Online Appendix

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

by Malin Gardberg and Lorenzo Pozzi

Appendix A Derivation of equation (1)

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

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

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

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

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

Appendix B Data

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

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

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

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

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

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

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

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

B.2 Data for the financial liberalization variable fl_t

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

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

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

B.3 Data for returns r_t

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

B.4 Other data

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

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

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

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

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

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

Appendix C Frequentist unit root test on 'cay'

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

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

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

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

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

Appendix D Estimation details state space model of Section 3

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

D.1 General outline

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

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

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

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

D.2 Details on the steps of the sampler

D.2.1 Regression framework

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

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

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

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

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

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

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

Sample the binary indicator ι

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

Sample the other parameters in Γ

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

D.2.2 State space framework

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

[4] We note that $s_0 = \nu_0 T$ and $S_0 = \nu_0 T \sigma_0^2$ with the values for ν_0 and σ_0^2 given in Table 1. We note that b_0^r is a $M^r \times 1$ vector containing the values of b_0 given in Table 1. Further, B_0^r is an $M^r \times M^r$ diagonal matrix containing as elements the variances 1 - i.e., the variable V_0 in Table1 - divided by the prior belief for σ_e^2 - i.e., the variable σ_0^2 in Table 1.

model is given by,

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

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

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

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

D.3 Convergence analysis

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

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

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

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

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

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

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

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

Appendix E Additional results and robustness checks

E.1 Other theories: uncertainty and demographics

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

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

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

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

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

E.2 Different lag/lead lengths and different priors

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

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

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

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

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

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

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

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

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

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

E.3 Alternative data

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

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

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

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

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

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

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

E.4 International evidence

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

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

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

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

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

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

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

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

Appendix F Estimation details regression model of Section 4

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

F.1 General outline

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

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

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

F.2 Details on the steps of the sampler

F.2.1 Regression framework

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

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

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

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

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

$$s = s_0 + T/2$$

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

F.2.2 Sample π^z

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

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

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

References

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

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

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