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MEASURING HOUSEHOLDS' EXPOSURE TO ECONOMIC SHOCKS: AN ANALYSIS AT THE INTERSECTION OF INCOME, FINANCIAL WEALTH, AND DEBT[1]

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ABSTRACT

We provide an analysis of financial fragilities of Italian households in the 2000-2020 period, using data from the Survey on Household Income and Wealth. We comment on the recent trends of financial illbeing, using different measures of poverty, and we provide a descriptive analysis of the fragile households' characteristics. Then, we model persistence in the dynamics of the poverty statuses using different specifications of the dynamic random-effects probit model, to account for observed and latent individual heterogeneity, and endogeneity of the initial conditions. A strong state dependence is found in all the considered poverty statuses, with financial and liquidity poverty representing the most persistent states.

1. Introduction

Financial wellbeing is an important factor contributing to general individual (emotional and material) wellbeing. It can be broadly defined as a state wherein a person can fully meet current and ongoing financial obligations, she can feel secure in her financial future and she is able to make choices that allow her to enjoy life. Sound financial and economic conditions have consequences on the financial and social stability at the macro-level, when they are widespread in the population. In fact, economic growth and fluctuations are influenced by households' consumption and saving choices (Deaton, 1991; Carrol 1992) as well as financial stability is affected by the borrowers' ability to repay debts (Mian et al. 2017; Mian et al., 2021).

Financial wellbeing is inherently a multidimensional concept. It entails both subjective and objective measures. Without neglecting the importance of people's perceptions or feelings about the level of control or autonomy over their own finances, in this work we focus on objective measures. According to this approach, household financial wellbeing in the short term hinges on the amount of existing assets that a household may use to prevent a worsening in living standards when facing an adverse shock.[2] The absence of financial soundness constitutes an early warning indicator, as the lack

[1] The views expressed herein are those of the authors and should not be attributed to the Bank of Italy.
[2] In the long run, households' financial wellbeing depends on the amount of both existing and potential (such as access to credit or liquidation of real assets) resources that a household may collect to deal with negative economic events. At the current stage of this work, we do not consider potential resources and we leave such evaluations for future research.

of resilience, and it can forecast future financial distress (Brunetti et al. 2016) both at household and systemic levels. This is relevant for designing policy interventions aimed either at alleviating a situation of (temporary) individual hardships or at preventing the risk of vicious circles during an economic downturn. In bad times, households with insufficient financial buffers would significantly shrink their expenditure in the face of an income shock, thus slowing the recovery and, possibly, exacerbating the downturn. Moreover, borrowers' capacity to continue servicing their financial commitments while maintaining reasonable levels of consumption is also fundamental to avoid the risk that an increase of defaults may threaten financial stability.

In this paper, we first provide a descriptive analysis of the financial fragility of Italian households along several dimensions, over the period 2000-2020, discussing its evolution in the last decades and evaluating observable characteristics correlating to fragility. Then, we take a further step and assess the extent of the persistence of households' financial fragility conditions over time, an important element for the design of targeted policy interventions. We use data from the Bank of Italy's Survey on Income and Wealth (SHIW) that uniquely collects joint information on the core economic variables of interest (income, assets, and debts). The SHIW allows us to depict the evolution of Italian households' financial fragilities over a long timespan including the last three recessions that hit the Italian economy (the global financial crisis, the sovereign debts crisis and the Covid-19 pandemic shock).

With this aim, we define different measures of fragility related to both income and assets, also focusing on the indebted subset of the population that is more at risk of financial distress during a recession. As for asset fragility, we distinguish between total financial asset poverty and liquid asset poverty. Indeed, in the case of an idiosyncratic shock most assets can be liquidated without incurring in significant losses while a common shock often implies sharp fluctuations in share prices and bond yields so that the market value of households' financial holdings may depart substantially from their pre-shock balance-sheet values. In the latter case, only liquid assets holdings provide an accurate picture of the households' ability to face the shock (Loschiavo and Mariano, 2022). We also highlight the importance of the joint condition of income and financial poverty to single out the most fragile part of the population towards which policy interventions may be prioritized in the presence of resources constraints.

We find that fragilities related to assets significantly increased during the first two recessions that hit the Italian economy. Interestingly, despite the economic impact of Covid-19 pandemic, the shares of asset- and liquidity-poor steeply decreased between 2016 and 2020, even though they remain above the minimum recorded in the last two decades. The shares of income-poor and jointly income- and asset-poor follow smoother but similar patterns. Moreover, indebted households are

more likely to be asset- or liquidity-poor, whereas their chances of being income- or jointly income and asset-poor are lower, with respect to non-indebted households.

Finally, we evaluate the extent of persistence of income, asset, and liquidity poverty. In the econometric literature, unit heterogeneity and true (or genuine) state dependence are often referred to as different drivers of persistence (Heckman, 1991). The correlation between past and current states may be due to unobservable and observable characteristics making certain households more prone to be poor. For instance, low levels of human capital and unemployment spells of household members, as well as unobserved traits such as low skills and lack of motivation, may be characteristics persisting over time and generating a spurious relation between past and current poverty status. On the other hand, poverty experience may have a causal impact on the likelihood of being poor in the following periods, with several mechanisms being at work in this respect (e.g., demotivating effects on household members, depreciation of human capital, etc.). It is crucial to disentangle these two channels determining the persistence in fragility conditions in order to design effective policy interventions, aimed either at supporting fragile households with income support measures and affordable credit conditions, or at training household members (for instance, by improving financial literacy to foster insurance against unexpected economic shocks).

The literature on poverty persistence focuses mainly on income/earnings and material deprivation dynamics. Previous findings highlight that state dependence at the individual income poverty level is relevant in Italy (and Europe) and increased after the great recession (Mussida and Sciulli, 2022), suggesting that measures aimed at lifting individuals out of poverty (e.g. cash transfers) have become even more important. In a similar framework, Fabrizi and Mussida (2020) analyze genuine state dependence in the poverty status of Italian households with dependent children, using different income poverty measures, and they provide qualitatively similar conclusions. Giarda and Moroni (2017) study Italy's regional disparities and their role in explaining poverty state dependence.[3]

To our knowledge, analyses on the persistence of financial/liquidity poverty and the joint condition of income and financial poverty are scarce. Yet, this topic is of critical importance for economic growth and financial stability. We fill this gap in the literature applying distinct dynamic random-effects probit specifications, to disentangle genuine state dependence from observed and unobserved heterogeneity, using different income, asset and liquidity poverty measures as response variables, at the household level.

[3] Related settings are those of Cappellari and Jenkins (2004), who adopt a different approach using UK survey data to model low-income persistence and find substantial state dependence, Biewen (2009), who accounts for feedback effects from past poverty to future employment and household composition outcome, and Devicienti and Poggi (2011), who study the dynamic cross-effects between poverty and social exclusion.

We find substantial state dependence in each considered poverty status. Financial poverty not only is more spread than income poverty, in the considered period, but it also represents the most persistent state. The joint income and financial poverty dynamic pattern is instead closely related to that of the univariate income process.

The remainder of this paper is organized as follows. The next section describes the data. In Section 3, we perform a descriptive analysis of the financial fragilities of Italian households. Section 4 presents the empirical analysis on fragility persistence. Concluding remarks are provided in the last section.

2. Data

We make use of the *Survey on Household Income and Wealth* (SHIW) conducted by the Banca d'Italia since 1965, which collects information on demographics, income, real and financial assets, and loans for a representative sample of Italian households. Each wave of the survey includes approximately 8,000 households, distributed over about 350 Italian municipalities, and the panel component covers approximately half of the sample, in each wave. We restrict our analysis to the last 10 waves, covering the period 2000-2020.[4]

Traditionally, the sampling design of the SHIW is based on a two-stage procedure, with the stratification of the primary sampling units (municipalities) by region and demographic size. Within each stratum, all municipalities with more than 40,000 inhabitants are included, whereas smaller municipalities are randomly selected with probability proportional to their resident population. Up to 2016, households were randomly selected within each selected municipality. Starting from 2020, the SHIW has undergone significant methodological changes to improve the statistical coverage of high-income households. In particular, in the second stage of the sampling design, households were further stratified according to their income class retrieved from administrative records (Barcaroli et al., 2021). This improved the survey's ability to observe segments of the population that are traditionally difficult to reach and hold proportionally higher shares of the core variables, thus painting a more accurate picture of the aggregate values and their distribution across the population (Banca d'Italia, 2022). At the same time, to obtain comparable estimates with previous waves, this methodological

[4] Starting from 1987, the survey was conducted every two years, with some exceptions. In the 2000-2020 timespan of our analysis, the 2018 wave was not carried out due to non-statistical reasons.

change required a revision of the sampling weights definition, which we label *historical* weights (as opposed to the *cross-sectional* 2020 weights) and use throughout our analysis.[5]

We define a set of poverty indicators at the household level relating to different dimensions of financial wellbeing: income, financial assets and liquid assets. First, households whose income is below a socially acceptable threshold - conventionally set at 60 per cent of median equivalent annual income, which is the common at-risk-of-poverty (ARP) threshold[6] - are deemed at risk of poverty.[7] This definition, however, does not take account of other financial resources that households may rely on to meet their needs. Therefore, to measure a household's inability to handle short-term financial difficulty, households are defined as asset poor when their financial assets (bank and postal deposits, government securities, and other securities including bonds, shares in listed and unlisted companies, and other financial assets), adjusted to take account of household structure, is less than one fourth of the ARP threshold.[8] In other words, a household is asset poor if it would not have sufficient resources to avoid the risk of poverty for at least three months even if it liquidated all its financial assets. Restricting the set of assets to the ones more readily accessible (bank and postal deposits) provides the definition of liquidity-poor households.

Figure 1 plots the frequency of income/asset/liquidity poor households in the period of analysis, along with the joint income and asset poverty rate (i.e. the share of households that are jointly income and asset poor). The share of income-poor households was quite stable at around 17 per cent until the sovereign debts crisis, increasing in the following 4 years. Between 2016 and 2020, despite the outbreak of the Covid-19 pandemic, the share decreased mainly due to the income support measures introduced in the period,[9] yet remaining slightly above the minimum recorded during the timespan.

Differently, the shares of financial (both total and liquid asset) poverty decreased until 2004 and kept increasing thereafter, reaching a peak in the midst of the sovereign debts crisis in 2012; the surge was remarkable (around 9 and 7.7 percentage points, respectively). In the following years, and

[5] See Faiella and Gambacorta (2007) for a thorough description of the traditional sampling design and weighting process of the SHIW, and Gambacorta and Porreca (2022) for a comparison of the new sampling design with the old one, and for technical details on the definition of historical weights.

[6] Equivalized income is defined as the total disposable household income (after taxes and social transfers) divided by an equivalized number of components (using the modified OECD-scale).

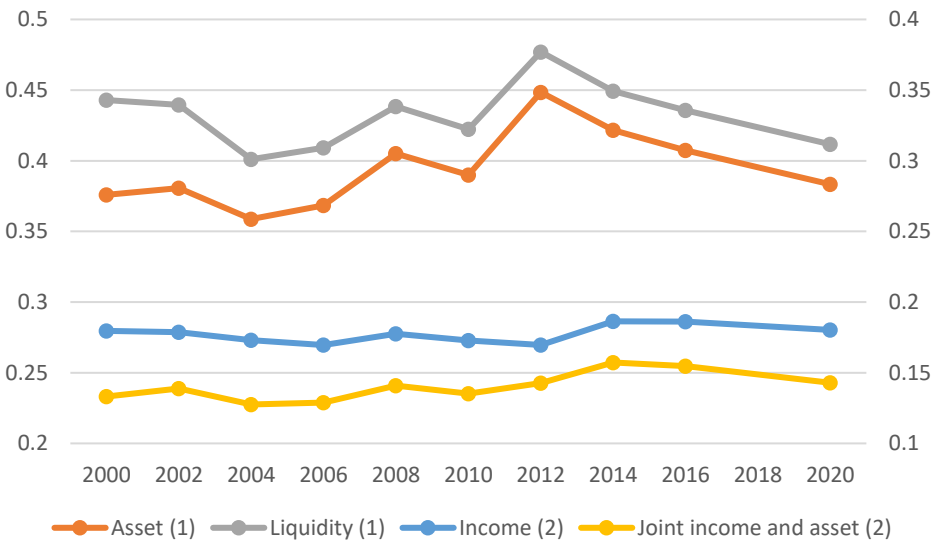
[7] Note that while the ARP rate is typically computed at the individual level (i.e. it represents the share of individuals whose equivalized income fall below the threshold), we define an income poverty indicator equal to one if a given household's equivalized income falls below the threshold.

[8] As for the threshold adopted, our approach is similar to the one of Brandolini et al. (2010) but, since we take a short-term perspective, it differs on the perimeter of the asset considered (Brandolini et al., 2010 include both financial and real assets while we include financial assets only).

[9] Such measures encompass both permanent and temporary interventions. Among the former there are the new minimum income scheme (Reddito di cittadinanza or RdC) and the new minimum pension scheme (Pensione di cittadinanza or PdC). Among the temporary measures there are those adopted in 2020 to cope with the effects of the pandemic, such as extraordinary wage supplementation (CIG straordinaria), emergency income (Reddito di emergenza) and COVID payments for certain categories of workers and other transfers specifically associated with the health emergency.

despite the recession due to the Covid pandemic, the shares steeply decreased, in connection with the surge in savings that involved also households at the lower end of the income distribution (cf. Banca d'Italia, 2022). Nonetheless, households with insufficient financial buffers to weather even a 3-month period of absence of income still constitute a large fraction of the population, higher than that recorded before the global financial crisis: in 2020, 38 per cent of Italian households were fragile with respect to an idiosyncratic shock (i.e. the asset-poor) while 41 per cent to a common shock (i.e. the liquidity-poor).

Figure 1 - Poverty rates
(Relative frequencies)



Notes: (1) Left scale. (2) Right scale. Weighted estimates.

Households in the most fragile condition are those that not only are at risk of poverty but also do not have enough assets to keep their essential consumption needs above the poverty threshold for at least three months (i.e. they are both income and asset poor).[10] In 2020, they represented 14 per cent of the population, down from the peak reached in 2014 but still 1.5 percentage points higher than before the three crises that hit Italian economy in the last two decades.

From a financial stability perspective, the intersection between the poverty conditions discussed above and indebtedness is also crucial. Indeed, risks to financial stability can arise if a significant part of the indebted households is not able to meet their financial commitments during a downturn due to the absence of adequate buffers. Losses or declines in borrowers' income, or increases in (adjustable) lending rates, can trigger such risks particularly for over-indebted (henceforth financially vulnerable) households that we define as such when their debt-service ratio is above 30 per cent and their equivalized disposable income is below the median. Hence, considering the joint condition of being

[10] A similar definition is adopted in Gambacorta et al., 2021.

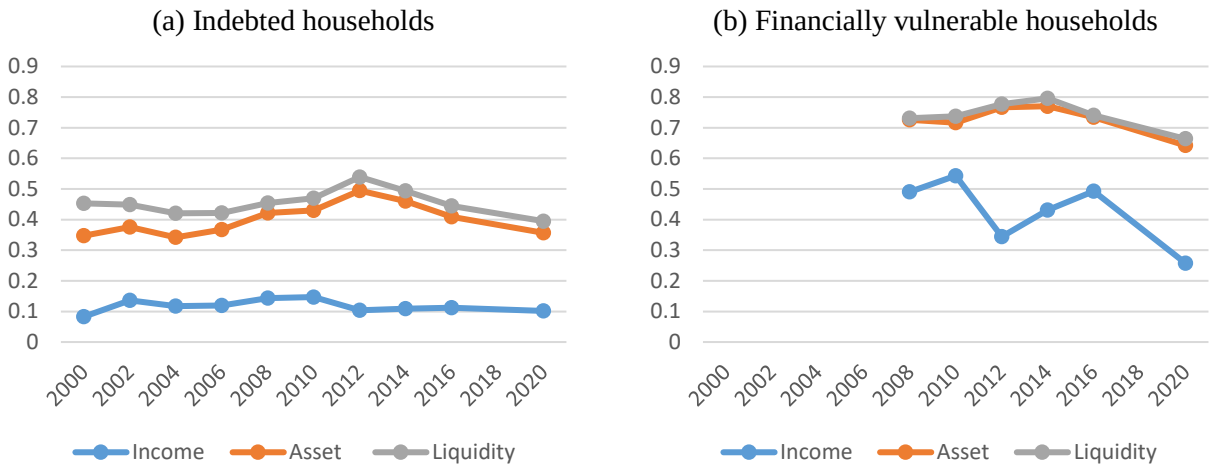
indebted or financially vulnerable is helpful for designing macroprudential tools targeted at lowering the exposure to default, because they can limit the amount that a household can borrow in relation to its accumulated savings or expected income.

Among indebted households, in 2020 the fraction of asset poor was 35.7 per cent (figure 2a), lower than in the total population. About 21 per cent of the overall household debt was attributable to them. The share of indebted households poor in liquidity was instead closer to the same share referred to all households, even though it decreased more intensively than the latter since the peak reached in 2014. The risk of illiquidity was more spread among financially vulnerable households, reaching approximately 66 per cent. Nonetheless, this value significantly declined since 2014 (by more than 13 percentage points; figure 2b).

All in all, despite the recent improvements in financial resilience, many indebted households might not weather even a short period of absence of income without falling behind on debt repayments.

Figure 2 - Poverty rates: Indebted and financially vulnerable households

(Relative frequencies)



Notes: Poverty rates among indebted and vulnerable households, namely, probability of being income/asset/liquidity poor conditional on being indebted or financially vulnerable. Data on financially vulnerable households are available from 2008.

3. Descriptive analysis

Table 1 reports the estimated average partial effects (APEs) of a probit regression of income/asset/liquidity poor indicators, along with the joint income and asset poor condition, as dependent variables, on several covariates, and it provides some descriptive evidence on which households are classified as poor along the four dimensions.

As expected, the probability of being asset or liquidity poor is higher among indebted households (Loschiavo and Graziano, 2022). This confirms how the risk of not having enough financial buffers can easily translate into difficulty in repaying debts. However, consistently with previous evidence on a larger access to credit in Italy by high-income households (Loschiavo, 2021), indebted households are less likely to be income poor or jointly income and asset poor.

Table 1 - Pooled probit models: APEs

	Income	Asset	Liquidity	Joint income and asset
Real Asset group				
Second	-0.139***	-0.105***	-0.105***	-0.126***
	(0.005)	(0.006)	(0.007)	(0.008)
Third	-0.221***	-0.111***	-0.114***	-0.188***
	(0.005)	(0.006)	(0.006)	(0.005)
Fourth	-0.257***	-0.122***	-0.116***	-0.217***
	(0.005)	(0.006)	(0.007)	(0.005)
Fifth	-0.285***	-0.153***	-0.143***	-0.243***
	(0.005)	(0.007)	(0.008)	(0.005)
Age				
31-40	-0.080***	-0.056***	-0.049***	-0.071***
	(0.008)	(0.009)	(0.009)	(0.008)
41-50	-0.074***	-0.067***	-0.052***	-0.071***
	(0.008)	(0.009)	(0.009)	(0.008)
51-60	-0.112***	-0.074***	-0.064***	-0.108***
	(0.008)	(0.009)	(0.009)	(0.008)
more than 60	-0.183***	-0.118***	-0.115***	-0.172***
	(0.008)	(0.010)	(0.010)	(0.008)
Female	0.038***	0.016***	0.011**	0.034***
	(0.003)	(0.004)	(0.004)	(0.003)
Education				
Primary	-0.040***	-0.022**	-0.023**	-0.037***
	(0.006)	(0.009)	(0.010)	(0.006)
Lower secondary	-0.088***	-0.058***	-0.053***	-0.080***
	(0.007)	(0.010)	(0.010)	(0.007)
Upper secondary	-0.139***	-0.114***	-0.097***	-0.125***
	(0.007)	(0.010)	(0.011)	(0.007)
University degree	-0.176***	-0.161***	-0.148***	-0.156***
	(0.007)	(0.011)	(0.012)	(0.007)
No. of hh members	0.080***	0.081***	0.090***	0.065***
	(0.001)	(0.002)	(0.002)	(0.001)
No. of income earners	-0.128***	0.017***	0.011***	-0.096***
	(0.002)	(0.003)	(0.003)	(0.002)
Occupation				
Independent worker	0.054***	-0.027***	-0.030***	0.027***
	(0.004)	(0.006)	(0.006)	(0.004)
Not employed	0.115***	-0.021***	-0.003	0.093***
	(0.004)	(0.006)	(0.006)	(0.004)
Geographical area				
North-East	0.010**	0.023***	0.032***	0.010***
	(0.004)	(0.006)	(0.006)	(0.003)

Centre	0.023***	0.024***	0.007	0.015***
	(0.004)	(0.005)	(0.006)	(0.003)
South	0.119***	0.109***	0.069***	0.096***
	(0.004)	(0.006)	(0.006)	(0.004)
Islands	0.110***	0.135***	0.099***	0.100***
	(0.005)	(0.007)	(0.007)	(0.004)
Indebted household	-0.020***	0.060***	0.062***	-0.017***
	(0.003)	(0.005)	(0.005)	(0.003)
Income group				
Second		-0.199***	-0.195***	
		(0.006)	(0.006)	
Third		-0.311***	-0.297***	
		(0.007)	(0.007)	
Fourth		-0.418***	-0.391***	
		(0.007)	(0.007)	
Fifth		-0.533***	-0.493***	
		(0.008)	(0.008)	

Notes: No. of observations: 77,686. Full sample. Unweighted regressions at the household level. Additional control variables: municipality size and time indicators. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the household level.

The regression analysis highlights other heterogeneity dimensions across demographic and economic groups. For example, all the considered poverty indicators decline with the education of the household head. It seems likely that higher education correlates with financial knowledge that, in turn, helps protect against financial insecurity. The chances of being in any of the four poverty conditions are higher among households whose head is woman, resident in the Islands or in the South, and increase with household size; they decrease with real assets holdings, and with the age of the household head. Interestingly, being a self-employed worker increases the likelihood of being income or jointly income and asset poor but reduces the probability of being asset or liquidity poor.

4. Analysis of fragility persistence

In this section, we briefly overview the dynamic random-effects probit model employed in the analysis of fragility persistence. The model accounts for latent heterogeneity and endogenous initial conditions to avoid overestimating the true effects of past states.

4.1 Econometric approach

Let y_{it} be a binary response variable equal to one if household *i* is (income, asset, liquidity or jointly income and asset) poor at time *t*, and zero otherwise. A dynamic unobserved-effects probit model for $y_{it}, t = 1, \dots, T$, may be written as:

$$y_{it} = \mathbf{1}\{\boldsymbol{\beta}'\boldsymbol{x}_{it} + \rho y_{i,t-1} + c_i + u_{it} > 0\}, \quad (1)$$

where $\mathbf{1}\{\cdot\}$ denotes the indicator function equal to one if the argument is true. The error terms u_{it} are assumed to be i.i.d. standard normal random variables, and $\boldsymbol{x}_{it}$ is a vector of exogenous covariates, namely, they are independent of all past, current and future values of u_{it}. c_i is the time-invariant unobserved effect and the parameter of interest is ρ.

The random-effects probit model either assumes $c_i \sim N(0, \sigma^2)$ or takes into account the dependency of c_i on the covariates as in Mundlak (1978) and Chamberlain (1984). Its standard conditional maximum likelihood (ML) estimator is not consistent unless the initial conditions y_{i0} are exogenous. To relax this assumption and to suitably account for the endogenous initial conditions problem, we adopt the methodology proposed by Wooldridge (2005) by specifying a conditional density for the unobserved effect of the form:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \boldsymbol{\alpha}_2' \boldsymbol{z}_i + a_i, \tag{2}$$

with $a_i \sim N(0, \sigma_a^2)$ and $\boldsymbol{z}_i$ is the vector including time-constant and time-averaged time-variant covariates.[11]

We restrict our sample to those households interviewed at least five times starting from 2000 to guarantee an appropriate duration of the panel, as suggested in Akay (2012) for the Wooldridge method. Because the first year of the five (or more) consecutive interviews may be staggered for different households (i.e., we have $t_i = 1, \dots, T_i$)[12], sampling weights are not included in the regressions. Nonetheless, striking differences do not emerge when we compare weighted and unweighted wave-to-wave raw transition rates among poverty and non-poverty statuses. Interestingly, the unweighted probability of remaining income poor, among households interviewed at least five times starting from 2000, is slightly higher than the corresponding weighted probability computed using the whole panel sample, approximately 1.6 percentage points (p.p.) throughout the timespan (Table 2). On the other hand, as one would expect, the unweighted probability of remaining financially poor is slightly higher than the corresponding weighted probability, albeit this difference being very low, approximately one p.p. on average throughout the timespan. Nonetheless, to take into account this issue, as in Fabrizi and Mussida (2020) we include in the regressions, as control variables, all the households' and location characteristics used in the sampling weight construction process.[13] As a robustness check, we also include the yearly cross-sectional weights among the covariates.

[11] Other possible parametrizations, less restrictive yet less parsimonious, may be found in Rabe-Hesketh and Skrondal (2013) and Skrondal and Rabe-Hesketh (2013). An alternative solution to tackle the endogeneity problem may be found in Heckman (1981).

[12] For instance, household A may be interviewed in 2000, 2002, 2004, 2006 and 2008, whereas household B may be interviewed in 2008, 2010, 2012, 2014 and 2016.

[13] These variables are: gender, level of education and age group of the household head; geographical area of residence and municipality size; household income group in the previous wave.

Table 2: Raw wave-to-wave transition rates between asset and income-poor and non-poor states (*Probabilities*)

	Remaining asset poor		Remaining income poor	
	(1)	(2)	(1)	(2)
Year				
2002	0.633	0.596	0.588	0.617
2004	0.614	0.621	0.615	0.632
2006	0.675	0.677	0.610	0.643
2008	0.692	0.666	0.639	0.640
2010	0.706	0.682	0.680	0.684
2012	0.687	0.690	0.605	0.609
2014	0.754	0.723	0.744	0.749
2016	0.682	0.685	0.684	0.698
2020	0.617	0.623	0.590	0.625
average	0.639	0.655	0.673	0.663
average difference		0.016		-0.011

Notes: (1) Weighted panel sample (weights for historical comparison). (2) Unweighted panel sample of households interviewed at least five times starting from 2000. Poverty line: 3-month ARP threshold.

We also replicate the descriptive analysis discussed in Section 3, restricting the sample to those households interviewed at least five times starting from 2000. Table A1 in the Appendix shows that significant differences in terms of APEs do not emerge between the two samples, except for those variables whose effects were already small in the full sample (e.g., female dummy in the asset and liquidity regressions), suggesting that hardly our regression results may be influenced by sample selection.

A final source of concern when estimating non-linear dynamic panel data model is the unbalancedness of the sample, which may cause inconsistent estimate of the parameters of interest. To deal with this structure of the data, we apply the correction method proposed by Albarran et al. (2019), ACC henceforth, allowing the unbalancedness process to be correlated with households' unobserved heterogeneity.

4.2 Results

Estimated effects of lagged poverty status on current poverty status are reported in Table 3, where for each response variable (i.e., poverty dimension), we compare the APEs obtained from a probit regression including the lagged dependent variable as a covariate with the APEs obtained from the dynamic model described by Equation (1), estimated using both the Wooldridge and ACC estimator.

Being poor increases the probability of being poor in the near future, regardless of the considered poverty measure. Nonetheless, the magnitude of the effect varies considerably across the

different dimensions of fragility. The probit estimators deliver APEs ranging between 17.9 p.p. of the lagged joint income and asset poverty status, and 28.3 p.p. of the asset poverty status in the previous period. Liquidity poverty dynamics is close to that of asset poverty (27.4 p.p.), given the high degree of overlap between the two groups, whereas income poverty persistence is slightly larger than joint income and asset poverty.

When accounting for unobserved heterogeneity and endogenous initial conditions (Columns 2, 3, 5, 6, 8, 9, 11 and 12 of Table 3), the APEs of all considered indicators decrease significantly. The drop is nonetheless heterogeneous across dimensions. Ignoring the unbalancedness of the data (i.e. using the Wooldridge estimator) the APEs of past asset and liquidity poverty statuses decrease approximately by 50 per cent, meaning that half of the effect is due to latent characteristics at the household level.[14] On the other hand, the APE of lagged income poverty shrinks by three fourths, to almost 5 p.p., again, similarly to that of the joint income and asset poverty condition.[15]

Regarding the ACC estimator, the estimated APE for each indicator is significantly larger than the corresponding APE estimated with the Wooldridge estimator (approximately from 4 to 6 p.p. higher). Overall, both approaches deliver qualitatively similar results according to which there is strong state dependence between past and present fragilities.

[14] To test whether these results are sensitive to the adopted poverty thresholds, we replicate the analysis on asset and liquidity poverty dependence using different poverty thresholds, namely, the equivalent of 1, 6 and 12-month ARP threshold. Results are reported in Table A2 in the Appendix and are stable across the different thresholds.

[15] Results remain unchanged if we include the yearly cross-sectional weights among the covariates; see Table A3 in the Appendix.

Table 3: Dynamic random-effects and probit models: APEs

	Income			Asset			Joint income and asset			Liquidity		
	probit	Wooldridge	ACC	probit	Wooldridge	ACC	probit	Wooldridge	ACC	probit	Wooldridge	ACC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lagged dependent variable	0.211***	0.049***	0.093***	0.283***	0.140***	0.194***	0.179***	0.043***	0.084***	0.274***	0.137***	0.197***
	(0.008)	(0.007)	(0.012)	(0.007)	(0.009)	(0.010)	(0.008)	(0.006)	(0.011)	(0.007)	(0.009)	(0.010)
Indebted household	-0.014***	-0.011**	-0.015***	0.052***	0.043***	0.045***	-0.008*	-0.005	-0.005	0.047***	0.038***	0.045***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)	(0.004)	(0.005)	(0.007)	(0.008)	(0.008)	(0.009)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: No. of observation: 22,678. Unweighted regressions at the household level. Additional control variables include the set of covariates listed in Table 1, the time-averages of the number of household members and income earners, and the income group in the previous wave. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Overall, these results highlight the importance of both household heterogeneity and genuine state dependence in explaining poverty persistence, regardless of the adopted estimator, pointing to the need of policies enhancing characteristics that are protective against poverty (e.g. higher education) as well as lifting households out of poverty (e.g. support measures and targeted affordable credit conditions).

We also replicate the analysis including an interaction term between past poverty conditions and the indicator for indebted households, to test whether past states affect heterogeneously indebted and non-indebted households. Results are reported in Table 4. All the APEs are computed with respect to the baseline category identifying households who are both non-poor (in the previous wave) and non-indebted. To get the causal effect of past poverty condition on current poverty status among indebted households the difference between the third and second row of column 1 in Table 4 must be computed, and it is equal to 0.033 + 0.010 = 0.043. This value is not statistically different from the APE of past poverty status among non-indebted households, which equals 5 p.p. (first row). Similar conclusions hold for all the other poverty indicators, and when making use of the ACC estimator. As a result, we do not find evidence on the heterogeneity of the effects of past on current states among indebted and non-indebted households.

Table 4 - Dynamic random-effects models with the interaction of lagged depedent variable and indebted indicator: APEs (Wooldridge estimator)

	Poverty	Asset	Joint income and asset	Liquidity
Lagged poor status and not indebted	0.050***	0.144***	0.044***	0.141***
	(0.007)	(0.010)	(0.007)	(0.009)
Lagged non-poor status and indebted	-0.010*	0.053***	-0.003	0.048***
	(0.006)	(0.010)	(0.005)	(0.011)
Lagged poor status and indebted	0.033***	0.179***	0.033***	0.171***
	(0.011)	(0.014)	(0.010)	(0.014)
Other controls	Yes	Yes	Yes	Yes

Notes: No. of observation: 22,678. Baseline category: Non-poor (in the previous wave) and not indebted. Unweighted regressions at the household level. Additional control variables include the set of covariates listed in Table 1, the time-averages of the number of household members and income earners, and the income group in the previous wave. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

5. Conclusions

The importance of financial security is well established in the literature on welfare analysis. Being in control of own financial situation means financial autonomy, that is, having options and the freedom to choose the way people live their life in the present, and in terms of longer term planning and life goals (Salignac et al., 2020). Furthermore, people's financial experiences influence also their families' expectations and goals for the future. They may also be linked to a broader sense of justice or injustice within the existing redistribution system (Porter and Garman, 1993) in comparisons to other people or benchmarks.

In this paper we provide a descriptive analysis of financial wellbeing of Italian households, and we study the persistence of their financial fragility conditions over the period 2000-2020, using data from the last ten waves of the SHIW.

Confirming previous findings, we find that the chances of being asset- or liquidity-poor are higher among indebted households, this representing a threat to the stability of the financial system, due to potential difficulties of poor households in repaying debts. On the other hand, indebted households are less likely to be income poor or jointly income and asset poor.

We also find significant state dependence in the considered financial fragility dimensions. In particular, financial poverty represents the most persistent state, followed by liquidity poverty, whereas the degree of persistence of joint income and financial poverty is lower and close to that of the univariate income process.

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Appendix

Table A1 - Pooled probit models: APEs

	Income	Asset	Liquidity	Joint income and asset
Real Asset group				
Second	-0.136***	-0.104***	-0.105***	-0.119***
	(0.011)	(0.012)	(0.013)	(0.010)
Third	-0.220***	-0.123***	-0.134***	-0.183***
	(0.011)	(0.013)	(0.013)	(0.010)
Fourth	-0.261***	-0.130***	-0.125***	-0.211***
	(0.011)	(0.013)	(0.014)	(0.010)
Fifth	-0.286***	-0.159***	-0.152***	-0.234***
	(0.011)	(0.015)	(0.015)	(0.010)
Age				
31-40	-0.080***	-0.057***	-0.047**	-0.072***
	(0.017)	(0.018)	(0.020)	(0.018)
41-50	-0.078***	-0.070***	-0.041**	-0.077***
	(0.017)	(0.018)	(0.019)	(0.018)
51-60	-0.107***	-0.068***	-0.055***	-0.107***
	(0.017)	(0.018)	(0.019)	(0.018)
more than 60	-0.163***	-0.099***	-0.090***	-0.158***
	(0.019)	(0.020)	(0.022)	(0.019)
Female	0.035***	0.005	-0.002	0.030***
	(0.007)	(0.008)	(0.009)	(0.006)
Education				
Primary	-0.030**	0.001	-0.005	-0.029**
	(0.012)	(0.018)	(0.020)	(0.012)
Lower secondary	-0.074***	-0.032*	-0.029	-0.075***
	(0.013)	(0.020)	(0.021)	(0.013)
Upper secondary	-0.124***	-0.084***	-0.069***	-0.115***
	(0.013)	(0.021)	(0.022)	(0.013)
University degree	-0.173***	-0.118***	-0.110***	-0.156***
	(0.014)	(0.023)	(0.025)	(0.013)
No. of hh members	0.077***	0.082***	0.091***	0.061***
	(0.003)	(0.004)	(0.004)	(0.002)
No. of income earners	-0.119***	0.014**	0.006	-0.088***
	(0.005)	(0.006)	(0.006)	(0.004)
Occupation				
Independent worker	0.061***	-0.024*	-0.026**	0.037***
	(0.009)	(0.012)	(0.013)	(0.008)
Not employed	0.088***	-0.037***	-0.017	0.067***
	(0.007)	(0.011)	(0.011)	(0.007)
Geographical area				
North-East	0.013	0.020	0.038***	0.011
	(0.009)	(0.012)	(0.013)	(0.007)
Centre	0.022**	0.026**	0.010	0.013*
	(0.009)	(0.012)	(0.013)	(0.008)
South	0.117***	0.126***	0.081***	0.096***
	(0.009)	(0.012)	(0.013)	(0.008)
Islands	0.095***	0.136***	0.091***	0.086***
	(0.009)	(0.014)	(0.014)	(0.008)

Indebted household	-0.022***	0.067***	0.066***	-0.014***
	(0.006)	(0.008)	(0.009)	(0.005)
Income group				
Second		-0.207***	-0.203***	
		(0.012)	(0.012)	
Third		-0.306***	-0.294***	
		(0.014)	(0.013)	
Fourth		-0.431***	-0.403***	
		(0.015)	(0.014)	
Fifth		-0.535***	-0.493***	
		(0.016)	(0.016)	

Notes: No of observations: 25,067. Households interviewed at least five times starting from 2000. Unweighted regressions at the household level. Additional control variables: municipality size and time indicators. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively. Standard errors are clustered at the household level.

Table A2: Sensitivity to different poverty thresholds - Dynamic random-effects and probit models: APEs

	Asset		Liquidity	
	probit	Wooldridge	probit	Wooldridge
no. of months				
12	0.300	0.137	0.248	0.131
6	0.298	0.156	0.283	0.166
3	0.283	0.140	0.274	0.137
1	0.254	0.123	0.260	0.129

Notes: No. of observation: 22,678. Unweighted regressions at the household level. Additional control variables include the set of covariates listed in Table 1, the time-averages of the number of household members and income earners, and the income group in the previous wave. All the estimates are significant at the 1 percent level.

Table A3: Dynamic random-effects probit models with the inclusion of sampling weights as covariates: APEs (Wooldridge estimator)

	Income	Asset	Joint income and asset	Liquidity
Lagged dependent variable	0.049***	0.140***	0.043***	0.138***
	(0.007)	(0.009)	(0.006)	(0.009)
Indebted household	-0.011**	0.043***	-0.005	0.038***
	(0.005)	(0.007)	(0.005)	(0.008)
Other controls	Yes	Yes	Yes	Yes

Notes: No. of observation: 22,678. Unweighted regressions at the household level. Additional control variables include the set of covariates listed in Table 1, the time-averages of the number of household members and income earners, and the income group in the previous wave. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.