Nonlinear Persistence and Partial Insurance: Income and Consumption Dynamics in the PSID

By MANUEL ARELLANO, RICHARD BLUNDELL AND STEPHANE BONHOMME*

In this paper we highlight the important role the PSID has played in developing our understanding of income dynamics and partial insurance, see for example, Krueger and Perri (2005), Blundell, Pistaferri and Preston (BPP, 2008) and Attanasio and Pistaferri (2016).[1] In the partial insurance approach, transmission parameters are specified that link 'shocks' to income with consumption growth. These transmission parameters can change across time and may differ across individuals reflecting the degree of 'insurance' available. They encompass self-insurance through simple credit markets as well as other mechanisms used to smooth consumption.

We explore the nonlinear nature of income shocks and describe a new quantile-based panel data framework for income dynamics, developed in Arellano, Blundell and Bonhomme (ABB, 2017). In this approach the persistence of past income shocks is allowed to vary according to the size and sign of the current shock. We find that the model provides a good match with data on family earnings and on individual wages from the PSID. We confirm the results on income dynamics using the extensive population register data from Norway.

Exploiting the enhanced consumption and asset data in recent waves of the PSID, we show that nonlinear persistence has key implications for consumption insurance. The approach is used to provide new empirical measures of partial insurance in which the transmission of income shocks to consumption varies systematically with assets, the level of the shock and the history of past shocks.

I. Earnings and consumption dynamics

A prototypical "canonical" panel data model of (log) family (earned) income y_{it} is:

$$y_{it} = \eta_{it} + \varepsilon_{it}, \quad i = 1, ..., N, \quad t = 1, ..., T.$$

where y_{it} is net of a *systematic component*, η_{it} is a *random walk* with innovation υ_{it},

$$\eta_{it} = \eta_{it-1} + \upsilon_{it}, \quad i = 1, ..., N, \quad t = 1, ..., T.$$

and ε_{it} is a *transitory shock*.

There is good economic reasoning behind this decomposition: persistent shocks to income are more difficult to insure, especially for young families with low assets. How families cope with persistent shocks is the main focus of this research. Short-run fluctuations will matter too, of course, especially for households with low assets (or low access to liquid assets).

In the partial insurance framework, consumption growth is related to income shocks:

$$\triangle c_{it} = \phi_t \upsilon_{it} + \psi_t \varepsilon_{it} + \nu_{it}, i = 1, .N, t = 1, .T.$$

where c_{it} is log consumption net of a systematic component, ϕ_t is the *transmission* of persistent shocks υ_{it}, and ψ_t the *transmission* of transitory shocks; the ν_{it} are taste shocks, assumed to be independent across periods, see BPP.

This baseline panel data model specification can be summarised as:

$$\triangle c_{it} = \phi \upsilon_{it} + \psi \varepsilon_{it} + \nu_{it},$$

$$\triangle y_{it} = \upsilon_{it} + \triangle \varepsilon_{it},$$

which implies covariance restrictions:

$$var(\triangle c_{it}) = \phi^2 \sigma_\upsilon^2 + \psi^2 \sigma_\varepsilon^2 + \sigma_\nu^2$$

* Arellano: Cemfi, Madrid, arellano@cemfi.es Blundell: University College London, Gower Street London, r.blundell@ucl.ac.uk Bonhomme: Chicago, sbonhomme@uchicago.edu Acknowledgements: We are particularly grateful to Luigi Pistaferri and Itay Saporta-Eksten for help with the PSID data, Magne Mogstad and Michael Graber for providing the estimations using the Norwegian population register data as part of the project on 'Labour Income Dynamics and the Insurance from Taxes, Transfers and the Family'. Arellano acknowledges research funding from the Ministerio de Economía y Competitividad, Grant ECO2016-79848-P. Blundell would like to thank the ESRC Centre CPP at IFS and the ERC MicroConLab project for financial assistance. Bonhomme acknowledges support from the European Research Council/ ERC grant agreement n^0 263107.

[1] Blundell and Preston (1998) develop a similar framework for repeated cross-section data.

$$var(\triangle y_{it}) = \sigma_\eta^2 + 2\sigma_\varepsilon^2$$
$$cov(\triangle y_{it} \triangle y_{it-1}) = -\sigma_\varepsilon^2$$
$$cov(\triangle c_{it} \triangle y_{it}) = \phi\sigma_v^2 + \psi\sigma_\varepsilon^2$$
$$cov(\triangle c_{it-1} \triangle y_{it}) = -\psi\sigma_\varepsilon^2$$

BPP show identification and efficient estimation using GMM. They include time(age) variation in the σ_*^2 terms and in the insurance parameters. They also allow for measurement error and extend to MA(1) transitory shocks.[2]

The parameters ϕ_t and ψ_t link the evolution of consumption inequality to income inequality. They indicate the degree of partial insurance, and will differ by age, assets and human capital. For example, using a linearised approximation to a simple benchmark intertemporal consumption model, Blundell, Low and Preston (2013) show

$$\phi_t = (1 - \pi_{it}) \text{ and } \psi_t = (1 - \pi_{it})\gamma_{Lt}$$

where

$$\pi_{it} \approx \frac{\text{Assets}_{it}}{\text{Assets}_{it} + \text{Human Wealth}_{it}}$$

and γ_{Lt} is the annuity value of a temporary shock to income for an individual aged t retiring at age L.

In the PSID estimates of $(1 - \pi_{it})$ typically average at around .82. BPP estimate a *partial insurance* coefficient of .642 (.09). They document higher values for samples without college education, for older cohorts, and for low wealth samples.

This linearised partial insurance framework provides key insights on the distributional dynamics of income and consumption. However, it rules out the nonlinear transmission of shocks and restricts interactions in consumption responses.

II. Nonlinear Persistence

The aim in the new work on nonlinear persistence is to step back from the standard panel data model of income dynamics and take a different track: develop *an alternative approach* in which the impact of past shocks can be altered by the size and sign of new shocks. The framework allows '*unusual'* shocks to wipe out the memory of past shocks. Additionally the future persistence of a current shock will depend on future shocks. We will see that the presence of 'unusual' shocks matches the data well and has a key impact on consumption and saving decisions over the life cycle.

In this framework we maintain the permanent-transitory factor structure

$$y_{it} = \eta_{it} + \varepsilon_{it}, \quad i = 1, ..., N, \quad t = 1, ..., T.$$

but allow η_{it} to follow a general first-order Markov process.[3] Denoting the τth conditional quantile of η_{it} given $\eta_{i,t-1}$ as $Q_t(\eta_{i,t-1}, \tau)$, we specify

$$\eta_{it} = Q_t(\eta_{i,t-1}, u_{it}),$$

where $(u_{it}|\eta_{i,t-1}, \eta_{i,t-2}, ..) \sim$ *Uniform* (0, 1), and ε_{it} has zero mean, independent over time.

The conditional quantile functions $Q_t(\eta_{i,t-1}, u_{it})$ and the marginal distributions F_{ε_t} can all be age specific.

This framework allows for quite general nonlinear dynamics of income, allowing a general form of conditional heteroscedasticity, skewness and kurtosis. To see this, consider the following measure of persistence

$$\rho_t(\eta_{i,t-1}, \tau) = \frac{\partial Q_t(\eta_{i,t-1}, \tau)}{\partial \eta}.$$

which measures the persistence of $\eta_{i,t-1}$ when, at age t, it is hit by a shock u_{it} that has rank τ. This measures the *persistence of histories*. Below we show strong evidence for such nonlinearities in persistence.

III. An Empirical Model for Consumption

To motivate the specification of consumption we use a standard life-cycle incomplete markets model (some arguments are latent). Let c_{it} and a_{it} denote log-consumption and assets (beginning of period) net of age dummies. We model consumption in levels and leave the nonlinear rule flexible. Our empirical specification is based on

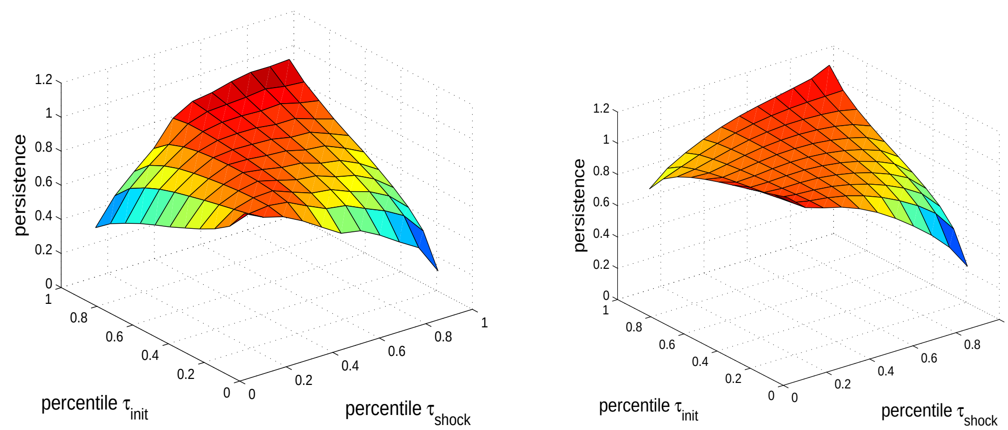
$$c_{it} = g_t\left(a_{it}, \eta_{it}, \varepsilon_{it}, \nu_{it}\right) \quad t = 1, ..., T,$$

[2]Blundell and Preston (1998) develop these covariance restrictions for repeated cross-sections.

[3]The first-order Markov assumption can be generalised to Markov (p), with any fixed p (although this requires larger T).

FIGURE 1. QUANTILE AUTOREGRESSIONS OF LOG-EARNINGS

(a) PSID data (b) Norwegian administrative data



Note: Residuals y_{it} of log pre-tax household labor earnings, Age 25-60 1999-2009 (US), Age 25-60 2005-2006 (Norway). Estimates of the average derivative of the conditional quantile function of y_{it} given $y_{i,t-1}$ with respect to $y_{i,t-1}$. Quantile functions are specified as third-order Hermite polynomials.
Source: Arellano, Blundell Bonhomme (2017).

where ν_{it} are independent across periods, and g_t is a nonlinear, age-dependent function, monotone in ν_{it}, ν_{it} may be interpreted a taste shifter that increases marginal utility. This consumption rule is consistent, in particular, with the standard life-cycle model, e.g. Kaplan and Violante (2010). ABB derive conditions under which g is nonparametrically identified.

With consumption specification given by

$$c_{it} = g_t\left(a_{it}, \eta_{it}, \varepsilon_{it}, \nu_{it}\right), \quad t = 1, ..., T,$$

consumption responses to η and ε are

$$\phi_t(a, \eta, \varepsilon) = \mathbb{E}\left[\frac{\partial g_t\left(a, \eta, \varepsilon, \nu\right)}{\partial \eta}\right],$$

$$\psi_t(a, \eta, \varepsilon) = \mathbb{E}\left[\frac{\partial g_t\left(a, \eta, \varepsilon, \nu\right)}{\partial \varepsilon}\right].$$

where $\phi_t(a, \eta, \varepsilon)$ and $\psi_t(a, \eta, \varepsilon)$ reflect the transmission of the persistent and transitory earnings components, respectively. They generalise the partial insurance coefficients of BPP.

Similar techniques can be used in the presence of *advance information*, e.g.

$$c_{it} = g_t\left(a_{it}, \eta_{it}, \eta_{i,t+1}, \varepsilon_{it}, \nu_{it}\right),$$

or *consumption habits*, e.g.

$$c_{it} = g_t\left(c_{i,t-1}, a_{it}, \eta_{it}, \varepsilon_{it}, \nu_{it}\right).$$

also cases where the consumption rule depends on lagged η, or when η follows a second-order Markov process, see Section 3 in *ABB*. The framework allow for additional, *unobserved heterogeneity* in earnings and consumption. Households will also differ in their initial productivity η_1 and initial assets.

IV. Data and Estimation

The PSID went through a redesign in the late 1990s, introducing new consumption and asset modules. Since 1999 it collects some 70% of consumption expenditures, and more than 90% since 2005. We use the sum of food at home, food away from home, gasoline, health, transportation, utilities, etc. We also make use of the more detailed asset data, see Blundell, Pistaferri and Saporta-Eksten (2016), BPS. For comparison we make use of family earnings data from administrative records from the Norwegian population registers see Blundell, Graber and Mogstad (2015).[4]

The results we present on the PSID use data from the 1999 - 2009 surveys. Assets holdings are the sum of financial assets, real estate value, pension funds, and car value, net of mortgages and other debt. Income y_{it} are residuals of log

[4]The Norwegian results are part of the project on 'Labour Income Dynamics and the Insurance from Taxes, Transfers and the Family'. See ABB Appendix C.

total pre-tax household labor earnings on a set of demographics - cohort and calendar time dummies, family size and composition, education, race, and state dummies. Log consumption c_{it} is also a residual, using the same set of demographics as for earnings. Following BPS, we select married male heads aged between 25 and 59. In this paper we focus on a balanced sub-sample of $N = 792$ households.

The conditional quantile function for the permanent income factor η_{it}, given $\eta_{i,t-1}$, is specified as

$$\begin{aligned} Q_t(\eta_{t-1}, \tau) &= Q(\eta_{t-1}, age_t, \tau) \\ &= \sum_{k=0}^{K} a_k^Q(\tau)\varphi_k(\eta_{t-1}, age_t), \end{aligned}$$

where φ_k, $k = 0, 1, ..., K$, are polynomials (Hermite). Similarly for ε_{it} etc. The consumption (log) function, $g(a_t, \eta_t, \varepsilon_t, age_t)$, is specified as a flexible polynomial in assets, permanent income factor, the transitory shock and age.

Estimation takes place in two steps, see ABB for details. The first step recovers estimates of the income parameters. The second step recovers estimates of the consumption parameters, given an estimate of the income parameters. The estimation algorithm alternates between draws of latent variables from candidate posteriors and quantile regressions using those draws, see also Arellano and Bonhomme (2016).

V. Empirical Results

Figure 1 provides our initial evidence for nonlinear income dynamics. It presents estimates of the average derivative of the conditional quantile function of y_{it} given $y_{i,t-1}$ with respect to $y_{i,t-1}$ for both the PSID in panel (a), and the Norwegian register data in panel (b). These are evaluated at percentiles of the shock τ_{shock} and at a value of $y_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $y_{i,t-1}$.

The estimates in Figure 1 display distinct and systematic nonlinearity. The persistence of income shocks is much lower for large negative (positive) shocks for high (low) initial incomes. The results for the PSID are confirmed in panel (b) for the Norwegian data.

Turning to the income model, Figure 2, panel (a) provides estimates of the average derivative of the conditional quantile function of the persistent income factor η_{it} on $\eta_{i,t-1}$ with respect to $\eta_{i,t-1}$, evaluated at percentile τ_{shock} and at a value of $\eta_{i,t-1}$ that corresponds to the τ_{init} percentile of the distribution of $\eta_{i,t-1}$. The estimates are evaluated at mean age in the sample. Panel (b) in Figure 2 is based on data simulated according to our nonlinear earnings model with parameters set to their estimated values. It shows a close accordance with the persistence in the PSID income data, see panel (a) of Figure 1.

Moving to the estimated consumption model, Figure 3 displays the average derivative of the conditional mean of c_{it} given y_{it}, a_{it} and age_{it} with respect to y_{it}, evaluated at values of a_{it} and age_{it} corresponding to their τ_{assets} and τ_{age} percentiles, and averaged over the values of y_{it}. It shows consumption responses vary systematically with age and assets and in a way that accords with stand life-cycle theory. It also shows a clear accordance between the consumption model and data.

Finally, we provide preliminary evidence that the nonlinear persistence we have uncovered in family earnings data is also evident in hourly wage data. Figure 4, panel (a), presents estimates of nonlinear persistence in the permanent component for PSID male hourly earnings. Panel (b) provides the implication from the simulated nonlinear model. These results show an important role for unusual shocks and nonlinear persistence in hourly wage data, suggesting nonlinear persistence maybe a key feature for life-cycle models of family labor supply.

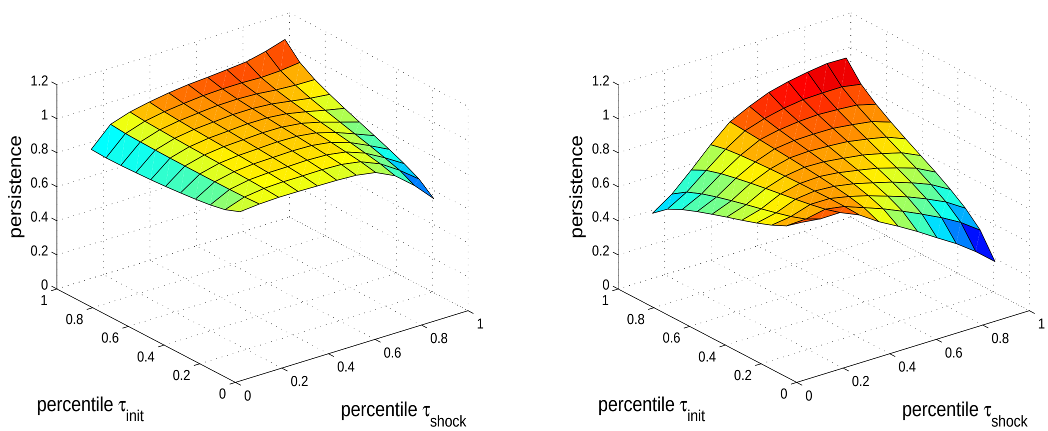
VI. Summary and Conclusions

In this paper we have outlined a new framework to shed new light on income dynamics and nonlinear transmission of income shocks to consumption. We have exploited important new measurements for consumption and assets in the PSID. We have also shown the complementarities between 'big' administrative data, like the Norwegian registers, and purpose designed panel surveys, like the PSID.

A Markovian permanent-transitory model of household income, which reveals asymmetric persistence of unusual shocks, is shown to accord well with the persistence of income in the PISD and in Norwegian register data. An age-dependent nonlinear consumption rule as a function of assets, permanent income and transitory income, is also applied to the PSID and shown to generate new empirical measures of the de-

FIGURE 2. NONLINEAR PERSISTENCE

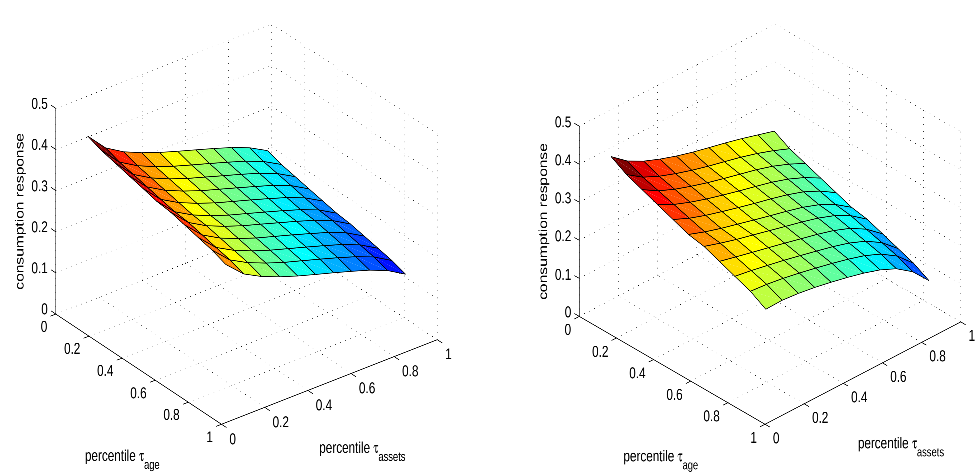
(a) Persistent component η_{it} (b) Earnings, nonlinear model



Note: PSID data. Graph (a) shows estimates of the average derivative of the conditional quantile function of η_{it} on $\eta_{i,t-1}$ with respect to $\eta_{i,t-1}$, based on estimates from the nonlinear earnings model. Graph (b) is based on data simulated according to our nonlinear earnings model with parameters set to their estimated values. Source: Arellano, Blundell and Bonhomme (2017).

FIGURE 3. CONSUMPTION RESPONSES TO y_{it}, BY ASSETS AND AGE

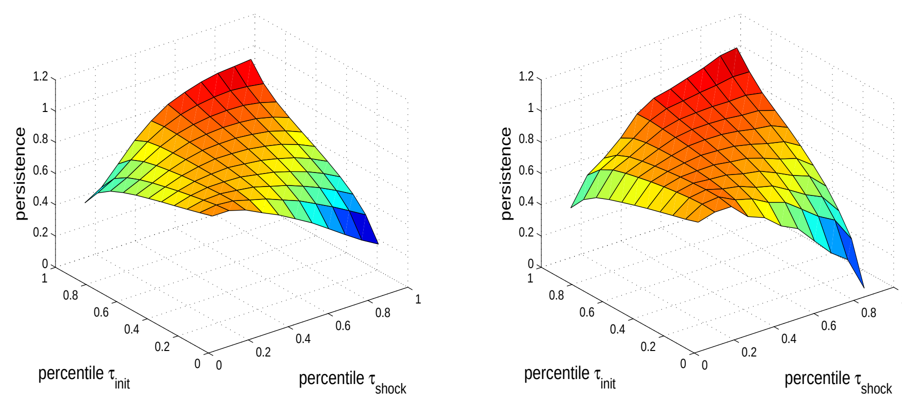
(a) PSID data (b) Nonlinear model



Note: Estimates of the average derivative of the conditional mean of c_{it} given y_{it}, a_{it} & age_{it} with respect to y_{it}, evaluated at values of a_{it} & age_{it} corresponding to their τ_{assets} & τ_{age} percentiles, and averaged over the values of y_{it}. Source: Arellano, Blundell and Bonhomme (2017).

FIGURE 4. NONLINEAR PERSISTENCE IN MALE HOURLY WAGES

(a) Persistent component η_{it} (b) Earnings, nonlinear model



Note: Log male wages, Age 30-60 PSID 1999-2013 (US). Estimates of the average derivative of the conditional quantile function. Source: Authors calculations.

gree of partial insurance.

The results also point to nonlinearities in the dynamics of individual male wages. In future research we will explore the impact of such nonlinear persistence on family labour supply and consumption smoothing, building on Blundell, Saporta-Eksten and Pistaferri (2010) and Heathcote, Storesletten, and Violante (2014).

Future research could also usefully examine firm to firm transitions and lay-offs, it could focus on the role of housing equity and local labour markets. It could also look at health and other types of (partially insured) shocks.

A final word to the PSID. Congratulations at 50! Thanks for everything, for all those many micro-data innovations and looking forward to the next 50 years!

REFERENCES

Arellano, M., and S. Bonhomme (2016): Panel Data Estimation via Quantile Regressions," Econometrics Journal, 19, C61-C94.

Arellano, M., Blundell, R. and S. Bonhomme (2017): Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework", Econometrica, 85, 693- 734

Attanasio, Orazio. P., Luigi Pistaferri (2016) 'Consumption Inequality', Journal of Economic Perspectives, vol. 30, no. 2, Spring (pp. 3-28)

Blundell, R., M. Graber and M. Mogstad (2015): Income Dynamics and the Insurance from Taxes, Transfers, and the Family," Journal of Public Economics, 127, 5873.

Blundell, Richard, Hamish Low and Ian Preston (2013) "Decomposing Changes in Income Risk Using Consumption Data", *Quantitative Economics*, vol. 4(1), pages 1-37, 03.

Blundell, Richard, and Ian Preston (1998) "Consumption Inequality and Income Uncertainty." *Quarterly Journal of Economics*, 113(2): 603-640.

Blundell, R., L. Pistaferri, and I. Preston (2008): Inequality and Partial Insurance," American Economic Review, 98(5): 18871921.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016): Smoothing and Family Labor Supply, American Economic Review, 106(2), 387-435.

Guvenen, F., F. Karahan, S. Ozcan, and J. Song (2015): What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?" NBER WP 20913.

Guvenen, F., and A. Smith (2014): Labor Income Risk from Economic Choices: An Indirect Inference Approach," Econometrica, November, 82(6), 20852129.

Heathcote, J., K. Storesletten, and G. Violante (2014): and Labor Supply with Partial Insurance: An Analytical Framework," American Economic Review, July, 104(7), 20752126.

Kaplan, Greg and Giovanni Violante (2010), "How Much Consumption Insurance Beyond Self-Insurance."*American Economic Journal*, 2(4), 53-87.

Krueger, Dirk, and Fabrizio Perri. 2006. "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *Review of Economic Studies*, 73(1): 163-193.