Buffer-stock saving and households' response to income shocks*

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Abstract

We exploit the information contained in the joint dynamics of household earnings, consumption and wealth in the Italian Survey of Household Income and Wealth (SHIW) to structurally estimate an incomplete-markets, buffer-stock saving model. We compare the degree of consumption smoothing implied by the model to the corresponding empirical estimates based on the same dataset. We find that Italian households have a degree of consumption insurance against permanent labor income shocks comparable to that in the model. We estimate that 12 percent of permanent labor income shocks in the data are insurable which is comparable to the model counterpart of 11 percent. This result contrasts with existing evidence, and our own findings in this paper, for the US that households in the data have a higher degree of insurance against permanent shocks than implied by an incomplete-markets model in which households can self-insure with a single, non-contingent asset.

Keywords: Consumption, Wealth, Incomplete markets, Insurance.

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1 Introduction

The degree to which self-insurance allows households to decouple consumption from income shocks determines the scope for tax and social insurance policies and the associated welfare gains. This paper investigates the extent of self-insurance in Italy through the lens of a structurally-estimated, buffer-stock saving model.

The paper's contribution is twofold. First, we estimate consumption-insurance coefficients for permanent and transitory idiosyncratic (labor)[1] income shocks in the Italian Survey of Household Income and Wealth (SHIW) for the sample period 1987-2012. These coefficients are defined as the fraction of the shocks that is not reflected in movements in consumption and are identified in the data by applying the methodology proposed by Blundell, Pistaferri and Preston (2008) (BPP hereafter). We estimate an insurance coefficient of 0.12 for permanent shocks and of 0.8 for transitory shocks based on the SHIW. For comparison, we conduct the same analysis using the US Panel Study for Income Dynamics (PSID) for the sample period 1999-2015, over which the PSID contains information on non-durable consumption, income and wealth as the SHIW. We estimate an insurance coefficient of 0.29 for permanent shocks and of 0.91 for transitory shocks. These estimates are in line with the corresponding empirical estimates—respectively 0.36 and 0.95—by BPP for the period 1978-92, using consumption data from the consumer expenditure survey (CEX) to impute total non-durable consumption in the PSID.[2]

Second, in the spirit of Kaplan and Violante (2010), we compare the degree of insurance implied by our empirical estimates to that implied by an incomplete-markets model. In particular, we use indirect inference to estimate a buffer-stock saving model on the same (SHIW

[1]Where it does not engender confusion, we write just 'income' rather than 'labor income' in the rest of the paper.

[2]The PSID contains information only on food consumption rather than total non-durable consumption during that period.

or PSID) dataset used for our empirical estimates. Rather than basing estimation on a set of unconditional moments, indirect inference targets the parameters of an auxiliary statistical model that provides a reduced form for the structural model. We choose as auxiliary model the reduced-form regressions of consumption and wealth changes over income changes at different time horizons. As argued by Krueger and Perri (2011), the long run wealth response to income shocks is potentially informative about the degree of partial insurance against permanent income shocks.

We use the estimated structural model to simulate a panel of individual histories for consumption and permanent and transitory income shocks and estimate insurance coefficients applying the BPP methodology on the simulated data. We find that, for Italy, the amount of insurance implied by the model is in line with the empirical estimates. Through the lens of the model, this suggests that households in Italy do not have access to more consumption insurance than implied by self-insurance through a single, non-contingent asset in the buffer-stock model. This contrasts with our findings for the US which, in line with Kaplan and Violante (2010), confirm that the empirical estimates imply a substantially higher degree of insurance than the self-insurance predicted by the model.

A large literature has tried to estimate the amount of insurance available to households by analyzing the response of consumption to income shocks. Two polar benchmark models have provided the theoretical framework for this effort. On the one hand, the complete-markets model assumes that agents can perfectly insure ex ante against all idiosyncratic contingencies. Tests of this hypothesis (Cochrane 1991, Mace 1991) do not need to distinguish between permanent and transitory income shocks since consumption should not respond to any kind of idiosyncratic income shock. The predictions of the complete-markets model are typically strongly rejected by the data (Attanasio and Davis 1996).

On the other hand, the textbook permanent income hypothesis (PIH) assumes that non-contingent borrowing and lending is the only way to (self-)insure against income shocks and implies that consumption should respond fully to permanent shocks but only marginally to temporary ones. Since the consumption response depends on the persistence of income shocks, testing the PIH requires identifying shocks of different persistence when only total income changes are observed. For this reason, some authors focus on the correlation between consumption and total income changes as a way to restrict the set of models consistent with it (Altonji and Siow 1987; Krueger and Perri 2005, 2006, 2011), while others use proxies for transitory and permanent income changes such as changes in hours or changes in wages and involuntary job loss, respectively (Cochrane 1991, Dynarski and Gruber 1997). Finally, some authors exploit panel data and the cross-equation restrictions implied by the linear or linearized consumption function to separately identify the consumption response to permanent and transitory income shocks (Hall and Mishkin 1982; BPP).

BPP's estimate of 0.36 for the consumption insurance coefficient for permanent shocks[3] suggests a substantial degree of excess insurance compared to the theoretical prediction of zero under the PIH, or of a value close to zero for the linear approximation of the consumption function. Although this finding constitutes *prima facie* evidence against the textbook PIH and, more generally, the linearized consumption function, it is not necessarily at odds with the non-linearized incomplete-markets model. Carroll (2009) shows that a buffer-stock saving model with impatient consumers, constant-relative-risk-aversion (CRRA) preferences and a single, non-contingent asset implies an insurance coefficient for permanent shocks ranging between 0.08 and 0.25, for plausible degrees of patience and risk aversion. For this reason, Kaplan and Violante (2010) suggest that a better way to assess the degree of excess insurance is to compare the empirical BPP estimates to their counterparts estimated on data simulated from a calibrated incomplete-markets model. This is the route we take in this paper with the only difference that,

[3] Hall and Mishkin (1982) impose zero insurance of permanent shocks and estimate only the response to transitory ones.

rather than calibrating our model as in Kaplan and Violante (2010), we structurally estimate by indirect inference. This last aspect is shared with Guvenen and Smith (2014) with the important difference that they model partial insurance explicitly as a transfer in the budget constraint and structurally estimate the associated parameter jointly with the other model parameters.[4]

The rest of the paper is structured as follows. Section 2 describes the SHIW data. Section 3 presents estimates for the consumption-insurance coefficients in Italy and the US. Section 4 introduces the buffer-stock model and discusses the model estimation. Section 5 presents the resulting parameter estimates, and compares the empirical estimates of the insurance coefficients to those obtained with the simulated model data for Italy. In subsection 5.3 we compare the evidence for Italy to the corresponding evidence for the US, while Section 6 concludes and discusses possible explanations for our findings.

2 Data

The Italian Survey of Households Income and Wealth (SHIW) is administered by the Bank of Italy. Since 1987 the survey has been conducted every two years (with the exception of a three-year gap between 1995 and 1998) and covers a representative sample of around $8,000$ households, a fraction of which are observed for a number of years. A rather unique feature of this data set is that it contains comprehensive panel information over a long time period about not only household income and consumption, but also wealth.[5] As pointed out by Krueger and Perri (2011), the combination of the panel dimension together with the availability of wealth, in addition to consumption and income, may help to infer the response of household consumption to different types of income shocks.

[4] From a methodological perspective, Gourinchas and Parker (2002) is the first paper to estimate an incomplete-markets model by simulated method of moments.

[5] The PSID in the US contains similarly rich information only since 1999.

We focus on households with a head aged 25-55 so that labor income is not substantially influenced by labor force participation decisions related to education and retirement, which we do not model.[6] We exclude entrepreneurs and the self-employed for whom labor income is hard to measure. Finally, since our estimation strategy exploits consumption and wealth responses to income changes at different horizons, we restrict our sample to only households for which such responses can be computed at all the horizons considered. We stop at a time horizon of six years because extending the horizon further would reduce the sample size by 50%. For computing at least one set of responses of a household, we need to observe that household for four waves in the biannual survey.

This leaves us with a sample of 545 households in the time period 1987 to 2012 for a total of $1,134$ sets of responses to income changes. All nominal variables are measured in constant year-2000 Euros and converted to adult-equivalents using the OECD equivalence scale to control for differences in household size. Variables are then normalized by expressing them in units of average equivalized net labor income in the sample (approximately $10,000$ Euros in the year 2000).[7]

We use non-durable consumption, labor income after taxes and transfers, and net worth as the data counterpart of consumption c_t, non-capital income y_t and wealth a_t in the model. Since our aim is to infer the response of consumption and wealth to unanticipated, idiosyncratic income changes, we purge the data from aggregate and predictable individual effects. We do so by regressing observed levels on: a quartic polynomial in the age of the household head, education, gender, time dummies and a set of additional controls detailed in Appendix A.2 so that the specification is as close as possible to BPP given the SHIW data. We use the residuals from these regressions in our empirical analysis.

[6] Furthermore, Gourinchas and Parker (2002) and Cagetti (2003) have shown that buffer-stock saving is most relevant for younger households.

[7] Appendix A.2 provides further details on how we clean the data and construct our sample and Table 7 in the appendix presents summary statistics.

3 Insurance coefficients

In this section we estimate consumption insurance coefficients for Italy, applying the methodology proposed by BPP, and compare these to their US counterparts. We briefly summarize the BPP methodology below and refer to Appendix A.4 for further details.

We assume that income of household i in period t follows the stochastic process

$$\log y_{it} = z_{it} + \varepsilon_{it}, \tag{1}$$
$$z_{it} = z_{i,t-1} + \eta_{it},$$

where ε_{it} and η_{it} are, respectively, a transitory and permanent idiosyncratic shock with zero mean and variances σ_{ε}^2 and σ_{η}^2. The two shocks are assumed to be uncorrelated with each other in each period t and i.i.d. over time.[8]

BPP show that, for such a canonical income process, the response of log-consumption changes $\Delta \log c_{it}$ to the shocks can be approximated by

$$\Delta \log c_{it} = (1 - \phi^{\eta})\eta_{it} + (1 - \phi^{\varepsilon})\varepsilon_{it} + \xi_{it}, \tag{2}$$

where ξ_{it} is an expectation error. The insurance coefficients of the permanent and transitory shock are ϕ^{η} and ϕ^{ε}, respectively. If $\phi^x = 1$ for shock $x = \eta, \varepsilon$, consumption is not affected by the shock implying full insurance. If $\phi^x = 0$ instead, there is no insurance and the shock fully passes through onto consumption.

Since the two shocks are not separately observable in the data, they cannot be identified with a finite income panel. Yet, BPP show that, for the canonical income process (1), the insurance coefficients are identified and can be estimated as[9]

[8]See Hryshko (2014) for the implications of correlated transitory and permanent shocks on the estimates of insurance against these shocks.

[9]In Appendix A.4 we detail how we adapt these conditions to allow for measurement error and the

$$\phi^{\eta} = 1 - \frac{\text{Cov}\left(\Delta \log c_{it}, \log y_{i,t+1} - \log y_{i,t-2}\right)}{\text{Cov}\left(\Delta \log y_{it}, \log y_{i,t+1} - \log y_{i,t-2}\right)}, \phi^{\varepsilon} = 1 - \frac{\text{Cov}\left(\Delta \log c_{it}, \Delta \log y_{i,t+1}\right)}{\text{Cov}\left(\Delta \log y_{it}, \Delta \log y_{i,t+1}\right)}. \quad (3)$$

Column (1) in Table 1 reports the estimates of the insurance coefficients for Italy. We find that Italian households can insure 80 percent of a transitory shock and 12 percent of a permanent one. Our estimates, based on the BPP methodology, are in line with existing empirical estimates by Jappelli and Pistaferri (2006) and Jappelli and Pistaferri (2011) based on the same data set but based on a different identification strategy.[10] Jappelli and Pistaferri (2006), Table 3, and Jappelli and Pistaferri (2011), Table 2, report a point estimate for the insurance coefficient of permanent income shocks between 0.01 and 0.15, and a point estimate for the insurance coefficient of transitory shocks between 0.71 and 0.95.

Column (2) in Table 1 presents our estimates for the US based on the PSID 1999-2015. For comparison, column (3) reports the original BPP estimates (see their table 7, column 1) based on the PSID 1978-1992.[11] The two sets of estimates are quite close. Compared to the estimates for Italy in column (1), they imply that US households can better insure against shocks. In particular, the point estimate of the insurance coefficient for permanent shocks is 2.5 to 3 times higher in the US than in Italy.[12]

biannual nature of the data.

[10]In their identification, Jappelli and Pistaferri (2011) rely on repeated cross-sectional, rather than panel, data for income and consumption, as this allows them to compare their estimates for Italy with estimates for the UK. In the UK only repeated cross-sectional data on consumption are available together with panel data on income. If the imputation of consumption for households in the income panel is not an option, then the identification strategy of BPP cannot be applied because that strategy requires panel data on income *and* consumption for the same household. Jappelli and Pistaferri (2006) use yet another strategy by identifying the insurance coefficients with a minimum-distance estimator that targets consumption mobility matrices estimated from the SHIW. As BPP, they obtain identification of permanent and transitory shocks for the canonical income process, using restrictions on the covariance matrix of income.

[11]For the earlier sample period, BPP imputed consumption in the PSID using data from the CEX.

[12]We have checked the robustness of our estimates for the US to restricting the PSID sample to the post-2004 period when the consumption categories recorded in the PSID are more comparable to the Italian SHIW. The differences in the estimated insurance coefficients for the two countries are very similar. Using the post-2004 sample, the estimated insurance coefficient for the transitory shock in the

Table 1: Estimates of the Insurance Coefficients

	Italy	United States	
		Our sample	BPP
		PSID 1999-2015	PSID 1978-92
	(1)	(2)	(3)
Permanent shock: ϕ^{η}	0.12	0.29	0.36
	(0.20)	(0.14)	(0.09)
Transitory shock: ϕ^{ε}	0.80	0.91	0.95
	(0.08)	(0.04)	(0.04)

Notes: Standard errors in parentheses, clustered at the household level.

4 The buffer-stock saving model

In this section, we introduce the buffer-stock saving model and discuss its estimation.

4.1 The model economy

The economy is populated by a continuum of households with an infinite horizon and time-separable CRRA utility function given by

$$E_0 \sum_{t=0}^{\infty} \frac{1}{(1+\delta)^t} \frac{(c_{it})^{1-\alpha} - 1}{1-\alpha},$$

where c_{it} denotes consumption of household i at time t and δ is the intertemporal discount rate.

In each period, consumers receive labor income y_{it} which follows the process in equation (1). Households can trade a non-contingent, one-period bond which pays a constant, after-tax, interest rate r. It follows that they face the period-by-period budget identity

$$c_{it} + a_{i,t+1} = (1+r)a_{it} + y_{it}, \tag{4}$$

US is 0.88 against 0.91. The estimated coefficient for permanent shocks is larger at 0.44 instead of 0.29, and thus even more different from its estimate of 0.12 for Italy.

where a_{it} denotes the stock of wealth (net worth) at the end of period t. The households' asset position is constrained to be non-negative.[13]

4.2 Econometric approach

Since the buffer-stock saving model does not imply closed-form policy functions, we estimate it by simulation. Before discussing the details of the estimation, we allow for the possibility that the econometrician does not observe the true (log-)income realization y_{it} but instead

$$\log \tilde{y}_{it} = \log y_{it} + \gamma_{it},$$

where γ_{it} is classical measurement error, with zero mean and variance σ_γ^2. Measurement error in income may be quantitatively important (Altonji and Siow 1987) and may affect the comparison of the insurance coefficients implied by the models and their counterparts estimated on the data.[14]

We estimate the model by indirect inference. Indirect inference is a simulation-based method that uses an auxiliary model to capture features of the data that inform the estimation. In what follows, we describe a set of linear equations suggested by the linear-quadratic approximation to our structural model under the assumption that the level of income y_{it}, rather than its logarithm, follows the stochastic process in equation (1). These equations will serve as auxiliary model in the estimation.

It is well known (e.g., Deaton 1992) that the changes in income, consumption and wealth

[13] This coincides with the theoretical natural borrowing limit under our assumption that labor earnings are lognormally distributed. The constraint may occasionally bind, however, in the simulated model in which the income process is discretized so that the lowest income value is strictly positive.

[14] As we discuss in Appendix A.4, BPP have shown that measurement error in income implies that the estimate of the insurance coefficient for transitory shocks based on their identification has to be interpreted as an upper bound.

in the linear-quadratic, permanent-income counterpart of our model satisfy

$$\Delta \tilde{y}_t = \eta_t + \Delta\varepsilon_t + \Delta\gamma_t \tag{5}$$

$$\Delta c_t = \frac{r}{1+r}\varepsilon_t + \eta_t \tag{6}$$

$$\Delta a_{t+1} = \frac{\varepsilon_t}{1+r}, \tag{7}$$

where we have dropped the household index i to simplify notation. The same changes can easily be expressed for an arbitrary time interval of length N, by noticing that

$$\Delta^N x_t = \frac{x_t - x_{t-N}}{N} = \frac{1}{N}\sum_{\tau=t-N+1}^{t} \Delta x_\tau.$$

As shown in Krueger and Perri (2011), it follows from (5)-(7) that

$$\begin{aligned}
\Delta^N y_t &= \frac{1}{N}\sum_{\tau=t-N+1}^{t} (\eta_\tau + \Delta\varepsilon_\tau + \Delta\gamma_\tau) \\
\Delta^N c_t &= \frac{1}{N}\sum_{\tau=t-N+1}^{t} \left(\frac{r}{1+r}\varepsilon_\tau + \eta_\tau\right) \\
\Delta^N a_{t+1} &= \frac{1}{N}\sum_{\tau=t-N+1}^{t} \frac{\varepsilon_\tau}{1+r}.
\end{aligned}$$

This implies that the coefficients of the linear regressions

$$\Delta^N c_t = \beta_c^N \Delta^N y_t + u_t^N \tag{8}$$

$$\Delta^N a_{t+1} = \beta_a^N \Delta^N y_t + v_t^N \tag{9}$$

satisfy

$$\beta_c^N = \frac{\mathrm{Cov}(\Delta^N c_t, \Delta^N y_t)}{\mathrm{Var}(\Delta^N y_t)} = \frac{N\sigma_\eta^2 + r\sigma_\varepsilon^2/(1+r)}{N\sigma_\eta^2 + 2(\sigma_\varepsilon^2 + \sigma_\gamma^2)} = \frac{NQ + (1-M)\frac{r}{1+r}}{NQ+2} \tag{10}$$

$$\beta_a^N = \frac{\mathrm{Cov}(\Delta^N a_{t+1}, \Delta^N y_t)}{\mathrm{Var}(\Delta^N y_t)} = \frac{\sigma_\varepsilon^2}{(1+r)[N\sigma_\eta^2 + 2(\sigma_\varepsilon^2 + \sigma_\gamma^2)]} = \frac{1-M}{(1+r)[NQ+2]}, \tag{11}$$

where $Q = \sigma_\eta^2/(\sigma_\varepsilon^2 + \sigma_\gamma^2)$ is the ratio of the variance of the permanent shock relative to the variance of transitory income (due to both ε_t and γ_t), and $M = \sigma_\gamma^2/(\sigma_\varepsilon^2 + \sigma_\gamma^2)$ is fraction of the variance of transitory income due to measurement error.[15]

Equations (10) and (11) imply that the consumption response β_c^N is increasing and the wealth response β_a^N is decreasing in the horizon length N. Intuitively, as N increases a given change in income is more likely to be permanent, as transitory shocks tend to average out while permanent shocks cumulate on average. Since the PIH implies that consumption responds one-to-one and wealth not at all to permanent shocks, the response of consumption increases with N while that of wealth decreases.

As shown by Carroll (2009), the presence of a precautionary saving motive in the buffer-stock model implies a positive response of wealth to permanent income shocks. Intuitively, consumption responds less than one-to-one to a positive (negative) permanent shock, as the permanent shock reduces (increases) the ratio of wealth to permanent income relative to the target ratio. While this has no qualitative effect on the profile of the consumption responses, it may, depending on its strength, imply that the wealth response is increasing in N. As a result, the wealth response may increase over time as permanent shocks cumulate on average as N increases. Therefore, the profile of the coefficients β_a^N is informative on the strength of the

[15]In the appendix of the working-paper version we derive the responses for persistent, possibly non-permanent, income shocks with a persistence parameter $0 \leq \rho \leq 1$. We show that, for plausible parameter values, the PIH model implies a negative relationship between the wealth response β_a^N and N only if income shocks are very persistent and the variance of the measurement error is not too large. In other words, the measured wealth response to income changes imposes restrictions on the persistence of the shocks η_t and the importance of measurement error in the permanent income model.

precautionary saving motive. Finally, the degree of measurement error M has little effect on the consumption responses β_c^N in equation (10) given that $r \approx 0$, but a strong effect on the wealth responses β_a^N in equation (11).

The above discussion implies that equations (8)-(9) are a useful candidate for the auxiliary model. Therefore, we target the regression coefficients β_c^N, β_a^N for $N = 2, 4, 6$ in our estimation. The goal of our estimation procedure is to choose the parameters of the structural model to minimize the distance between the regression coefficients estimated on the SHIW data and those estimated on the model-simulated data. The metric we use is the weighted sum of the squared percentage deviations of the simulated model coefficients from the data targets. The weighting matrix is the variance-covariance matrix based on the model-simulated data, thus taking into account the model's predictions about the precision with which the targets are estimated.

The estimation is conducted in the following way. We draw an initial distribution of wealth for 25,000 individuals according to the wealth distribution of our benchmark sample in the data and, for each individual, simulate a 45-period long shock history together with the associated optimal choices based on the solution of the buffer-stock saving model. We solve and simulate the model and compute the targeted moments for each combination of parameter values on a grid to select the one that maximizes the objective function. See Appendix A.6 for further information on the model solution and estimation.

5 Estimation

This section presents the estimation results. Section 5.1 discusses the identification of the structural parameters. Section 5.2 presents the estimates for Italy and compares the insurance coefficients implied by the model to their empirical counterparts. Section 5.3 conducts the same exercise on the US PSID and compares the results for the US to those for Italy.

5.1 Structural parameters and identification

The model has six parameters: $\{\sigma_\eta^2,\ \sigma_\varepsilon^2,\ \sigma_\gamma^2,\ \delta,\ \alpha,\ r\}$. We estimate only a subset of the model parameters and use external estimates for the others. In particular, we set the risk-free real interest rate to $r = 0.02$ and the CRRA coefficient to $\alpha = 2$.[16] We estimate the variance of permanent shocks σ_η^2 and the total variance of transitory shocks $\sigma_\varepsilon^2 + \sigma_\gamma^2$ using only income data and use indirect inference, as described above, for the discount rate δ and the variance of the measurement error σ_γ^2.

We conduct our estimation in two steps. We first estimate the variances of income shocks using income data alone. As a result, in that step we cannot identify separately the variance of the transitory shock ε and of the measurement error γ. In the second step, we use indirect inference to estimate the discount rate and the variance of the measurement error. Our targets are the six regression coefficients $\beta_c^N, \beta_a^N,\ N = 2, 4, 6$ from the auxiliary model. The auxiliary model does not imply a target for the wealth-to-income ratio. Yet, the ability to self-insure and the marginal propensity to consume out of transitory and permanent income shocks depend on the stock of assets available. For this reason, we also consider a specification that adds the aggregate wealth-income ratio as a target moment.[17] In Appendix A.5 we illustrate which moments contribute most to the identification of the two estimated parameters. We find that the wealth-income ratio and, to a smaller extent, the consumption responses identify the discount rate whereas the wealth responses identify the variance of the measurement error.

[16] Preliminary estimations revealed that the identification of the discount rate together with the coefficient of relative risk aversion is tenuous. For this reason, we follow Guvenen and Smith (2014) and fix its value at the standard value of 2. In the working-paper version we report that the results for the insurance coefficients do not vary substantially for alternative preset values of risk aversion between 1 and 4 given that the estimate of the discount rate adjusts to match the data targets.

[17] In the working-paper version, we also provide robustness checks for a specification in which we target normalized median wealth following Cagetti (2003). Guvenen and Smith (2014) target the median wealth income ratio. The two numbers are very close in our dataset, being respectively 0.66 and 0.69 in units of average equivalized net labor income in the sample.

5.2 Estimation results for Italy

5.2.1 Parameter estimates

The first two rows in Table 2 report the estimates for the variances of the permanent shocks and of total transitory shocks. Our estimates are about half the size of the estimates $\hat{\sigma}_{\eta}^2 = 0.0267$ and $\widehat{\sigma_{\varepsilon}^2 + \sigma_{\gamma}^2} = 0.0794$ by Jappelli and Pistaferri (2006) using the SHIW 1987-95 (see their Table 3). The estimates are somewhat sensitive to the specification of the first-stage regressions and the sample period. We choose our first-stage specification so that it is as comparable to the specification chosen by BPP in their analysis for the US which we revisit in Section 5.3.[18] Yet, both our estimates and those in Jappelli and Pistaferri (2006) imply a similar *ratio* of the variance of total transitory income to the variance of the permanent shock. As we discussed in Section 4.2, this ratio shapes the responses of consumption and wealth to income shocks in the linear-quadratic approximation to the structural model.

Unlike the estimates of σ_{η}^2 and $\sigma_{\varepsilon}^2 + \sigma_{\gamma}^2$, that are obtained from income moments alone, the estimates of the discount rate and the variance of measurement error depend on the set of the other targeted moments. Column (1) in Table 2 reports the empirical estimates of the responses of non-durable consumption and net worth to income changes over two, four and six years that we target. Since there are some outlier wealth observations, we report estimation results for median regressions.

Table 2 shows that the responses of consumption and wealth to income shocks are positive, as one would expect. The responses of consumption are increasing in the length of the time horizon N. Contrary to the predictions of PIH, the estimated wealth responses are also increasing, although imprecisely estimated. In fact, given the standard errors, one cannot reject at conventional significance levels the hypothesis that the profile of the wealth responses is flat

[18] Appendix A.2 provides further details.

Table 2: Structural Estimation Results - Italy

	Data	Model	
	(1)	(2)	(3)
Parameter estimates			
σ_η^2	0.011	-	-
	(0.002)	-	-
$\sigma_\varepsilon^2 + \sigma_\gamma^2$	0.032	-	-
	(0.003)	-	-
Discount Rate δ		0.028	0.045
		(0.0023)	(0.0004)
Measurement Error σ_γ^2		0.000	0.000
		(0.0128)	(0.0026)
Targeted moments			
β_c^2	0.261	**0.197**	0.252
	(0.024)	(0.014)	(0.017)
β_c^4	0.298	0.307	**0.387**
	(0.023)	(0.016)	(0.020)
β_c^6	0.345	**0.382**	**0.476**
	(0.023)	(0.016)	(0.020)
β_a^2	0.768	0.455	**0.395**
	(0.142)	(0.177)	(0.035)
β_a^4	0.855	0.532	**0.372**
	(0.149)	(0.413)	(0.049)
β_a^6	0.902	0.660	**0.372**
	(0.180)	(0.663)	(0.058)
Wealth/Income	2.635	$\boxed{\mathbf{7.427}}$	**2.921**
	(0.130)	(0.146)	(0.084)

[a] The coefficient of relative risk aversion is preset to 2. Standard errors in parentheses, clustered at the household level for the data estimates. The unit of average wealth is average equivalized net labor income in the sample (see Section 2). Boldface indicates that the estimated value is statistically different from its target at a 5% level. Framed values are not targeted in the estimation.

or decreasing. Column (1) also reports that agents in the sample hold an average net worth amounting to 2.6 times average net labor income.

Lines 3 and 4 in Table 2 report the estimates of the discount rate and the variance of measurement error. Column (2) in Table 2 reports the results for the specification which does not target any wealth moment. The estimated time-preference rate δ is 0.028 and the point estimate of the variance of the measurement error σ_γ^2 is zero. Both parameters are precisely estimated. In terms of the targets, the model captures the upward sloping profiles of the consumption and wealth responses, although the point estimates of the consumption responses β_c^N at horizon $N = \{2, 6\}$ in the model are statistically different from those in the data. The specification, however, implies counterfactually high saving, with the untargeted ratio of mean wealth to mean income being more than twice as high than in the data.

Column (3) in Table 2 reports results for the alternative specification in which, similarly to Kaplan and Violante (2010) and Guvenen and Smith (2014), we also target the aggregate wealth-income ratio. The estimate for the discount rate increases to 0.045 to help match the wealth target. In terms of matching the other targets, the specification captures the upward sloping profile of the consumption responses β_c^N, although the latter is steeper than the profile for the specification reported in column (2). Contrary to specification (2), the specification fails to capture the upward sloping profile of the point estimates of the wealth response β_a^N in the data. This finding qualifies Krueger and Perri's (2011) conjecture that a downward sloping profile of wealth responses is qualitatively consistent with the PIH, but not the buffer stock model. Their result applies when the rate of time preference is sufficiently close to the interest rate.[19] Yet, as is apparent from comparing columns (2) and (3) in Table 2—and also Table 4 for the US and Table 6 in the appendix—the buffer stock model does indeed imply a downward sloping profile of wealth responses as long as consumers' impatience, measured by the difference between the time-preference rate and the interest rate, is large enough to match the average wealth observed in the data.[20]

Table 2 also shows that it is difficult for the model to match the size of the wealth responses. This may be due to the fact that, as pointed out by Krueger and Perri (2011), the large responses in the data are possibly due to the positive correlation between income shocks and valuation effects for real estate wealth. In Appendix A.1 we provide robustness results for a subsample, considered in Krueger and Perri (2011), that excludes home owners and therefore breaks the

[19] In fact, the two rates are equal in their calibration. As is well known, the buffer-stock model has no finite wealth-permanent-income target in such a case.

[20] In the working-paper version, we have shown that the PIH model generates quite similar consumption and wealth responses as the estimated specification of the buffer stock model in which the average wealth is targeted.

Table 3: Insurance Coefficients in the Buffer-Stock Saving Model - Italy

	Data	Model	
	(1)	(2)	(3)
Permanent shock	0.12	0.22	0.11
	(0.199)	(0.003)	(0.003)
Transitory shock	0.80	0.97	0.96
	(0.075)	(0.006)	(0.006)

correlation between income and wealth changes. We find that, for this subsample, the empirical estimates of the wealth responses are lower and better matched by the model. Our full sample including home owners follows BPP and has the advantage of accounting for housing which is a substantial part of net worth and is, therefore, an important determinant of the ability to self-insure against income shocks.

5.2.2 BPP insurance coefficients in the data and in the model

As discussed in Section 4 there is a connection between the strength of the precautionary saving motive, the profile of the wealth responses, and the marginal propensity to consume out of permanent income shocks. The larger the saving response to permanent income shocks—i.e., the larger the fraction of the shock that is insured and thus does not translate into a consumption change—the more likely it is that the wealth response to income shocks increases rather than decreases with the time horizon.

Columns (2) and (3) in Table 3 report the insurance coefficients implied by the two model specifications in the corresponding columns (2) and (3) in Table 2. For ease of comparison, we report in column (1) the empirical estimates from Table 1. The insurance coefficient for permanent shocks in the model is 0.22 when we do not target the wealth-income ratio (column

(2)), and it is 0.11 for our preferred specification in which we also target the wealth-income ratio in the estimation (column (3)) to align the amount of wealth available for self-insurance in the model and the data. In line with economic intuition, the estimated insurance coefficients for both permanent and temporary shocks are higher for the specification reported in column (2), which implies the higher wealth-income ratio: 7.4 rather than 2.9 for the specification reported in column (3).

Turning to the insurance coefficient for transitory shocks, we find that its estimates across the specifications in columns (2) and (3) in Table 3 are respectively 0.97 and 0.96, indicating that households in the model can effectively smooth most of the transitory shocks.

Finally, if we compare the model-based insurance coefficients of our preferred specification in column (3) with the empirical estimates, we find that the insurance coefficient for the permanent shock predicted by the model is close to the empirical estimate. This contrasts with the findings for the US in Kaplan and Violante (2010) who conclude that the degree of self-insurance against permanent shocks implied by a buffer-stock, life-cycle model is substantially lower than what would be consistent with BPP's estimates in the PSID.

Instead, the fact that the model-implied insurance coefficients are very close to (column (3)), or even larger than (column (2)), the empirical estimates suggests that Italian households do not have access to significantly more insurance than the self-insurance through a single, non-contingent asset implied by the model.

5.3 Comparison with the US

In this section we show that, in contrast to our findings for Italy and confirming results in Kaplan and Violante (2010), consumers in the US seem to be able to insure a substantially larger fraction of permanent shocks than predicted by a buffer-stock saving model calibrated to US data. To provide an exact comparison, we estimate the same model we used for Italy using

Table 4: Structural Estimation Results - US

	Data	Model	
	(1)	(2)	(3)
Parameter estimates			
σ_η^2	0.012	-	-
	(0.002)	-	-
$\sigma_\varepsilon^2 + \sigma_\gamma^2$	0.046	-	-
	(0.003)	-	-
Discount Rate δ		0.021	0.050
		(0.0007)	(0.0003)
Measurement Error σ_γ^2		0.046	0.000
		(0.0102)	(0.0022)
Targeted moments			
β_c^2	0.085	**0.128**	**0.216**
	(0.007)	(0.007)	(0.010)
β_c^4	0.105	**0.214**	**0.337**
	(0.007)	(0.008)	(0.012)
β_c^6	0.118	**0.277**	**0.422**
	(0.007)	(0.009)	(0.012)
β_a^2	0.686	0.110	**0.417**
	(0.051)	(0.583)	(0.021)
β_a^4	0.859	0.299	**0.399**
	(0.053)	(1.057)	(0.028)
β_a^6	0.911	0.527	**0.398**
	(0.054)	(1.466)	(0.032)
Wealth/Income	1.824	$\boxed{\mathbf{9.579}}$	**2.082**
	(0.073)	0.116	0.044

[a] The coefficient of relative risk aversion is preset to 2. Standard errors in parentheses, clustered at the household level for the data estimates. The unit of average wealth is average equivalized net labor income in the sample (see Section 2). Boldface indicates that the estimated value is statistically different from its target at a 5% level. Framed values are not targeted in the estimation.

PSID data for the survey years 1999-2015. For this period the PSID contains information on income, consumption and wealth so that we can compute the consumption and wealth responses for the estimation of the model. As for Italy, we then compute the model-implied insurance coefficients and compare them to our empirical estimates for the same sample.[21]

Table 4 reports the targeted moments and parameter estimates. These results are very much in line with those for Italy, as is revealed by comparing it with the corresponding Table 2. Our

[21] The estimates of BPP are based on the sample period 1978-1992, using income data in the PSID and imputing consumption data based on the CEX. See Table 1 in Section 3 for a comparison of the empirical estimates.

Table 5: Insurance Coefficients in the Buffer-Stock Saving Model - US

	Data	Model	
	(1)	(2)	(3)
Permanent shock	0.29	0.29	0.07
	(0.142)	(0.014)	(0.015)
Transitory shock	0.91	–†	0.94
	(0.045)		(0.007)

† No insurance coefficient reported for reasons discussed in footnote 23.

estimates for the variance of permanent shocks and total transitory income changes for the US are comparable to those in BPP for the period 1978-1992. Compared to our estimates for Italy in Table 2, the estimated variance of transitory shocks is similar in the two countries whereas the variance of permanent shocks is slightly higher for the US.

The model can match the upward sloping profiles of the consumption and wealth responses in the data when we do not target the wealth-income ratio in the estimation (column (2)). Yet, as was the case for Italy, the model then implies a wealth to income ratio that is counterfactually high. When we target the ratio instead (column (3)) and thus account for the extent of self insurance through asset accumulation observed in the data, the model still matches qualitatively the slope of the consumption profile but, *quantitatively,* it overestimates both the slope and intercept to a larger extent. Compared to Italy, the discrepancy between the consumption responses predicted by the model and the empirical estimates is larger for the US. This suggests that US households can reduce the consumption response to permanent income shocks by other means beyond accumulation of a non-contingent asset as in the buffer-stock saving model.[22]

[22]The estimation results in columns (2) and (3) suggest that there is a trade-off in the estimation of the discount rate between matching the wealth-income ratio and the level of the consumption responses. To assess the nature of this trade-off we have also re-estimated the model in column (3), but dropping the targets for the consumption responses. In line with with our analysis of identification in Appendix A.5, the resulting estimates are very similar to those in column (3). In particular, the estimated discount is only 0.0025 higher, both for Italy and the US.

As for Italy, the model predictions in column (3) also fail to match the sign of the slope of the profile of the wealth responses.

The implied insurance coefficients for the US are reported in Table 5, that is the counterpart of Table 3 for Italy. The results for the insurance coefficients confirm the finding of Kaplan and Violante (2010). They find that an incomplete-markets model calibrated to the US implies an insurance coefficient against permanent shocks of at most 0.22, which is well below BPP's empirical estimate of 0.36. In our sample, we estimate an insurance coefficient for permanent shocks equal to 0.29 in the data, while the corresponding point estimates for our preferred specification in which we target the wealth-income ratio is much lower at 0.07. In the specification in column (2), the model predicts an insurance coefficient of 0.29 only by overestimating average wealth by a factor of 5 compared to the data. We thus interpret our findings for the insurance coefficients as evidence that the buffer-stock model cannot account for the amount of insurance against permanent shocks that seems to be available to US households. Concerning the insurance of transitory income shocks, instead, the model-implied and empirical coefficients are very similar for the US, and similar to those which we reported for Italy.[23]

Finally, it is worth pointing out that our model-based estimates would be quantitatively similar if one were to replace the zero borrowing limit with the natural one. Given that income is log-normally distributed, the *theoretical* natural borrowing limit is in fact zero. A discrepancy between the natural and zero limit is only a feature of the *numerical* model stemming from the discretized income having a strictly positive lower bound. We find that this discrepancy does not matter quantitatively in our simulation, as only 1 percent of individuals are at the borrowing

[23] For the specification in column (2) of Table 5, we do not report an insurance coefficient of transitory shocks. Column (2) in Table 4 shows that, for this specification, the variance of transitory shocks is estimated to be zero and the variance of the measurement error thus equals the estimate of the total variance of the transitory component $\sigma_\varepsilon^2 + \sigma_\gamma^2$. Inspection of the objective function reveals that identification of the contribution of the variance of the measurement error σ_γ^2 to the total variance is somewhat tenuous for that specification. If we use the identity matrix instead of the variance-covariance matrix as weighting matrix in the estimation, the variance of the measurement error is estimated to be $\sigma_\gamma^2 = 0$.

constraint.

6 Conclusions

We use a rather unique Italian panel data set on consumption, income and wealth to estimate the extent to which households self-insure against income shocks. We build on Krueger and Perri's (2011) insight that the profile of consumption and wealth responses to income shocks at different horizons is informative about the strength of the precautionary-saving motive. Exploiting these responses, together with information on wealth holdings, we estimate the structural parameters of a buffer-stock saving model by indirect inference. The estimated model implies that Italian households insure 11 percent of a permanent shock and 96 percent of a transitory shock. These estimates are in line with empirical estimates of respectively 12 percent and 80 percent on the same sample. Through the lens of the model, this suggests that Italian households do not have access to significant insurance beyond the self-insurance implied by the non-contingent asset in the model.

We also find that Italian households have substantially less insurance possibilities against permanent shocks than their American counterparts who can insure more than implied by the buffer-stock saving model. Based on PSID data on consumption, income and wealth available since 1999, we estimate an insurance coefficient for the permanent shock of 0.29 that is of similar size as the empirical estimate of 0.36 by BPP based on PSID and CEX data in the period 1978 to 1992. Both empirical estimates are larger than the coefficient of 7 percent implied by the buffer-stock saving model for the US, confirming results by Kaplan and Violante (2010).

What may explain the large difference in households' ability to insure against permanent shocks between Italy and the US? One possible explanation is that income shocks are more persistent in Italy than in the US. Kaplan and Violante (2010) show that the standard incomplete-markets model predicts a degree of insurance against persistent income shocks in line with estimates for the US if the persistence of the shocks is not too strong. Indeed, De Nardi, Fella and Paz-Pardo (2020) have shown that a substantially lower estimate of the average degree of persistence for persistent shocks in the PSID obtains if one relaxes the assumption that income follows a canonical log-linear income process, with a persistent and transitory component. Hryshko and Manovskii (2018) also propose a modification of the canonical income process to capture the irregular nature of income observations in the PSID and Hryshko and Manovskii (2017) allow for heterogeneous persistence of income shocks across different subsamples in the PSID. They show that these modifications allow to align the estimated degree of insurance against persistent shocks with the predictions of the standard incomplete-markets model in the US.

An alternative economic explanation for the differences in insurance against permanent shocks in Italy and the US may be differences in the regulation of consumer bankruptcy in the US and Italy. Households in the US have the option to declare bankruptcy whereas this option is not available to Italian households. The buffer-stock saving model does not allow for bankruptcy and the option to declare bankruptcy is particularly attractive after persistent shocks. Hence, a potentially interesting avenue for future research is to investigate to which extent a modified model, that allows for consumer bankruptcy, helps to align the insurance coefficients for permanent shocks predicted by such a model for the US with the empirical estimates.

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A Appendix

A.1 Robustness: estimation results for the subsample of renters

Krueger and Perri (2011) have argued that the residual income changes may be correlated with residual changes in real-estate wealth. Thus, we perform a robustness check for Italy in this appendix and exclude homeowners from our sample as in Krueger and Perri (2011). This sample selection is not innocuous because housing tenure may respond to income shocks and renters have less net worth to smooth out income shocks. The advantage of considering only renters is that the residual income changes are not correlated with changes in housing wealth for this subsample by construction. This makes it more likely that the responses to these income changes capture the effect of pure income shocks.

Our subsample of renters in the SHIW consists of 335 households in the time period 1987 to 2012 accounting for 638 sets of responses. The summary statistics in column (3) of Table 7 in Appendix A.2 show that these households are fairly similar to our benchmark sample in column (2) but for their smaller net worth. This implies that the data targets for wealth in the estimation are smaller: the (normalized) mean net worth of 0.58 is much lower for renters than in our benchmark sample (see Table 2 in the main text). The consumption responses to income shocks of renters, reported in the bottom panel of Table 6, are similar to the benchmark sample. The wealth responses of renters are much smaller instead than in the benchmark sample, which is consistent with valuation changes of real estate that are correlated with income changes in the benchmark sample.

Given the differences in the data targets for the subsample of renters, it is not obvious whether a buffer-stock saving model that matches these targets implies similar insurance coefficients as the estimated model for the benchmark sample. Focusing on our preferred specification where we target (normalized) mean net worth, Table 6 shows that the smaller net worth target requires a smaller buffer-stock saving motive which the model achieves with a higher discount rate: for the same preset level of relative risk aversion of 2, the discount rate increases to 0.055 from 0.045 in the benchmark. Furthermore, the model matches the smaller wealth responses in the data for the sample of renters with a larger variance of the measurement error $\sigma_\gamma^2 = 0.013$. Equation (11) in the main text, and its discussion, as well as Appendix A.5 provide intuition for this finding.

Parameters (std.err.)	$\delta = 0.055$ (0.001), $\sigma_\gamma^2 = 0.013$ (0.002)						
	Wealth/Income	Consumption response β_c^N			Wealth response β_a^N		
		N=2	N=4	N=6	N=2	N=4	N=6
Model estimates	0.60	0.276	0.415	0.506	0.251	0.247	0.246
Standard errors	(0.029)	(0.024)	(0.027)	(0.028)	(0.032)	(0.040)	(0.044)
SHIW-data estimates	0.58	0.254	0.253	0.343	0.262	0.392	0.329
Standard errors	(0.05)	(0.029)	(0.034)	(0.034)	(0.069)	(0.070)	(0.079)

Table 6: Estimation results for the subsample of renters in the SHIW. Source: Authors' calculation. Standard errors are clustered at the household level. Notes: The coefficient of relative risk aversion is preset to 2.

The subsample of renters has less net worth which is matched in the model with a smaller buffer-stock of savings to self-insure against shocks. It is thus intuitive that the model estimated on this sample implies smaller insurance coefficients than in our benchmark, predicting that 92% of a temporary shock and 3% of a permanent shock can be insured compared with 96% and 11%, respectively, in the benchmark.

A.2 Data appendix for Italy

The variables used in the analysis are defined based on the definitions in the SHIW and in Krueger and Perri (2011):

Non-durable consumption: all expenditures but for expenditures on transport equipment, valuables, household equipment, home improvement, insurance premia and contributions to pension funds. The measure includes the effectively paid or the imputed rent.

After-tax and transfer labor income: after-tax wages and salaries, fringe benefits and transfers (pensions, arrears and other transfers).

Net-financial assets: sum of deposits, checked deposits, repos, postal savings certificates, government securities and other securities (bonds, mutual funds, equity, shares in private limited companies and partnerships, foreign securities, loans to cooperatives) net of financial liabilities (liabilities to banks and financial companies, trade debt and liabilities to other households).

Net worth: sum of net-financial assets and real estate wealth.

Education: the categories are elementary school, middle school, high school, college degree and postgraduate education.

Regions: regions are Northern, Centre and Southern regions (including islands), respectively.

Sample construction:

The SHIW data between 1987 and 2012 includes 103,707 observations for 61,925 households. We express all nominal variables in units of Euro in the year 2000. We select the prime-age households whose head has an age between 25 and 55 (52,199 observations for 33,505 households) and whose members are not in self-employment or employed in the entrepreneurial activities (34,933 observations for 23,033 households).

In the Krueger-Perri sample, only households without real estate are considered. For our benchmark sample, we also select households that own the home in which they reside, but do not own other real-estate properties (29,429 observations). The latter restriction reduces the noise when measuring wealth responses to income shocks. For this reason, we also do not consider those households that have inherited their main residence in any of the survey years (dropping 3,308 observations); and we exclude those households that adjusted the size of their dwelling in the sample period because the implied change in wealth is too noisily measured (dropping 11,205 observations). We allow, however, for transitions from renting to owning the main residence or vice-versa. As we are interested in changes in consumption or net worth to changes on income at two, four and six years, we keep households that are observed at least in four consecutive waves (dropping 12,098 observations), so we are left with 2,818 observations. Following Blundell et al. (2008) we further clean the sample from income growth outliers (dropping 31 observations): we remove those households that reported income growth higher than 500%, below −80% or with an income of less than 100 Euro per year. This leaves us with 2,787 observations corresponding to 545 households.

Following Blundell et al. (2008) we construct measures for shocks to labor income, consumption and net worth by purging these variables from their predictable component. We thus regress the respective observed levels in the data on a quartic polynomial of the age of the household head, on education, gender, family size, employment status, the number of children, a dummy which takes the value of one if there is an income earner additional to the household

Variables	Prime-age sample (aged 25-55)	Benchmark sample (aged 25-55 & not self-employed & obs. in 4 consecutive waves)	Krueger-Perri sample (benchmark sample & no real estate)
Age of household head	42.89	45.69	45.45
	(7.91)	(6.24)	(6.44)
Household size	3.30	3.42	3.38
	(1.28)	(1.23)	(1.26)
Labor income	10,347	9,261	8,640
(after tax/transfer)	(8,794)	(4,374)	(4,208)
Standard deviation of changes in residual income:			
2-period change	-	(1,252)	(1,220)
4-period change	-	(711)	(645)
6-period change	-	(496)	(466)
Net worth	70,590	24,405	4,978
	(159,901)	(40,627)	(11,206)
Non-durable consumption	8,758	7,628	7,095
	(5,009)	(3,449)	(3,364)
Education: none	0.01	0.01	0.01
	(0.11)	(0.08)	(0.10)
Education: elementary school	0.15	0.13	0.16
	(0.36)	(0.33)	(0.37)
Education: middle school	0.36	0.46	0.51
	(0.48)	(0.50)	(0.50)
Education: high school	0.35	0.34	0.28
	(0.48)	(0.47)	(0.45)
Education: college degree	0.11	0.07	0.04
	(0.31)	(0.25)	(0.20)
Education: postgraduate	0.007	0.003	0
	(0.08)	(0.05)	(-)
Region: North	0.44	0.47	0.46
	(0.50)	(0.50)	(0.50)
Region: Center	0.20	0.16	0.17
	(0.40)	(0.37)	(0.38)
Region: South (incl. islands)	0.36	0.36	0.37
	(0.48)	(0.48)	(0.48)
Number of households	33,505	545	335

Table 7: Summary statistics for the SHIW sample of households with a head aged $25-55$, for our benchmark sample of households observed in at least three consecutive waves excluding households in self-employment or entrepreneurial activities, and for the sample of Krueger and Perri (2011) in which also households with real estate wealth are excluded. Sources: Authors' calculation based on SHIW data $1987-2012$. Notes: Standard deviation in brackets. Monetary variables are converted to Euro in 2000 and to adult-equivalent units.

head, time and regional dummies as well as the age-education, year-education, year-region, year-employment status interaction dummies. We then use the residuals of these regressions as our measure of shocks. Specifically, we compute the second, fourth and sixth difference for income, consumption and net worth, and we annualize the changes of variables because the SHIW is a biannual survey with the exception of the three-year difference between the wave of 1995 and 1998. In the estimations we take into account that income shocks are measured with error.

From our sample of 2,787 observations for 545 of households, we thus obtain 1,134 sets of responses to income changes over two, four and six years $(2,787 - 3 \times 551)$, where for 6 households we have two sets of responses based on four consecutive observations each but with interrupted spells.

Table 7 provides summary statistics for (i) the full prime-age sample, (ii) the benchmark sample of households observed in at least four consecutive waves (to compute changes over a time horizon up to six years) excluding households with members in self-employment or entrepreneurial activities, and (iii) the Krueger-Perri sample in which also households with real estate wealth are excluded. The statistics in column (2) show that households in the benchmark sample are less wealthy and less educated than in the full prime-age sample in column (1). This is partly because attrition in the panel is correlated with these characteristics illustrating the trade-off between exploiting the panel dimension of the data and maintaining the representativeness of the sample. Table 7 further shows that the standard deviation of the changes in residual income decreases with the time horizon as transitory changes and measurement error wash out over longer time horizons.

A.3 Data appendix for the US

The variables used in the analysis are defined as follows (see also the definitions in the PSID documentation):

Non-durable consumption: Our measure for non-durable consumption can be constructed from 1999 onwards and it includes food consumption (at home, delivered, away and food stamps), utilities expenditure (electricity, heating, water and other utilities), transportation expenditure (car repairs and maintenance, gasoline, parking, bus and train fares, taxi expenses, other transportation cost and other vehicle expenditures), education expenses and child care.

After-tax and transfer labor income: We construct the labor income of the household as the sum of the taxable income of the household head, the spouse and other household members plus their transfers and social security income. We use the TAXSIM model from the NBER to compute the federal and state taxes that we deduct.

Net worth: The PSID provides wealth supplement files which include variables containing information on the assets and debts of the households. The wealth of the household reported by the PSID is net of debts and includes seven asset categories: farm or business wealth, savings, real estate, stocks (including mutual funds or investment trusts), vehicles, other assets (bond funds, life insurance, valuables), and private annuities or individual retirement accounts. We exclude the last category to make the measure comparable with the wealth measure we use for Italy.

Education: We construct sixteen dummy variables for each year of completed schooling. We also construct a dummy which indicates whether the head of the household completed at least some postgraduate education.

Regions: We consider the regions Northeast, North Central, South, West, Alaska - Hawaii and foreign country.

Variables	Prime-age sample (aged 25-55)	Benchmark sample (aged 25-55 & not self-employed & obs. in 4 consecutive waves)	Krueger-Perri sample (benchmark sample & no real estate)
Age of household head	39.20	46.35	42.30
	(8.86)	(5.97)	(7.12)
Household size	2.98	3.01	2.57
	(1.54)	(1.53)	(1.57)
Labor income	30,772	28,149	18,718
(after tax/transfer)	(45,366)	(19,816)	(13,999)
Standard deviation of changes in residual income:			
2-period change	-	(5,348)	(4,118)
4-period change	-	(3,012)	(2,359)
6-period change	-	(2,145)	(1,702)
Net worth	66,226	51,330	3,723
	(421,086)	(114,237)	(70,898)
Non-durable consumption	13,693	14,018	10,967
	(9,348)	(7,664)	(5,959)
Education: none	0.00	0.00	0.00
	(0.05)	(0.06)	(0.05)
Education: elementary school	0.01	0.04	0.03
	(0.12)	(0.20)	(0.17)
Education: high school	0.46	0.48	0.59
	(0.50)	(0.50)	(0.49)
Education: college	0.42	0.39	0.34
	(0.49)	(0.49)	(0.47)
Education: postgraduate	0.10	0.08	0.04
	(0.30)	(0.27)	(0.20)
Region: Northeast	0.13	0.17	0.13
	(0.34)	(0.37)	(0.33)
Region: North Central	0.24	0.22	0.22
	(0.43)	(0.41)	(0.42)
Region: South	0.44	0.44	0.48
	(0.50)	(0.50)	(0.50)
Region: West	0.18	0.17	0.17
	(0.38)	(0.37)	(0.37)
Number of households	11,802	1,288	941

Table 8: Summary statistics for the PSID sample of households with a head aged $25-55$, for our benchmark sample of households observed in at least three consecutive waves excluding households in self-employment or entrepreneurial activities, and for the sample of Krueger and Perri (2011) in which also households with real estate wealth are excluded. Sources: Authors' calculation based on PSID data $1999-2015$. Notes: Standard deviation in brackets. Monetary variables are converted to US Dollars in 2002 and to adult-equivalent units. The education categories correspond to the share of household heads with zero, one to six, seven to twelve, thirteen to sixteen years of completed schooling, and to the share of household heads with at least some postgraduate education.

Sample construction:

We use the survey years 1999 to 2015 of the PSID because, for this period, the PSID has a similar structure as the SHIW for Italy, containing information on income, consumption and wealth. We account for the fact that questions in the PSID are retrospective. For example, the interviewed households are asked for their labor income in the last year and we account for this timing when deflating nominal variables.

The PSID data between 1999 and 2015 includes 137,745 observations for 15,305 households. We report all nominal values in units of dollars in the year 2002, where we use the consumer price index for all urban consumers and all items to deflate nominal variables. We further convert variables into adult-equivalent units using the OECD scale. Changes are annualized.

As for the Italian data, we are interested in prime-age households with a head aged between 25 and 55 (49,709 observations for 11,802 households) and households with non-retired members that are not self-employed or employed in entrepreneurial activities (39,667 observations for 10,731 households).

Furthermore, for the same reasons explained in Appendix A.2, we keep households that are owner occupiers, renters or freely using the dwelling, and that do not have any other real estate property (17,524 observations). We clean the sample of those households that do not provide information on education (we drop 228 observations), race (1 observation), income (30 observations), and region (5 observations). We also remove households that report zero food consumption (1,226 observations) and negative labor income (3 observations). In order to estimate the responses, we impose that households appear in at least four waves in a consecutive spell (dropping 8,829 observations). As for the Italian data, we follow Blundell et al. (2008) who in their work with the PSID remove income outliers from the sample (so that we drop 286 observations). This leaves us with a sample of $6,916$ observations for $1,288$ households so that we can compute $3,052$ sets of responses to income changes over two, four and six years $(6,916 - 3 \times 1,288)$.

Table 8 provides summary statistics for (i) the full prime-age sample, (ii) the benchmark sample of households observed in at least four consecutive waves (to compute changes over a time horizon up to six years) excluding households with members in self-employment or entrepreneurial activities, and (iii) the Krueger-Perri sample in which also households with real estate wealth are excluded.

As for the summary statistics for the Italian data reported in Table 7, the statistics in column (2) show that households in the benchmark sample are less wealthy, somewhat less educated and older than in the full prime-age sample in column (1). As for the Italian data, Table 8 further shows that the standard deviation of the changes in residual income decreases with the time horizon as transitory changes and measurement error wash out over longer time horizons.

A.4 Implementation of the BPP methodology

BPP proceed in two steps. In the first step they use panel data on income to identify the variance of the transitory and permanent shock for a canonical income process such as (1). In the second step they then use additional information on the covariances of consumption and income to identify the insurance coefficients. In the following we present these two steps briefly (for further details see Appendix C and the Web Appendix of BPP). We then discuss some modifications that are necessary in our application because of the biannual survey structure. These modifications build on Jappelli and Pistaferri (2011) who identify the insurance coefficients differently because of their comparison of Italy with the UK where only repeated cross-sectional data are available. See footnote 10 for further details.

BPP assume a process for log-income that has a permanent component z_{it} and a transitory MA(q)-component ϵ_{it}:

$$z_{it} = z_{i,t-1} + \eta_{it} \tag{12}$$

$$\epsilon_{it} = \sum_{j=0}^{q} \theta_j \varepsilon_{i,t-j} \ , \tag{13}$$

where η_{it} is serially uncorrelated and $\theta_0 = 1$. We now assume, as in the paper, that the transitory component is MA(0). This assumption is consistent with the autocovariance structure of income in the data where the biannual surveys allow us to check whether the transitory component is MA(2) or larger.[24] As Jappelli and Pistaferri (2011), we do not find evidence for autocorrelations that would support a MA(2) process of the transitory shock or higher-order autocorrelations in the transitory component. We refer to BPP for how serially correlated transitory shocks could be accommodated in principle.

The changes in log income and log consumption are, purged from predictable components as explained in Section 2,

$$\Delta \log y_{it} = \eta_{it} + \Delta\varepsilon_{it} \tag{14}$$

$$\Delta \log c_{it} = \widetilde{\phi}^{\eta}_{it}\eta_{it} + \widetilde{\phi}^{\varepsilon}_{it}\varepsilon_{it} + \xi_{it} \ , \tag{15}$$

where the coefficients $\widetilde{\phi}^{\eta}$ and $\widetilde{\phi}^{\varepsilon}$ are equal to $1-\phi^{\eta}$ and $1-\phi^{\varepsilon}$, respectively, in equation (2) of the main text. They measure the pass through of the permanent shock and the transitory shock to consumption. The random variable ξ_{it} is independent from the other random variables in the income process and captures expectation errors, measurement error in consumption or preference shocks.

In our derivations, we do not separately account for measurement error in income given that we assume i.i.d. transitory shocks. BPP show that i.i.d. measurement error in income adds noise to the income process that does not affect the identification of the pass-through coefficient of the permanent shock and that implies an interpretation of the pass-through coefficient of the transitory shock as a lower bound (i.e., the estimate of the insurance coefficient then has to be interpreted as an upper bound).

Identifying the variances of the transitory and permanent shock–Assuming that η_{it}, ε_{it} and ξ_{it} are uncorrelated, equation (14) implies the following restrictions on the covariances of changes in log income:

[24] With biannual observations it is not possible to distinguish whether transitory shocks are i.i.d. or MA(1) without making further assumptions. To see this, suppose that the transitory shocks follow a MA(1) process, $\epsilon_{it} = \varepsilon_{it} - \theta\varepsilon_{it-1}$. Under this assumption,

$$\Delta^2 \log y_{it} = \eta_{it} + \Delta\varepsilon_{it} - \theta\Delta\varepsilon_{it-1} + \eta_{it-1} + \Delta\varepsilon_{it-1} - \theta\Delta\varepsilon_{it-2}.$$

and the covariance for income changes across two survey periods is

$$cov(\Delta^2 y_{it}, \Delta^2 \log y_{it-2}) = -\sigma^2_{\varepsilon,t-2} - \theta^2\sigma^2_{\varepsilon,t-3} \ .$$

This differs from the covariance in equation (22), derived under assumption that transitory shocks are i.i.d., due to the term $\theta^2\sigma^2_{\varepsilon,t-3}$. Given the biannual surveys, we do not have information on $\Delta^2 \log y_{i,t-1}$ or $\Delta^2 \log y_{i,t-3}$ to separately identify $\sigma^2_{\varepsilon,t-2}$, $\sigma^2_{\varepsilon,t-3}$ and θ without further assumptions.

$$cov(\Delta \log y_{it}, \Delta \log y_{i,t+s}) = \begin{cases} \sigma^2_{\eta,t} + \sigma^2_{\varepsilon,t} + \sigma^2_{\varepsilon,t-1} & \text{for } s = 0 \\ -\sigma^2_{\varepsilon,t-1} & \text{for } s = -1 \\ -\sigma^2_{\varepsilon,t} & \text{for } s = 1 \\ 0 & \text{for } |s| > 1 \end{cases} \tag{16}$$

where $\sigma^2_{x,t}$ denotes the variance of x in period t. The restrictions in equation (16) show how the covariances of changes in log income identify the variances of the temporary and the permanent shocks.

Identifying the pass-through coefficients–Given the identification of the variances of the shocks in the first step, the restrictions on the covariance matrix of changes in income and consumption identify the pass-through coefficients as follows:

$$cov(\Delta \log c_{it}, \Delta \log y_{i,t+s}) = \begin{cases} \widetilde{\phi}^{\eta}_t \sigma^2_{\eta,t} + \widetilde{\phi}^{\varepsilon}_t \sigma^2_{\varepsilon,t} & \text{for } s = 0 \\ -\widetilde{\phi}^{\varepsilon}_t \sigma^2_{\varepsilon,t} & \text{for } s = 1 \\ 0 & \text{for } s > 1 \text{ or } s < 0. \end{cases} \tag{17}$$

Combining restrictions of the type (16) and (17) yields the insurance coefficients in (3) in the main text, noting that $\log y_{i,t+1} - \log y_{i,t-2} = \Delta \log y_{i,t+1} + \Delta \log y_{i,t} + \Delta \log y_{i,t-1}$. See BPP for further details.

Finally, equipped with the variances of the permanent and transitory shocks and the pass-through coefficients, equation (15) implies restrictions on the covariance of changes in log consumption that allow to identify the variances $\sigma^2_{\xi,t}$:

$$cov(\Delta \log c_{it}, \Delta \log c_{i,t+s}) = (\widetilde{\phi}^{\eta}_t)^2 \sigma^2_{\eta,t} + (\widetilde{\phi}^{\varepsilon}_t)^2 \sigma^2_{\varepsilon,t} + \sigma^2_{\xi,t} \tag{18}$$

for $s = 0$. The covariance is zero otherwise if consumption follows a martingale.

For their estimation BPP use the PSID surveys from 1978 to 1992. They exploit the annual panel data on income and impute a consumption measure based on the CEX survey. Instead we use biannual surveys of the PSID from 1999 to 2015 and the SHIW from 1987 to 2012, with the exception of a three-year gap between 1995 and 1998 in the SHIW. The advantage is that, in both surveys, we have panel data on income and consumption from the same source for these years. The biannual surveys imply some restrictions, however, on what we can infer from the data. We thus discuss in the next subsection how we have to modify BPP's methodology to identify the variances and insurance coefficients.

A.4.1 Modifications with biannual surveys

Maintaining the assumption of serially uncorrelated transitory shocks, equations (14) and (15) imply

$$\Delta^2 \log y_{it} = \eta_{it} + \eta_{i,t-1} + \Delta\varepsilon_{it} + \Delta\varepsilon_{i,t-1} \tag{19}$$

$$\Delta^2 \log c_{it} = \widetilde{\phi}^{\eta}(\eta_{it} + \eta_{i,t-1}) + \widetilde{\phi}^{\varepsilon}(\varepsilon_{it} + \varepsilon_{i,t-1}) + \xi_{it} + \xi_{i,t-1} \tag{20}$$

where $\Delta^2 x = x_t - x_{t-2}$ and the pass-through coefficients are constant over time as assumed in the main analysis of BPP.

Based on (19) and (20), we derive the following covariances for income

$$
\begin{aligned}
cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it}) &= \sigma^2_{\eta,t} + \sigma^2_{\eta,t-1} + \sigma^2_{\varepsilon,t} + \sigma^2_{\varepsilon,t-2} \ , && (21)\\
cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it-2}) &= -\sigma^2_{\varepsilon,t-2} \ , && (22)\\
cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it+2}) &= -\sigma^2_{\varepsilon,t} \ , && (23)
\end{aligned}
$$

the following covariances for consumption

$$
\begin{aligned}
cov(\Delta^2 \log c_{it}, \Delta^2 \log c_{it}) &= \left(\widetilde{\phi}^{\eta}\right)^2 (\sigma^2_{\eta,t} + \sigma^2_{\eta,t-1}) + \left(\widetilde{\phi}^{\varepsilon}\right)^2 (\sigma^2_{\varepsilon,t} + \sigma^2_{\varepsilon,t-1}) + \sigma^2_{\xi,t} + \sigma^2_{\xi,t-1} \ , && (24)\\
cov(\Delta^2 \log c_{it}, \Delta^2 \log c_{it-2}) &= cov(\Delta^2 \log c_{it}, \Delta^2 \log c_{it+2}) = 0 \ , && (25)
\end{aligned}
$$

and the following covariances between consumption and income

$$
\begin{aligned}
cov(\Delta^2 \log c_{it}, \Delta^2 \log y_{it}) &= \widetilde{\phi}^{\eta} (\sigma^2_{\eta,t} + \sigma^2_{\eta,t-1}) + \widetilde{\phi}^{\varepsilon} \sigma^2_{\varepsilon,t} \ , && (26)\\
cov(\Delta^2 \log c_{it}, \Delta^2 \log y_{it-2}) &= 0 \ , && (27)\\
cov(\Delta^2 \log c_{it}, \Delta^2 \log y_{it+2}) &= -\widetilde{\phi}^{\varepsilon} \sigma^2_{\varepsilon,t} \ . && (28)
\end{aligned}
$$

Given the biannual survey structure, we need to make some further assumptions on the variances of the intermediate years, in-between two adjacent surveys. We assume that the consecutive permanent-shock variances enter additively with equal weight in equation (21) because we can only identify the sum $\sigma^2_{\eta,t} + \sigma^2_{\eta,t-1}$ for all t. For the three-year gap in the SHIW between 1995 and 1998, we use $\sigma^2_{\eta,t} + \sigma^2_{\eta,t-1} + \sigma^2_{\eta,t-2}$. Furthermore, we cannot back out $\sigma^2_{\varepsilon,t-1}$ in equation (24) because we do not have data for intermediate survey years. We follow Jappelli and Pistaferri (2011) and approximate it as the average of the variances in the adjacent periods, i.e., $\sigma^2_{\varepsilon,t-1} = (\sigma^2_{\varepsilon,t} + \sigma^2_{\varepsilon,t-2})/2$ where for the SHIW in 1998 we use linear interpolation $\sigma^2_{\varepsilon,t-1} = \sigma^2_{\varepsilon,t-3} + 2(\sigma^2_{\varepsilon,t} - \sigma^2_{\varepsilon,t-3})/3$ and $\sigma^2_{\varepsilon,t-2} = \sigma^2_{\varepsilon,t-3} + (\sigma^2_{\varepsilon,t} - \sigma^2_{\varepsilon,t-3})/3)$. Finally, we assume a constant variance $\sigma^2_{\xi,t} = \sigma^2_{\xi}$ for all t.

Given that the sample size for some of the covariances, which require long, continuous spells of panel data, becomes rather small in the Italian data, we impose the restriction for the analysis with the SHIW that the covariances are constant across time. This modifies the set of previous equations as follows. The equations (21) to (23) for the covariances of income changes become

$$
\begin{aligned}
&cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it}) = 2(\sigma^2_{\eta} + \sigma^2_{\varepsilon}) \qquad \text{for } t = 1989, \ldots, 1995, 2000, \ldots, 2012,\\
&cov(\Delta^3 \log y_{it}, \Delta^3 \log y_{it}) = 3(\sigma^2_{\eta} + \sigma^2_{\varepsilon}) \qquad \text{for } t = 1998,\\
&cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it-2}) = cov(\Delta^3 \log y_{it}, \Delta^2 \log y_{it-3}) = -\sigma^2_{\varepsilon} \qquad \text{for } t = 1989, \ldots, 2012,\\
&cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it+2}) = cov(\Delta^2 \log y_{it}, \Delta^2 \log y_{it+3}) = -\sigma^2_{\varepsilon} \qquad \text{for } t = 1989, \ldots, 2012.
\end{aligned}
$$

Equation (24) for the covariance of consumption changes simplifies to

$$
\begin{aligned}
&cov(\Delta^2 \log c_{it}, \Delta^2 \log c_{it}) = 2\left(\left(\widetilde{\phi}^{\eta}\right)^2 \sigma^2_{\eta} + \left(\widetilde{\phi}^{\varepsilon}\right)^2 \sigma^2_{\varepsilon} + \sigma^2_{\xi}\right) \qquad \text{for } t = 1989, \ldots, 1995, 2000, \ldots, 2012,\\
&cov(\Delta^3 \log c_{it}, \Delta^3 \log c_{it}) = 3\left(\left(\widetilde{\phi}^{\eta}\right)^2 \sigma^2_{\eta} + \left(\widetilde{\phi}^{\varepsilon}\right)^2 \sigma^2_{\varepsilon} + \sigma^2_{\xi}\right) \qquad \text{for } t = 1998.
\end{aligned}
$$

Finally, equations (26) and (28) for the covariances between consumption and income changes are then

$$
\begin{aligned}
cov(\Delta^2 \log c_{it}, \Delta^2 \log y_{it}) &= 2\widetilde{\phi}^{\eta}\sigma_{\eta}^2 + \widetilde{\phi}^{\varepsilon}\sigma_{\varepsilon}^2 \qquad \text{for } t = 1989, \ldots, 1995, 2000, \ldots, 2012, \\
cov(\Delta^3 \log c_{it}, \Delta^3 \log y_{it}) &= 3\widetilde{\phi}^{\eta}\sigma_{\eta}^2 + \widetilde{\phi}^{\varepsilon}\sigma_{\varepsilon}^2 \qquad \text{for } t = 1998, \\
cov(\Delta^2 \log c_{it}, \Delta^2 \log y_{it+2}) &= cov(\Delta^3 c_{it}, \Delta^2 y_{it+2}) = -\widetilde{\phi}^{\varepsilon}\sigma_{\varepsilon}^2 \qquad \text{for } t = 1989, \ldots, 2012.
\end{aligned}
$$

We compute the data moments for the changes of log consumption and log income and their covariance matrix in the SHIW and PSID. With the equations derived in this appendix for the survey structure in the SHIW and PSID, we then estimate the variances of the transitory and permanent shocks and the pass-through coefficients with minimum distance estimation as BPP.

A.5 Illustration of the model identification

Figures 1 and 2 illustrate how perturbations of the two estimated parameters, at the reported point estimates, affect the moments. The first row in each figure shows that changes in the discount rate affect mainly the wealth-income ratio but have little effect on the consumption and wealth responses, particularly at short horizons. The second row of each figure shows that changes in the variance of the measurement error instead shift the profile of the wealth responses but have little effect on the consumption responses and the wealth-income ratio. These results illustrate that the aggregate wealth-income ratio and, to a smaller extent, the consumption responses largely identify the discount rate, whereas the wealth responses identify the variance of the measurement error. The results are intuitive. Higher impatience, because of a higher discount rate, reduces the aggregate wealth-income ratio so that households' ability to self-insure decreases. Hence, the consumption responses to shocks increase. The wealth responses decrease accordingly but the figures show that the quantitative effect is smaller at short horizons. The much stronger effect of the variance of the measurement error on the wealth responses than on the consumption responses confirms the intuition, discussed in the main text, from the analytic characterization of the responses in equations (10) and (11) for the linear-quadratic approximation of our structural model.

A.6 Solution and estimation of the model

The solution and estimations follow Hintermaier and Koeniger (2011) so that we only mention computational issues which are not discussed in that paper. We use 12 states to approximate the permanent part of the income process. The additional transitory shock ε_t is discretized with the quadrature method using 12 points. The grid for wealth is triple-exponential with 1,600 points (being much finer where the policies have more curvature). We employ the endogenous-grid method (EGM) proposed by Carroll (2006) to solve the model.

After some experimentation with coarser grids, we specify the following finer grid with $1/(1+\delta) \in [0.90, 0.98]$ with distance 0.0025 between adjacent gridpoints of the discount rate δ. For the variance of the measurement error $\sigma_{\gamma}^2 \in [0, b]$ with distance 0.0025 between adjacent gridpoints and b corresponding to the empirical estimate of the total variance of transitory income changes.

In the model solution, we scale the variance of the transitory shock σ_{ε}^2 when we vary the variance of the measurement error σ_{γ}^2 across model cases so that the sum of the two variances equals the empirical estimate of the total variance of the transitory income changes $\sigma_{\varepsilon}^2 + \sigma_{\gamma}^2$. In the simulations, we draw initial wealth from the empirical wealth distribution of our benchmark

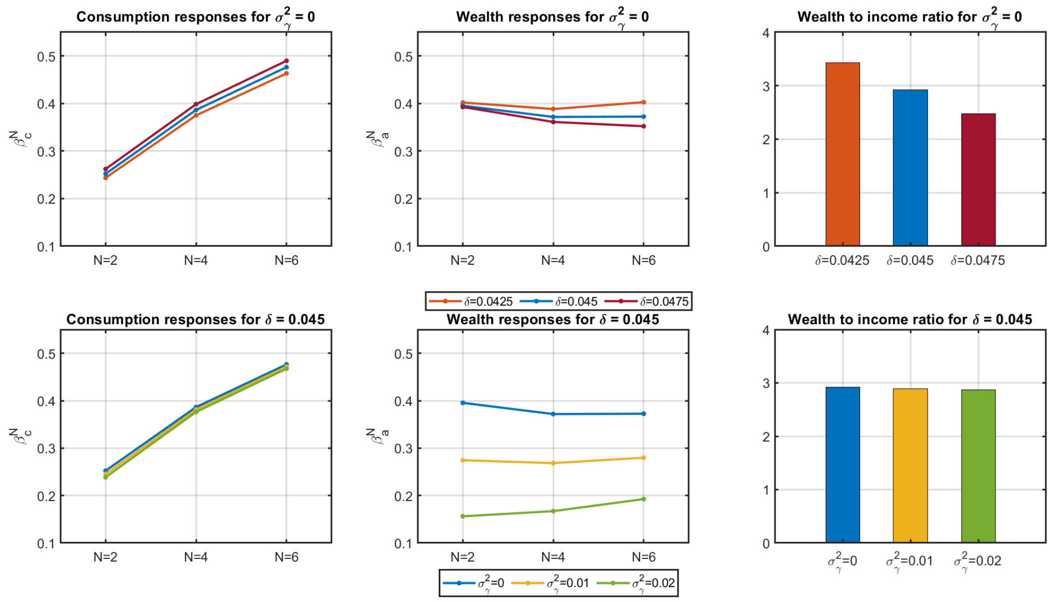

Figure 1: Illustration for the model identification for Italy. *Notes:* Changes of moments for perturbations of the discount rate (first row) and the variance of the measurement error (second row).

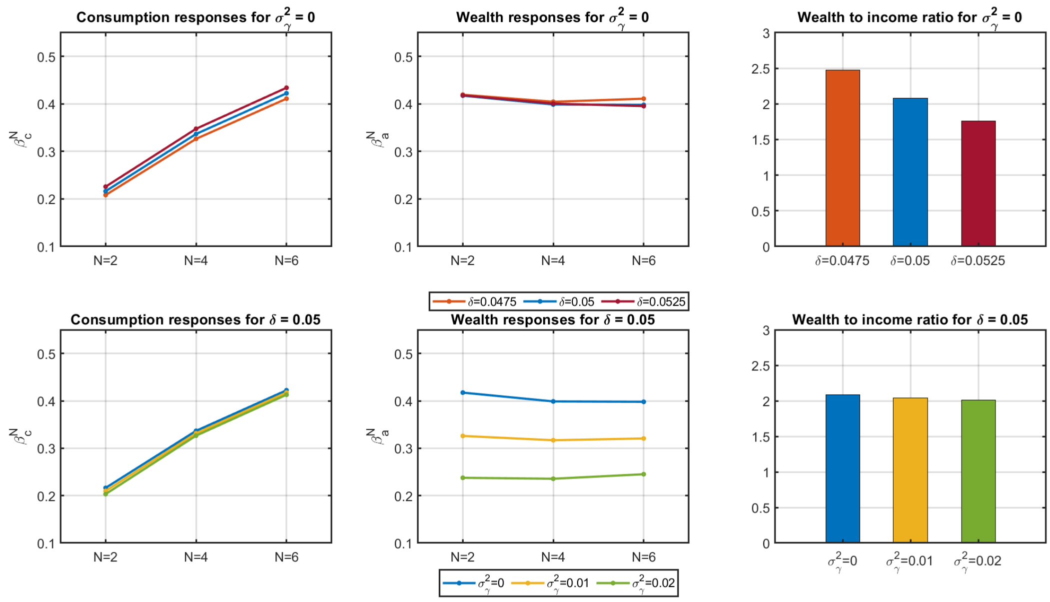

Figure 2: Illustration for the model identification for the US. *Notes:* Changes of moments for perturbations of the discount rate (first row) and the variance of the measurement error (second row).

sample and set initial income to the mean. We simulate the model economy for 45 periods for 25,000 consumers, drawing both the transitory and the permanent shock with the normal random number generator and interpolating the policy functions to obtain consumption and savings for the simulated values of income and wealth. We add the measurement error for income and then estimate the responses of consumption and wealth to income changes.

To compute the variance-covariance matrix we draw, with replacement, 10,000 random samples of the corresponding sample size constructed from the SHIW or the PSID. We compute the regression coefficients and the wealth moment for each of these finite samples and their variance/covariance across the 10,000 samples.