5%	10%
PCE	$\iota = 0$	ϕ	3	0.95	0.84	0.98	-	-	0.00	0.00
		μ	1	0.81	0.81	0.81	-	-	0.00	0.00
		σ_e^2	1	0.98	0.98	0.98	-	-	0.00	1.00
		κ	39	0.99	0.83	1.34	-	-	0.08	0.13
	$\iota = 1$	ϕ	3	1.59	1.47	11.45	-	-	0.00	0.00
		μ	1	1.00	1.00	1.00	-	-	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	1.29	1.29	1.29	-	-	0.00	0.00
		σ_e^2	1	0.94	0.94	0.94	-	-	0.00	0.00
		κ	39	0.97	0.77	1.31	-	-	0.00	0.02
		μ^*	189	1.02	0.89	1.26	0.94	1.20	0.05	0.10
NDS	$\iota = 0$	ϕ	3	0.95	0.85	0.98	-	-	0.00	0.00
		μ	1	0.81	0.81	0.81	-	-	0.00	0.00
		σ_e^2	1	0.98	0.98	0.98	-	-	1.00	1.00
		κ	39	0.99	0.83	1.34	-	-	0.05	0.13
	$\iota = 1$	ϕ	3	1.26	1.20	4.70	-	-	0.00	0.00
		μ	1	0.94	0.94	0.94	-	-	0.00	0.00
		$\lvert\sigma_\eta\rvert$	1	1.87	1.87	1.87	-	-	0.00	0.00
		σ_e^2	1	0.91	0.91	0.91	-	-	0.00	0.00
		κ	39	0.96	0.75	1.27	-	-	0.00	0.00
		μ^*	189	0.92	0.82	1.24	0.85	1.12	0.00	0.00

Notes: See Table C-1.

The calculated inefficiency factors suggest that the MCMC sampler performs well and that all parameters are well converged using our retained 10.000 draws. In fact, an accurate analysis could have been conducted with less than 10.000 draws. From Table C-1, we note that more draws of in particular the parameters 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 $\iota = 0$ (irrespective of the dataset used). As discussed in the text, once the financial liberalization variable is included in the model, the unobserved stochastic trend is less relevant. This is reflected by the more similar inefficiency factors for $\iota = 1$ and $\iota = 0$ in Table C-2. 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 20% and last 40% of the retained draws are equal. In a few instances, higher rejection rates are observed, in particular for the parameters κ and σ_e^2. We argue that these rejection rates are due to the particular sample of draws and are not indicative of non-convergence as these rejection rates are not withheld when we rerun the sampler using another seed. Hence, in general, we can conclude that the convergence of the sampler for the retained number of draws is satisfactory.

Appendix D Estimation details regression model of Section 4

This appendix discusses the estimation of the regression eqs.(27)-(28) through Gibbs sampling. 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. We do not report the convergence analysis, but it is available from the authors upon request.

D.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 20.000 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 10.000 retained draws.

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,

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

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 $\varphi \sim iid\mathcal{N}\left(0, \sigma_\varphi^2 I_T\right)$. 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 $\sigma_\varphi^2 \sim \mathcal{IG}(s_0, S_0)$ 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 $\sigma_\varphi^2 \sim \mathcal{IG}(s, S)$ with,

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

D.2.2 Sample π^z

To sample π^z conditional on the parameters Ψ_0^z, Ψ_1^z, $\sigma_{o^z}^2$ and the data, we note that eq.(28) in the text can be cast in the framework of eq.(D-1). We calculate $\chi_{t+1}^z \equiv z_{t+1} - \Psi_0^z - \Psi_1^z fl_t$ so that the dependent variable is $Z = \chi_{+1}^z$ where χ_{+1}^z is the $T \times 1$ vector containing χ_{t+1}^z stacked over time. The regressor is $X = \chi^z$ where χ^z contains χ_t^z stacked over time. The regression coefficient is $\zeta = \pi^z$. The error term is $\varphi = o_{+1}^z$ where o_{+1}^z contains o_{t+1}^z stacked over time. The variance $\sigma_\varphi^2 = \sigma_{o^z}^2$ is assumed to be given in this step (it is sampled in the next step). Once the matrices of eq.(D-1) are determined, the parameter ζ can be sampled from the Gaussian posterior distribution given above with the prior distribution as specified in Table 6 in the text.[3]

D.2.3 Sample Ψ_0^z, Ψ_1^z and $\sigma_{o^z}^2$

To sample the parameters Ψ_0^z, Ψ_1^z and $\sigma_{o^z}^2$ conditional on the parameter π^z and the data, we first transform eq.(27) in the text so that it can be cast in the framework of eq.(D-1). First, we write eq.(27) as $z_{t+1} = x_t\Psi^z + \chi_{t+1}^z$ 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 $z_{t+1} = x_t\Psi^z + \chi_{t+1}^z$ by $(1 - \pi^z L)$ (with L the lag operator) to obtain $\tilde{z}_{t+1} = \tilde{x}_t\Psi^z + o_{t+1}^z$ where $\tilde{z}_{t+1} = (1 - \pi^z L)z_{t+1}$ and $\tilde{x}_t = (1 - \pi^z L)x_t$. Equation $\tilde{z}_{t+1} = \tilde{x}_t\Psi^z + o_{t+1}^z$ is in accordance with eq.(D-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 $\varphi = o_{+1}^z$ where o_{+1}^z contains o_{t+1}^z stacked over time. The variance $\sigma_\varphi^2 = \sigma_{o^z}^2$. Once the matrices of eq.(D-1) are determined, the parameters ζ and σ_φ^2 can be sampled from the posterior distributions given above with the prior distributions as specified in Table 6 in the text.[4]

[3] 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 6.

[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 6. 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 6. Further, B_0 is an 2×2 diagonal matrix containing as elements the variances 1 - i.e., the variable V_0 in Table 6 - divided by the prior belief for $\sigma_{o^z}^2$ - i.e., the variable σ_0^2 in Table 6.