Online Appendix: MPC Heterogeneity and the Dynamic Response of Consumption to Monetary Policy

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1 Online Appendix

This online appendix contains further details and additional material to augment the presentation in the text of the paper.

1.1 Income processes

We estimate household income processes using the European Community Household Panel (ECHP) during the period of 1994-2001 (8 waves). The ECHP is a panel survey collecting internationally comparable data on income and demographics of a representative sample of households year after year in several euro area countries.[1] Our income measure is defined as total reported after-tax, non-asset household income. This definition includes labor income received by the household head and all other members of the household, such as income from work (wages, salaries and self-employment earnings) and social cash transfers (government transfers, workers compensation, unemployment insurance and old-age pensions), net of any taxes and social contributions paid. We use a broad definition of labor income to allow for insurance mechanisms other than asset accumulation within each country, such as unemployment benefits and other welfare programs present in the European countries we consider. Including only labor income would overstate the variability in income that households face while including also financial asset

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[1]In 2001, the ECHP was discontinued, and since 2004, replaced by the EU Statistics on Income and Living Conditions (EU-SILC), an income survey. But it is not suitable for our analysis due to its limited panel dimension. Note that the exposition of the estimation of labour income processes follows closely Le Blanc and Georgarakos (2013).

and capital income would understate the risk coming from earnings.[2] Income from the ECHP relates to the year immediately preceding the survey (e.g. 2000 for wave 8 conducted in 2001), whereas the household composition and the sociodemographic characteristics of household members are those registered at the moment of the interview. To ensure international comparability, income data are PPP-adjusted.[3]

1.1.1 Profiles

As the slope of the deterministic income profiles and the risk properties of labor income differ by education, we split households in each country into a subsample of households whose head has a college degree and a subsample of households with a head without college degree.[4] For each education group and country, data from various years are pooled together. We then regress log income on household characteristics, an age polynomial of order three and either cohort or time effects. As age, time and birth year are perfectly correlated, we estimate age-income profiles controlling for time effects and assume that cohort effects are fixed:[5]

$$log(Y_{it}) = const. + polynomial(age_{it}) + HHComp_{it} + Time_t. \quad (1)$$

Household composition, $HHComp_{it}$, includes the number of children in the household, the number of dependent adults, the number of heads in the household and time dummies. The ECHP population weights are used in the regression equation (1).[6]

For each country and education group, we estimate this equation twice, once for households in the labor force and once for households above age 65. We assume for now that retirement takes place exogenously at age 65, the statutory retirement age in all countries, which makes the profiles comparable over all ages. To obtain smoothed age-income profiles suitable as ingredients into the model, we fit a cubic age polynomial for our pre-retirement regression and assume that income is linear in age for the post-retirement period.[7]

The resulting profiles illustrate age and education-specific variations in expected income over the life-cycle for a household that has a typical life-cycle evolution in household size and has a typical time effect.[8]

Figure 1 displays the fitted (exponentiated) values of the income predictions for each education group and each country. The dots around the lines in Figure 1 represent the means of observed household income by age, suggesting

[2] There are other important insurance mechanisms that our definition does not capture, namely: receipts in kind, transfers paid to and received from other households, negative capital income and imputed rents (i.e. the money value by not having to pay full market rent by living in one's own accommodation) The latter could be meaningful in particular in the Southern European countries where home ownership rates are high.

[3] We exclude all households whose heads are younger than 20 years of age, that report annual income smaller than zero euro, that have any crucial variable missing or who have not participated for at least two years in the survey.

[4] Ideally, one would define smaller education groups depending on number of years in schooling (see e.g. Cooper and Zhu (2015), Laibson, Repetto, and Tobacman (2001)) or differentiate by highest degree obtained (no high school, high school, college), see e.g. Cocco, Gomes, and Maenhout (2005), Hubbard, Skinner, and Zeldes (1994). Unfortunately, this would make the number of observations in some cells too small.

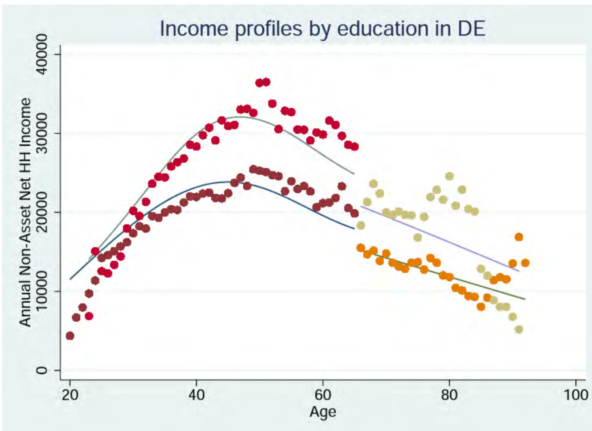
[5] We also estimated a version of the same equation including cohort instead of time effects. The shapes, levels and growth rates of these estimations are very similar to our profiles. We therefore conclude that our specification is robust to using cohort or time effects.

[6] Unweighted results are essentially the same.

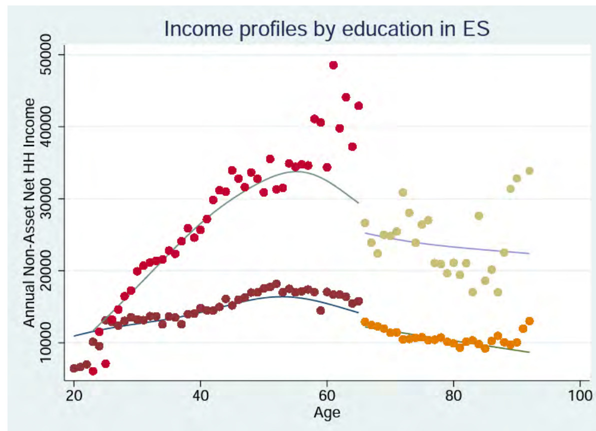
[7] Note that the retirement period is left out by most papers and many authors assume a flat income scheme after retirement, e.g. Cocco, Gomes, and Maenhout (2005). We find the resulting age-decreasing pattern more plausible.

[8] For details on the exact regressions and robustness checks of the income profiles see Le Blanc and Georgarakos (2013) and the literature therein.

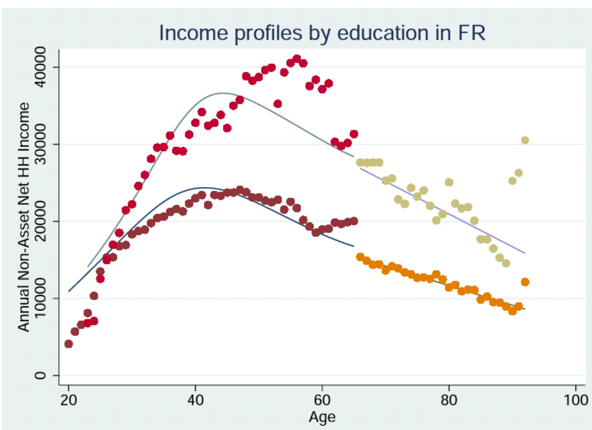
Figure 1: Age-Income Profiles



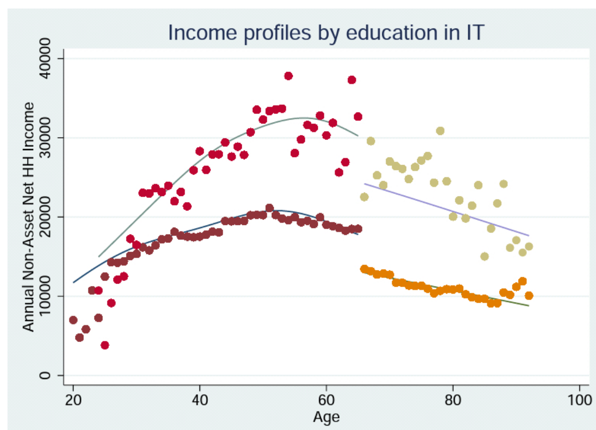
(a) Germany



(b) Spain



(c) France



(d) Italy

The figures display fitted household income over the life-cycle for those headed by college graduates and those whose heads do not have a college degree. We fit a cubic age polynomial for our pre-retirement regression and assume a linear relation between income and age for the post-retirement period. The higher curve represents higher education households in all countries.

that we fit the data reasonably well.

The resulting age-income profiles display heterogeneity with respect to both the steepness and peaks of the income profiles. After a sharp increase in the beginning of working life, income for college graduates peaks in mid-working life in Germany and France. Households whose heads are without a college degree present relatively flat profiles at a lower level than college graduates, reflecting the college premium. In the two southern countries income of college graduates grows slowly until it reaches a peak late in working life, around age 55 to 60 when the income of households within the same education group already decreases in Germany and France. Households without a college degree in Italy and Spain have on average an even flatter income profile that hardly grows over the life-cycle. The gap between employment income and retirement income varies across countries, reflecting the different generosity of the pension systems and other transfers after retirement. In particular, in Italy and Spain, reaching retirement age is connected to a large loss in income.

1.1.2 Stochastic Components

We use the variation in log income residuals from our estimation of the country- and education-specific income profiles from equation (1) to characterize the uncertainty of earnings over the life-cycle. Following Carroll (1992), Guvenen (2009), Laibson, Repetto, and Tobacman (2001), among others, we assume that the log income residuals, $\tilde{y}_{i,t}$, reflect income shocks and follow the stochastic process given by:

$$\begin{aligned} \tilde{y}_{i,t} &= z_{i,t} + \epsilon_{i,t} \\ z_{i,t} &= \rho z_{i,t-1} + \eta_{i,t} \end{aligned} \tag{2}$$

where $\epsilon_{i,t}$ and $\eta_{i,t}$ are independent zero-mean random shocks, with variance σ_ϵ^2 and σ_η^2 respectively. The shock $\eta_{i,t}$ is persistent, with a persistence parameter of ρ.

The identification of the structural parameters in equation (2), i.e. $(\sigma_\epsilon^2, \sigma_\eta^2, \rho)$, is achieved by minimizing the distance between the theoretical and the empirical autocovariances of the process using an iterative process that employs an optimal weighting matrix, as proposed by Hansen (1982) and Chamberlain (1984).[9]

Table 1 displays the estimates of the variances of the persistent and transitory shocks and the persistence parameter by education level for each country. Over the whole sample, households in Germany face the lowest persistence of income shocks ($\rho = 0.91$) while Italian and French households have highly persistent shocks ($\rho =$0.98 and 0.96 respectively). Permanent shocks to income are lower for college graduates than for non-college educated households. This is consistent with the notion that shocks to more educated households are small but they could be very persistent as their human capital is more specific. Also, the transitory component of income is usually lower for households with a college degree (with the exception of France). College graduates in Germany display low permanent and transitory shocks. In Italy and Spain, lower educated households face large and very persistent permanent shocks.[10] Over time the large and persistent shocks are translated into more income dispersion, which in turn generates more dispersion in MPCs in our simulated data. As we will show, Spain and Italy exhibit much larger consumption responses to monetary innovation because of the large MPCs of low income households in these countries.

[9] In particular, we use a Generalized Method of Moments (GMM) estimator to minimize the distance between the theoretical and empirical autocovariance. For details about moments construction and the estimation method, see Le Blanc and Georgarakos (2013) and Guvenen (2009).

[10] On interpretation of this result is that the economic expansion that started roughly 10 years before the first wave of our data set (in particular in Spain but also in Italy) mostly benefited the more educated while permanent income uncertainty increased for the less educated.

Table 1: Stochastic Processes by education and country

	Germany			Spain		
	ρ	σ^2_ϵ	σ^2_η	ρ	σ^2_ϵ	σ^2_η
No college	0.895	0.022	0.016	0.951	0.092	0.016
	(0.005)	(0.001)	(0.001)	(0.007)	(0.004)	(0.002)
College	0.937	0.020	0.011	0.986	0.058	0.004
	(0.008)	(0.001)	(0.001)	(0.007)	(0.004)	(0.002)
	France			**Italy**		
	ρ	σ^2_ϵ	σ^2_η	ρ	σ^2_ϵ	σ^2_η
No college	0.971	0.031	0.006	0.944	0.072	0.020
	(0.014)	(0.006)	(0.003)	(0.005)	(0.003)	(0.002)
College	0.941	0.023	0.018	0.921	0.029	0.022
	(0.007)	(0.003)	(0.002)	(0.016)	(0.01)	(0.006)

The model is $\tilde{y}_{i,t} = z_{i,t} + \epsilon_{i,t}$; $z_{i,t} = \rho z_{i,t-1} + \eta_{i,t}$ where $\tilde{y}_{i,t}$ is the logarithm of after-tax, after unemployment benefits, non-capital income of the household head and spouse (if present), net of the predictable part of income. The regression includes year dummies. The error structure is estimated by optimally weighted GMM, minimizing the distance between the theoretical and the empirical first six autocovariances (including the auto-covariance of lag 0, i.e. the cross-sectional variance). The reported variances are pooled over the sample period and over cohorts.

1.2 Standard Errors of Data Moments

Table 2 provides the standard errors for the data moments used in the estimation.

Table 2: Standard Errors of Data Moments

		con.	*age*	age^2	*college* (**age*)	*college* $*age^2$
DE	Part.	0.030	0.0012	0.00001	0.007	
	Share	0.003	0.0001	0.000001	0.001	
	W/I	0.211	0.0085	0.00008	0.004	0.00006
ES	Part.	0.027	0.0011	0.00001	0.006	
	Share	0.004	0.0002	0.00000	0.001	
	W/I	0.459	0.0177	0.00016	0.007	0.00012
FR	Part.	0.015	0.0006	0.00001	0.004	
	Share	0.001	0.0001	0.00000	0.000	
	W/I	0.124	0.0049	0.00004	0.003	0.00005
IT	Part.	0.023	0.0008	0.00001	0.006	
	Share	0.005	0.0002	0.00000	0.001	
	W/I	0.336	0.0123	0.00010	0.007	0.00011

1.2.1 Local Identification

Another perspective on the link between parameters and moments is given in Table 3. The table shows the elasticity of the model moments, i.e., coefficients in the participation, share, and wealth-to-income ratio regressions, with respect to a small variation in the structural parameters, one at a time. A large elasticity indicates that a moment is important in identifying a particular parameter. These elasticities are informative about local identification as the variations in parameters are in the neighborhood of the estimated values. This table provides information about local identification for a single country, Spain.

The local changes in discount factors exhibit large effects on simulated moments, leading to the precise estimates for both parameters. An increase in β_0 leads to more savings and hence higher wealth-to-income ratios for the less educated group. As reflected in the negative elasticities on the coefficients of $age * edu$ and $age^2 * edu$ in the wealth-to-income ratio regression, an increase in β_0 also leads to a smaller education gap in terms of the wealth-to-income ratio. Also for β_0, the elasticity is negative for the coefficients on the education dummy in the participation regression, which indicates a reduced education gap in terms of stock market participation. The negative elasticity for the constant term in the participation regression reflects earlier participation of the less educated group.[11] Similarly, an increase in β_1 widens the education gap in terms of stock market participation rates and wealth-to-income ratios, which is evident in the second row of the table.

An increase in the coefficient of relative risk aversion, γ, decreases stock market participation and the stock share in wealth, conditional on participation. The signs are exactly what is expected and it is clear that this response is key to the identification of γ. The effect of γ on wealth accumulation is less straightforward. On the one hand, a higher γ leads to a safer portfolio that generates lower return and hence less wealth accumulation. On the

[11] This is confirmed when we compare the participation profiles before and after the local changes in β_0. The comparison shows that the the less educated group leave the stock market earlier given the higher β_0. This is because the higher β_0 causes some low income households to enter the stock market when they are young, and they exit early after retirement as they rely on the consumption floor toward the later stage of life.

Table 3: Elasticity of Moments to Parameter Values (Spain)

	Participation				Share				Wealth-to-income Ratio				
	con	*age*	age^2	*edu* (*high*)	*con*	*age*	age^2	*edu* (*high*)	*con*	*age*	age^2	$age\times$ *edu*	$age^2\times$ *edu*
β_0	-3.750	-0.796	-2.394	-10.699	-37.342	-4.917	-5.356	10.287	10.837	68.218	217.171	-2.407	-3.314
β_1	2.105	1.347	1.743	2.701	-83.992	-8.179	-5.496	2.882	19.376	85.911	156.090	14.300	16.448
γ	-152.996	-67.535	-65.666	25.662	-79.517	-11.363	-11.423 6.564	-5.428	-27.783	-52.286	0.516	0.415	
Γ	-0.290	-0.304	-0.389	0.144	3.284	0.190	0.095	-2.160	-0.037	-0.112	-0.196	-0.007	-0.004
F	-0.245	-0.164	-0.185	0.024	0.321	-0.169	-0.281	1.386	0.148	0.883	1.890	-0.023	-0.022
L	0.003	-0.002	0.002	0.008	-2.049	-0.332	-0.377	0.177	-1.681	-8.015	-15.516	-0.419	-0.412
ϕ	-0.025	-0.015	-0.016	0.007	-0.021	-0.038	-0.062	-0.353	-0.218	-1.075	-2.197	-0.050	-0.051
$\underline{c}$	-153.518	-68.623	-67.024	27.777	-56.592	-7.634	-7.559	-0.885	-2.781	-8.498	-14.281	0.217	0.210
θ	-0.298	-0.518	-0.283	2.444	0.312	-0.270	-0.575	-5.213	-3.150	-15.981	-42.495	-1.492	-1.495
$\underline{A}^b$	0.022	0.012	0.016	-0.005	-0.116	-0.012	-0.009	0.013	-0.007	-0.020	-0.011	0.001	0.001

This table reports the elasticity of moments with respect to parameter values, one at a time, at the baseline estimations for Spain.

other hand, a higher γ implies the lower certainty equivalent future value due to Jensen's inequality, which leads to more wealth accumulation. Table 3 indicates that the first effect is more important around the point estimate of γ, especially for the less educated households.

Variations in the inter-temporal elasticity of substitution, θ, also have substantial effects on the wealth-to-income ratio. A higher θ implies a higher degree of inter-temporal substitution and the lower preference for consumption smoothing over time, which leads to less wealth accumulation.

The participation cost, Γ, has a negative effect on stock market participation. Consequently, the participants are wealthier due to the selection effect, thus they have a higher stock share in total wealth on average. The participation cost also widens the gap in participation rates between the two education groups, as indicated by the positive coefficient on education dummy. This is because the more educated households care less about the participation cost which is small relative to their income and wealth.

The stock market adjustment cost, F, has a negative effect on both the stock market participation rate and stock share. It also widens the gap in stock shares between the two education groups.

A larger consumption floor lowers the precautionary saving motives, thus has a significantly negative effect on wealth accumulation, especially for the less educated households who rely more on the consumption floor. With the much reduced wealth, it is less attractive for less educated households to participate in the stock market or rebalance the portfolio, which lowers their stock market participation rate and stock share in wealth.

1.3 Simulated Distributions

Table 4 summarizes the distribution of households by education and permanent income within each country based upon a simulation using the initial distribution of households in the state space from the data and then averaging over aggregate return shocks to obtain a cross sectional distribution, conditional on age. This is used as a basis for construction of the MPC distributions.

Table 4: Household Distribution by Income and Education

Country	Ed \ Inc	low	middle	high
DE	low	0.146	0.292	0.146
	high	0.104	0.208	0.104
ES	low	0.181	0.361	0.181
	high	0.070	0.139	0.070
FR	low	0.161	0.322	0.161
	high	0.089	0.178	0.089
IT	low	0.221	0.441	0.221
	high	0.030	0.059	0.030

This table summarizes the distribution of households by education and permanent income for each country in the simulated data.

1.4 Decomposing the MPC out of Returns

Table 5 presents regression results to summarize how the households' state variables impact the MPC from a stock market return shock. There is no strong dependence of the MPC on age. The MPC falls with both income and with the wealth-to-income ratio, and in general with education.

Table 5: MPC Regressions: Return Shocks for Participants

						wealth percentile				
	const.	age	age2	income	edu	10-50%	50-70%	70-90%	90-95%	95-100%
1% increase in stock value										
DE	0.231	0.018	-0.0002	-0.043	-0.007	0.0000	-0.099	-0.122	-0.126	-0.129
ES	0.155	0.018	-0.0002	-0.017	0.006	0.0000	-0.137	-0.158	-0.173	-0.150
FR	0.570	-0.004	0.0000	-0.012	-0.112	0.0000	-0.101	-0.053	-0.045	0.005
IT	0.267	0.011	-0.0001	-0.030	-0.048	0.0000	-0.149	-0.165	-0.167	-0.110
10% increase in stock value										
DE	0.225	0.018	-0.0002	-0.043	-0.006	0.0000	-0.098	-0.122	-0.125	-0.132
ES	0.117	0.019	-0.0002	-0.017	-0.001	0.0000	-0.171	-0.192	-0.204	-0.171
FR	0.590	-0.005	0.0000	-0.012	-0.110	0.0000	-0.098	-0.054	-0.043	0.011
IT	0.263	0.011	-0.0001	-0.030	-0.049	0.0000	-0.151	-0.167	-0.170	-0.114

This table presents regression results. The dependent variable is the MPC from a return shock for stock market participants. The explanatory variables are a constant, age, age-squared, income, the wealth-to-income ratio and education.

1.5 Monetary Innovations and Stock Returns

For each country a separate VAR is estimated over the period 1999 Q1 -2018 Q4 using data on the HICP index, GDP, stock price index and Eonia. The HICP index and GDP are used in log-levels and Eonia in levels. The stock price index is deflated by the HICP index and log-first differences are taken to obtain a measure of real stock returns.

The structural VAR can be written as

$$B_0 z_t = k + B_1 z_{t-1} + B_2 z_{t-2} + ... + B_p z_{t-p} + u_t$$

where $z_t = [\pi_t, y_t, R_t^S, \text{Eonia}_t]$ defined as described above and we set the number of lags p to 4. The monetary policy shock is identified by putting restrictions on the matrix B_0. We follow a similar approach as Ludvigson et al. (2002) and apply the following nonrecursive identifying assumption on B_0

$$B_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \beta_{21} & 1 & 0 & 0 \\ \beta_{31} & \beta_{32} & 1 & \beta_{34} \\ \beta_{41} & \beta_{42} & 0 & 1 \end{bmatrix}$$

The VAR is estimated using maximum likelihood estimation.

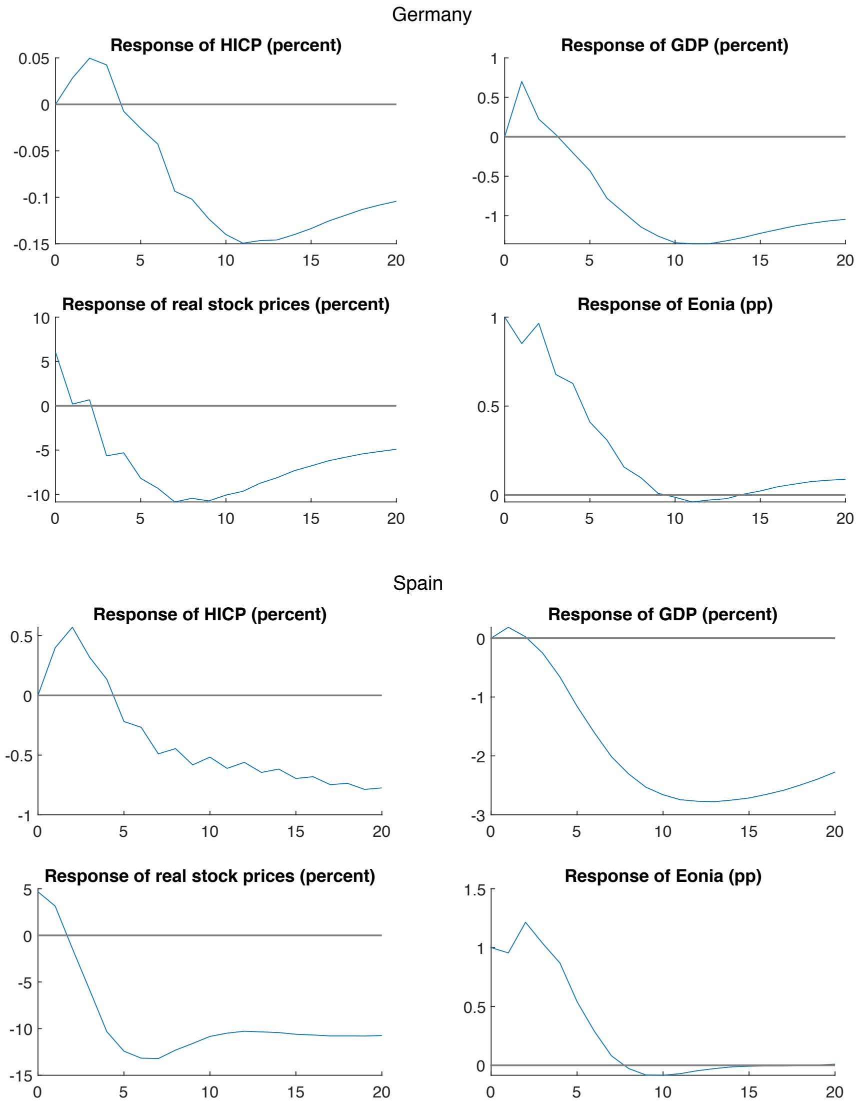
The following table summarizes the stock market response to monetary policy obtained from the 4 VARs estimated for France, Germany, Italy and Spain. The shock to the Eonia is normalized to a 1 percentage point increase on impact. The first row for every country corresponds to the estimates that come directly out of the VAR which includes deflated/real stock market **returns**. Overall the response of stock market returns is very volatile, maybe due to the relatively short sample period. Therefore, the second row for every country shows a centered three-quarter moving average of the response of stock market returns. The third row for every country contains the cumulative sum of the effect on returns, i.e. the change in the deflated stock price **index**.

Table 6: Real/Deflated Stock Market Response to 1 pp. Increase in Eonia

Quarter	0	1	2	3	4	5	6	7	8
FR: Stock returns	0.086	-0.065	-0.001	-0.075	-0.007	-0.035	0.002	-0.013	0.008
FR: 3 quarter MA	0.011	0.007	-0.047	-0.028	-0.039	-0.013	-0.015	-0.001	-0.001
FR: Stock price	0.086	0.021	0.02	-0.055	-0.062	-0.097	-0.095	-0.108	-0.1
DE: Stock returns	0.061	-0.059	0.005	-0.063	0.004	-0.029	-0.011	-0.016	0.004
DE: 3 quarter MA	0.001	0.002	-0.039	-0.018	-0.029	-0.012	-0.019	-0.008	-0.005
DE: Stock price	0.061	0.002	0.007	-0.056	-0.052	-0.081	-0.092	-0.108	-0.104
IT: Stock returns	0.089	-0.008	0.008	-0.079	-0.042	-0.05	-0.026	-0.026	-0.009
IT: 3 quarter MA	0.041	0.03	-0.026	-0.038	-0.057	-0.039	-0.034	-0.02	-0.013
IT: Stock price	0.089	0.081	0.089	0.01	-0.032	-0.082	-0.108	-0.134	-0.143
ES: Stock returns	0.047	-0.015	-0.046	-0.044	-0.045	-0.021	-0.007	0	0.009
ES: 3 quarter MA	0.016	-0.005	-0.035	-0.045	-0.037	-0.024	-0.009	0.001	0.005
ES: Stock price	0.047	0.032	-0.014	-0.058	-0.103	-0.124	-0.131	-0.131	-0.122

The detailed responses of all variables are shown in figures 2-3. The shock to the Eonia is normalized to a 1 percentage point increase on impact and the responses of the other variables are multiplied by 100 to be interpreted as percent change. Moreover, for illustrative reasons the bottom left chart shows the cumulative sum of real stock return response which can be interpreted as the percentage change in the deflated stock market index.

Figure 2: Response to a Monetary Shock



1.6 Analyzing the General Equilibrium Response to Shocks

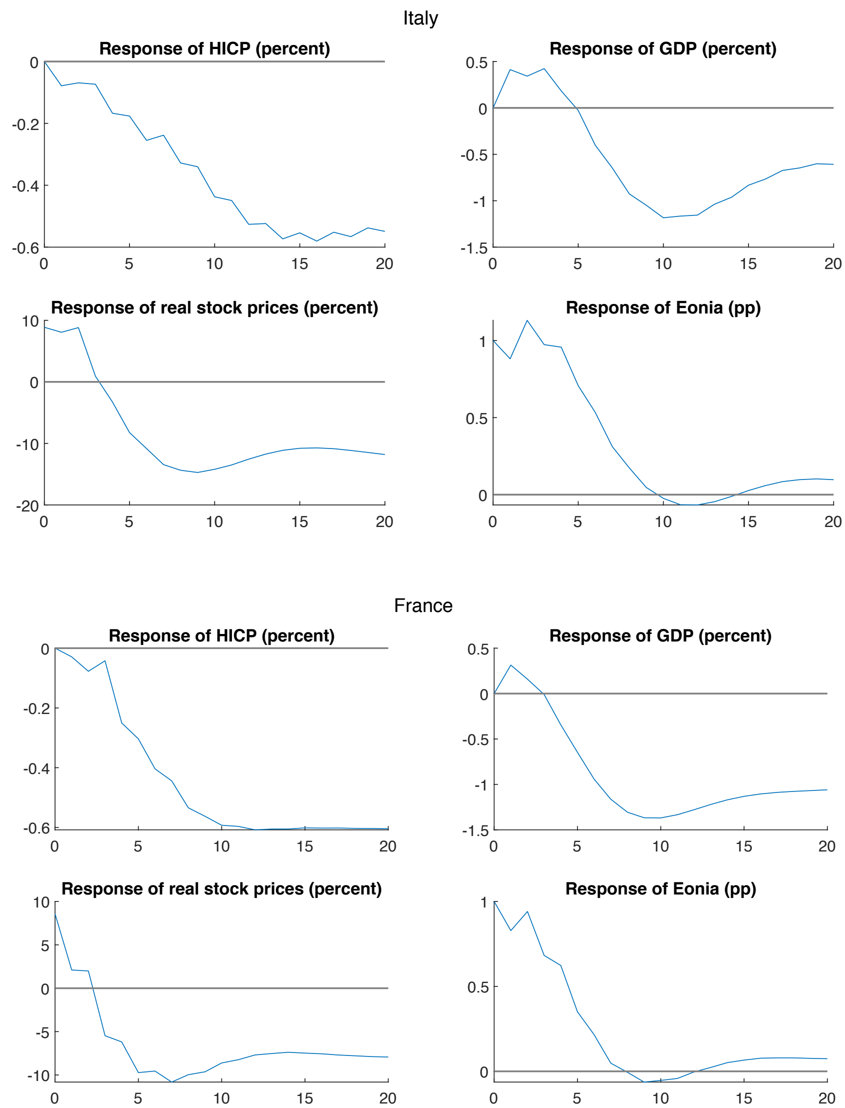
The point of this section of the appendix is to make clear how we use the model of household choice to analyze the response of the household to monetary shocks in a general equilibrium. The neat feature of the analysis is that we are able to do so without embedding the household choice problem into an explicit general equilibrium model.

It is easier to illustrate our empirical approach through a transparent version of the now standard RBC model. We then return to the monetary economy below.

Consider a version of the RBC model in which there are:

- homogenous households who consume and supply labor inelastically;

Figure 3: Response to a Monetary Shock



- competitive firms who produce with a CRS technology
- technology (TRP, productivity) shocks
- no frictions

In this setting, the solution of the planner's problem generates a law of motion for the aggregate capital stock given by $k' = \phi_\Theta(A, k)$ where k is the per capita stock of capital and A is productivity. Here the policy function is indexed by Θ, a vector of parameters characterizing preferences, technology and the process of the technology shocks.

From the resource constraint, consumption is given by: $c_\theta(A,k) = Af(k) + (1-\delta)k - \phi_\theta(A,k)$. Here $f(k)$ is the production function, $Af(k)$ is total output and $(1-\delta)k$ is the undepreciated capital stock.

For a given Θ, the model can be solved to generate the policy function for capital dynamics. The model can be simulated using realizations of A to generate paths for the capital stock, output, consumption and investment.

Now, to generate an impulse response, one could simply design a shock to A and, given an initial capital stock, derive the paths for capital, consumption, output, etc. In the decentralized model, this would include the paths for wages and returns. This is the general equilibrium response to a technology shock.

Of course, from the fundamental welfare theorem, the planner's allocation can be decentralized as a recursive competitive equilibrium in which consumption depends on current wages and returns, $c(A,k,K) = \chi(\omega(A,k), R(A,k), K)$. In this decentralized setting, the household responds to the aggregate current state, (A,k) through wages and returns, having individual capital K. Using factor demand and factor market clearing, state contingent wages, $\omega(A,k)$ and capital returns, $R(A,k)$, are derived. This is a standard recursive equilibrium representation and it decentralizes the planner's solution.

What about an impulse response? Again there is a shock to A and in the recursive competitive equilibrium we have the evolution of the aggregate capital stock as well as wages and interest rates. To determine consumption, we would just substitute the evolution and wages and capital returns into the $\chi(\omega(A,k), R(A,k), K)$, given initial capital holdings.

Focusing on the impulse response to consumption alone it would be equivalent to that from the planner's problem. The general equilibrium effects are all fully captured by the evolution of wages and capital returns created by the initial shock to A.

The approach taken in this paper is to essentially estimate the policy function $c(A,k,k) = \chi(\omega(A,k), R(A,k), k)$ from the data, with $k = K$ in equilibrium. The responses of wages and capital returns are estimated from the data and substituted into the household decision rule. As long as the data comes from an equilibrium model, we capture the response in equilibrium of the household.

Of course, the economy we study is richer than this standard RBC model. It includes heterogeneity as well as non-convexities at the household level. But the logic of the argument still stands. The response to wages and capital returns to a monetary shock from the data capture the general equilibrium effects of the policy. We focus on the consumption response alone.

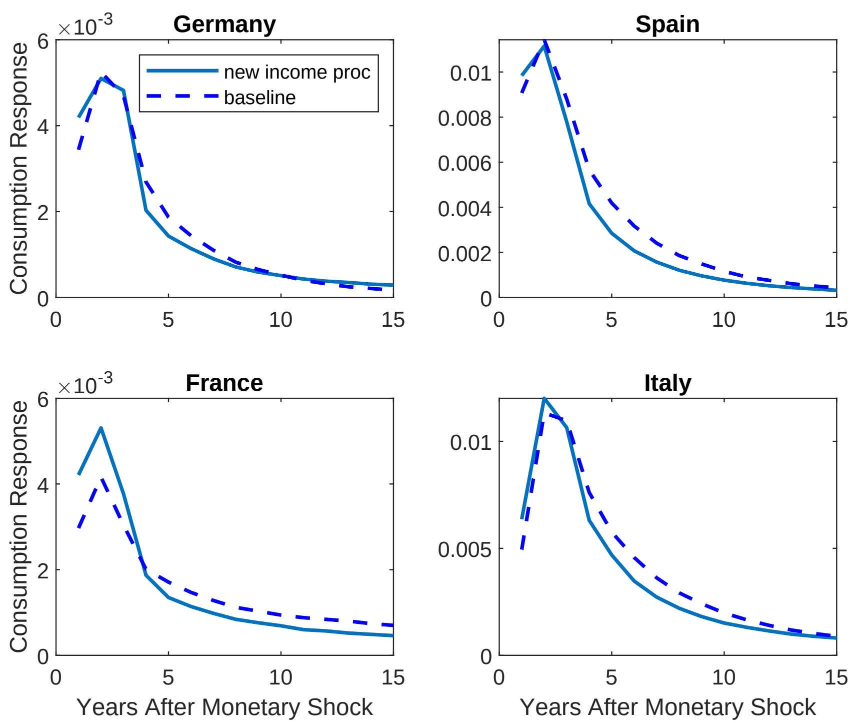
1.7 Robustness to Income Process

In the baseline model we have estimated income processes where government transfers are included in the household's income. We check how excluding the transfers affects our quantitative results.

With government transfers excluded, household income faces more uncertainty. As shown in table 8, compared with the baseline income processes, the new income processes features large variances of transitory and permanent income shocks.

We re-simulate the model based on the new income process, using the same parameter values estimated in the base case. Compared with the base case, the new income processes generate higher wealth-income ratios, lower stock market participation rates, and slightly higher stock share in wealth. Figure 4 compares dynamic consumption responses based on the new income processes relative to those generated from the base case. As the figure shows, the dynamic consumption responses exhibit time series patterns and cross country comparisons that are very similar to those generated from the base case.

Figure 4: Dynamic Consumption Response (New Income Process)



This figure compare the dynamic consumption responses to a monetary shock of 100 basis points using the new income processes to those from the baseline model.

Table 7: Real/deflated stock market response to 1 pp. increase in Eonia

Quarter	0	1	2	3	4	5	6	7	8	9	10	11	12
FR: Stock returns	0.086	-0.065	-0.001	-0.075	-0.007	-0.035	0.002	-0.013	0.008	0.003	0.01	0.004	0.005
FR: 3 quarter MA	0.011	0.007	-0.047	-0.028	-0.039	-0.013	-0.015	-0.001	-0.001	0.007	0.006	0.006	0.004
FR: Stock price	0.086	0.021	0.02	-0.055	-0.062	-0.097	-0.095	-0.108	-0.1	-0.097	-0.087	-0.083	-0.078
DE: Stock returns	0.061	-0.059	0.005	-0.063	0.004	-0.029	-0.011	-0.016	0.004	-0.003	0.007	0.004	0.009
DE: 3 quarter MA	0.001	0.002	-0.039	-0.018	-0.029	-0.012	-0.019	-0.008	-0.005	0.003	0.003	0.007	0.006
DE: Stock price	0.061	0.002	0.007	-0.056	-0.052	-0.081	-0.092	-0.108	-0.104	-0.107	-0.1	-0.096	-0.087
IT: Stock returns	0.089	-0.008	0.008	-0.079	-0.042	-0.05	-0.026	-0.026	-0.009	-0.004	0.005	0.007	0.009
IT: 3 quarter MA	0.041	0.03	-0.026	-0.038	-0.057	-0.039	-0.034	-0.02	-0.013	-0.003	0.003	0.007	0.008
IT: Stock price	0.089	0.081	0.089	0.01	-0.032	-0.082	-0.108	-0.134	-0.143	-0.147	-0.142	-0.135	-0.126
ES: Stock returns	0.047	-0.015	-0.046	-0.044	-0.045	-0.021	-0.007	0	0.009	0.007	0.008	0.004	0.002
ES: 3 quarter MA	0.016	-0.005	-0.035	-0.045	-0.037	-0.024	-0.009	0.001	0.005	0.008	0.006	0.005	0.002
ES: Stock price	0.047	0.032	-0.014	-0.058	-0.103	-0.124	-0.131	-0.131	-0.122	-0.115	-0.107	-0.103	-0.101

Table 8: Comparison of Income Processes

	Baseline			New Process		
	ρ	σ_ϵ^2	σ_η^2	ρ	σ_ϵ^2	σ_η^2
DE						
No College	0.895	0.022	0.016	0.906	0.022	0.031
College	0.937	0.02	0.011	0.933	0.024	0.018
ES						
No College	0.951	0.092	0.016	0.966	0.135	0.014
College	0.986	0.058	0.004	0.987	0.008	0.004
FR						
No College	0.971	0.031	0.006	0.969	0.047	0.01
College	0.941	0.023	0.018	0.958	0.026	0.02
IT						
No College	0.944	0.072	0.02	0.92	0.117	0.039
College	0.921	0.029	0.022	0.956	0.08	0.016

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