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Financial Inclusion and Poverty Transitions: An Empirical Analysis for Italy

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Abstract
We estimate the causal effect of financial inclusion on transition probabilities into and out of poverty. By exploiting a longitudinal sample from the Bank of Italy's Survey on Household Income and Wealth between 2002 and 2016, we find that financial inclusion is effective in both reducing the likelihood of falling into poverty and helping the poor to improve their economic condition and climb out of poverty. According to our baseline estimates, access to a deposit account actually reduces the risk of falling below the poverty line by 3 percentage points and increases the chance of exiting poverty by 5 percentage points. The significance and magnitude of such effects are also confirmed when considering alternative proxies for financial inclusion (availability of debit/credit/pre-paid cards, use of remote banking services) and are robust to alternative empirical strategies (bivariate model with overidentifying restrictions) and to misspecification problems related to omitted factors, such as the level of household indebtedness.

Keywords: Employment, relationship banking, insurance

JEL Classification: C23, D14, I32

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1 Introduction

People living in poverty constitute a large share of the population in many developed countries. According to OECD statistics, in 2017 17.8% of the US population lived below the poverty line after considering taxes and transfers (26.8% when the poverty line is computed before taxes and transfers).[1] These shares were 15.7% (33%) in Japan, 13.9% (33.2%) in Italy, 11.9% (29.0%) in the United Kingdom and 10.4% (32.8%) in Germany.

Besides being a widespread phenomenon, even more worryingly poverty tends to be an absorbing and recurrent state at the individual level, causing permanent deprivation and social exclusion. In Europe, in the period 2008-2012 11% of the total population remained poor year-on-year, while the share of the poor exiting poverty yearly and the share of the non-poor entering poverty yearly were 34.9% and 6.6%, respectively (Vaalavuo, 2015). On average, 37% of poor were poor for just one year, while more than 20% were poor for the whole four-year period 2008-2012.[2] Out of individuals exiting poverty in a given year, 26.6% re-entered poverty after one year and 47.6% within a three-year period (Andriopoulou and Tsakloglou, 2011).[3] For the US, Bernstein et al. (2018) reports that 26.9% of individuals classified as poor in 2009 exited poverty in 2010 and 35.4% in 2011, while the poverty entry rate was 4.1%.

To the extent that being currently poor has causal adverse effects on the likelihood of being poor in future periods, poverty alleviation policies should aim to reduce the risks of individuals entering and being trapped in poverty. It is from this dynamic perspective that the role of financial inclusion as a key tool to eradicate poverty has to be carefully assessed. However, despite the strong feeling that access to formal savings and credit "may provide an important pathway out of poverty" (Mullainathan and Shafir, 2009, p. 126),[4] full understanding of the role of financial inclusion in the dynamics in and out of poverty at the individual level is still lacking. In the present study, we contribute to fill this gap by investigating empirically whether and to what extent financial inclusion influences the likelihood of households exiting and entering poverty in Italy.

Financial inclusion can be broadly defined as the opportunity to access financial services

[1]OECD statistics define the poverty line in relative terms as 50% of the median household equivalised disposable income in the country of residence (similarly, Eurostat defines the at-risk-of-poverty threshold as 60% of the median income). The US Census Bureau measures absolute poverty income thresholds as a dollar amount considered to be the minimum level of resources required to meet the basic needs of a household, given its size and composition. In 2017, the poverty threshold for a family unit of four people with two children was set at $ 24,858, approximately 40% of the median household income ($ 61,372). Using the US Census poverty thresholds, in 2017 the percentage of the US population below the poverty line was 12.3%, while the shares of people with an income below 1.25×, 1.5× and 2× the poverty line were, respectively, 16.5%, 21% and 29.7%.

[2]These figures are based on European Union Statistics on Income and Living Conditions (EU-SILC). According to this same source, in the 2008-2012 period in Italy the poverty exit, entry and persistence rates were 31%, 7% and 13%, respectively, while the transitory and long-term poverty rates were 31% and 27%. These figures place Italy among the EU countries with the lowest poverty dynamics, together with Portugal, Spain and Eastern European countries. By contrast, the UK shows a strong poverty dynamics with the above figures equal to 49%, 9%, 9%, 48% and 12% (Germany is not covered by the EU-SILC (Vaalavuo, 2015).

[3]These figures were 30.1% and 50.6% for Italy, and 24.5% and 48.3% for the UK.

[4]Statements of a similar tenor, which consider financial inclusion a key policy in the strategy to fight poverty and social exclusion in both developing and advanced countries, can be found in many official reports such as Financial Services Authority (2000), HM Treasury (2004), United Nations (2006), House of Lords (2017) or Demirguc-Kunt et al. (2018) at the World Bank.

(payments, savings, credit) from formal financial intermediaries at a cost affordable to the customer and sustainable for the provider (Carbó et al., 2005). According to the 2017 Global Findex database, 69% of adults worldwide have an account with a financial institution or use mobile money services, while almost 1.7 billion adults remain unbanked (Demirguc-Kunt et al., 2018). In high-income economies, people without a bank account, although significantly less than in low-income countries, represent a non-marginal share of the adult population especially of the poorest part of society. In the United States, 7% of adults are still unbanked, 2% in the richest 60% of households and 15% in the poorest 40%; in Italy the share of unbanked adults is 6%, with a gap of 5 percentage points between richer and poorer (9% versus 4%).

There are several reasons that help to explain why the poor lack access to financial services. Physical distance from bank branches and financial institutions, which tend to locate in richer areas, and high account opening and maintaining costs (relative to the amount of money available to save) are the main determinants of financial exclusion (Beck et al., 2009; Allen et al., 2016; Bachas et al., 2018a; Dupas et al., 2018). Inadequate financial education makes it difficult for poor people to trust banks and understand terms and conditions of formal credit and saving services (Cole et al., 2011; Dupas et al., 2016; Bachas et al., 2018b). Finally, with regard to credit availability, information asymmetries and transaction costs can be binding constraints for the poor, who usually lack credit history and pledgeable collateral or do not want to risk losing the few things they have (Banerjee and Newman, 1993; Dupas et al., 2016).

Likewise, the literature has recognized different channels through which inclusive finance benefits the poor and most vulnerable to the risk of poverty.[5] Access to bank accounts and debit instruments stimulates an increase in savings as people learn to use bank payment systems and trust banks and their safekeeping services (Bachas et al., 2018b; Dupas et al., 2018). In addition, payment facilities help individuals to be integrated in market economies and increase earning opportunities, while saving and insurance services allow consumption smoothing and can absorb unexpected shocks (the so-called "conduit effect", McKinnon, 1973). Access to formal credit services enables low-income people to invest in education and health for themselves and their children, and start up self-employment and micro-entrepreneurial activities (Besley et al., 2018), while it discourages borrowing from informal moneylenders at usury rates (Berg et al., 2013; Islam et al., 2015; Mookherjee and Motta, 2016).

However, financial inclusion also has a dark side adversely affecting poverty dynamics. For example, having relationships with financial institutions generates financial costs, which for low-income people close to the poverty line can result in a higher risk of entering poverty and a lower probability of exiting. Similarly, the design and use of debt instruments may lack sufficient flexibility and be unresponsive to the needs of indebted households in bad times, trapping the poor in poverty (Mian and Sufi, 2014). At the same time, improving credit access can lead low-income individuals to overborrow by gambling on resurrection at the risk of reducing their ability to repay and increasing the probability of default (Melzer, 2011; Bhutta et al., 2015;

[5] In addition to the individual gains for the poor from using formal financial services, the literature has documented significant positive aggregate effects of financial development for the poorest groups of the population via a boosting effect on economic growth (Levine, 2008).

Agarwal et al., 2017; Skiba and Tobacman, 2019).

There are two major empirical challenges to estimate the causal effects of financial inclusion on transition probabilities between poverty and non-poverty states. The first entails identifying the "true" dynamic effects of poverty status, taking into account the unobserved heterogeneity that can make individuals permanently more or less prone to experience poverty in any period, and the feedback effects from previous periods spent in poverty on the observed determinants of current poverty. The second challenge is to allow for the potential endogeneity of financial inclusion which may stem from reverse causality and feedback effects from poverty to financial inclusion and from common omitted variables affecting both poverty and financial inclusion.

To address the first concern, we set up a transition probability model (Jenkins, 2000) with individual random effects and account for the non-randomness of the initial poverty status (Wooldridge, 2005). With regard to the endogeneity problems, we take the lagged values of the financial inclusion variable to rule out possible contemporaneous endogeneity and feedback effects with the poverty status (Cappellari and Jenkins, 2002, 2004). In addition, among the several robustness checks, we follow an instrumental variable approach and estimate a bivariate model with a valid overidentifying restriction, which confirms the soundness of our baseline strategy.

The empirical analysis is conducted on a longitudinal sample from eight waves of the Bank of Italy's Survey on Household Income and Wealth between 2002 and 2016. Our results show that financial inclusion is effective in both reducing the likelihood of entering poverty and helping the poor to climb out of poverty. According to the baseline specification, access to financial services reduces the risk of falling below the poverty line by 3 percentage points and increases the chance of exiting poverty by 5 percentage points. These effects are confirmed irrespective of the monetary poverty measures considered (consumption- vs. income-based) and the different proxies for financial inclusion (access to a deposit account, availability of debit/credit/pre-paid cards, use of remote banking services). They are also shown to be robust to alternative empirical strategies and to misspecification problems related to omitted factors, such as the level of household indebtedness. Finally, the beneficial effects of financial inclusion on poverty dynamics seem to be heterogeneous across gender and age: the poverty-reducing role of financial inclusion is stronger among males and over 45-year-olds, whereas females and the young are confirmed as the most fragile categories especially in terms of income poverty.

The structure of the paper is as follows. Section 2 offers a review of the existing literature on poverty dynamics and the role of financial inclusion in poverty alleviation. The empirical methodology is presented in Section 3, while Section 4 describes our data sources and shows preliminary descriptive evidence on the distribution of poverty and financial inclusion indexes, and poverty transition matrices for financially included and financially excluded individuals. Econometric results are discussed in Section 5, together with several robustness checks, and Section 6 concludes.

2 Related literature

Our paper is related to two strands of research on the determinants of poverty dynamics and the effects of financial inclusion on poverty.

2.1 Poverty dynamics

The academic debate on poverty and the relevant public policies to alleviate it has focused increasingly on the determinants of the transitions in and out of the poverty status and its persistence. The higher likelihood of experiencing poverty in the future for individuals who are currently poor is a well-established finding in the empirical literature regardless of the econometric methods applied. The analysis of single and repeated poverty spells through hazard rate models (Bane and Ellwood, 1986; Stevens, 1994, 1999; Jenkins, 2000; Devicienti, 2011), the modelling of period-to-period transitions in poverty status by means of first-order Markov models (Cappellari and Jenkins, 2002, 2004) and the application of different variants of dynamic binary response models (Poggi, 2007; Biewen, 2009; Devicienti and Poggi, 2011; Giarda and Moroni, 2017) consistently confirm the nature of poverty as a highly persistent phenomenon.

Two different mechanisms can explain poverty persistence. On the one hand, poor individuals might have specific characteristics that are relevant for their own poverty status. Some of these characteristics might be observable (low human capital endowment, long-term unemployment, large household size, etc.) but there are other unobservable personal attributes that affect the likelihood of being poor, such as lack of skills and/or motivation. As long as these factors have a persistent nature, they not only affect the current poverty status but contribute to future poverty as well. On the other hand, experiencing poverty in a given period, in itself, might increase the probability of experiencing it again in the future due to many effects of personal demoralization, depreciation of human capital, negative signaling and social stigma. This self-reinforcing effect of poverty, known in the literature as "true" state dependence, can generate poverty traps from which it is difficult for individuals to escape.

The existence of a true state dependence in poverty has been widely confirmed across countries and time periods. Cappellari and Jenkins (2002, 2004), for example, show that it explains a substantial part of the dynamics of poverty in Britain during the 1990s, adding to the persistence induced by individual heterogeneity. Poggi (2007) and Biewen (2009) provide very similar evidence for, respectively, Spain and Germany. In Italy as well, income poverty and social exclusion have been found to be state-dependent, mutually reinforcing each other (Devicienti and Poggi, 2011). Structural features of the Italian economy and society, such as weak and poorly functioning labour markets and the strong long-lasting geographical dualism between the northern and the southern regions, are the main factors responsible for the persistent poverty condition of certain groups of the population (Devicienti et al., 2014; Coppola and Di Laurea, 2016; Giarda and Moroni, 2017).

Among the observable factors that have been found to be significant determinants of poverty dynamics and persistence in the literature, there are individual characteristics such as gender, age, citizenship, educational level, health conditions and employment status, as well as household characteristics, mostly in terms of size, presence of children and number of income earners. No attention has been paid so far to indicators of financial inclusion in the standard set of poverty determinants and in analyzing to what extent access to financial services might influence income and poverty transitions.

2.2 Financial inclusion and poverty

While we are aware of no prior studies that have directly explored how financial inclusion affects the likelihood of individuals entering and exiting poverty, a number of recent contributions have analyzed the nexus between access to financial services and poverty alleviation for the most vulnerable part of the population.

Even if existing evidence is not unanimous (Rewilak, 2013), the majority of cross-country studies indicate that financial development improves living standards of the poorest and reduces the share of the population under the poverty line (Honohan, 2004; Beck et al., 2007a,b). According to Perez-Moreno (2011) and Jeanneney and Kpodar (2011), this effect is mainly due to the role of financial intermediaries in facilitating payments and providing savings opportunities to the most vulnerable groups of people rather than in guaranteeing them greater access to credit. However, Imai et al. (2012) show that countries with larger microfinance loans per capita have lower poverty, in terms of incidence, depth and severity. A significant contribution to poverty reduction through easier access to credit is also found by Donou-Adonsou and Sylwester (2016), who however show that the formal banking sector contributes the most, while microfinance institutions only play a minor role in poverty reduction.

In all the above-mentioned studies, financial inclusion is proxied by financial deepening rather than the accessibility and inclusiveness of financial institutions for the local population. The latter aspect is taken into account in a few cross-country analyses that find that greater physical access to bank branches and ATMs reduces both income inequality (Mookerjee and Kalipioni, 2010) and the fraction of individuals in poverty (Rewilak, 2017). Related evidence can be drawn from studies on specific countries. For example, in the context of the Indian social banking program, Burgess and Pande (2005) and Burgess et al. (2005) document that the opening of bank branches in previously unserved rural regions caused a dramatic drop in the poverty headcount through saving mobilization and credit provision. In the case of Mexico, Bruhn and Love (2014) find that the establishment of a new nationwide bank caused a sizable effect on informal business ownership, employment and income levels in municipalities where the bank opened a branch, especially among poor individuals in municipalities with a lower bank presence. Similarly, a positive impact of branch penetration of large bank institutions in poorly bank-served regions on the use of bank accounts and bank credit among the most vulnerable groups of people has been documented by Allen et al. (2014) for the case of Kenya, Brown et al. (2016) for South-East European countries and Agarwal et al. (2019) for Rwanda. However, on the negative side, Agarwal et al. (2017) report that following the largest public program for financial inclusion launched in India in 2014, the regions most exposed to the program (i.e., those where ex-ante bank penetration and financial inclusion were lowest) experienced a significant increase in lending and the default rate on new loans relative to other Indian regions.

A number of studies have used randomized field experiments at the individual level in different developing countries to assess whether access to saving and credit facilities improves the condition of those in poverty and at risk of poverty. A first strand of this literature documents that favoring access to saving accounts by waiving fees (Dupas and Robinson, 2013; Prina, 2015; Dupas et al., 2016, 2018) or easing their actual use by tying debit instruments to the account (Bachas et al., 2018b) increases the number of previously unbanked people that use the bank account actively and boosts their savings. The bulk of field experiments, however, has focused on the poverty-reducing effects of microcredit programs (Armendàriz and Morduch, 2010). Although early studies offered a positive picture on the role of microfinance lending, especially for women, recent evidence based on randomized control trials (RCTs) has revealed that the average impact of microcredit is modest or limited only to specific groups of borrowers, and in most cases is not transformative, in terms of income levels, savings accumulation and even female empowerment (Van Rooyen et al., 2012; Banerjee et al., 2015, 2017; Meager, 2019).

The vast majority of inquiries on the poverty-reducing effects of financial inclusion has focused on low- and middle-income countries. However, exclusion from formal financial facilities is a tight constraint for the poor in advanced countries as well (Coffinet and Jadeau, 2017). In this context, Célerier and Matray (2019) find that the increase in bank branch expansion in the US counties following the interstate branching deregulation between 1994 and 2005 has significantly reduced the number of unbanked households and increased asset accumulation and financial security of low-income households. Going back in history, Stein and Yannelis (2020) show that in the aftermath of the American Civil War the creation of the Freedman's Savings Bank in order to serve formerly enslaved African Americans affected their economic performance. Households who were able to get access to a bank account made higher human capital investments, were more likely to participate in the labour market either as employees or as self-employed, and had both higher incomes and real estate wealth. Along the same lines, Brown et al. (2019) document that individuals who have grown up on financially underserved Native American reservations are more likely to remain outside the formal credit markets, and when accessing credit are more likely to default. However, as the studies on payday lending markets in the US highlight, inclusive finance easing access of low-income households to formal credit facilities is not unquestionably beneficial: those who access payday loans experience greater difficulty servicing their debt and are more likely to go bankrupt, while their economic and financial hardships do not significantly improve (Melzer, 2011; Bhutta et al., 2015; Skiba and Tobacman, 2019).

3 Methodology

In this section, we discuss the specification and identification issues of the model used to investigate the relationship between poverty transitions and financial inclusion. We then turn to the formulation of partial effects and transition probabilities, for which the detailed formal derivation is given in Appendix A, Section A.1.

3.1 Model specification and identification issues

In order to quantify the transition probabilities between poverty states, we specify a first-order Markov model for the binary poverty indicator, also known as transition probability model in the related literature (Jenkins, 2000). Let us define the poverty status for individual i at time t, with $i = 1, \dots, n$ and $t = 1, \dots, T$, as

$$\text{poor}_{it} = \mathbb{I}(\gamma\, \text{poor}_{i,t-1} + \phi\, \text{FI}_{i,t-1} + \psi\, \text{poor}_{i,t-1} \times \text{FI}_{i,t-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it} > 0), \tag{1}$$

where poor_{it} is a binary variable equal to 1 if individual i is poor at time t, meaning that his/her equivalised income is lower than the poverty threshold defined in Section 4.1, and 0 otherwise, and $\mathbb{I}(\cdot)$ is an indicator function. In a first-order Markov model, the poverty status at time t depends on the poverty status in $t-1$. As our aim is to investigate the heterogeneity in poverty transitions according to access to bank financial services, we add a binary variable for financial inclusion, $\mathrm{FI_{i,t-1}}$, equal to 1 if individual i at time $t-1$ owns a deposit account and 0 otherwise (see Section 4.2), and its interaction with $\text{poor}_{i,t-1}$. Furthermore, $\boldsymbol{x}_{it}$ is a set of (both time-constant and time-varying) individual, household and regional characteristics. Finally, α_i denotes the individual permanent unobserved heterogeneity and ε_{it} is a standard normal error term. Credible identification of poverty transition probabilities therefore relies on consistent estimates of ϕ, ψ, and γ.

As regards the effect of financial inclusion on poverty transitions, ϕ, endogeneity problems may arise because of simultaneity between the two states, as being poor at time t may have a direct effect on the degree of financial inclusion at time t if, for instance, being poor entails a lack of resources to feed a bank account and keep it open. In addition, reverse causality problems might be generated by feedback effects from the past poverty state in $t-1$ to the present probability of being financially included in t. To limit possible simultaneity and reverse causality biases, we include a lagged value of financial inclusion variable $\mathrm{FI_{i,t-1}}$, instead of its contemporaneous value at time t.

However, there might still be the issue of the permanent unobserved heterogeneity α_i collecting characteristics – for example, general ability, motivation, risk attitude or time preference – that have an impact on both the probability of being poor and the probability of accessing financial services. We investigate this possibility by setting up a bivariate model based on a valid overidentifying restriction in the equation for financial inclusion, using the growth rate of bank branches in the individual's region of residence. Details on the model specification and estimation are given in Appendix A (Section A.2). Regression results are discussed in Section 5.2.1, and are in line with those obtained with the single-equation first-order Markov model based on equation (1).

The consistent estimation of γ and ψ rests on properly disentangling *true* state dependence, that is, how the experience of being currently poor affects the probability of being poor in the future, from the individual unobserved heterogeneity α_i, which is the latent propensity to be poor at all times (Heckman, 1981a). The issue of distinguishing between state dependence and unobserved heterogeneity has been dealt with in studies employing first-order Markov models for poverty transitions (see, among others, Cappellari and Jenkins, 2002, 2004; Poggi, 2007; Biewen, 2009; Devicienti and Poggi, 2011; Thomas and Gaspart, 2015; Giarda and Moroni, 2017). Here we follow the common strategy in the literature based on a random-effects estimation approach, where α_i is assumed to be normally distributed and independent of $\boldsymbol{x}_{it}$ and $\mathrm{FI}_{i,t-1}$.

The dynamic structure of the model entails that $\mathrm{poor}_{i,t-1}$ is correlated with α_i and therefore requires the process to be initialized at poor_{i0} conditional on α_i (the so-called "initial conditions" problem). We follow Wooldridge (2005) and approximate the conditional distribution of poor_{i0} given the unobserved heterogeneity with the distribution of α_i conditional on the initial values of the dependent variable. We also condition the distribution of α_i on FI_{i0}, in order to capture some of the potential correlation between unobserved traits and financial inclusion. Therefore:

$$\alpha_i|\mathrm{poor}_{i0}, \mathrm{FI}_{i0} \sim \zeta_1 \,\mathrm{poor}_{i0} + \zeta_2 \,\mathrm{FI}_{i0} + \alpha_i^*, \tag{2}$$

where $\alpha_i^* \sim N(0, \sigma_\alpha^2)$. An alternative strategy to model initial conditions is that proposed by Heckman (1981b), which requires to specify an additional equation that approximates the conditional distributions of poor_{i0} given α_i. Although Heckman's approach has been proven to exhibit superior finite sample properties with respect to Wooldridge's solution when T is small (Akay, 2012), we rely on the latter since we encountered some complete separation problems when estimating the initial conditions for a series of robustness checks. Nevertheless, estimation results for the baseline specification based on Heckman's approach are reported as a robustness check in Section 5.2.1.

Let $\boldsymbol{\varphi}$ be the vector collecting the model parameters $\boldsymbol{\varphi} = (\gamma, \phi, \psi, \boldsymbol{\beta}', \boldsymbol{\zeta}', \sigma_\alpha^2)'$, with $\boldsymbol{\zeta} = (\zeta_1, \zeta_2)'$, and let μ_{it} be the index function for (1) and (2), that is

$$\begin{aligned}\mu_{it} \;&=\; \gamma \,\mathrm{poor}_{i,t-1} + \phi \,\mathrm{FI}_{i,t-1} + \psi \,\mathrm{poor}_{i,t-1} \times \mathrm{FI}_{i,t-1} + \\ &\quad\; \boldsymbol{x}_{it}'\boldsymbol{\beta} + \zeta_1 \,\mathrm{poor}_{i0} + \zeta_2 \,\mathrm{deposit}_{i0}.\end{aligned} \tag{3}$$

Then the likelihood function for individual i is

$$\mathscr{L}_i(\boldsymbol{\varphi}) = \int_{\Re} \Phi\left[s_{it}\left(\mu_{it} + \alpha_i^*\right)\right] \,\mathrm{d}\Phi\left(\frac{\alpha_i^*}{\sigma_\alpha}\right),$$

where $s_{it} = 2\mathrm{poor}_{it} - 1$, $\Phi(\cdot)$ is the standard normal distribution function, and the integral can be evaluated numerically by the Gauss-Hermite quadrature technique (Butler and Moffitt, 1982).

The choice of the random-effects approach is mainly driven by the need to account for unobserved heterogeneity in the estimation of transition probabilities and partial effects. Any strategy based on eliminating the individual effects by differencing or conditioning on sufficient statistics for the individual effects α_i is therefore unfit for our purpose. Alternatively, one could rely on dummy variables for the individual effects, with a suitable correction for the bias generated by the incidental parameters problem (Fernández-Val, 2009; Dhaene and Jochmans, 2015). These estimators, however, have been proved to perform well in finite samples when the time series dimension has at least the same order of magnitude of $n^{1/3}$, which unfortunately is not the case in our empirical setting.

Finally, it is worth mentioning that the literature on poverty transitions has considered models where the time-varying error term is allowed to be autocorrelated, so as to further disentangle the different sources of time persistence.(Cappellari and Jenkins, 2004). Therefore, we also estimated a model specification where ε_{it} follows an AR(1) process, as an additional source of time dependence in the unobservables, along with state dependence and time-invariant unobserved heterogeneity. However, the results obtained were unreliable due to the fact that, in our sample, the individual time series is often short (for 50% of individuals, $T \leq 3$) and the autocorrelation parameter is weakly identified.

3.2 Transition probabilities and partial effects

The specification of the first-order Markov model for the poverty status is such that it allows us to estimate transition probabilities. These are conditional probabilities of the poverty status at time t given the poverty status in $t-1$. For the purpose of our analysis, the transition probabilities of main interest are the *entry* and *exit* rates. The entry rate for individual i is the probability of being poor at time t conditional on not having been in the poverty status in the previous period $t-1$ and, based on model (1), can be computed as

$$\text{entry}_{it} = P(\text{poor}_{it} = 1|\text{poor}_{i,t-1} = 0). \tag{4}$$

Similarly, the exit rate is the probability of not being poor at time t conditional on being in poverty in $t-1$:

$$\text{exit}_{it} = P(\text{poor}_{it} = 0|\text{poor}_{i,t-1} = 1). \tag{5}$$

The main interest of our analysis is to investigate how financial inclusion affects the transition probabilities in and out of poverty. Based on (1), the partial effect of being included in $t-1$ on the probability of entering poverty is

$$\begin{aligned}\Delta\text{entry}_{it} = P(&\text{poor}_{it} = 1|\text{poor}_{i,t-1} = 0, \text{FI}_{i,t-1} = 1) - \\ &P(\text{poor}_{it} = 1|\text{poor}_{i,t-1} = 0, \text{FI}_{i,t-1} = 0),\end{aligned} \tag{6}$$

and the effect on the exit rate is

$$\begin{aligned}\Delta\text{exit}_{it} = P(&\text{poor}_{it} = 0|\text{poor}_{i,t-1} = 1, \text{FI}_{i,t-1} = 1) - \\ &P(\text{poor}_{it} = 0|\text{poor}_{i,t-1} = 1, \text{FI}_{i,t-1} = 0).\end{aligned} \tag{7}$$

The sample averages of these quantities will be reported along with the estimation results in Section 5. Detailed formulations of the transition probabilities and partial effects are given in Appendix A.1. Their estimated counterparts can be obtained by evaluating these expressions at the Maximum Likelihood estimates of the model parameters, and standard errors for the average partial effects can be computed by using the delta method.

4 Data and descriptive evidence

Our analysis is based on data from the Bank of Italy's Survey on Household Income and Wealth (SHIW) for the period 2002 to 2016. This survey is conducted every other year on a representative sample of the Italian resident population and is designed as a rotating panel with about 8,000 households per wave. The panel component of the sample consists of all households participating from at least two waves and an additional share that is randomly extracted from those interviewed only in the previous edition. Non-panel households are instead randomly extracted from the demographic register of the municipalities that represent the primary sampling units, stratified by region and population size. The panel component represents about 50 percent of the sample in the most recent waves of the survey.

The SHIW collects detailed information on household and individual demographics, labor supply, consumption, income and relationships with the banking sector. However, questions on financial inclusion were incorporated in the survey questionnaire from the 2002 wave onwards. As the interviews are performed every other year, our analysis considers eight waves from 2002 to 2016. The sample unit is the individual, as is customary in the poverty modeling literature, and we include all those individuals that participated in the survey for at least two consecutive waves in our reference period.

4.1 Measuring poverty

Individual poverty can be measured on the basis of monetary and non-monetary indicators. The former refer to disposable income or consumption expenditures compared either to a relative standard based on the overall distribution of individual income or consumption in a country or to an absolute standard of income and consumption deemed necessary to satisfy basic human needs, namely food, health, shelter and education. Non-monetary poverty indexes are used in the literature to capture the wider concept of human capability and evaluate the deprivation in essential domains of human life concerning longevity, nutrition, knowledge and living standards.

In this paper, we focus on relative monetary poverty indicators. In particular, following the OECD definition, we consider an individual poor if the equivalised disposable income of the household she/he belongs to is lower than 50% of the median equivalised net household income.[6] Along the same lines, an individual is considered poor in terms of consumption if her/his household consumption expenditure per equivalent adult is lower than 50% of the median equivalised household consumption.[7]

There is a long-lasting, unresolved debate in the literature which has highlighted advantages and disadvantages of poverty measures based on consumption versus those based on income. Consumption provides a more accurate picture of permanent material conditions of life than current income, which can be more erratic and subject to transitory shocks (Cutler and Katz,

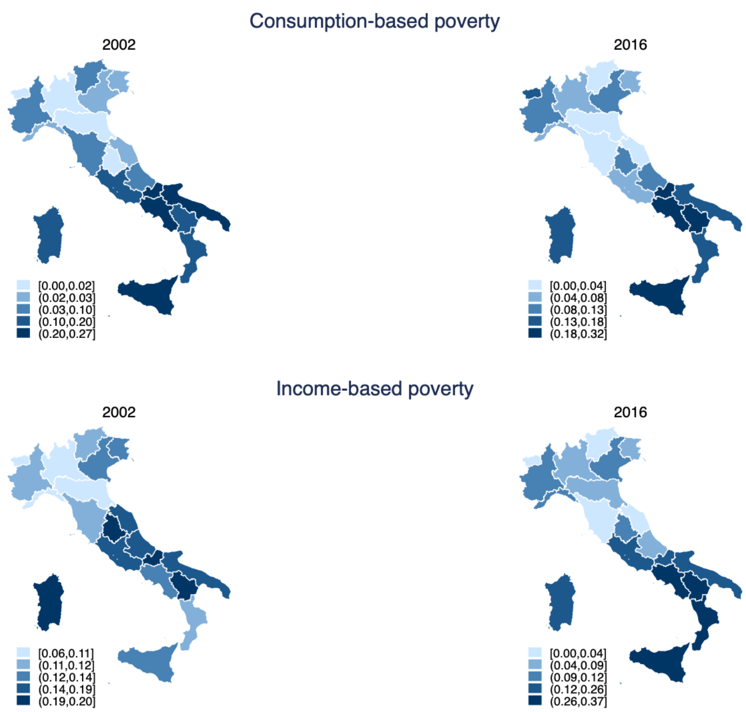
[6]Equivalised household income is given by the total nominal income after taxes from any household member divided by the number of equivalised adults. The number of equivalised adults is obtained through the "OECD–modified equivalence scale" (Hagenaars et al., 1994). This scale assigns a value of 1 to the household head, 0.5 to each additional adult member (aged 14 or over) and 0.3 to each child under 14.

[7]The same definition reported in footnote 6 holds for consumption.

1991; Sabelhaus and Groen, 2000). Indeed, consumption better captures the actual capabilitiy of a person to meet current basic needs by drawing on household savings and financial wealth, accessing credit and receiving inter-household transfers from relatives and friends (Meyer and Sullivan, 2012). Furthermore, income does not take into account flows of utility derived from home ownership and the possession of other durable goods (Garner and Short, 2005; Slesnick, 1994). However, consumption depends on household habits and behaviors, overestimating poverty of frugal households and underestimating that of indebted households. Given these conflicting arguments, throughout the paper we carry out the analysis by using both the income- and consumption-based poverty indicators.

Figure 1 depicts the spread of poverty across Italian regions in our sample period. According to both the consumption- and income-based poverty definitions, the share of poor individuals is noticeably higher in southern regions, with an average of 16% of respondents over the 2002-2016 period. Due to the long and severe recession that hit the Italian economy from 2008, the average

Figure 1: Incidence of individuals with consumption and income lower than 50% of the median equivalised consumption and disposable income, 2002-2016



Notes: authors' elaboration on SHIW data. An individual is poor if her/his household consumption expenditure/disposable income per equivalent adult is lower than 50% of the median equivalised household consumption/net income. Equivalised household consumption is total consumption expenditure divided by the number of equivalised adults whereas equivalised household income is total nominal income after taxes from any household member divided by the number of equivalised adults obtained through the "OECD–modified equivalence scale" (Hagenaars et al., 1994). This scale assigns a value of 1 to the household head, 0.5 to each additional adult member (aged 14 or over) and 0.3 to each child under 14.

percentage of individuals with income below the poverty level has increased from 9.5% in 2002 to

13.5% in 2016; the maximum incidence of poverty at the regional level has also greatly increased (from 20% in Basilicata in 2012 to 37% in Campania in 2016). When considering consumption, the incidence of poor individuals is only slightly lower, with the highest value corresponding to 32% in Campania in 2016. This is in line with existing empirical evidence, according to which consumption-based poverty rates are usually lower than income-based poverty rates (Hurd and Rohwedder, 2006) even if material hardship tends to be more severe for those who are below the consumption poverty line than for those with low income below the poverty line (Meyer and Sullivan, 2012).

Moving on to examine poverty transitions, the unconditional persistence rates are rather high both in terms of consumption and income (Table 1): 66.6% of poor individuals in $t-1$ are still classified as poor in t based on their consumption level; this share is only somewhat lower (61.1%) with the income-based poverty indicator. On the other hand, entry rates are slightly lower with the consumption-based indicator: 5.1% of individuals who are not consumption-poor in $t-1$ become consumption-poor in t, against 8.7% for income poor individuals.

Table 1: Transition matrices: poverty

Panel A. Consumption-based poverty		
	not poor$_t$	poor$_t$
not poor$_{t-1}$	94.9	5.1 (*entry rate*)
poor$_{t-1}$	33.4 (*exit rate*)	66.6 (*persistence rate*)
Panel B. Income-based poverty		
	not poor$_t$	poor$_t$
not poor$_{t-1}$	91.3	8.7 (*entry rate*)
poor$_{t-1}$	38.9 (*exit rate*)	61.1 (*persistence rate*)

We consider also alternative poverty thresholds more and less conservative than 50% of the median consumption/income in order to test the robustness of our results for the dynamics of entering and exiting extreme poverty or risk of poverty. On the one hand, we define as extremely poor those individuals with an equivalised consumption/income lower than either 30% or 40% of the median equivalised household consumption/income. On the other, we consider an individual at risk of poverty if the equivalised consumption/income of the household she/he belongs to is lower than 60% of the median value in the sample. The regional distributions for extreme poverty and at-risk-of-poverty rates as well as their transition matrices are reported in Appendix B, Figures B1/B3 and Tables B1/B3.

4.2 Financial inclusion

The notion of financial inclusion designates the actual capability of individuals to access payment, savings and credit services from formal financial intermediaries, not prevented by prohibitively high pecuniary and non-pecuniary costs. Measuring whether people have this potential opportunity is obviously very difficult. At the aggregate level, the literature has typically used some structural features of the banking industry, such as the number of bank branches and/or ATMs per thousand inhabitants or square kilometers, the incidence of accounts/loans over total population, the average cost of opening and maintaining an account at a financial institution or the documentation required when applying for a loan to proxy for financial outreach and inclusion across countries (Beck et al., 2007b, 2009). At the household or individual level, apart from controlled field experiments in which a random sample of treated individuals is given the real opportunity to open a bank account or access financial services by relieving the related pecuniary and non-pecuniary costs (Dupas et al., 2018; Bachas et al., 2018b), financial inclusion has been measured by indicators for the ownership of a bank account or the frequency and intensity of account use (Allen et al., 2016).

In this paper, we measure financial inclusion by account ownership at the household level. In particular, we exploit the survey question asking "Did you or a member of the household have any of the following on 31 December last year: (i) a bank current account; (ii) a bank saving account; (iii) a post office current account; (iv) a post office saving account". Therefore, the indicator variable FI is equal to 1 for individuals who have access to one or more bank or postal accounts in the household.[8]

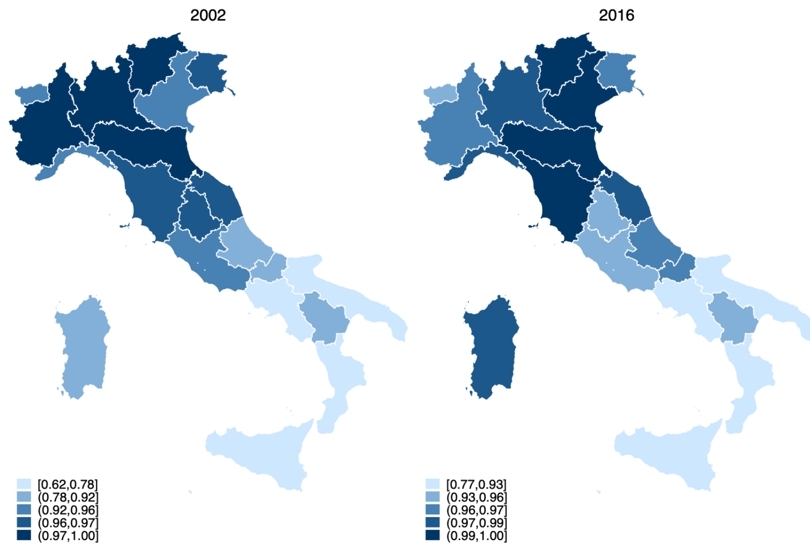
This indicator has obvious shortcomings. First, account ownership does not distinguish financially excluded individuals from those who voluntarily choose not to have relationships with financial institutions for any cultural reason or because they do not need financial services. Second, ownership of a bank/postal account does not reveal anything about the actual use of financial services and their quality. Third, bank/postal accounts provide payment and savings services, while credit services are limited to possible overdrafts if provided for in the contract. However, having a bank account is not only a requirement to access credit, but often it creates the conditions for recognizing and formulating one's financial needs. In addition, to the extent that the poor represent the riskier tail of individuals, measures of access to credit would suffer from serious concerns in terms of feedback effects and reverse causality in the poverty-financial inclusion nexus (Allen et al., 2016).

The incidence of individuals with a bank account across Italian regions in 2002 and 2016 is depicted in Figure 2. Financial inclusion is far from universal among Italian households. Heterogeneity across regions and over time is closely correlated with the local level of economic development. However, a general increasing trend in financial inclusion can be easily detected looking at the first quintile of its regional–level distribution: in four regions (Calabria, Campania, Puglia and Sicily) the share of households without a bank or postal account was between 22 and 38 percent in 2002; in the same four regions (still representing the first quintile of the regional

[8] According to the information provided by "Poste Italiane", there were 6.4 million postal accounts in 2015, corresponding approximately to a 14% market share.

distribution of financial inclusion) this range shrank to 7%-23% in 2016. Evidence gathered from the SHIW data is consistent with the information collected by the World Bank's Global Findex Database, according to which Italy lags behind other European countries such as France, Germany and the United Kingdom, even if the latest wave collected in 2017 shows that the gap has narrowed and is now equal to that of the other Southern European countries.

Figure 2: Incidence of account ownership, 2002-2016



Notes: authors' elaboration on SHIW data. Account ownership refers to the availability of at least one of the following accounts at the household level: bank current accounts, bank saving accounts, post office current accounts and post office saving accounts.

When we replicate poverty transition matrices by conditioning on financial inclusion, interesting differences emerge between the two groups.[9] For individuals who have access to deposit accounts, the persistence rate into income poverty is 11 percentage points lower than that of financially excluded individuals (Table 2, panel B), while the entry rate is less than half (7.54 vs 16.78). The gap widens when looking at the consumption-based indicator (Table 2, panel A): the likelihood of remaining poor is 30 percentage points higher for individuals who are unbanked while the entry rate is almost four times greater compared to banked individuals.

This descriptive evidence suggests a positive role of financial inclusion in reducing poverty persistence, and this seems to work both in helping poor people to exit out of poverty and in decreasing the likelihood to fall into poverty for the non-poor.

To test the robustness of our results, we also employ two alternative – although more restrictive – proxies for financial inclusion available in the SHIW questionnaire. First, we use the availability of at least one debit, credit or prepaid card among household members.[10] Second, we

[9]Here we consider as financially included individuals with deposit ownership both at time t and at time $t-1$, while individuals who are unbanked in both periods are considered financially excluded. Results are very similar when considering households at risk of poverty. See instead Appendix B.

[10]We consider the following three questions in the survey: "Did you or a member of the household have at least one credit card in the last calendar year?"; "Did you or a member of the household have at least one debit card in the last calendar year?"; "Did you or a member of the household own at least one prepaid card from a bank or post office in the last calendar year?".

Table 2: Transition matrices: poverty conditional on financial inclusion

Panel A. Consumption-based poverty

	Deposit account		No deposit account	
	not poor$_t$	poor$_t$	not poor$_t$	poor$_t$
not poor$_{t-1}$	93.83	6.17 (*entry rate*)	77.36	22.64 (*entry rate*)
poor$_{t-1}$	54.05 (*entry rate*)	45.95 (*persistence rate*)	24.73 (*entry rate*)	75.27 (*persistence rate*)

Panel B. Income-based poverty

	Deposit account		No deposit account	
	not poor$_t$	poor$_t$	not poor$_t$	poor$_t$
not poor$_{t-1}$	92.46	7.54 (*entry rate*)	83.22	16.78 (*entry rate*)
poor$_{t-1}$	45.72 (*entry rate*)	54.28 (*persistence rate*)	34.13 (*entry rate*)	65.87 (*persistence rate*)

consider financially included the individuals that make use of remote access to banking services (mobile banking technology, such as apps and text banking, home banking etc.) at the household level.[11] In both cases, the idea is to consider financially included only the individuals who use deposit accounts and financial services actively. In our sample, on average, almost three out of four households (73.82%) have at least one type of card, a share which has increased over time, from 70.00% in 2002 to 79.76% in 2016. Even among the poor, cards (mainly debit cards) were available for slightly less than two thirds of individuals over the whole period. The incidence of the use of remote access banking services has risen as well, from 5.58% (4.62% among the poor) in 2002 to 29.10% (21.60%) in 2016. This trend resembles that shown by aggregate data, with slightly more than nine million users of internet banking services in 2002 that rose to 42 million in 2016.

4.3 Control variables

Our set of control variables includes individual-level, household-level and regional-level characteristics (description, source and summary statistics are reported in Table B4). At the individual level, we consider gender, age and its square, and marital status that is coded into four different dummies: married (reference group), single, divorce/separated and widowed. The level of educational attainment is divided into five categories: no education (reference group), primary, lower secondary, upper secondary and higher education. Finally, occupational status is divided into

[11] The specific survey questionnaire is "Did you or a member of the household do business with banks or financial intermediaries by telephone or computer in the last calendar year (home banking, online account, ..)?".

nine different classes: blue collar (reference group), white collar, manager/CEO, self–employed, atypical/temporary workers, unemployed, first job seeker/student, retired, other inactive.

In terms of household characteristics, we include the household size, the number of children according to different age brackets (0-5, 6-11, 12-17 years) and a dummy for home ownership. We also include a set of dummies controlling for the size of the municipality where individuals are residing: less than 20,000 inhabitants (reference group), 20,000-40,000 inhabitants, 40,000-500,000 inhabitants and more than 500,000 inhabitants.

Finally, GDP growth rate and employment growth rate are the two regional-level controls included in our estimated specification, all provided by the Italian National Statistics Institute (ISTAT) , along with NUTS2 dummies, corresponding to Italian regions. Time dummies are also included in the specification.

5 Estimation results

5.1 Main evidence

Table 3 reports the results obtained by estimating the dynamic random-effects probit model for our baseline specification, with and without the interaction term between the proxy for financial inclusion and the lag of the poverty status. Columns [1] and [2] refer to the consumption-based poverty indicator, whereas columns [3] and [4] refer to the income-based one. For the sake of brevity, we report only the estimated parameters for the key variables of interest, the average partial effects of financial inclusion on poverty entry and the statistics for permanent unobserved heterogeneity. Results for the full specification of (1) and (2) are available in Table B5 in Appendix B.

First, let us note that the results in Table 3 show that the state dependence parameter associated with the lagged poverty measures is statistically significant in both specifications for each poverty indicator, thus confirming the appropriateness of a first-order Markov formulation for modeling poverty transitions. The estimated log of the variance of permanent unobserved heterogeneity ($\ln \sigma_\alpha^2$) denotes a non-negligible role of the unobserved heterogeneity in predicting the probability of deposit ownership and poverty, however measured.

Moving on to financial inclusion, owning deposits at time $t-1$ (i.e., $FI_{t-1} = 1$) significantly reduces the probability of being poor at time t both in terms of consumption and income, even if the decreasing effect is larger for the consumption-based measure of poverty. This indicates a key role for financial inclusion in helping people to escape poverty by enabling them to smooth consumption in the face of negative income shocks, improving savings behavior in good times and easing access to credit in bad times.

In order to assess the effect of being banked on the transition probabilities in and out of poverty, we consider the estimation results reported in columns [2] and [4], so as to allow for the state dependence parameter to switch according to the deposit account ownership in $t-1$. Poverty state dependence remains positive and strongly significant in both models. The effect of financial inclusion on poverty seems to be almost entirely captured by the lagged value of deposit account ownership, whereas the interaction terms with poverty status are not statistically

Table 3: Estimation results: Dynamic random-effects probit model (baseline specification)

	Consumption-based measure		**Income-based measure**	
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.517***	0.527***	0.728***	0.708***
	[0.038]	[0.053]	[0.029]	[0.055]
FI_{t-1}	-0.303***	-0.297***	-0.110***	-0.118***
	[0.035]	[0.041]	[0.036]	[0.040]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		-0.015		0.024
		[0.055]		[0.054]
$\ln \sigma^2_\alpha$	-1.669***	-1.667***	-0.978***	-0.980***
	[0.142]	[0.142]	[0.076]	[0.076]
Log-likelihood	-10868.89	-10868.85	-19019.38	-19019.28
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495
Δentry		-0.029***		-0.018***
		[0.005]		[0.006]
Δexit		0.050***		0.023***
		[0.008]		[0.013]

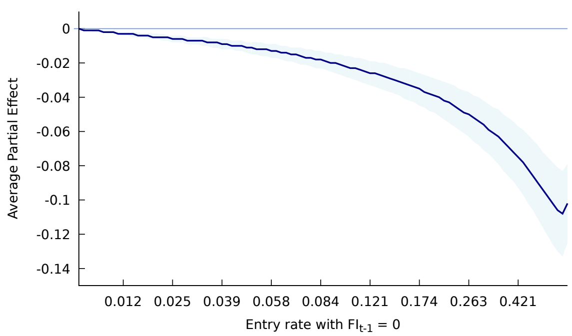
Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. Both specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B5. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated entry and exit rates in columns [2] and [4] are computed as per expression (6) and (7).

significant. However, as is well known, single coefficients may not be informative about the sign and magnitude of the average partial effects of deposit account ownership on the probability of being poor as well as on the entry and exit rates (Ai and Norton, 2003). Therefore, we compute the average partial effects of financial inclusion on poverty entry and exit rates, as derived in expressions (6) and (7).

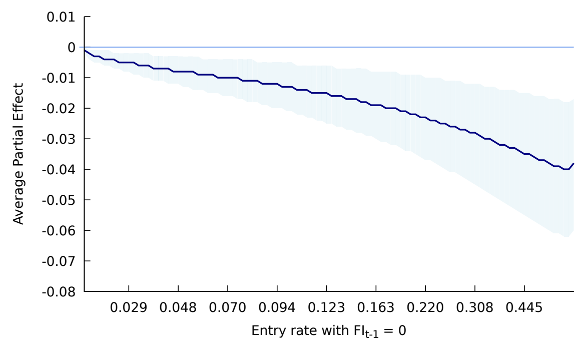
With respect to the consumption-based poverty measure, the average partial effects are statistically significant on both the entry and exit rates: as shown at the bottom of Table 3, on average, deposit account ownership reduces the probability of entering poverty by about 3 percentage points, whereas it increases the probability of exiting poverty by 5 percentage points. As for the income-based poverty measure, having access to a deposit account in $t-1$ significantly reduces, on average, the probability of entering poverty at time t by 1.8 percentage points and increases the probability of exiting poverty by 2.3 percentage points. Considering the average entry and exit rates reported in Table 1, the economic impact of financial inclusion on poverty dynamics seems to be sizable, especially on the probability of entering poverty.

The average effect of financial inclusion on poverty dynamics for the whole sample may be reasonably expected to hide very differentiated effects according to whether the probability of individuals entering and exiting poverty is however high or low. To explore this possibility, we compute the average partial effects of FI on Δentry and Δexit by centiles of the probability of entering/exiting poverty, conditional on not owning deposit accounts in $t-1$. These are depicted in Figure 3. For both consumption- and income-based poverty measures, the effect on the entry rate is always negative, statistically significant, and increasing in the probability of entering poverty for those who do not own any deposit account. As expected, being financially included has nearly no effect for individuals that have virtually no risk of becoming poor. However, for those whose chance of entering consumption or income poverty is 40%, financial inclusion reduces the entry rate by, respectively, 10 or 3 percentage points. Similarly, the average effect of financial inclusion on the exit rates is always positive and overall decreasing in the unconditional exit rates. When looking at the consumption-based (resp., income-based) measure, having a deposit account may increase the likelihood of exiting poverty by up to 12 (resp., 3) percentage points for those whose exit rate is about 35%.

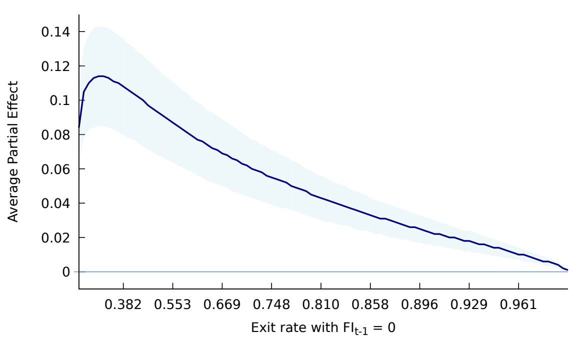
Figure 3: Average partial effects of FI_{t-1} on entry/exit rate by percentiles of the entry/exit rate conditional on $\mathrm{FI}_{t-1} = 0$



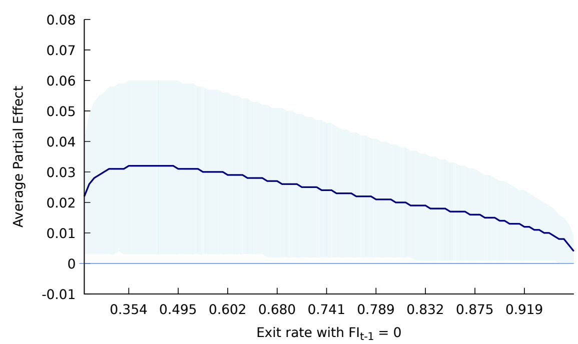
(a) Δentry_{it}, Consumption



(b) Δentry_{it}, Income



(c) Δexit_{it}, Consumption



(d) Δexit_{it}, Income

Notes: The light blue area represents the confidence interval at the 95% level.

5.2 Robustness checks

5.2.1 Alternative estimation methods

In this section we provide the results of two exercises aimed at assessing the appropriateness of the estimation method used in our baseline model to address some identification issues.

First, we investigate an alternative method for dealing with the problem of the initial conditions entailed by the recursive nature of the first–order Markov model. The unobserved heterogeneity α_i in (1) is correlated with $\text{poor}_{i,t-1}$, and this requires the initialization for the conditional distribution of $\text{poor}_{i0}|\alpha_i$. As discussed in Section 3, we rely on Wooldridge's (2005) approach and specify the conditional distribution of α_i given poor_{i0} as in (2). Alternatively, one could follow Heckman (1981b) and specify an additional equation that approximates the conditional distribution of poor_{i0} given α_i.

The estimation results obtained by using Heckman's (1981b) approach are reported in Table 4. The different initialization for the dependent variable leads to estimated state dependence parameters that are sizably larger than those reported in Table 3, whereas the effect of the lagged financial inclusion is the same order of magnitude. Also, the patterns of the effects of financial inclusion on poverty entry and exit rates are broadly similar to those obtained with the baseline specification.

Table 4: Estimation results: dynamic random-effects probit model with Heckman's initial conditions, baseline specification, consumption- and income-based poverty measures

	Consumption-based measure		**Income-based measure**	
	[1]	[2]	[3]	[4]
Poor_{t-1}	1.094***	1.082***	0.961***	1.062***
	[0.032]	[0.061]	[0.033]	[0.061]
FI_{t-1}	-0.302***	-0.323***	-0.176***	-0.217***
	[0.037]	[0.047]	[0.035]	[0.039]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		0.057		0.039**
		[0.064]		[0.061]
σ_α	0.111***	0.111***	0.486***	0.481***
	[0.021]	[0.020]	[0.034]	[0.034]
Log-likelihood	-11195.33	-11006.13	-17307.42	-16768.31
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495
Δentry		-0.023***		-0.041***
		[0.008]		[0.010]
Δexit		0.019***		0.017
		[0.007]		[0.011]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method.. Both specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B6. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated entry end exit rates in Columns [2] and [4] are computed as per expression (6) and (7).

The second exercise concerns the endogeneity issue potentially arising because of time-invariant unobserved factors that may influence both the poverty status and financial inclusion in all periods. In our baseline specification, we try to approximate the correlation between α_i and financial inclusion by including FI_{i0} in equation (2). In order to investigate whether this identification issue is properly dealt with, we set up a bivariate model that requires the set of covariates in the financial inclusion equation to include an overidentifying restriction. This helps improve the model's identification which would otherwise rely exclusively on the distributional assumptions concerning the error terms. Details on the bivariate model specification and estimation are given in Appendix A, Section A.2.

The variable we choose as the overidentifying restriction is the growth rate of the number of bank branches per 10,000 inhabitants at the regional level as provided by the Bank of Italy's Statistical Database, which captures the local supply of financial services. The density of bank branches has often been used as an aggregate proxy for financial inclusion when no information on deposit account ownership was available at the individual level. In addition, evidence has been provided on how the expansion of bank branches improves financial inclusion at the individual level, both in developed and developing countries, especially for low–income households (Allen et al., 2014; Brown et al., 2016, 2019; Célerier and Matray, 2019). Therefore, we exploit the strong, positive correlation between household-level account ownership and the local supply of banking services. At the same time, we can be confident that the latter is independent of the individual poverty status conditional on the macroeconomic phenomena, such as GDP and employment growth rates, that may be driving variations in the aggregate demand side of financial services. Moreover, regional-level structural characteristics affecting both individual poverty and bank branch growth rates are captured by the NUTS2 fixed-effects included in our estimated specification. The identification strategy thus relies on the intraregional variation in the stock of bank branches over time.

Estimation results for the dynamic bivariate random-effects probit model are reported in Table 5. The relevance of the overidentifying restriction is confirmed by the values of the first–stage F tests for all the specifications considered. The estimated coefficients for the poverty equations closely mirror those in Table 3. Moreover, the estimated correlation coefficient between the unobserved effects entering the poverty and financial inclusion equations, κ, is never statistically significant, suggesting that the presence of common permanent traits affecting both poverty and financial inclusion is not relevant in this context. On the contrary, the estimated correlation coefficient between time-varying error terms, ρ, is statistically significant in all the specifications considered, suggesting some residual correlation in the unobservables unaddressed by the baseline specification. Yet the average effects on entry and exit rates are very similar to those obtained by estimating the single–equation model.

5.2.2 Misspecification: the role of household indebtedness

Poverty status can be significantly affected by the level of household indebtedness, especially for those individuals that are very close to the poverty line. For the highly indebted, even a transient negative income shock could then accelerate entry into poverty, or translate into persistent poverty. In turn, household indebtedness could also be correlated with proxies for financial inclusion. Getting a house mortgage indeed requires the availability of a deposit account where the bank can first credit the requested amount and, then, charge the arranged installments. At the same time, households that have no relationship with the banking system could rely on alternative forms of debt, such as consumer credit and informal loans received from their relatives, which are likely to impact poverty status as well.

For these reasons, we estimate an alternative version of our baseline specification where we control for the different proxies of household indebtedness available in the survey: house mortgage, consumer credit and informal debts towards relatives and friends. These are all defined as dummy variables that take value 1 when the household currently has that type of

Table 5: Estimation results: dynamic bivariate random-effects probit model, baseline specification, consumption- and income-based poverty measures

	Consumption-based measure		**Income-based measure**	
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.828***	0.731***	0.822***	0.740***
	[0.058]	[0.084]	[0.030]	[0.054]
FI_{t-1}	-0.272***	-0.326***	-0.119***	-0.152***
	[0.047]	[0.058]	[0.033]	[0.038]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		0.121		0.097*
		[0.075]		[0.052]
σ_α	0.391***	0.389***	0.529***	0.526***
	[0.007]	[0.007]	[0.006]	[0.006]
σ_η	0.609***	0.609***	0.627***	0.627***
	[0.021]	[0.021]	[0.022]	[0.022]
κ	-0.12	-0.112	-0.086	-0.085
	[0.110]	[0.111]	[0.063]	[0.063]
ρ	-0.269***	-0.271***	-0.054**	-0.054**
	[0.029]	[0.029]	[0.024]	[0.024]
First-stage F test	20.531	20.531	21.516	21.516
Log-likelihood	-22513.92	-22511.22	-29134.75	-29133.07
# observations	60098	60098	60098	60098
# subjects	22562	22562	22562	22562
Δentry		-0.045***		-0.024***
		[0.009]		[0.006]
Δexit		0.037***		0.011
		[0.011]		[0.010]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. Both specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B7. The first-stage F test is based on a linear probability model for the deposit equation. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated entry end exit rates in Columns [2] and [4] are computed as per expression (6) and (7).

debt.

Results are reported in Table 6. The proxy for financial inclusion is still highly significant across all specifications, with a negative effect on the likelihood of being poor. Among the different forms of debt, whereas house mortgages and consumer credit hardly exert any impact on the poverty status, the latter is positively correlated with the presence of informal loans from relatives and friends. The average effects of financial inclusion on poverty entry and exit rates, reported in the lower part of the Table, are consistent with our baseline specifications. Even if we control for household indebtedness, financial inclusion significantly reduces the likelihood of falling into poverty and increases the chances of escaping poverty, with effects that are in some cases larger in magnitude than those reported in Table 3. When considering house mortgages, for example, the effect of financial inclusion on the probability of exiting consumption-based poverty is three percentage points greater compared to the baseline specification (8% vs. 5%).

5.3 Alternative poverty and financial inclusion measures

In order to further test the validity of our results, we perform the baseline estimates by employing either different thresholds for poverty or different proxies for financial inclusion.

Table 6: Estimation results: dynamic random-effects probit model, specification with proxies for household indebtedness, consumption- and income-based poverty measures

	Consumption	Income	Consumption	Income	Consumption	Income
	[1]	[2]	[3]	[4]	[5]	[6]
Poor_{t-1}	0.811***	1.101***	0.540***	0.809***	0.535***	0.844***
	[0.091]	[0.086]	[0.075]	[0.062]	[0.075]	[0.069]
FI_{t-1}	-0.290***	-0.127*	-0.334***	-0.181***	-0.335***	-0.241***
	[0.073]	[0.065]	[0.059]	[0.050]	[0.059]	[0.050]
House mortgage_{t-1}	0.012	-0.055				
	[0.046]	[0.034]				
Consumption debt_{t-1}			-0.068*	0.035		
			[0.040]	[0.028]		
Debt toward $\text{relative/friends}_{t-1}$					0.171***	0.144***
					[0.057]	[0.048]
$\text{Poor}_{t-1} \times FI_{t-1}$	-0.111	-0.065	0.092	0.177***	0.095	0.113*
	[0.090]	[0.084]	[0.071]	[0.063]	[0.071]	[0.063]
$\ln \sigma_{\alpha}^{2}$	-3.301***	-3.960***	-2.141***	-9.000	-2.187***	-3.796***
	[0.990]	[1.493]	[0.311]	[11.860]	[0.323]	[1.228]
Log-likelihood	-4960.798	-8772.595	-6464.273	-11371.740	-6461.308	-11201.020
# observations	29131	29131	35037	35037	35037	35037
# subjects	13387	13387	16350	16350	16350	16350
Δentry	-0.029***	-0.020*	-0.035***	-0.033***	-0.035***	-0.043***
	[0.008]	[0.011]	[0.007]	[0.010]	[0.007]	[0.010]
Δexit	0.081***	0.062**	0.043***	0.001	0.043***	0.041**
	[0.018]	[0.026]	[0.013]	[0.020]	[0.013]	[0.020]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B8. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated entry end exit rates are computed as per expression (6) and (7).

5.3.1 Poverty thresholds

As far as poverty indicators are concerned, we alternatively consider the effect of financial inclusion on extreme-poverty and risk-of-poverty dynamics. We consider extremely poor those individuals whose equivalised household consumption/income is below 40% or 30% of the median equivalised household consumption/income, and at risk of poverty those whose equivalised household consumption/income is lower than 60% of the median threshold (these are the thresholds used by Eurostat to compute the dispersion around the poverty line).

Results are reported in Table 7. The effects of financial inclusion on poverty entry and exit rates in terms of consumption are similar to the baseline specification, even if they are greater for the at-risk-of poverty threshold than for extreme-poverty thresholds. When we consider income-based poverty, financial inclusion reduces the entry rates into extreme poverty and at risk of poverty status, while the impact of FI_{t-1} on exit rates is not statistically significant when considering either lower or higher poverty thresholds.

5.3.2 Financial inclusion proxies

We also consider alternative proxies for financial inclusion available in the SHIW dataset. First, we use a dummy variable that takes the value 1 if at least one debit, credit or prepaid card is available to the household in period $t-1$, and 0 otherwise. Following Bachas et al. (2018a,b),

Table 7: Estimation results: dynamic random-effects probit model, specification with alternative poverty thresholds, consumption- and income-based poverty

	Extreme poverty (30% median)		**Extreme poverty (40% median)**		**Risk of poverty (60% median)**	
	Consumption	**Income**	**Consumption**	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]	[5]	[6]
Poor_{t-1}	0.736***	0.554***	0.775***	0.669***	0.528***	0.669***
	[0.077]	[0.068]	[0.062]	[0.059]	[0.049]	[0.051]
FI_{t-1}	-0.148***	-0.199***	-0.245***	-0.131***	-0.225***	-0.110***
	[0.057]	[0.046]	[0.047]	[0.042]	[0.041]	[0.038]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$	-0.141*	0.224***	0.056	0.090	-0.002	0.086*
	[0.074]	[0.066]	[0.059]	[0.059]	[0.049]	[0.050]
$\ln \sigma_\alpha^2$	-1.529***	-1.213***	-1.766***	-1.284***	-1.575***	-1.121***
	[0.171]	[0.107]	[0.163]	[0.096]	[0.106]	[0.075]
Log-likelihood	-6572.63	-12006.93	-9833.15	-15553.62	-16184.75	-22158.69
# observations	60098	60098	60098	60098	60098	60098
# subjects	22495	22495	22495	22495	22495	22495
Δentry	-0.008***	-0.019***	-0.022***	-0.017***	-0.033***	-0.020***
	[0.003]	[0.005]	[0.005]	[0.006]	[0.006]	[0.007]
Δexit	0.030***	-0.004	0.033***	0.009	0.047***	0.007
	[0.008]	[0.011]	[0.010]	[0.013]	[0.009]	[0.013]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B9. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated variations in entry and exit rates are computed as per expression (6) and (7).

the idea is that having access to a bank card for managing the deposit account, withdrawing and depositing money, and making payments improves saving behavior and the ability to use credit and savings services.

The second alternative proxy for financial inclusion refers to remote access to banking services such as mobile banking or home banking technologies and is equal to 1 if someone in the household makes use of such services, and 0 otherwise. Once again, the idea is that using remote banking services captures the ability of individuals to exploit the credit and savings opportunities that financial inclusion opens up.

Whatever the proxy used for financial inclusion, the related coefficient is always negative and significant. When considering the availability of bank cards, the effect on poverty exit rates is slightly greater compared to the baseline specification where financial inclusion is measured by the simple ownership of a deposit account (6.7% for consumption-based poverty, and 3.7% for income-based poverty, respectively). When we consider remote banking services, there is no such clear pattern with respect to the baseline specification. Effects on poverty entry rates are broadly similar, whereas the impact on exit rates is smaller with the consumption-based poverty indicator, but greater with the income-based one.

5.4 Heterogeneity

Finally, we explore whether the effects of financial inclusion on poverty vary by gender and age. Females and young adults tend to be less financially included than males and older adults (Demirguc-Kunt et al., 2018). However, they are also more credit-constrained if financially

Table 8: Estimation results: dynamic random-effects probit model, specification with alternative measures of financial inclusion, consumption- and income-based poverty measures

	Debit, credit, prepaid card		**On-line banking**	
	Consumption	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.955***	0.802***	0.835***	0.828***
	[0.048]	[0.043]	[0.035]	[0.029]
FI_{t-1}	-0.184**	-0.105***	-0.089*	-0.086**
	[0.030]	[0.026]	[0.046]	[0.037]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$	-0.127***	-0.001	-0.045	-0.070
	[0.046]	[0.042]	[0.061]	[0.051]
$\ln \sigma^2_\alpha$	-2.189***	-1.232***	-1.828***	-1.263***
	[0.210]	[0.091]	[0.146]	[0.086]
Log-likelihood	-10889.58	-17057.82	-12928.03	-19406.13
# observations	54653	54653	60098	60098
# subjects	20930	20930	22495	22495
Δentry	-0.019***	-0.016***	-0.010**	-0.013**
	[0.003]	[0.004]	[0.004]	[0.006]
Δexit	0.065***	0.027***	0.026**	0.040***
	[0.009]	[0.004]	[0.010]	[0.012]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B10. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated variations in entry and exit rates are computed as per expression (6) and (7).

included (Bellucci et al., 2010; Alesina et al., 2013). In addition, females have a higher propensity to save and have conservative saving plans (Sunden and Surette, 1998; Seguino and Floro, 2003). For such reasons we can expect that financial inclusion matters more in explaining poverty dynamics of males and mature adults.

Both gender and age are measured by indicator variables: $Female$ takes the value 1 for females and 0 for males; $Age > 45$ distinguishes people above (value 1) or below (value 0) the median age in our sample, which is 45. In order to allow for heterogeneous impacts of financial inclusion according to the gender and age of individuals, we interact these two variables with the proxy for financial inclusion, past poverty status and with the interaction between FI_{t-1} and $Poor_{t-1}$. The inclusion of this triple interaction, in particular, is essential to separately compute the impact of financial inclusion on transition matrices for different groups of individuals.

Results reported in Table 9 are consistent with the hypothesis that the impact of financial inclusion is heterogenous across demographic groups. In particular, the effects on poverty entry and exit rates are highly significant for male individuals, and for people over 45 years old. For females and for the young, instead, such effects are much weaker, especially as far as the income-based measure is considered. This may become a further disadvantage for fragile categories that are usually overrepresented among precarious low-paid jobs as well as among the unemployed and/or inactive.

6 Conclusions

The evidence provided in this paper supports a positive role of financial inclusion in reducing the incidence of poverty among Italian households in recent years. In particular, access to a bank account has been shown to reduce entry rates and increase exit rates, when both income-based and consumption-based poverty indicators are considered. Results are robust to the use of alternative proxies for financial inclusion, such as the availability of debit, credit or pre–paid cards and the use of remote banking services. We also take into account different poverty thresholds, which correspond to 30%, 40% and 60% of the median consumption/income in our sample, 50% being our baseline reference.

By reducing the risk of impoverishment and the likelihood of getting trapped into poverty, access to financial services improves the living conditions of the poorest households and is likely to exert long-lasting effects on their economic well–being. According to our baseline specification, the risk of falling below the poverty line is reduced by 3 percentage points and the chance of exiting poverty increases by 5 percentage points.

Access to bank accounts stimulates savings, improves consumption smoothing possibilities and helps people to become integrated in market economies and increase earning opportunities through payment facilities. At the same time, access to formal credit services enables low-income individuals to invest in education, health and micro-entrepreneurial activities. Although the existing debate focuses mainly on developing countries, the evidence provided for Italy in this paper shows that the poverty-reducing role for financial inclusion may be significant in the context of advanced economies as well. Granting access to financial services therefore needs to be a worldwide target, and the efforts in this direction may prove effective in alleviating poverty.

Finally, our results provide evidence that the beneficial effects of financial inclusion are highly heterogeneous across gender and age. Females and young people are confirmed as risk categories for which the poverty–reducing role of financial inclusion is weaker compared to males and mature people. Due to their economic fragility they need therefore to be safeguarded in order to achieve both gender and intergenerational equity.

Table 9: Estimation results: dynamic random-effects probit model, specification with interaction terms with gender and age, consumption- and income-based poverty measures

	Female		**Age > 45**	
	Consumption	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.406***	0.370***	0.587***	0.616***
	[0.073]	[0.077]	[0.090]	[0.085]
FI_{t-1}	-0.340***	-0.285***	-0.214***	0.099*
	[0.055]	[0.052]	[0.073]	[0.058]
$\text{Poor}_{t-1}\times\text{FI}_{t-1}$	0.071	0.117	0.145	0.016
	[0.079]	[0.081]	[0.091]	[0.086]
Female	-0.112*	0.134**		
	[0.063]	[0.060]		
$\text{Female}\times\text{FI}_{t-1}$	0.076	0.319***		
	[0.066]	[0.063]		
$\text{Female}\times\text{Poor}_{t-1}$	0.224**	0.633***		
	[0.091]	[0.101]		
$\text{Female}\times\text{Poor}_{t-1}\times\text{FI}_{t-1}$	-0.156	-0.245**		
	[0.108]	[0.109]		
Age>45			-0.371***	-0.085
			[0.078]	[0.064]
$\text{Age>45}\times\text{FI}_{t-1}$			-0.112	-0.348***
			[0.079]	[0.064]
$\text{Age>45}\times\text{Poor}_{t-1}$			0.207**	0.211**
			[0.103]	[0.102]
$\text{Age>45}\times\text{Poor}_{t-1}\times\text{FI}_{t-1}$			0.007	0.170
			[0.111]	[0.108]
$\ln\sigma^2_\alpha$	-1.671***	-1.014***	-1.966***	-1.403***
	[0.143]	[0.077]	[0.161]	[0.095]
Log-likelihood	-10865.18	-18948.45	-12883.61	-19305.82
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495
Male: Δentry	-0.035***	-0.038***		
	[0.006]	[0.008]		
Male: Δexit	0.042***	0.032**		
	[0.011]	[0.014]		
Female: Δentry	-0.025***	0.006		
	[0.005]	[0.008]		
Female: Δexit	0.030*	-0.041		
	[0.016]	[0.025]		
Age≤45: Δentry			-0.034***	0.019*
			[0.012]	[0.011]
Age≤45: Δexit			0.016***	-0.031
			[0.017]	[0.020]
Age>45: Δentry			-0.036***	-0.038***
			[0.006]	[0.007]
Age>45: Δexit			0.039*	0.066**
			[0.023]	[0.029]

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, regional dummies, and all the explanatory variables listed in Appendix B, Table B11. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points. The average estimated entry and exit rates are computed as per expression (6) and (7).

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A Estimation

A.1 Partial effects and transition probabilities

In the following, we provide a formalization for the computation of partial effects and transition probabilities given in Section 3.2. Consider the index function μ_{it} defined in (3). Let us write this function as $\mu_{it}(\text{poor}_{i,t-1}, \text{FI}_{i,t-1})$ in order to emphasize their evaluation at specific values of $\text{poor}_{i,t-1}$ and $\text{FI}_{i,t-1}$.

The entry and exit rates defined in Equations (4) and (5) can be expressed as

$$\text{entry}_{it} = \Phi\left(\frac{\mu_{1it}(0, \text{FI}_{it})}{\sqrt{1+\sigma_\alpha^2}}\right),$$

and

$$\text{exit}_{it} = \Phi\left(-\frac{\mu_{1it}(1, \text{FI}_{it})}{\sqrt{1+\sigma_\alpha^2}}\right).$$

The partial effect of financial inclusion on the entry rate Δentry_{it} in (6) can be written as

$$\Delta\text{entry}_{it} = \Phi\left(\frac{\nu_{1it}(0,1)}{\sqrt{1+\sigma_\alpha^2}}\right) - \Phi\left(\frac{\nu_{1it}(0,0)}{\sqrt{1+\sigma_\alpha^2}}\right),$$

and the partial effect Δexit_{it} in (7) can be written as

$$\Delta\text{exit}_{it} = \Phi\left(-\frac{\nu_{1it}(1,1)}{\sqrt{1+\sigma_\alpha^2}}\right) - \Phi\left(-\frac{\nu_{1it}(1,0)}{\sqrt{1+\sigma_\alpha^2}}\right).$$

The estimated counterparts of all the above expressions can be obtained by evaluating them in the ML estimate of $\boldsymbol{\varphi}$ and standard errors for the average partial effects can be computed via the Delta Method.

A.2 Dynamic bivariate random–effects probit model

We specify a separate equation for financial inclusion for individual i at time t, with $i = 1, \ldots, n$ and $t = 1, \ldots, T$, as follows:

$$\text{FI}_{it} = \mathbb{I}(\theta\, \text{FI}_{i,t-1} + \lambda\, \text{poor}_{i,t-1} + \boldsymbol{z}_{it}'\boldsymbol{\pi} + \eta_i + u_{it} > 0). \tag{8}$$

Here we let FI_{it} be a function of its lag, since it is likely to be persistent over time, of the lagged poverty status $\text{poor}_{i,t-1}$, which captures the feedback effect (Wooldridge, 2000), and of a set of covariates $\boldsymbol{z}_{it}$ containing the explanatory variables $\boldsymbol{x}_{it}$ in (1) and one overidentifying restriction discussed in Section 5.2.1. Moreover, η_i represents the permanent unobserved heterogeneity, which is allowed to be correlated with α_i in (1), and similarly u_{it} is a zero mean error term correlated with ε_{it}.

The two-equation setting described by (1)–(8) is similar to the model specifications adopted by Biewen (2009) and Devicienti and Poggi (2011) to study poverty transitions. Biewen (2009) builds a multivariate model to account for the feedback effects of past poverty history on the present occupational status and number of family members, whereas Devicienti and Poggi (2011) specify a bivariate binary choice models for poverty risk and social exclusion.

In order to estimate the parameters in (1) and (8), we rely on Maximum Likelihood based on the following distributional assumptions on α_i, η_i, ε_{it}, and u_{it}. For $i = 1, \ldots, n$:

A1 Conditional on $\text{poor}_{it}, \text{poor}_{i,t-1}, \text{FI}_{i,t-1}, \boldsymbol{x}_{it}, \boldsymbol{z}_{it}\alpha_i, \eta_i$, the terms ε_{it} and u_{it} are distributed as a bivariate normal with zero mean and variance-covariance matrix with elements $\mathrm{E}\left(\varepsilon_{it}\varepsilon_{il}\right) = 1$, $\mathrm{E}\left(u_{it}u_{il}\right) = 1$, $\mathrm{E}\left(\varepsilon_{it}u_{il}\right) = \rho$ if $t = l$, 0 otherwise, for $t, l = 1, \ldots, T$.

Assumption A1 implies that the joint density of $\text{poor}_{it}, \text{FI}_{it}$ for individual i at time t will be specified as the bivariate normal probability. Furthermore, A1 contains the obvious scale normalization for ε_{it} and u_{it}, $t = 1, \ldots, T$ and rules out autocorrelation. Implicitly, we are assuming that the persistence in poverty and financial inclusion histories are completely captured by *true* state dependence, permanent unobserved heterogeneity, and by the individual characteristics contained in the sets of explanatory variables.

The dynamic structure of model (1)-(8) requires the process to be initialized at poor_{i0} and FI_{i0} conditional on α_i and η_i, respectively, that is the so-called "initial conditions" problem (Heckman, 1981b). In order to tackle this issue, we follow Wooldridge (2005) and approximate the conditional distribution of $\text{poor}_{i0}, \text{FI}_{i0}$ given the unobserved heterogeneity with the distribution of α_i, η_i conditional on the initial values of the dependent variables:

A2 Conditional on $\boldsymbol{x}_{i0}, \boldsymbol{z}_{i0}$, the conditional distribution of α_i given poor_{i0} is $\alpha_i|\text{poor}_{i0} \sim \zeta\,\text{poor}_{i0} + \alpha_i^*$, and the conditional distribution of η_i given FI_{i0} is $\eta_i|\text{FI}_{i0} \sim \xi\,\text{FI}_{i0} + \eta_i^*$, where α_i^* and η_i^* are zero-mean error terms.

Notice that Assumption A2 does not parametrize the correlation between the unobserved individual effects, which is left for the joint distribution of α_i^* and η_i^*.

A3 Conditional on $\text{poor}_{it}, \text{poor}_{i,t-1}, \text{FI}_{i,t-1}, \boldsymbol{x}_{it}, \boldsymbol{z}_{it}$, for $t = 1, \ldots, T$, the terms α_i^* and η_i^* are jointly distributed as a bivariate normal with zero mean and variance-covariance matrix with elements $\mathrm{E}(\alpha_i^{*2}) = \sigma_\alpha^2$, $\mathrm{E}(\eta_i^{*2}) = \sigma_\eta^2$, and $\mathrm{E}(\alpha_i^*\eta_i^*) = \sigma_\alpha\sigma_\eta\kappa$.

Assumption A3 parametrizes the dependence between the two individual effects by means of the correlation coefficient κ. Also note that the scale parameters σ_α and σ_η represent the importance of unobserved heterogeneity in explaining the probability of being poor and of owning deposits, respectively.

Based on Assumptions A1, A2, and A3, the joint probability for the poverty status and deposit ownership for the i-th individual can be written as

$$P_i = \prod_{t=1}^{T} \Phi_2\left[s_{1it}(\mu_{1it} + \alpha_i^*), s_{2it}(\mu_{2it} + \eta_i^*), s_{1it}s_{2it}\rho\right], \tag{9}$$

where $\Phi_2(\cdot)$ is the bivariate standard normal distribution function, $s_{1it} = 2\text{poor}_{it} - 1$, $s_{2it} = 2\text{FI}_{it} - 1$, and

$$\begin{aligned} \mu_{1it} &= \gamma\,\text{poor}_{i,t-1} + \phi\,\text{FI}_{i,t-1} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \zeta\,\text{poor}_{i0} && (10) \\ \mu_{2it} &= \theta\,\text{FI}_{i,t-1} + \lambda\,\text{poor}_{i,t-1} + \boldsymbol{z}'_{it}\boldsymbol{\pi} + \xi\,\text{FI0}_{i0}. && (11) \end{aligned}$$

Because we adopt a random-effects approach, the above probability needs to be marginalized with respect to the joint distribution of α_i^*, η_i^*, which amounts to evaluating a double integral. Assumption A3 allows us to exploit the standard properties of the bivariate normal to derive the conditional distribution of η_i^* on α_i^*, that is $\eta_i^*|\alpha_i^* \sim N\left[\kappa\frac{\sigma_\eta}{\sigma_\alpha}\alpha_i^*\ ;\ \sigma_\eta^2(1-\kappa^2)\right]$. The random effect of the deposit equation can therefore be written as $\eta_i^* = \kappa\frac{\sigma_\eta}{\sigma_\alpha}\alpha_i^* + \delta_i^*$ where $\delta_i^* \sim N\left[0\ ;\sigma_\eta^2(1-\kappa^2)\right]$, and $\alpha_i^* \perp\!\!\!\perp \delta_i^*$, for $i = 1, \ldots, n$. This parametrization is similar to that adopted by Semykina and Wooldridge (2018) for binary panel data models with a binary endogenous explanatory variable in a static framework. The assumption of a bivariate normal distribution for the unobserved heterogeneity allows us to write the model as a function of two independent normally distributed random variables and the marginalization with respect to the random-effects is then performed by two independent consecutive integrations (Raymond et al., 2010). Let $\boldsymbol{\varphi}$ be the vector collecting the model parameters $\boldsymbol{\varphi} = (\gamma, \phi, \boldsymbol{\beta}', \zeta, \theta, \lambda, \boldsymbol{\pi}', \xi, \kappa, \rho, \sigma_\alpha, \sigma_\eta)'$. Then the likelihood function for individual i is

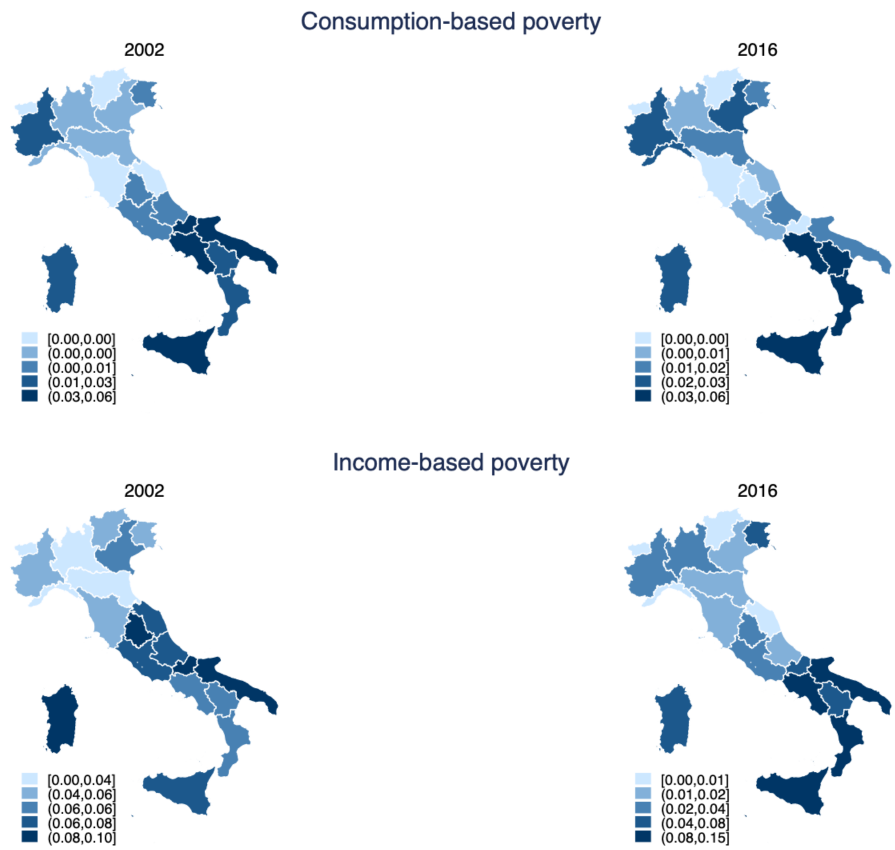
$$\mathscr{L}_i(\boldsymbol{\varphi}) = \int_{\Re}\int_{\Re} P_i \;\mathrm{d}\Phi\left(\frac{\alpha_i^*}{\sigma_\alpha}\right)\mathrm{d}\Phi\left(\frac{\delta_i^*}{\sigma_\eta\sqrt{1-\kappa^2}}\right), \tag{12}$$

where $\Phi(\cdot)$ is the standard normal distribution function and the independence of α_i^* and δ_i^* makes it possible to evaluate the double integral sequentially, which in turn becomes a simple application of the Gauss-Hermite quadrature technique (Butler and Moffitt, 1982).[12]

[12] Devicienti and Poggi (2011) adopt a different strategy to evaluate the double integral, which is based on Monte Carlo simulation for the computation of the bivariate normal probability. However quadrature methods, when feasible, are an equivalent and less computationally demanding strategy.

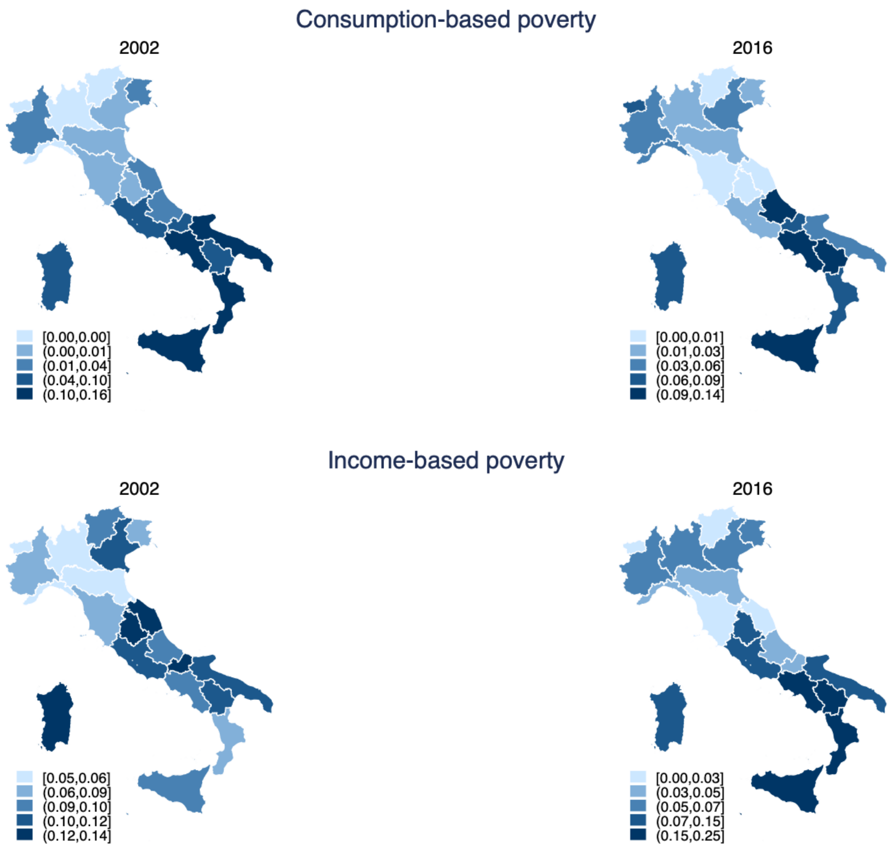
B Additional tables

Figure B1: Incidence of individuals with consumption and income lower than 30% of the median equivalised consumption and disposable income, 2002-2016



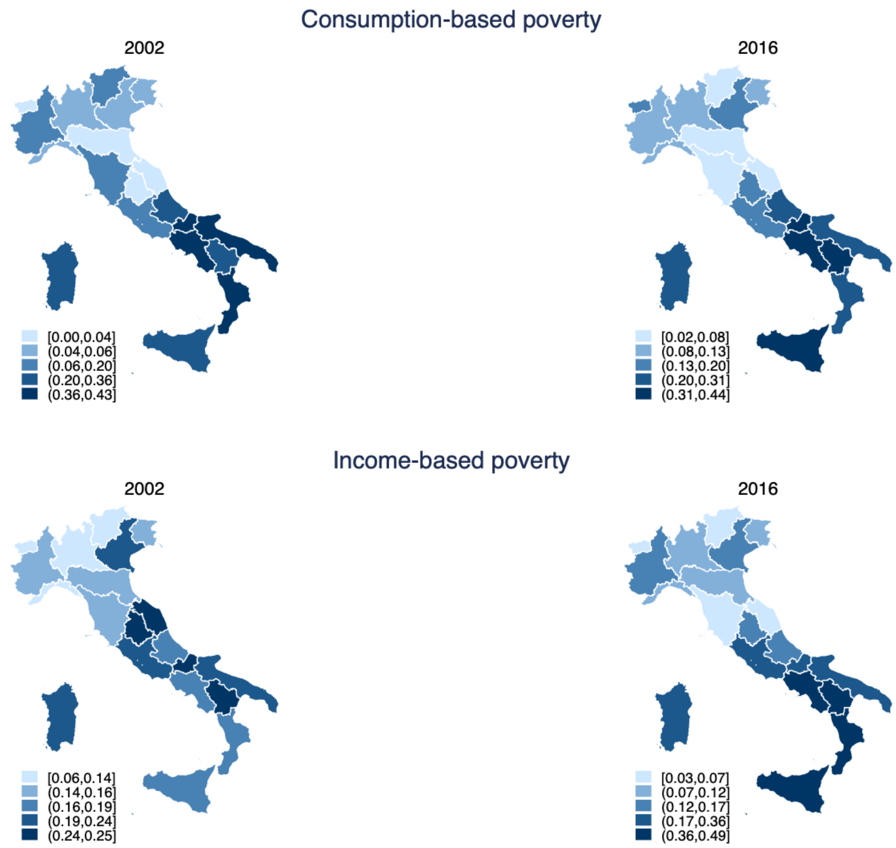
Notes: authors' elaboration on the SHIW data. An individual is poor if her/his household consumption expenditure/disposable income per equivalent adult is lower than 30% of the median equivalised household consumption/net income. Equivalised household consumption is total consumption expenditure divided by the number of equivalised adults whereas equivalised household income is total nominal income after taxes from any household member divided by the number of equivalised adults obtained through the "OECD–modified equivalence scale" (Hagenaars et al., 1994). This scale assigns a value of 1 to the household head, of 0.5 to each additional adult member (aged 14 or over) and of 0.3 to each child under age 14.

Figure B2: Incidence of individuals with consumption and income lower than 40% of the median equivalised consumption and disposable income, 2002-2016



Notes: authors' elaboration on SHIW data. An individual is poor if her/his household consumption expenditure/disposable income per equivalent adult is lower than40% of the median equivalised household consumption/net income. Equivalised household consumption is total consumption expenditure divided by the number of equivalised adults whereas equivalised household income is total nominal income after taxes from any household member divided by the number of equivalised adults obtained through the "OECD–modified equivalence scale" (Hagenaars et al., 1994). This scale assigns a value of 1 to the household head, 0.5 to each additional adult member (aged 14 or over) and 0.3 to each child under 14.

Figure B3: Incidence of individuals with consumption and income lower than 60% of the median equivalised consumption and disposable income, 2002-2016



Notes: authors' elaboration on SHIW data. An individual is poor if her/his household consumption expenditure/disposable income per equivalent adult is lower than 60% of the median equivalised household consumption/net income. Equivalised household consumption is total consumption expenditure divided by the number of equivalised adults whereas equivalised household income is total nominal income after taxes from any household member divided by the number of equivalised adults obtained through the "OECD–modified equivalence scale" (Hagenaars et al., 1994). This scale assigns a value of 1 to the household head, 0.5 to each additional adult member (aged 14 or over) and 0.3 to each child under 14.

Table B1: Transition matrices: extreme poverty (30% median)

Panel A. Consumption-based poverty		
	not at risk of poverty$_t$	at risk of poverty$_t$
not at risk of poverty$_{t-1}$	97.7	2.3 (*entry rate*)
(at risk of poverty)$_{t-1}$	44.1 (*exit rate*)	55.9 (*persistence rate*)
Panel B. Income-based poverty		
	not at risk of poverty$_t$	at risk of poverty$_t$
not at risk of poverty$_{t-1}$	95.3	4.7 (*entry rate*)
at risk of poverty$_{t-1}$	51.5 (*exit rate*)	48.5 (*persistence rate*)

Table B2: Transition matrices: extreme poverty (40% median)

Panel A. Consumption-based poverty		
	not at risk of poverty$_t$	at risk of poverty$_t$
not at risk of poverty$_{t-1}$	96.4	3.6 (*entry rate*)
(at risk of poverty)$_{t-1}$	36.7 (*exit rate*)	63.3 (*persistence rate*)
Panel B. Income-based poverty		
	not at risk of poverty$_t$	at risk of poverty$_t$
not at risk of poverty$_{t-1}$	93.5	6.5 (*entry rate*)
at risk of poverty$_{t-1}$	45.7 (*exit rate*)	54.3 (*persistence rate*)

Table B3: Transition matrices: at risk of poverty

Panel A. Consumption-based poverty		
	not at risk of poverty_t	at risk of poverty_t
not at risk of poverty_{t-1}	92.5	7.5 (*entry rate*)
(at risk of $\text{poverty})_{t-1}$	30.5 (*exit rate*)	69.5 (*persistence rate*)

Panel B. Income-based poverty		
	not at risk of poverty_t	at risk of poverty_t
not at risk of poverty_{t-1}	89.5	10.5 (*entry rate*)
at risk of poverty_{t-1}	34.6 (*exit rate*)	65.4 (*persistence rate*)

Table B4: Variables: definition, sources and summary statistics

Variable	Definition	Source	Mean	St. Dev.
poor50_consumption	1 if the equivalised household consumption is lower than 50% of the median equivalised household consumption expenditure, 0 otherwise	SHIW	0.168	0.374
poor60_consumption	1 if the equivalised household consumption is lower than 60% of the median equivalised household consumption expenditure, 0 otherwise	SHIW	0.228	0.420
poor40_consumption	1 if the equivalised household consumption is lower than 40% of the median equivalised household consumption expenditure, 0 otherwise	SHIW	0.115	0.319
poor30_consumption	1 if the equivalised household consumption is lower than 30% of the median equivalised household consumption expenditure, 0 otherwise	SHIW	0.063	0.244
poor50_income	1 if the equivalised household disposable income is lower than 50% of the median equivalised net household income, 0 otherwise	SHIW	0.188	0.391
poor60_income	1 if the equivalised household disposable income is lower than 60% of the median equivalised net household income, 0 otherwise	SHIW	0.236	0.425
poor40_income	1 if the equivalised household disposable income is lower than 40% of the median equivalised net household income, 0 otherwise	SHIW	0.130	0.336
poor30_income	1 if the equivalised household disposable income is lower than 30% of the median equivalised net household income, 0 otherwise	SHIW	0.088	0.283
deposit	1 if one or more bank or postal accounts are available in the household, 0 otherwise	SHIW	0.916	0.278
coldis	1 if anybody in the household makes use of remote access to banking services, 0 otherwise	SHIW	0.160	0.366
carta_all	1 if one or more debit, credit or pre-paid cards are available in the household, 0 otherwise	SHIW	0.738	0.440
sex	1 if male, 2 if female	SHIW	1.521	0.500
age	Age (in years)	SHIW	52.594	1.809
No education	1 for no education, 0 otherwise	SHIW	0.039	0.193
Primary	1 for primary education, 0 otherwise	SHIW	0.221	0.415
Lower secondary	1 for lower secondary education, 0 otherwise	SHIW	0.277	0.447
Upper secondary	1 for upper secondary education, 0 otherwise	SHIW	0.355	0.479
Higher education	1 for higher education, 0 otherwise	SHIW	0.107	0.310
Married	1 if married/in a couple, 0 otherwise	SHIW	0.620	0.485
Single	1 if single, 0 otherwise	SHIW	0.236	0.425
Divorced/separated	1 if divorced/separated, 0 otherwise	SHIW	0.039	0.195
Widowed	1 if widowed, 0 otherwise	SHIW	0.102	0.302
Blue collar	1 if blue collar, 0 otherwise	SHIW	0.151	0.358
White collar	1 if white collar, 0 otherwise	SHIW	0.146	0.353
Manager/CEO	1 if manager/CEO, 0 otherwise	SHIW	0.027	0.163
Self-employed	1 if self-employed, 0 otherwise	SHIW	0.067	0.249
Atypical/temporary worker	1 if atypical/temporary worker, 0 otherwise	SHIW	0.017	0.128
Unemployed	1 if unemployed, 0 otherwise	SHIW	0.036	0.186
First job seeker/student	1 if first job seeker/student, 0 otherwise	SHIW	0.083	0.275
Retired	1 if retired, 0 otherwise	SHIW	0.335	0.472
Other inactive	1 for other forms of inactivity, 0 otherwise	SHIW	0.137	0.344
Number of members	Number of household members	SHIW	2.948	1.270
Number of children_0-5	Presence of children under 5	SHIW	0.074	0.261
Number of children_6-11	Presence of children between 6 and 11 years	SHIW	0.107	0.309
Number of children_12-17	Presence of children between 12 and 17 years	SHIW	0.142	0.349
House ownership	1 for house ownership, 0 otherwise	SHIW	0.746	0.435
Employment growth rate	Growth rate of employment, 20-64 years	ISTAT	-0.265	2.685
Per-capita GDP growth rate	Growth rate of GDP per capita	ISTAT	-0.619	4.722

Table B5: Estimation results: dynamic random-effects probit model, complete baseline specification, consumption- and income-based poverty measures

	Consumption-based measure		Income-based measure	
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.517***	0.527***	0.728***	0.708***
	[0.038]	[0.053]	[0.029]	[0.055]
FI_{t-1}	-0.303***	-0.297***	-0.110***	-0.118***
	[0.035]	[0.041]	[0.036]	[0.040]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		-0.015		0.024
		[0.055]		[0.054]
Female	-0.022	-0.023	0.529***	0.528***
	[0.024]	[0.024]	[0.021]	[0.021]
Age	0.132***	0.131***	-0.008	-0.007
	[0.045]	[0.045]	[0.039]	[0.039]
Age^2	-0.142***	-0.142***	-0.003	-0.004
	[0.041]	[0.041]	[0.036]	[0.036]
Education (ref: none)				
Primary	-0.210***	-0.210***	-0.192***	-0.192***
	[0.048]	[0.048]	[0.047]	[0.047]
Lower secondary	-0.379***	-0.379***	-0.398***	-0.398***
	[0.053]	[0.053]	[0.051]	[0.051]
Upper secondary	-0.632***	-0.632***	-0.628***	-0.627***
	[0.057]	[0.057]	[0.053]	[0.053]
Higher education	-0.922***	-0.923***	-0.820***	-0.819***
	[0.077]	[0.077]	[0.063]	[0.063]
Marital status (ref: married)				
Single	0.323***	0.324***	0.170***	0.170***
	[0.040]	[0.040]	[0.035]	[0.034]
Divorced/separated	0.212***	0.213***	-0.090	-0.090
	[0.062]	[0.062]	[0.055]	[0.055]
Widower	0.161***	0.161***	-0.421***	-0.421***
	[0.045]	[0.045]	[0.042]	[0.042]
Occupational status (ref: Blue collar)				
White collar	-0.287***	-0.287***	-0.371***	-0.371***
	[0.048]	[0.048]	[0.037]	[0.037]
Manager/CEO	-0.584***	-0.584***	-0.559***	-0.559***
	[0.140]	[0.140]	[0.092]	[0.092]
Self-employed	-0.097*	-0.097*	-0.085**	-0.085**
	[0.054]	[0.054]	[0.043]	[0.043]
Atypical/temporary worker	0.120	0.120	-0.043	-0.043
	[0.087]	[0.087]	[0.065]	[0.065]
Unemployed	0.279***	0.278***	0.305***	0.305***
	[0.046]	[0.046]	[0.041]	[0.041]
First job seeker/student	0.044	0.044	0.173***	0.173***
	[0.047]	[0.047]	[0.040]	[0.040]
Retired	-0.040	-0.040	-0.148***	-0.148***
	[0.043]	[0.043]	[0.037]	[0.037]
Other inactive	0.032	0.032	-0.038	-0.038
	[0.039]	[0.039]	[0.033]	[0.033]
Number of children (0-5)	-0.275***	-0.275***	-0.187***	-0.186***
	[0.044]	[0.044]	[0.036]	[0.036]
Number of children (6-11)	-0.390***	-0.390***	-0.238***	-0.238***
	[0.037]	[0.037]	[0.031]	[0.031]
Number of children (12-17)	0.254***	0.255***	0.063**	0.063**
	[0.029]	[0.029]	[0.025]	[0.025]
House ownership	-0.465***	-0.465***	-0.207***	-0.206***
	[0.025]	[0.026]	[0.022]	[0.022]
Number of household members	0.247***	0.247***	0.212***	0.212***
	[0.011]	[0.011]	[0.010]	[0.010]
Size of municipality (ref: less than 20,000 inhab.)				
20,000 - 40,000	-0.086**	-0.086**	-0.080***	-0.080***
	[0.035]	[0.035]	[0.029]	[0.029]
40,000 - 500,000	-0.152***	-0.152***	-0.068***	-0.068***
	[0.029]	[0.029]	[0.024]	[0.024]
More than 500,000	-0.156***	-0.157***	-0.136***	-0.136***
	[0.049]	[0.049]	[0.044]	[0.044]
Per-capita GDP growth rate	-0.001	-0.001	0.003	0.003
	[0.003]	[0.003]	[0.002]	[0.002]
Employment growth rate	0.000	0.000	0.020***	0.020***
	[0.005]	[0.005]	[0.005]	[0.005]
Wealth_0	-0.005***	-0.005***	-0.001***	-0.001***
	[0.001]	[0.001]	[0.000]	[0.000]
Poor_0	0.436***	0.437***	0.757***	0.756***
	[0.040]	[0.040]	[0.036]	[0.036]
FI_0	-0.129***	-0.129***	-0.117***	-0.116***
	[0.037]	[0.037]	[0.038]	[0.038]
$\ln \sigma^2_\alpha$	-1.669***	-1.667***	-0.978***	-0.980***
	[0.142]	[0.142]	[0.076]	[0.076]
Log-likelihood	-10868.89	-10868.85	-19019.38	-19019.28
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. Both specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B6: Estimation results: dynamic random-effects probit model with Heckman's initial conditions, complete baseline specification, consumption- and income-based poverty measures

	Consumption-based measure		**Income-based measure**	
	[1]	[2]	[3]	[4]
Poor_{t-1}	1.094***	1.082***	0.961***	1.062***
	[0.032]	[0.061]	[0.033]	[0.061]
FI_{t-1}	-0.302***	-0.323***	-0.176***	-0.217***
	[0.037]	[0.047]	[0.035]	[0.039]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		0.057		0.039**
		[0.064]		[0.061]
Female	0.008	0.008	0.428***	0.383***
	[0.025]	[0.025]	[0.023]	[0.022]
Age	-0.261***	-0.256***	-0.172***	-0.135***
	[0.053]	[0.053]	[0.048]	[0.044]
Age^2	0.124***	0.122***	0.101**	0.082**
	[0.047]	[0.047]	[0.043]	[0.040]
Education (ref: none)				
Primary	-0.227***	-0.224***	-0.227***	-0.200***
	[0.053]	[0.053]	[0.056]	[0.051]
Lower secondary	-0.360***	-0.356***	-0.498***	-0.437***
	[0.060]	[0.060]	[0.061]	[0.056]
Upper secondary	-0.498***	-0.493***	-0.695***	-0.610***
	[0.063]	[0.063]	[0.065]	[0.059]
Higher education	-0.572***	-0.567***	-0.818***	-0.725***
	[0.074]	[0.074]	[0.076]	[0.069]
Marital status (ref: married)				
Single	-0.100**	-0.091**	-0.088**	-0.045
	[0.040]	[0.040]	[0.041]	[0.037]
Divorced/separated	0.209***	0.209***	-0.087	-0.079
	[0.056]	[0.056]	[0.062]	[0.057]
Widower	0.291***	0.287***	-0.316***	-0.288***
	[0.045]	[0.045]	[0.047]	[0.043]
Occupational status (ref: Blue collar)				
White collar	-0.159***	-0.159***	-0.258***	-0.238***
	[0.045]	[0.045]	[0.041]	[0.039]
Manager/CEO	-0.258***	-0.259***	-0.457***	-0.415***
	[0.080]	[0.080]	[0.085]	[0.080]
Self-employed	0.018	0.016	-0.070	-0.058
	[0.052]	[0.052]	[0.050]	[0.047]
Atypical/temporary worker	0.134	0.131	-0.089	-0.078
	[0.099]	[0.099]	[0.073]	[0.069]
Unemployed	0.201***	0.200***	0.245***	0.244***
	[0.057]	[0.057]	[0.048]	[0.046]
First job seeker/student	-0.237***	-0.233***	0.075	0.087 *
	[0.068]	[0.069]	[0.050]	[0.047]
Retired	-0.017	-0.018	-0.219***	-0.195***
	[0.053]	[0.053]	[0.045]	[0.041]
Other inactive	-0.026	-0.027	-0.118***	-0.100***
	[0.047]	[0.047]	[0.037]	[0.035]
Number of children (0-5)	1.563***	1.552***	0.887***	0.810***
	[0.041]	[0.042]	[0.039]	[0.037]
Number of children (6-11)	1.422***	1.405***	0.916***	0.808***
	[0.037]	[0.039]	[0.035]	[0.033]
Number of children (12-17)	0.080**	0.077**	-0.010	-0.038
	[0.035]	[0.036]	[0.032]	[0.030]
House ownership	-0.315***	-0.312***	-0.188***	-0.168***
	[0.028]	[0.028]	[0.026]	[0.023]
Number of household members	-0.137***	-0.137***	0.004	-0.003
	[0.012]	[0.012]	[0.012]	[0.011]
Size of municipality (ref: less than 20,000 inhab.)				
20,000 - 40,000	-0.099***	-0.099***	-0.078**	-0.064**
	[0.036]	[0.036]	[0.033]	[0.030]
40,000 - 500,000	-0.060**	-0.059**	-0.047*	-0.037
	[0.030]	[0.030]	[0.029]	[0.026]
More than 500,000	0.020	0.022	-0.055	-0.034
	[0.054]	[0.054]	[0.051]	[0.046]
Per-capita GDP growth rate	-0.004	-0.026	0.000	0.001
	[0.004]	[0.053]	[0.002]	[0.001]
Employment growth rate	0.004	0.036	0.023***	0.022***
	[0.007]	[0.073]	[0.005]	[0.005]
Wealth_0	-0.007***	-0.007***	-0.003***	-0.002***
	[0.001]	[0.001]	[0.000]	[0.000]
Poor_0				
σ_α	0.111***	0.111***	0.486***	0.481***
	[0.021]	[0.020]	[0.034]	[0.034]
First-stage F test				
Log-likelihood	-11195.33	-11006.13	-17307.42	-16768.31
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. Both specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B7: Estimation results: dynamic bivariate random-effects probit model, complete baseline specification, consumption- and income-based poverty measures

	Consumption-based measure		**Income-based measure**	
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.828***	0.731***	0.822***	0.740***
	[0.058]	[0.084]	[0.030]	[0.054]
FI_{t-1}	-0.271***	-0.325***	-0.119***	-0.152***
	[0.047]	[0.058]	[0.033]	[0.038]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$		0.121		0.097*
		[0.075]		[0.052]
Female	0.021	0.022	0.397***	0.395***
	[0.015]	[0.015]	[0.018]	[0.018]
Age	-0.360***	-0.358***	-0.208***	-0.207***
	[0.045]	[0.045]	[0.037]	[0.037]
Age^2	0.184***	0.182***	0.125***	0.124***
	[0.040]	[0.040]	[0.034]	[0.034]
Education (ref: none)				
Primary	-0.245***	-0.244***	-0.210***	-0.209***
	[0.047]	[0.047]	[0.044]	[0.044]
Lower secondary	-0.428***	-0.427***	-0.469***	-0.467***
	[0.056]	[0.056]	[0.048]	[0.048]
Upper secondary	-0.617***	-0.616***	-0.638***	-0.636***
	[0.062]	[0.062]	[0.052]	[0.052]
Higher education	-0.630***	-0.629***	-0.724***	-0.721***
	[0.073]	[0.073]	[0.061]	[0.061]
Marital status (ref: married)				
Single	-0.217***	-0.214***	-0.164***	-0.164***
	[0.040]	[0.040]	[0.034]	[0.034]
Divorced/separated	0.081	0.083	-0.116**	-0.115**
	[0.052]	[0.053]	[0.050]	[0.050]
Widower	0.262***	0.262***	-0.351***	-0.350***
	[0.043]	[0.043]	[0.041]	[0.041]
Occupational status (ref: Blue collar)				
White collar	-0.153***	-0.152***	-0.240***	-0.240***
	[0.040]	[0.040]	[0.034]	[0.034]
Manager/CEO	-0.315***	-0.313***	-0.494***	-0.493***
	[0.071]	[0.071]	[0.073]	[0.073]
Self-employed	0.001	0.002	-0.041	-0.041
	[0.045]	[0.045]	[0.041]	[0.041]
Atypical/temporary worker	0.074	0.072	-0.148**	-0.148**
	[0.093]	[0.093]	[0.065]	[0.065]
Unemployed	0.222***	0.224***	0.240***	0.240***
	[0.049]	[0.049]	[0.039]	[0.039]
First job seeker/student	-0.294***	-0.292***	0.048	0.047
	[0.058]	[0.058]	[0.040]	[0.040]
Retired	-0.011	-0.010	-0.217***	-0.217***
	[0.045]	[0.045]	[0.037]	[0.037]
Other inactive	-0.043	-0.043	-0.149***	-0.149***
	[0.036]	[0.036]	[0.031]	[0.031]
Number of children (0-5)	1.624***	1.619***	0.808***	0.806***
	[0.062]	[0.062]	[0.034]	[0.034]
Number of children (6-11)	1.401***	1.395***	0.741***	0.739***
	[0.058]	[0.058]	[0.030]	[0.030]
Number of children (12-17)	0.064	0.062	-0.110***	-0.110***
	[0.047]	[0.047]	[0.028]	[0.028]
House ownership	-0.334***	-0.334***	-0.168***	-0.167***
	[0.033]	[0.033]	[0.023]	[0.023]
Number of household members	-0.163***	-0.163***	-0.006	-0.006
	[0.018]	[0.018]	[0.010]	[0.010]
Size of municipality (ref: less than 20,000 inhab.)				
20,000 - 40,000	-0.085*	-0.084*	-0.094***	-0.094***
	[0.044]	[0.044]	[0.028]	[0.028]
40,000 - 500,000	-0.041	-0.040	-0.047*	-0.047*
	[0.037]	[0.037]	[0.025]	[0.025]
More than 500,000	-0.051	-0.051	-0.075*	-0.074*
	[0.066]	[0.066]	[0.045]	[0.045]
Per-capita GDP growth rate	-0.003	-0.003	0.001	0.001
	[0.004]	[0.004]	[0.001]	[0.001]
Employment growth rate	0.010	0.010	0.014***	0.014***
	[0.007]	[0.007]	[0.005]	[0.005]
Wealth_0	-0.007***	-0.007***	-0.002***	-0.002***
	[0.001]	[0.001]	[0.000]	[0.000]
Poor_0	0.428***	0.428***	0.660***	0.658***
	[0.068]	[0.068]	[0.039]	[0.039]
σ_α	0.391	0.389	0.529	0.526
	[0.007]	[0.007]	[0.006]	[0.006]
σ_η	0.619***	0.618***	0.638***	0.638***
	[0.021]	[0.021]	[0.022]	[0.022]
κ	-0.125	-0.116	-0.087	-0.085
	[0.108]	[0.109]	[0.062]	[0.062]
ρ	-0.268***	-0.270***	-0.055**	-0.055**
	[0.029]	[0.029]	[0.024]	[0.024]
First-stage F test	23.498	23.498	24.078	24.078
Log-likelihood	-22514.10	-22511.39	-29134.61	-29132.93
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. Both specifications include an intercept term, year dummies, and regional dummies. The first-stage F test is based on a linear probability model for the deposit equation. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B8: Estimation results: dynamic random-effects probit model, complete specification with house mortgage, consumption debt, and debt towards relatives/friends, consumption- and income-based poverty measures

	Consumption	**Income**	**Consumption**	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]	[5]	[6]
Poor$_{t-1}$	0.811***	1.101***	0.540***	0.809***	0.535***	0.844***
	[0.091]	[0.086]	[0.075]	[0.062]	[0.075]	[0.069]
FI$_{t-1}$	-0.290***	-0.127*	-0.334***	-0.181***	-0.335***	-0.241***
	[0.073]	[0.065]	[0.059]	[0.050]	[0.059]	[0.050]
House mortgage$_{t-1}$	0.012	-0.055				
	[0.046]	[0.034]				
Consumption debt$_{t-1}$			-0.068*	0.035		
			[0.040]	[0.028]		
Debt toward relative/friends$_{t-1}$					0.171***	0.144***
					[0.057]	[0.048]
Poor$_{t-1}$ × Deposit$_{t-1}$	-0.111	-0.065	0.092	0.177***	0.095	0.113*
	[0.090]	[0.084]	[0.071]	[0.063]	[0.071]	[0.063]
Female	-0.044	0.376***	-0.014	0.305***	-0.013	0.343***
	[0.032]	[0.025]	[0.029]	[0.021]	[0.029]	[0.023]
Age	0.025	-0.046	0.106*	-0.122***	0.107*	0.063
	[0.064]	[0.048]	[0.056]	[0.040]	[0.056]	[0.041]
Age^2	-0.080	0.022	-0.145***	0.063*	-0.143***	-0.070*
	[0.058]	[0.043]	[0.052]	[0.037]	[0.051]	[0.038]
Education (ref: none)						
Primary	-0.278***	-0.152**	-0.232***	-0.205***	-0.232***	-0.199***
	[0.072]	[0.062]	[0.064]	[0.050]	[0.064]	[0.052]
Lower secondary	-0.493***	-0.358***	-0.411***	-0.421***	-0.408***	-0.387***
	[0.080]	[0.067]	[0.070]	[0.054]	[0.069]	[0.056]
Upper secondary	-0.742***	-0.583***	-0.636***	-0.543***	-0.631***	-0.571***
	[0.084]	[0.070]	[0.074]	[0.056]	[0.074]	[0.059]
Higher education	-1.038***	-0.786***	-0.970***	-0.661***	-0.963***	-0.794***
	[0.105]	[0.080]	[0.098]	[0.064]	[0.097]	[0.070]
Marital status (ref: married)						
Single	0.150**	0.143***	0.267***	-0.080**	0.274***	0.136***
	[0.059]	[0.043]	[0.049]	[0.035]	[0.049]	[0.036]
Divorced/separated	0.072	-0.024	0.140*	-0.044	0.138*	-0.087
	[0.096]	[0.072]	[0.073]	[0.049]	[0.072]	[0.054]
Widower	0.064	-0.289***	0.161***	-0.148***	0.160***	-0.285***
	[0.064]	[0.051]	[0.056]	[0.040]	[0.056]	[0.044]
Occupational status (ref: Blue collar)						
White collar	-0.315***	-0.360***	-0.288***	-0.256***	-0.288***	-0.361***
	[0.062]	[0.045]	[0.059]	[0.037]	[0.059]	[0.041]
Manager/CEO	-0.499***	-0.585***	-0.492***	-0.503***	-0.490***	-0.629***
	[0.157]	[0.112]	[0.163]	[0.082]	[0.163]	[0.112]
Self-employed	-0.040	-0.067	-0.127*	-0.028	-0.124*	-0.068
	[0.068]	[0.051]	[0.068]	[0.044]	[0.068]	[0.046]
Atypical/temporary worker	-0.033	-0.158*	0.141	-0.185**	0.143	-0.125
	[0.124]	[0.086]	[0.108]	[0.080]	[0.108]	[0.078]
Unemployed	0.215***	0.271***	0.298***	0.187***	0.287***	0.284***
	[0.064]	[0.053]	[0.053]	[0.044]	[0.053]	[0.043]
First job seeker/student	-0.022	0.106**	-0.023	-0.012	-0.024	0.146***
	[0.066]	[0.052]	[0.059]	[0.047]	[0.058]	[0.045]
Retired	-0.121**	-0.219***	-0.070	-0.266***	-0.070	-0.199***
	[0.060]	[0.046]	[0.054]	[0.040]	[0.054]	[0.040]
Other inactive	0.013	-0.051	-0.011	-0.114***	-0.009	-0.008
	[0.054]	[0.042]	[0.048]	[0.035]	[0.048]	[0.035]
Number of children (0-5)	-0.332***	-0.078	-0.221***	0.771***	-0.225***	-0.095**
	[0.066]	[0.047]	[0.054]	[0.035]	[0.054]	[0.040]
Number of children (6-11)	-0.244***	-0.180***	-0.283***	0.668***	-0.285***	-0.154***
	[0.050]	[0.039]	[0.045]	[0.030]	[0.045]	[0.034]
Number of children (12-17)	0.343***	0.136***	0.343***	-0.069 **	0.336***	0.110***
	[0.039]	[0.032]	[0.037]	[0.029]	[0.037]	[0.029]
House ownership	-0.096*	-0.026	-0.396***	-0.182***	-0.389***	-0.235***
	[0.055]	[0.047]	[0.032]	[0.022]	[0.032]	[0.023]
Number of household members	0.214***	0.162***	0.204***	-0.021**	0.203***	0.145***
	[0.016]	[0.012]	[0.014]	[0.010]	[0.014]	[0.011]
Size of municipality (ref: less than 20,000 inhab.)						
20,000 - 40,000	-0.088**	-0.040	-0.031	-0.060**	-0.031	-0.074**
	[0.044]	[0.032]	[0.043]	[0.029]	[0.042]	[0.030]
40,000 - 500,000	-0.143***	-0.030	-0.096***	-0.024	-0.100***	-0.026
	[0.037]	[0.027]	[0.036]	[0.024]	[0.036]	[0.025]
More than 500,000	-0.209***	-0.093*	-0.069	-0.047	-0.065	-0.084*
	[0.071]	[0.054]	[0.059]	[0.043]	[0.059]	[0.045]
Per-capita GDP growth rate	0.001	-0.001	-0.001	0.001	-0.001	0.003
	[0.005]	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]
Employment growth rate	-0.002	0.037***	-0.014*	0.022***	-0.013*	0.028***
	[0.009]	[0.007]	[0.007]	[0.006]	[0.007]	[0.006]
Wealth$_0$	-0.005***	-0.001***	-0.006***	-0.002***	-0.005***	-0.001***
	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]
Poor$_0$	0.227***	0.445***	0.500***	0.472***	0.497***	0.458***
	[0.059]	[0.050]	[0.058]	[0.029]	[0.058]	[0.048]
FI$_0$	-0.149**	-0.121**	-0.092*	-0.075*	-0.091*	-0.032
	[0.061]	[0.056]	[0.052]	[0.044]	[0.052]	[0.045]
$\ln \sigma_\alpha^2$	-3.301***	-3.960***	-2.141***	-9.000	-2.187***	-3.796***
	[0.990]	[1.493]	[0.311]	[11.860]	[0.323]	[1.228]
Log-likelihood	-4960.798	-8772.595	-6464.273	-11371.740	-6461.308	-11201.020
# observations	29131	29131	35037	35037	35037	35037
# subjects	13387	13387	16350	16350	16350	16350

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B9: Estimation results: dynamic random-effects probit model, complete specification with alternative measures of poverty, consumption- and income-based poverty measures

	Extreme poverty (30% median)		Extreme poverty (40% median)		Risk of poverty	
	Consumption	Income	Consumption	Income	Consumption	Income
	[1]	[2]	[3]	[4]	[5]	[6]
Poor_{t-1}	0.735***	0.553***	0.776***	0.669***	0.528***	0.669***
	[0.077]	[0.068]	[0.061]	[0.060]	[0.049]	[0.051]
FI_{t-1}	-0.149***	-0.199***	-0.245***	-0.131***	-0.225***	-0.110***
	[0.057]	[0.046]	[0.047]	[0.042]	[0.041]	[0.038]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$	-0.141*	0.224***	0.056	0.090	-0.002	0.086*
	[0.074]	[0.066]	[0.059]	[0.059]	[0.049]	[0.050]
Female	-0.006	0.355***	0.011	0.414***	-0.019	0.456***
	[0.031]	[0.024]	[0.023]	[0.021]	[0.020]	[0.019]
Age	-0.228**	-0.112**	-0.401***	-0.242***	0.087**	-0.079**
	[0.065]	[0.048]	[0.045]	[0.040]	[0.038]	[0.036]
Age^2	-0.019	-0.014	0.201***	0.145***	-0.095***	0.057*
	[0.064]	[0.047]	[0.041]	[0.037]	[0.035]	[0.032]
Education (ref: none)						
Primary	-0.255***	-0.159***	-0.303***	-0.274***	-0.259***	-0.209***
	[0.074]	[0.062]	[0.053]	[0.052]	[0.042]	[0.043]
Lower secondary	-0.348***	-0.323***	-0.476***	-0.557***	-0.440***	-0.427***
	[0.080]	[0.065]	[0.058]	[0.056]	[0.046]	[0.047]
Upper secondary	-0.521***	-0.477***	-0.645***	-0.726***	-0.710***	-0.662***
	[0.084]	[0.068]	[0.061]	[0.058]	0.049]	[0.049]
Higher education	-0.521***	-0.535***	-0.650***	-0.796***	1.066***	-0.829***
	[0.098]	[0.078]	[0.069]	[0.066]	[0.064]	[0.058]
Marital status (ref: married)						
Single	-0.312***	-0.160***	-0.310***	-0.203***	0.277***	0.136***
	[0.054]	[0.041]	[0.039]	[0.036]	[0.034]	[0.032]
Divorced/separated	0.232***	0.041	0.086*	-0.105**	0.162***	-0.043
	[0.068]	[0.058]	[0.051]	[0.052]	0.052]	[0.050]
Widower	0.230***	-0.254***	0.291***	-0.325***	0.072*	-0.366***
	[0.065]	[0.056]	[0.042]	[0.043]	[0.038]	[0.037]
Occupational status (ref: Blue collar)						
White collar	-0.236***	-0.309***	-0.107***	-0.227***	-0.301***	-0.337***
	[0.050]	[0.041]	[0.038]	[0.035]	[0.038]	[0.033]
Manager/CEO	-0.555***	-0.637***	-0.247***	-0.468***	-0.516***	-0.554***
	[0.118]	[0.101]	[0.072]	[0.074]	[0.097]	[0.080]
Self-employed	-0.005	-0.078*	0.039	-0.039	-0.145***	-0.085**
	[0.057]	[0.047]	[0.045]	[0.042]	[0.045]	[0.039]
Atypical/temporary worker	0.034	0.012	0.115	-0.116*	0.035	-0.064
	[0.109]	[0.074]	[0.079]	[0.067]	[0.073]	[0.060]
Unemployed	0.194***	0.314***	0.264***	0.270***	0.242***	0.253***
	[0.058]	[0.046]	[0.052]	[0.046]	[0.042]	[0.039]
First job seeker/student	-0.190***	0.117**	-0.290***	0.074*	0.057	0.076**
	[0.069]	[0.048]	[0.054]	[0.045]	[0.041]	[0.038]
Retired	0.065	-0.232***	-0.011	-0.240***	-0.083**	-0.167***
	[0.064]	[0.046]	[0.045]	[0.039]	[0.036]	[0.034]
Other inactive	0.041	-0.009	-0.044	-0.155***	0.024	-0.102***
	[0.046]	[0.036]	[0.039]	[0.034]	[0.033]	[0.031]
Number of children (0-5)	1.209***	-0.666***	1.579***	0.864***	-0.412***	-0.209***
	[0.041]	[0.033]	[0.040]	[0.033]	[0.039]	[0.034]
Number of children (6-11)	1.033***	0.612***	1.316***	0.757***	-0.356***	-0.249***
	[0.038]	[0.030]	[0.035]	[0.029]	[0.032]	[0.028]
Number of children (12-17)	-0.080**	-0.056*	0.027	-0.111***	0.301***	0.053**
	[0.037]	[0.029]	[0.031]	[0.027]	[0.025]	[0.024]
House ownership	-0.254***	-0.185***	-0.311***	-0.174***	-0.465***	-0.185***
	[0.033]	[0.025]	[0.024]	[0.022]	[0.022]	[0.020]
Number of household members	-0.012	0.051***	-0.143***	-0.005	0.232***	0.210***
	[0.014]	[0.011]	[0.012]	[0.010]	[0.010]	[0.009]
Size of municipality (ref: less than 20,000 inhab.)						
20,000 - 40,000	-0.061	-0.090***	-0.106***	-0.102***	-0.134***	-0.077***
	[0.044]	[0.034]	[0.031]	[0.029]	[0.029]	[0.026]
40,000 - 500,000	-0.075**	0.001	-0.054**	-0.050**	-0.116***	-0.071***
	[0.037]	[0.028]	[0.026]	[0.024]	[0.024]	[0.022]
More than 500,000	0.018	-0.049	-0.037	-0.053	-0.206***	-0.162***
	[0.062]	[0.050]	[0.048]	[0.044]	[0.043]	[0.040]
Per-capita GDP growth rate	-0.005**	0.001	-0.002	0.001	-0.004*	0.004*
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Employment growth rate	0.020***	0.011**	0.012**	0.016***	0.000	0.029***
	[0.007]	[0.005]	[0.006]	[0.005]	[0.005]	[0.004]
Wealth_0	-0.011***	-0.001**	-0.006***	-0.002***	-0.006***	-0.001***
	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
Poor_0	0.560***	0.587***	0.452***	0.589***	0.485***	0.745***
	[0.055]	[0.043]	[0.044]	[0.037]	[0.032]	[0.032]
FI_0	-0.159***	-0.115***	-0.093**	-0.106***	-0.158***	-0.087**
	[0.051]	[0.044]	[0.042]	[0.040]	[0.034]	[0.036]
$\ln \sigma_\alpha^2$	-1.529***	-1.213***	-1.766***	-1.284***	-1.575***	-1.121***
	[0.051]	[0.107]	[0.163]	[0.096]	[0.106]	[0.075]
Log-likelihood	-6572.63	-12006.93	-9833.15	-15553.62	-16184.75	-22158.69
# observations	60098	60098	54653	54653	60098	60098
# subjects	22495	22495	20930	20930	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B10: Estimation results: dynamic random-effects probit model, complete specification with alternative measures of financial inclusion, consumption- and income-based poverty measures

	Debit, credit and pre-paid card		**On-line banking**	
	Consumption	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.955***	0.802***	0.835***	0.828***
	[0.048]	[0.043]	[0.035]	[0.029]
FI_{t-1}	-0.184***	-0.105***	-0.089*	-0.086**
	[0.030]	[0.026]	[0.046]	[0.037]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$	-0.127***	-0.001	-0.045	-0.070
	[0.046]	[0.042]	[0.061]	[0.052]
Female	0.007	0.412***	0.022	0.396***
	[0.022]	[0.021]	[0.022]	[0.020]
Age	-0.395***	-0.238***	-0.344***	-0.203***
	[0.045]	[0.040]	[0.042]	[0.037]
Age^2	0.186***	0.138***	0.167***	0.119***
	[0.041]	[0.037]	[0.038]	[0.034]
Education (ref: none)				
Primary	-0.274***	-0.258***	-0.284***	-0.227***
	[0.053]	[0.052]	[0.045]	[0.044]
Lower secondary	-0.420***	-0.528***	-0.489***	-0.493***
	[0.058]	[0.056]	[0.050]	[0.048]
Upper secondary	-0.571***	-0.688***	-0.684***	-0.664***
	[[0.061]	[0.058]	[0.053]	[0.050]
Higher education	-0.574***	-0.759***	-0.679***	-0.742***
	[0.069]	[0.066]	[0.063]	[0.059]
Marital status (ref: married)				
Single	-0.333***	-0.212***	-0.204***	-0.161***
	[0.039]	[0.036]	[0.036]	[0.033]
Divorced/separated	0.082	-0.108**	0.094*	-0.108**
	[0.051]	[0.052]	[0.048]	[0.048]
Widower	0.293***	-0.325***	0.270***	-0.345***
	[0.042]	[0.043]	[0.038]	[0.038]
Occupational status (ref: Blue collar)				
White collar	-0.112***	-0.226***	-0.146***	-0.233***
	[0.038]	[0.035]	[0.037]	[0.033]
Manager/CEO	-0.267***	-0.469***	-0.290***	-0.482***
	[0.072]	[0.074]	[0.073]	[0.072]
Self-employed	0.022	-0.043	0.007	-0.037
	[0.045]	[0.042]	[0.044]	[0.040]
Atypical/temporary worker	0.093	-0.122*	0.077	-0.143**
	[0.079]	[0.067]	[0.078]	[0.064]
Unemployed	0.233***	0.258***	0.261***	0.255***
	[0.052]	[0.046]	[0.047]	[0.041]
First job seeker/student	-0.301***	0.069	-0.274***	0.055
	[0.054]	[0.044]	[0.051]	[0.041]
Retired	-0.016	-0.242***	-0.022	-0.219***
	[0.045]	[0.039]	[0.042]	[0.036]
Other inactive	-0.046	-0.157***	-0.043	-0.148***
	[0.039]	[0.034]	[0.037]	[0.032]
Number of children (0-5)	1.581***	0.858***	1.635***	0.816***
	[0.040]	[0.033]	[0.038]	[0.031]
Number of children (6-11)	1.321***	0.750***	1.401***	0.748***
	[0.035]	[0.029]	[0.034]	[0.027]
Number of children (12-17)	0.032	-0.114***	0.053 *	-0.107***
	[0.031]	[0.027]	[0.029]	[0.025]
House ownership	-0.311***	-0.170***	-0.345***	-0.175***
	[0.024]	[0.022]	[0.023]	[0.021]
Number of household members	-0.137***	-0.001	-0.166***	-0.006
	[0.012]	[0.010]	[0.011]	[0.009]
Size of municipality (ref: less than 20,000 inhab.)				
20,000 - 40,000	-0.100***	-0.098***	-0.084***	-0.091***
	[0.031]	[0.029]	[0.030]	[0.027]
40,000 - 500,000	-0.047*	-0.050**	-0.033	-0.044*
	[0.026]	[0.024]	[0.025]	[0.023]
More than 500,000	-0.032	-0.052	-0.030	-0.060
	[0.048]	[0.044]	[0.045]	[0.041]
Per-capita GDP growth rate	-0.002	0.001	-0.003	0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Employment growth rate	0.012**	0.016***	0.009*	0.014***
	[0.006]	[0.005]	[0.005]	[0.005]
Wealth_0	-0.006***	-0.002***	-0.007***	-0.002***
	[0.001]	[0.000]	[0.001]	[0.000]
Poor_0	0.380***	0.683***	0.460***	0.665***
	[0.040]	[0.036]	[0.037]	[0.033]
FI_0	-0.132***	-0.111***	-0.086*	0.023
	[0.027]	[0.024]	[0.048]	[0.040]
$\ln \sigma^2_\alpha$	-2.175***	-1.232***	-1.828***	-1.263***
	[0.209]	[0.091]	[0.146]	[0.086]
Log-likelihood	-10889.58	-17057.82	-12928.03	-19406.13
# observations	54653	54653	60098	60098
# subjects	20930	20930	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.

Table B11: Estimation results: dynamic random-effects probit model, complete specification with interaction terms with gender and age, consumption- and income-based poverty measures

	Female		**Age > 45**	
	Consumption	**Income**	**Consumption**	**Income**
	[1]	[2]	[3]	[4]
Poor_{t-1}	0.406***	0.370***	0.587***	0.616***
	[0.073]	[0.077]	[0.090]	[0.085]
FI_{t-1}	-0.340***	-0.285***	-0.214***	0.099*
	[0.055]	[0.052]	[0.073]	[0.058]
$\text{Poor}_{t-1} \times \text{FI}_{t-1}$	0.071	0.117	0.145	0.016
	[0.079]	[0.081]	[0.091]	[0.086]
Female	-0.112*	0.134**		
	[0.063]	[0.060]		
$\text{Female}\times\text{FI}_{t-1}$	0.076	0.319***		
	[0.066]	[0.063]		
$\text{Female}\times\text{Poor}_{t-1}$	0.224**	0.633***		
	[0.091]	[0.101]		
$\text{Female}\times\text{Poor}_{t-1}\times\text{FI}_{t-1}$	-0.156	-0.245**		
	[0.108]	[0.109]		
Age>45			-0.371***	-0.085
			[0.078]	[0.064]
Age>45 $\times\text{FI}_{t-1}$			-0.112	-0.348***
			[0.079]	[0.064]
Age>45 $\times\text{Poor}_{t-1}$			0.207**	0.211**
			[0.103]	[0.102]
Age>45 $\times\text{Poor}_{t-1}\times\text{FI}_{t-1}$			0.007	0.170
			[0.111]	[0.108]
Female			0.020	0.386***
			[0.021]	[0.019]
Age	0.132***	-0.021		
	[0.045]	[0.039]		
Age^2	-0.143***	0.007		
	[0.041]	[0.035]		
Education (ref: none)				
Primary	-0.211***	-0.198***	-0.195***	-0.168***
	[0.048]	[0.046]	[0.044]	[0.043]
Lower secondary	-0.380***	-0.404***	-0.307***	-0.395***
	[0.053]	[0.051]	[0.048]	[0.046]
Upper secondary	-0.633***	-0.628***	-0.483***	-0.561***
	[0.057]	[0.053]	[0.051]	[0.048]
Higher education	-0.923***	-0.816***	-0.520***	-0.663***
	[0.077]	[0.063]	[0.061]	[0.057]
Marital status (ref: married)				
Single	0.324***	0.190***	-0.125***	-0.150***
	[0.040]	[0.034]	[0.032]	[0.028]
Divorced/separated	0.211***	-0.072	0.106**	-0.101**
	[0.062]	[0.055]	[0.048]	[0.047]
Widower	0.163***	-0.392***	0.225***	-0.349***
	[0.045]	[0.042]	[0.037]	[0.037]
Occupational status (ref: Blue collar)				
White collar	-0.287***	-0.367***	-0.168***	-0.244***
	[0.048]	[0.037]	[0.037]	[0.033]
Manager/CEO	-0.586***	-0.563***	-0.327***	-0.493***
	[0.140]	[0.092]	[0.072]	[0.071]
Self-employed	-0.099*	-0.077*	-0.030	-0.057
	[0.054]	[0.042]	[0.043]	[0.039]
Atypical/temporary worker	0.121	-0.028	0.060	-0.157**
	[0.087]	[0.064]	[0.077]	[0.064]
Unemployed	0.283***	0.308***	0.219***	0.210***
	[0.046]	[0.041]	[0.047]	[0.041]
First job seeker/student	0.045	0.148***	-0.148***	0.054
	[0.047]	[0.040]	[0.048]	[0.039]
Retired	-0.040	-0.144***	-0.151***	-0.255***
	[0.043]	[0.037]	[0.037]	[0.031]
Other inactive	0.031	-0.020	-0.063*	-0.170***
	[0.039]	[0.033]	[0.036]	[0.031]
Number of children (0-5)	-0.275***	-0.191***	1.597***	0.775***
	[0.044]	[0.036]	[0.038]	[0.031]
Number of children (6-11)	-0.390***	-0.242***	1.363***	0.702***
	[0.037]	[0.031]	[0.033]	[0.027]
Number of children (12-17)	0.255***	0.062**	0.066**	-0.110***
	[0.029]	[0.025]	[0.029]	[0.025]
House ownership	-0.465***	-0.208***	-0.335***	-0.161***
	[0.026]	[0.022]	[0.023]	[0.020]
Number of household members	0.247***	0.213***	-0.141***	0.004
	[0.011]	[0.010]	[0.011]	[0.009]
Size of municipality (ref: less than 20,000 inhab.)				
20,000 - 40,000	-0.086**	-0.079***	-0.085***	-0.089***
	[0.035]	[0.029]	[0.030]	[0.027]
40,000 - 500,000	-0.152***	-0.066***	-0.043*	-0.043*
	[0.029]	[0.024]	[0.025]	[0.022]
More than 500,000	-0.156***	-0.132***	-0.052	-0.066*
	[0.049]	[0.044]	[0.044]	[0.040]
Per-capita GDP growth rate	-0.001	0.003	-0.003	0.001
	[0.003]	[0.002]	[0.002]	[0.002]
Employment growth rate	0.000	0.021***	0.011**	0.013***
	[0.005]	[0.005]	[0.005]	[0.005]
Wealth_0	-0.005***	-0.001***	-0.007***	-0.002***
	[0.001]	[0.000]	[0.001]	[0.000]
Poor_0	0.436***	0.737***	0.430***	0.632***
	[0.040]	[0.036]	[0.037]	[0.033]
FI_0	-0.129***	-0.120***	-0.078**	-0.087**
	[0.037]	[0.038]	[0.037]	[0.036]
$\ln \sigma_\alpha^2$	-1.671***	-1.014***	-1.966***	-1.403***
	[0.143]	[0.077]	[0.161]	[0.095]
Log-likelihood	-10865.18	-18948.45	-12883.61	-19305.82
# observations	60098	60098	60098	60098
# subjects	22495	22495	22495	22495

Notes: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors in square brackets are clustered at the household level and computed by the Delta method. All specifications include an intercept term, year dummies, and regional dummies. Integral approximation was performed by the Gauss-Hermite quadrature method with 24 grid points.