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Essays on Poverty Dynamics and Household Perceived Financial Hardship

Lippo Enrico

Registration number: 798705

Supervisor: prof. Lorenzo Cappellari

Tutor and Coordinator: prof. Matteo Manera

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Introduction

In the last ten years Italy has experienced a dramatic increase in the number of individuals and households in economic hardship. According to data from the Italian National Statistical Institute (ISTAT), in 2016 the incidence of absolute poverty was 6.3% in terms of households (1 million 600 thousand) and 7.9% in terms of individuals (4 million 700 thousand people). These figures are more impressive if we think that in 2007, at the dawn of the economic crisis, individuals in absolute poverty were 2 million 400 thousand, roughly a half (Istat (2017)). Looking at Eurostat indicators, Italy had in 2016 an at-risk-of-poverty-rate (ARPR), an indicator anchoring the poverty line to the current median income, of 20.6%. But snapshots of who is poor in a given period could be an incomplete measure of poverty, providing a blurry picture of it. For this reason, Eurostat computes a longitudinal indicator, which takes into account the fact that poverty may be a persistent phenomenon. The persistent-at-risk-of-poverty-rate (PARPR) considers poverty state both in the current year and in the preceding three years. For Italy, the PARPR amounted in 2016 to 14.5%, one of the highest value in the EU-28. Previous literature analyzing the Italian case has identified in the weakness of the labour market, the deep territorial dualism and the gaps of the social security system the main reasons of such high persistence. As far as the latter point, Italy traditionally lacks a national minimum income scheme to contrast poverty and the interventions have been relegated to local or national discontinuous policies. This situation has been changing in the last few years. In September 2016, a means-tested benefit named Support for Active Inclusion (SIA) has been implemented to the whole national territory. At the same time, a proposed legislation mandated the Government to reform anti-poverty measures by decree, including the introduction of a new national means-tested benefit named Inclusion Income (REI) which is in force since January 2018 and replaced the SIA. This novel and renewed interest towards anti-poverty measures is showing up also in the electoral campaign for the 2018 Italian general election. Apart from the REI, implemented by the current government, all the main political actors are proposing their strategies to eradicate poverty and, with respect to previous political competitions, poverty and anti-poverty measure would seem to have gained a central role in the italian debate.

In my thesis I investigate the themes of poverty dynamics and perceived economic difficulty in Italy. In the first chapter, I study poverty in Italy from a dynamic perspective, investigating the determinants of poverty entry and poverty persistence. A special emphasis is dedicated to the issue of state dependence. Persistence in poverty status (i.e. the fact that an individual is found in poverty status for two consecutive periods) may be due to observed or unobserved differences among individuals or to the causal effect of past on current poverty. To decompose the effect of individual heterogeneity from true state dependence, econometric techniques have been developed by previous economic literature. Moreover, estimating the magnitude of poverty genuine state dependence has important policy implications. If individuals remain in poverty mainly because they have experienced poverty in the past, policies should focus on income transfers that break the poverty trap. On the other hand, if persistence is explained mainly by individual heterogeneity, policies should focus on those characteristics that protect against economic hardship. Data used are those from nine consecutive waves of the Bank of Italy Survey on Household Income and Wealth (SHIW), running from 1998 to 2014. My econometric strategy relies on a first order Markov model. In particular, I estimate a bivariate endogenous switching probit model, controlling for the initial condition problem and using parental background as exclusion restrictions. To validate my results, I also take into account non-random panel attrition, estimating a trivariate probit model with endogenous switching and using the general climate of the interview as instrument. One of the main findings of the first chapter is that more roughly the 65% of the probability of being poor in a given period is caused by the fact of having experienced poverty in the past.

In the second chapter, I investigate the causal effect of fiscal policy on perception of households regarding their own economic situation. To do this, I examine a national massive tax rebate introduced in Italy in 2014, using data from the Bank of Italy Survey on Household Income and Wealth (SHIW) for years 2012 and 2014. The policy under investigation has been implemented in Italy in May 2014 and consists in a fiscal bonus for employees who were in a determined income interval. Household perception is measured using a specific survey question on individual self-assessed ability to make ends meet. My analysis relies on a difference-in-differences (DD) methodology and shows that a causal impact of the policy on individuals perception do exist. In particular, I find that household who received the tax bonus experienced a reduction in the probability of perceive financial hardship, according to the econometric specification, from 8% to 5%.

Chapter 1

Poverty Dynamics in Italy

1.1 Introduction

Poverty is a state dependent phenomenon. The chances of being poor for an individual differ according to the fact that he or she has experienced poverty in the past. An explanation for this is that individuals differ for those characteristics that make them more or less prone to poverty in any given period. These might be observed characteristics, such as age, educational qualification, job market and health status, or unobservable characteristics, such as motivation or ability. An alternative explanation is given by the existence of a causal effect of past on current poverty. Being poor in one period may increase, *per se*, the likelihood of being poor in the future. This mechanism is known as poverty trap or genuine state dependence and may occur because slipping into poverty triggers processes that make future poverty more likely, such as demoralization, habituation, stigmatization and depreciation of human capital or because of incentives linked to the social welfare system (Biewen (2014)).

Learning to distinguish between Genuine State Dependence (GSD) and individual observed, or unobserved, heterogeneity has important policy implications. If individuals remain in poverty mainly because they have been poor the past, policies should focus on income transfers that break the poverty trap. On the other hand, if persistence is caused largely by individual heterogeneity, policies should focus on those characteristics that protect against economic hardship.

This perspective has been also embraced by Eurostat which computes, along with the indicator for current poverty, the at-risk-of-poverty rate (ARPR) defined as the share of people with an equivalised disposable income below the poverty threshold, a measure for persistent poverty. The persistent at-risk-of-poverty rate (PARPR) represents the percentage of the population living in households where the equivalised disposable income was below the poverty threshold for the current year and at least two out of three of the preceding three years. Its calculation requires a longitudinal instrument through which the individuals are followed over four years. Italy is one of the EU countries with the highest values of both ARPR and PARPR. In 2015 (the most recent year for which is possible to make international comparisons) the ARPR for Italy was 19.9%, the highest rate in the EU-28 after Romania (25.4%), Latvia (22.25%), Lithuania (22.2%), Spain (22.1%), Bulgaria (22%), Estonia (21.6%), Greece (21.4%) and Croatia (20%). In the same year, the PARP for Italy amounted to 14.3%, the highest in the EU-28 after Romania (20.2%), Bulgaria (16.2%), Spain (15.8%) and Croatia (14.7%).

The distinction between Genuine State Dependence and individual heterogeneity is also relevant in the light of the anti-poverty measures recently introduced in Italy. In September 2016, a means-tested benefit named Support for Active Inclusion (SIA) has been implemented to the whole national territory. At the same time, a proposed legislation mandated the Government to reform low-income support measures by decree, including the introduction of a new national means-tested benefit named Inclusion Income (REI) which is in force since January 2018 and replaced SIA. These measures can be interpreted as the first steps towards the introduction of a national minimum income scheme, traditionally lacking in Italy. This chapter studies poverty in Italy from a dynamic perspective. To do this we use data from nine waves of the Bank of Italy Survey on Household Income and Wealth (SHIW), running from 1998 to 2014. We provide summary statistics of poverty dynamics for the whole period and estimate a first-order Markovian model to detect the determinants of poverty entry and persistence, and to quantify the role played by the poverty trap. As far as the econometric strategy, we rely on the model provided by Cappellari and Jenkins (2004) which allow to take into account simultaneously both the initial condition issue and non-random attrition. More in detail, when modeling poverty dynamics is important to take into account that individuals at risk of being poor in the initial year may not be a random sample of the population. This issue is well known in the literature and represents an example of the initial condition problem (Heckman (1981)). At the same time, considering that we rely on longitudinal data, the dynamics of poverty can be observed only for the subset of individuals surveyed for more than one point in time. If panel attrition is a non-random process, it may bias our estimates. Moreover, the model is estimated pooling all the individual transitions across two consecutive point in time and controlling for time-fixed effects, a strategy particularly suited for our dataset in which households (and individuals) are observed only for short passes. Our main finding is that roughly 65% of the probability of being poor in a given period is caused by past poverty, thus indicating a remarkable degree of

Genuine State Dependence. The remaining part is associated with factors such as age, human capital, the fact of having children within the household, having a head of household unemployed and living in the South of Italy.
The chapter is organized as follows. In Section 2 we provide a review of the literature analyzing poverty dynamics in Italy. Section 3 introduces the reader to the data and presents summary statistics. Section 4 describes the econometric strategy used in this chapter and Section 5 discusses the results of our estimations. Finally, Section 6 concludes.

1.2 Literature review

Addabbo (2000) analyses poverty dynamics using the panel component drawn from the 1993 and 1995 SHIW waves. She deals with the initial condition problem using a bivariate probit model to estimate the persistence probability. From a static point of view, she concludes that, after the 1993 recession, poverty did not decrease overall and, for households living in the South, did worsen after the crisis. Looking at the dynamics, she founds a stronger persistence for households living in the South of Italy, with an unemployed husband and whose income was further below the poverty line in 1993. In their work, Addabbo and Baldini (2000) study poverty dynamics and social transfers in Italy using the 1991, 1993 and 1995 SHIW waves. In doing this, they exploit an ordered probit model to estimate the probability of being poor for more than one poverty spell. As concerning poverty dynamics, the authors conclude that households most exposed to poverty persistence live in the South of Italy, have a larger size and a young or female head with a low educational level or a discontinuous work profile. Devicienti and Poggi (2011) study the interrelation between the dynamics of income poverty and social exclusion using the Italian component of the European Community Household Panel (ECHP) for years 1994 to 2001 (waves 1-8). They model the two processes by means of a dynamic bivariate probit model, controlling for unobserved heterogeneity and using Wooldridge (2005) type initial conditions. They find a considerable degree of state dependence in both processes and the presence of dynamic cross-effects. Devicienti et al. (2014) exploit the same dataset (ECHP 1994-2001) to estimate multiple-spell hazard rate models for income poverty and lifestyle deprivation. Among the main factors generating persistence the authors highlight the weakness of the Italian labor market, the frailty of the social security system and the deep territorial dualism. Coppola and Di Laurea (2016) focus on the Persistent at Risk of Poverty (PARP) as poverty status indicator. They examine the period at the beginning of the Great Recession (2007-2010), using data from the EU-SILC and logit model specifications to estimate the probability of being persistently poor. Also in their paper, the economic dualism, the frailty of the labor market and the inadequacy of the social security system are identified as determinants of poverty persistence. Giarda and Moroni (2017) analyze the dynamics of poverty in Italy comparing them with those in Spain, France and the UK. They use the longitudinal component of the EU-SILC for the period 2009-2012, estimating a dynamic random effects probit model and dealing with the initial condition issue à la Heckman (1981) and using the extension provided by Hyslop (1999). They find for Italy that past poverty status increases of 15.9% the probability of being poor. This effect decreases to 12.1% when adding regional dummies in the econometric specification, thus the authors conclude that the higher degree of GSD found for Italy, with respect to the other European countries analyzed in the paper, is mainly due the regional polarization of the Italian economy.

Regarding the econometric strategy on which we rely on, apart from the original article of Cappellari and Jenkins (2004) analyzing the UK for the period 1991 to 2000, Buddelmeyer and Verick (2008) use the same model for Australia, Fusco and Islam (2012) for Luxembourg, Faye et al. (2011) for the case of Nairobi's slums, Ayllón (2013) for Spain and Fusco (2016) for the dynamics of poverty perception in Luxembourg. Variations to the original model can be found in Van Kerm (2004) for Belgium and Nilsson (2012) for Sweden twins.

1.3 Definitions, dataset and summary statistics

Data used in this paper are drawn from the Bank of Italy Survey on Household Income and Wealth (SHIW). The SHIW is one of the main sources of micro data in Italy, providing detailed information on demographics, household and individual income, labor supply, consumption and wealth. Since 1987 the survey is administered on a biannual basis (with the only exception of the wave postponed in 1998) and includes a panel component. Moreover, since 1993, it contains specific questions on intergenerational mobility. Data from 1989 onwards are freely available on the Bank of Italy's web site.

According to the survey sampling mechanism, the panel component is built including all households that had participated in at least two earlier surveys plus some of those interviewed only in the previous wave. Then, additional non-panel households are selected randomly from official registers. To give an example of this, considering the 2014 wave, 5,254 of the 8,151 households interviewed also in 2012 and 15,302 additional non-panel households were contacted. The final

2014 sample was composed of 4,459 panel (response rate of 84.9%) and 3,697 non-panel (response rate of 53.3%) households, resulting in 8,156 households of which roughly a half (54.7%) were surveyed also in the previous SHIW wave. For further details on the survey and on its panel component see the Statistical Bulletin that accompanies each SHIW wave (Bullettin (2014)). Our analysis is performed at the individual level. The SHIW income variable we use refers to yearly net household disposable income, given by the sum of net payroll income, pensions and net transfers, net self-employement income and property income. We assign to each individual his or her equivalised household income using the OECD modified equivalence scale which weights 1 the household head, 0.5 each additional adult member and 0.3 each child aged under 14. Then, we set the poverty line at the 60% of the median equivalised household income, a common choice in the literature. As a result, an individual is defined as poor if her or his equivalised income in year t is below the contemporaneous poverty line. We restrict our analysis to individuals aged between 18 and 65 and to waves from 1998 onwards. We operate the first choice to focus on working age individuals, while the latter is linked to some particular features of the survey. First, information on intergenerational mobility, which will be essential in our econometric specification, has been collected only since 1993; second, the 1997 wave has been postponed to 1998, returning the three-year 1995 to 1998 transition not homogeneous with respect to the other two-year transitions; third, some of the variables from the 1993 wave are coded in a way that makes comparisons with following waves more difficult. For these reasons, also if the panel component would be in principle available since 1989, we choice to perform the analysis on a continuous set of 8 transitions spanning from 1998 to 2014. Our final dataset results in 105,809 individual-year observations, 60,364 individuals and 26,994 households. If we consider only observations which allow to track individuals for two consecutive points in time, we have 53,789 individual-year observations, 21,874 individuals and 9,709 households.

1.3.1 Covariates

Here we introduce the regressors that will be used in our econometric specifications. We can classify our covariates in three main groups: (1) individual characteristics; (2) head of household characteristics and (3) household characteristics. Individual characteristics are gender, age and its square. Head of household characteristics are gender, age and its square, civil status, educational qualification and job market status. The head of household is defined as the household component primarily responsible for, or most knowledgeable about, the household budget. Household characteristics are: the number of income earners; the presence of children between 0 and 2 years, 3 and 5 years, 6 and 13 years, 14 and 18 years; the presence of adults aged between 65 and 75 years and with more than 75 years; the household's area of residence. In all regressions we include year-wave dummies. In order to identify the model, we will need variables affecting initial poverty and retention status but not poverty transitions. Regarding the former, as suggested by Heckman (1981), initial conditions can be instrumented using information prior the individual's labour market entry. The exclusion restrictions we use for base year poverty status are thus four variables indicating the years of education and its square of the head of household's parents. Our assumption is that parental education affect the level of household equivalised income but not its change. Regarding sample retention, we use information on the general climate of the interview reported by the interviewer to build a set of four dummy variables. We assume that a good general climate during the interview positively affect the probability of staying in the panel but does not affect conditional poverty transition probabilities. Similar choices on the set of instruments have been made by previous literature on low income and low earnings dynamics (Stewart and Swaffield (1999), Cappellari (2002), Cappellari and Jenkins (2004), Fusco and Islam (2012), Ayllón (2013)). For a more detailed description of all the variables used in this chapter refer to Table 1.1.

1.3.2 Poverty Dynamics descriptive statistics

In order to describe poverty form a dynamic point of view we use Markov first order transition matrices. In general, a first order transition matrix allows to organize observations with respect to a certain current status and the corresponding status in the previous period. In our case, we have a dichotomous variable (poverty status) which leads to four possible outcomes: an individual may be not poor in t and not poor in $t-2$; poor in year t and not poor in year $t-2$; not poor in year t and poor in year $t-2$; poor in year t and poor in year $t-2$. Table 1.2 pools all the biannual poverty transitions of our dataset from 1998 to 2014. The poverty rate in year t among those who were poor in year $t-2$ is 66.32%. This percentage is the probability of being poor conditional on being poor in the previous period and is known as poverty persistence probability. The poverty rate among individuals who were not poor in year $t-2$, known as poverty entry probability, is 6.87%. The difference between the persistence probability and the entry probability allows to compute a first measure of state dependence, knowns as Aggregate (or Raw) State Dependence (ASD), that is equal to 59.45%. It is important to clarify that RSD does not take into account individual observed or unobserved heterogeneity.

If we also consider panel attrition, an individual in a certain poverty status in year $t-2$ may be not poor, poor or missing (i.e. unobserved, not present in the survey) in year t. Table 1.2 panel B shows that the probability of attrition conditional on poverty status in year $t-2$ does not show a big difference comparing poor and non-poor individuals in the base year. The probability of attrition for individuals poor in the base year is 51.88%, while the same probability for non poor in the base year is 51.66%. This fact could suggest that poverty status is not endogenous with respect to the attrition process. Moreover, we regress the dummy for attrition (observed in year t) on the dummy for poverty status (observed in year $t-2$) to show that the two conditional probabilities are not statistically different (t-statistic for the poverty dummy is 0.20).

In order to follow the time trend of the persistence and entry probabilities, and of their differences (ASD), we now decompose transitions year-by-year. Figure 1.1 shows the pattern of the persistence probability for the period 1998 to 2014 (notice that the first point of the graph refers to transition 1998 to 2000 and is labeled as 2000, the remaining points follow the same convention). Since year 2004 the persistence probability shows an overall increasing pattern, raising of about 15 percentage points and passing from 60.4% in 2000 to 75.9% 2014, when it reaches its maximum value. This pattern has the remarkable exception of 2012. The entry probability, illustrated in Figure 1.2, ranges between 6.12% (2004) and 8.02% (2006). After a fluctuating period (2000 to 2010) it shows a sustained growth since 2010, reaching its peak of 7.98% in 2014, the maximum level since 2006. Figure 1.3 shows the time pattern of the Aggregate State Dependence. ASD ranges between 53.06% (2002) and 67.96% (2014), is increasing since 2000 with the exception of 2012 and reaches its maximum in 2014. In particular, the latter transition shows an increase of about 11 percentage points, the highest in absolute and relative terms.

1.4 Econometric strategy

In this section we outline our econometric strategy. First, we present a bivariate endogenous switching probit model which allows to take into account non-random selection into base year poverty status. Then, we also consider non-random attrition, introducing a trivariate probit model with endogenous swithcing.

1.4.1 Bivariate probit model

To model poverty transitions between two consecutive points in time, $t - 2$ and t, we first rely on an endogenous switching bivariate probit model. As already mentioned, individuals poor in the initial period of a transition may not be a random sample of the population and this may result in biased estimates for poverty dynamics. Our econometric specification tackles this point by explicitly modeling base year poverty status and letting the unobservables affecting initial condition and poverty transitions being associated through a freely estimated correlation parameter. Moreover, the switching structure of the model allows to estimate different parameters for poverty persistence and entry, and to explicitly test the presence of state dependence. The model consists of three main components: (1) an equation for base year poverty status; (2) a switching equation for current year poverty status and (3) a parameter for the correlation between the unobservables affecting these two processes. The latent poverty propensity process p^*_{it-2} of individual i in period $t-2$ is assumed to be characterized by the equation:

$$p^*_{it-2} = \beta' x_{it-2} + \mu_i + \delta_{it-2} \tag{1.1}$$

where $i = 1, ..., N$ indexes individuals, x_{it-2} is a vector of individual and household characteristics, β is the associated vector of parameters and u_{it-2} is the error term, given by the sum of an individual specific effect μ_i plus an orthogonal white noise error δ_{it-2}. The latter two terms are assumed to be normally distributed and, in particular, the error term u_{it-2} is standard normally distributed: $u_{it-2} \sim \mathcal{N}(0,1)$. This specification is analogous to assume a suitable monotonic transformation of the equivalised income process $g(y_{it-2})$, where y_{it-2} is the equivalised household income in year $t-2$ for individual i, as a function of a set of covariates plus a standard normally distributed error term, for more details on this issue see Stewart and Swaffield (1999). If the latent poverty propensity of an individual exceeds some unobservable value, which can be set to zero without loss of generality, she is observed to be poor. Consequently, we observe $P_{it-2} = 1$ if $p^*_{it-2} > 0$ and $P_{it-2} = 0$ otherwise.

The second equation of the model concerns poverty status in year t, which is assumed to be characterized by the individual latent process:

$$p^*_{it} = [(P_{it-2})\gamma'_1 + (1 - P_{it-2})\gamma'_2)]z_{it-2} + \tau_i + \zeta_{it} \tag{1.2}$$

where z_{it-2} is a vector of individual and household characteristics, γ_1 is a vector of parameters associated with poverty persistence, γ_2 is the column vector for poverty entry and the error term $\varepsilon_{it} \sim \mathcal{N}(0,1)$ is given by the sum of the individual-specific effect τ_i and a random shock ζ_{it}. We observe $P_{it} = 1$ if $p^*_{it} > 0$ and $P_{it} = 0$ otherwise.

The joint distribution of the error terms u_{it-2} and ε_{it} is assumed to be bivariate standard normal and characterized by a correlation parameters which is freely estimated through the model. Given the latter assumptions, it can be written as:

$$\rho \equiv corr(u_{it-2}, \varepsilon_{it}) = cov(\mu_i, \tau_i) \tag{1.3}$$

The parameter ρ summarizes the association between the individual unobservables affecting base year and current year poverty status.

1.4.2 Trivariate probit model

Another element which may bias poverty transition estimates is non- random panel attrition. In their model, Cappellari and Jenkins (2004) explicitly introduce panel retention in an endogenous switching trivariate probit model that is built on four main components: (1) the determination of base year poverty status to account for the initial condition issue; (2) the determination of panel retention; (3) the determination of poverty status in year t; (4) the correlations between unobservables affecting these three processes. With respect to the bivariate case, now a new equation characterizing individual latent propensity of retention between $t-2$ and t enters in the model:

$$r^*_{it} = \psi' w_{it-2} + \eta_i + \xi_{it} \tag{1.4}$$

where ψ is a vector of coefficients, w_{t-2} is a vector of retention related characteristics and the composite error term $\upsilon_{it} \sim \mathcal{N}(0,1)$ is given by the sum of a normal individual-specific effect η_i and a normal orthogonal white noise error ξ_{it}. Again, we define a dummy variable $R_{it} = 1$ if $r^*_{it} > 0$ and 0 otherwise. Notice that poverty transition is observed only if $R_{it} = 1$.

The final component of the model is a set of three correlation parameters, freely estimated given the assumption that the joint distribution of the error terms u_{it-2}, ε_{it} and υ_{it} is trivariate standard normal:

$$\begin{aligned} \rho_1 &\equiv corr(u_{it-2}, \upsilon_{it}) = cov(\mu_i, \eta_i) \\ \rho_2 &\equiv corr(u_{it-2}, \varepsilon_{it}) = cov(\mu_i, \tau_i) \\ \rho_3 &\equiv corr(\upsilon_{it}, \varepsilon_{it}) = cov(\eta_i, \tau_i) \end{aligned} \tag{1.5}$$

The correlation parameter ρ_1 summarizes the association between the individual specific factors determining panel retention and those affecting base year poverty status. A positive (resp. negative) sign indicates that individuals who are more likely to be poor in the base year are more (resp. less) likely to remain in the survey with respect to the non-poor. The parameter ρ_2 represents the correlation between the individual specific factors affecting base year poverty status and poverty transitions. A positive (resp. negative) sign indicates that individuals more likely to be poor in the base year are more (resp. less) likely to remain or fall into poverty status compared to the non-poor. Finally, ρ_3 indicates the correlation between the individual specific factors determining panel retention and conditional current poverty status. A positive (resp. negative) sign indicates that individuals who are more likely to be observed in two consecutive years are more (resp. less) likely to remain into, or fall in, poverty status.

If the parameters linking survey retention to the remaining equations of the model are equal to zero ($\rho_1 = \rho_2 = 0$), then attrition is ignorable and the model can be estimated by means of the previously described bivariate probit. In this regard, see the applications to low earning dynamics of Stewart and Swaffield (1999) for a model with endogenous selection and Cappellari (2002) for a bivariate probit model with endogenous switching. If $\rho_1 = \rho_3 = 0$ there is no initial condition issue and poverty status in $t-2$ can be treated as exogenous. Finally, if $\rho_1 = \rho_2 = \rho_3 = 0$, both the retention process and the initial poverty status may be treated as exogenous. As a consequence, in this case poverty dynamics can be estimated through simple univariate probit models for poverty entry and persistence, as in the pioneering approach on welfare receipt dynamics of Boskin and Nold (1975).

Given unconstrained equation correlations, a set of exclusion restrictions is needed to identify the model. We require variables entering in the initial poverty or retention status equation but not directly affecting conditional poverty status (i.e. variables entering the x_{it-2} or w_{it-2} vectors but not the z_{it-2} one). As already mentioned, we use the head of household parental educational background in the base year equation and the general climate of the interview in the retention equation. In order to take into account that there are repeated observations within each household and for the same individuals across time, we compute, also for the bivariate case, robust standard errors clustered at the household level.

It is important to stress that the approach used in this chapter is not the unique in the literature and different types of models, although if developed for different economic outcomes such as unemployment or earnings dynamics, have been used. We refer to covariance structure models (Lillard and Willis (1978)), hazard regression models (Stevens (1999); Devicienti and Poggi (2011)) and random effects probit models. (Arulampalam et al. (2000); Biewen (2009); Poggi (2007)). With respect to these families of models our approach presents several advantages. First, requiring pooled transitions from the same individual, the model adapts well to different designs of panel surveys. Second, the attrition is explicitly introduced in the model. Third, differently from dynamic random effects probit models, state dependence is estimated using all explanatory variables and not only through the coefficient of the lagged dependent variable. Finally, the model does not suffer from left-censoring and exploits all information from always or never poor individuals. On the other hand, pooling transitions between two consecutive points in time does not allow to control for duration dependence and the entire history of poverty is expressed by last periods individual poverty status. Moreover, the estimation is computationally more demanding with respect to random-effect probit models and candidate instruments may be difficult to find in different datasets.

1.4.3 Transition Probabilities

The probabilities of being poor at t conditional on being poor at $t-2$ (persistence probability) and of being poor at t conditional on being non poor at $t-2$ (entry probability) implied by the model are given by:

$$Pr[P_{it} = 1 | P_{it-2} = 1] = \frac{\Phi_2(\gamma_1' z_{it-2}, \beta' x_{it-2}; \rho)}{\Phi(\beta' x_{it-2})} \tag{1.6}$$

$$Pr[P_{it} = 1 | P_{it-2} = 0] = \frac{\Phi_2(\gamma_2' z_{it-2}, -\beta' x_{it-2}; -\rho)}{\Phi(-\beta' x_{it-2})} \tag{1.7}$$

where $\Phi(.)$ and $\Phi_2(.)$ represent the cumulative density functions of the univariate and bivariate standard normal distribution. In the case of the trivariate probit, the relevant correlation parameter is ρ_2.

1.4.4 State Dependence

Aggregate State Dependence (ASD) is defined as the difference between the probability of being poor in year t for those who were poor in the base year and the probability of being poor in year t for those who were not poor in the base year (i.e. the difference between poverty persistence and poverty entry probability). Using estimated parameters from the model it can be computed as:

$$ASD = \left(\frac{\sum\limits_{i \in (P_{it-2}=1)} Pr[P_{it} = 1 | P_{it-2} = 1]}{\sum\limits_{i} P_{it-2}} \right) - \left(\frac{\sum\limits_{i \in (P_{it-2}=1)} Pr[P_{it} = 1 | P_{it-2} = 0]}{\sum\limits_{i} (1 - P_{it-2})} \right) \tag{1.8}$$

Genuine State Dependence (GSD) is computed calculating, for each individual, the difference between the predicted persistence probability and the predicted entry probability from the model and then averaging across all N individuals:

$$GSD = N^{-1} \sum_{i=1}^{N} \{Pr[P_{it} = 1 | P_{it-2} = 1] - Pr[P_{it} = 1 | P_{it-2} = 0] \tag{1.9}$$

The use of the individual differences between predicted probabilities allows to control for observed and unobserved heterogeneity.

Finally, the hypothesis of absence of state dependence can be tested using the parameter vectors for poverty persistence and entry: $H_0 : \gamma_1 = \gamma_2$.

1.5 Results

1.5.1 Bivariate probit model

Table 1.3 panel A reports estimates and test statistics for the case of the bivariate probit model. The correlation parameter between unobservables affecting initial poverty status and conditional poverty status is estimated at -0.390. The unobservables affecting the two processes are thus negatively associated and this can be interpreted as a sign of Galtonian regression towards the mean (Stewart and Swaffield (1999)). A test for the exogeneity of the initial condition is strongly rejected, being the ρ parameter statistically different from zero at the 1% level. Regarding state dependence, a test for the absence of state dependence strongly rejects the null hypothesis (p-value of 0.000). ASD and GSD are computed in the way described in the previous section using model estimated parameters. ASD amounts at 59.7%, a percentage very close to that found using the transitions matrix (59.45%). GSD is equal to 39.3%, 65.8% of the ASD. Considering that GSD is equal to 65.8% of ASD, roughly two-thirds of aggregate state dependence can be explained by the causal effect of past poverty. The remaining part can be attributed to the role played by observed and unobserved heterogeneity.

As far as model parameters estimates, reported in Table 1.4, most of the γs (i.e. the parameters of the transition equation) are not statistically significant. Considering that most of the coefficients for base year poverty (reported in Table 1.6) are statistically significant and have the expected sign, the non-significance of transition parameters may be attributed to the endogeneity of the unobservables, an hypothesis validated by the strong significance of the ρ parameter. Moreover, the weaker significance of persistence parameters relative to the entry ones may be attributed to the fact that observations for individuals poor in the base year are relatively less than observation for individual non-poor in the base year. Nonetheless, the statistically significant regressors for poverty persistence are head of household age and its square, the number of income earners, the presence in the household of children aged between 6 and 13, the presence of adult individuals aged more than 76 and living in the South of Italy. Head of household age decreases the probability of remaining poor with a decreasing effect as he gets older. The presence of a children aged between 6 and 13 increases the persistence probability. Conversely, living with an adult aged more than 76 decreases the probability of remaining poor. Living in the South of Italy is positively correlated with persistence in poverty status. A controversial result is that the number of income earners, also if marginally significant, is positively correlated with poverty persistence. Regarding the determinants of poverty entry, head of household age negatively affects the probability of enter in poverty status with a decreasing effect, as for poverty persistence. Living in an household where the head is separated or divorced increases the risk of entering poverty. An educational level of the head of household higher than junior high school protect from falling into poverty. Having a head of household unemployed positively affect the probability of becoming poor. The presence of children aged between 6 and 13 or between 14 and 18 increases the entry probability. Finally, living in the South or in the Center of Italy increases the probability of enter into poverty.

1.5.2 Trivariate probit model

Table 1.3 panel B, reports model test statistics and estimates for the trivariate probit model. The correlation parameter (ρ_1) between unobservables affecting initial poverty status and panel retention is negative (-0.005) and not statistically different from zero (p-value=0.783). The correlation between unobservables affecting initial poverty status and conditional current poverty (ρ_2) is estimated at -0.419 and is statistically different from zero (p-value=0.000). A result very close to that found for the bivariate model. Finally, the ρ_3 parameter, that summarizes the association between the unobservables affecting retention and initial condition, is positive (0.306) and marginally statistically significant (p-value=0.098). A test for the exogeneity of initial condition ($\rho_1 = \rho_2 = 0$) is strongly rejected (p-value=0.000), while a test for the exogeneity of panel retention ($\rho_2 = \rho_3 = 0$) is rejected at the 10% confidence level. When considering both panel retention and initial condition ($\rho_1 = \rho_2 = \rho_3 = 0$), the null hypothesis of joint exogeneity of the two processes is rejected at the 1% confidence level. Also for the trivariate model, the hypothesis of no state dependence is strongly rejected (p-value=0.000). The amount of aggregate state dependence is estimated at 51.51%, while the amount of genuine state dependence is 32.51%. Genuine State Dependence as a percentage of Aggregate State Dependence is 63.1%. Overall, when we also consider attrition (and attritors) in our model, both ASD and GSD decreases and the percentage ratio of GSD over ASD is 2.7 percentage points lower than in the bivariate case. Overall, coefficient estimates are stable relative to the bivariate model.

Results from Cappellari and Jenkins (2004) indicate that, in Britain and for the period 1991 to 2000, GSD constitutes 59% of ASD. Concerning the same statistic, Fusco and Islam (2012) find 60% for Luxembourg and Ayllón (2013) 52% for Spain. Our estimates show higher values from both the bivariate (65.8%) and the trivariate (63.7%) model, indicating that in Italy the causal effect of past poverty is stronger than in the other analysed countries. Nevertheless, considering that our dataset allows to consider only biannual transitions, this comparison should be taken with caution.

1.6 Conclusion

In this chapter we have analyzed poverty dynamics in Italy for the period 1998 to 2014. The analysis has been performed using data from the Bank of Italy Survey on Household Income and Wealth, a biannual survey which contains a longitudinal component. Poverty has been defined in relative terms with the poverty line set at the 60% of the median equivalised household income, a choice in line with previous literature and the Eurostat indicators.

We computed summary statistics using first order transition matrices, first, pooling all the two-year transitions, then, decomposing each single transition. From the graphical analysis, we learned that the poverty persistence probability shows, since 2004, an increasing pattern, with a maximum in 2014 and a remarkable exception in 2012. The entry probability presents an oscillating pattern from 2000 to 2006 and is U-shaped in the following years, with a maximum reached in 2014. The difference between the persistence probability and the entry probability, known as Aggregate (or Raw) State Dependence is increasing since 2002, again with the exception of transition 2010-2012.

Then, we modeled poverty dynamics using the strategy provided by Cappellari and Jenkins (2004). First, we considered only non-random selection into initial poverty status, estimating an endogenous switching bivariate probit model and using parental background as our instruments. Results from this model indicate a strong and significant association between the unobservables affecting base and current year poverty status. The hypothesis of absence of state dependence is strongly rejected and Genuine State Dependence accounts for 65.8% of Aggregate State Dependence. We moved from the bivariate model, adding an equation for non-random attrition and estimating an endogenous switching trivariate probit model using the general climate of the interview as exclusion restriction. Also in this case, the exogeneity of initial condition and the absence of state dependence hypothesis have been strongly rejected, while results for the exogeneity test for panel retention are less straightforward (p-value=0.096). Estimates for the trivariate model show an higher degree of both ASD and GSD that results in a percentage of GSD over ASD of 63.1%, very similar to that calculated from the bivariate model. For what concerns observed heterogeneity, both model agree on the determinants of poverty transitions. Head of household age and living with an adult aged 76 or more negatively affect the probability of remaining poor, while having children between 6 and 13 and living in the South of Italy have a positive effect on it. Having an head of household separated or divorced and unemployed, children aged between 6 and 18, living in the Center or in the South of Italy positively affect the poverty entry probability. An head of household high educated and its age have lower chances of entering into poverty.

Our estimates showed that, in Italy, GSD plays a major role in explaining current poverty. Moreover, this role is stronger than that found for other countries in the previous literature. This result suggests that, in order to fight poverty, more resources should be allocated to income transfers rather than to policies focusing on individual heterogeneity.

This work can be improved testing if our results are robust to different specifications of the poverty line (e.g. 50% or 70% of the median income) or using absolute poverty. One of the main limitations of this chapter is that GSD has been only quantified and its source can be only conjectured. It could be interesting, for future research, to analyze the role played by subjective factors, interrelating (income) poverty dynamics with those of subjective poverty and happiness.

Variable name	Description
Dependent variable	
Poverty	dummy for individual in poverty status - poverty line set at the 60% of the median equivalised household income
Individual characteristics	
Female	dummy for individual gender (1 if female)
Age	individual age
Age squared	individual age squared
Head of household characteristics	
Female	dummy for head of household gender (1 if female)
Age	head of household age
Age squared	head of household age squared
Married (ref.)	dummy for head of household married
Single	dummy for head of household single
Separated or divorced	dummy for head of household separated or divorced
Widowed	dummy for head of household widowed
High educated	dummy for head of household with high school diploma or higher educational qualification
Pensioner or inactive (ref.)	dummy for head of household pensioner or inactive in the labour market
Employee	dummy for head of household employee
Self employed	dummy for head of household self-employee
Unemployed	dummy for head of household unemployed
Household characteristics	
Number of income earners	number of individuals at work within the household
Children aged 0-2	dummy for kid(s) in the household aged between 0 and 2
Children aged 3-5	dummy for kid(s) in the household aged between 3 and 5
Children aged 6-13	dummy for kid(s) in the household aged between 6 and 13
Children aged 14-18	dummy for kid(s) in the household aged between 14 and 18
Adult aged 65-75	dummy for household component(s)aged between 65 and 75
Adult aged 76+	dummy for household component(s) aged more than 75
North (ref.)	household lives in the North of Italy
Center	household lives in the Centre of Italy
South	household lives in the South of Italy
Instruments for base year poverty	
HH father's education	head of household father's years of education
HH father's education squared	head of household father's years of education squared
HH mother's education	head of household mother's years of education
HH mother's education squared	head of household mother's years of education squared
Instruments for panel retention	
Climate 1 (ref.)	dummy for general climate of the interview rated 1 or 2
Climate 2	dummy for general climate of the interview rated 3 or 4
Climate 3	dummy for general climate of the interview rated 5 or 6
Climate 4	dummy for general climate of the interview rated 7 or 8
Climate 5	dummy for general climate of the interview rated 9 or 10

Table 1.1: List of variables and description

Year	t		
	panel A		
	Not poor	Poor	Missing
$t-2$			
Not poor	93.13	6.87	-
Poor	33.68	66.32	-
All	81.45	18.55	-
	panel B		
	Not poor	Poor	Missing
$t-2$			
Not poor	45.02	3.32	51.66
Poor	16.20	31.92	51.88
All	39.34	8.96	51.71

Table 1.2: Poverty status at t conditional on poverty status at $t-2$ (row %). Pooled transitions from the SHIW, waves from 1998 to 2014. Poverty line set at the 60% of the median equivalised household income. Adults aged between 18 and 65. Missing data at t arise from sample attrition. Sample size is 53,789 individual-year observations (panel A) and 105,809 individual-year observations (panel B). Analytical weights used.

	Estimate or test statistic	p-value
Panel A: bivariate probit model		
Correlation coefficient		
Initial and conditional current poverty (ρ)	-0.442	0.000
State Dependence		
No state dependence $\gamma_1 = \gamma_2$ (d.f.=30)	432.90	0.000
Aggregate State Dependence (ASD)	0.597	
Genuine State Dependence (GSD)	0.393	
GSD as a % of ASD	65.8%	
Panel B: trivariate probit model		
Correlation coefficients		
Initial poverty status and retention (ρ_1)	-0.005	0.783
Initial and conditional current poverty (ρ_2)	-0.419	0.000
Retention and conditional current poverty (ρ_3)	0.306	0.098
Test for exogeneity of initial conditions and retention		
Initial condition ($\rho_1 = \rho_2 = 0$)	20.31	0.000
Retention ($\rho_1 = \rho_3 = 0$)	2.77	0.096
Both retention and initial condition ($\rho_1 = \rho_2 = \rho_3 = 0$)	28.86	0.000
State Dependence		
Absence of State Dependence $\gamma_1 = \gamma_2$ (d.f.=30)	273.37	0.000
Aggregate State Dependence (ASD%)	0.515	
Genuine State Dependence (GSD%)	0.325	
GSD as a % of ASD	63.1%	

Table 1.3: Models correlation parameters, test statistics and State Dependence.

Covariate (measured at $t-2$)	Persistence (poor at $t-2$)		Entry (non poor at $t-2$)	
	Coefficient	|t-ratio|	Coefficient	|t-ratio|
Individual characteristics				
Female	0.035	1.56	0.005	0.26
Age	0.003	0.30	-0.002	0.27
Age squared	3.25e-06	0.03	-7.94e-06	0.09
Head of Household characteristics				
Female	-0.047	0.58	-0.005	0.26
Age	-0.029	1.69	-0.046	3.01
Age squared	0.0003	1.72	0.0004	2.42
Single	0.012	0.09	0.064	0.71
Separated or divorced	-0.022	0.14	0.222	2.49
Widowed	0.079	0.65	0.109	1.14
High educated	-0.109	1.39	-0.435	8.70
Employee	0.012	0.14	-0.081	1.20
Self employed	-0.122	1.14	0.057	0.65
Unemployed	-0.004	0.03	0.248	1.70
Household characteristics				
Number if income earners	0.115	1.91	-0.044	1.19
Children aged 0-2	-0.0002	0.00	0.037	0.39
Children aged 3-5	0.151	1.50	0.007	0.08
Children aged 6-13	0.264	3.67	0.272	4.61
Children aged 14-18	0.088	1.20	0.166	2.87
Adult aged 65-75	0.001	0.01	-0.038	0.42
Adult aged 76+	-0.343	2.08	0.024	0.22
Center	0.032	0.25	0.203	2.73
South	0.293	2.95	0.669	12.26
Constant	0.732	1.56	-0.316	0.75
ρ	-0.398	5.45		
Log-likelihood	-31,458			
Number of observations	53,798			
Number of individuals	21,874			
Number of households	9,709			
Model χ^2(d.f.=91)	2556.08	(p<0.000)		

Table 1.4: Bivariate probit model with endogenous switching. Equation for current poverty status. Regression include year dummies (reference year is 1998). Reference categories for dummy variables are: male, HH male, HH married, HH education less than high school, HH pensioner or other, household with no children or elderly individuals, living in the North of Italy.

Covariate (measured at t-2)	Persistence (poor at $t-2$)		Entry (non poor at $t-2$)	
	Coefficient	|t-ratio|	Coefficient	|t-ratio|
Individual characteristics				
Female	0.033	1.47	0.006	0.33
Age	0.004	0.42	-0.002	0.29
Age squared	3.56e-07	0.00	6.83e-06	0.07
Head of Household characteristics				
Female	-0.047	0.60	-0.006	0.11
Age	-0.021	1.19	-0.038	2.46
Age squared	0.0002	1.27	0.0003	1.93
Single	-0.026	0.19	0.002	0.36
Separated or divorced	-0.043	0.27	0.196	2.23
Widowed	0.043	0.37	0.087	0.93
High educated	-0.106	1.38	-0.417	8.20
Employee	0.022	0.25	-0.07	1.06
Self employed	-0.117	1.11	0.051	0.59
Unemployed	-0.004	0.03	0.249	1.76
Household characteristics				
Number if income earners	0.111	1.88	-0.043	1.19
Children aged 0-2	-0.013	0.12	0.026	0.27
Children aged 3-5	0.154	1.57	0.013	0.14
Children aged 6-13	0.253	3.54	0.268	4.62
Children aged 14-18	1.23	0.014	0.166	2.93
Adult aged 65-75	-0.023	0.23	-0.046	0.53
Adult aged 76+	-0.307	1.89	0.044	0.41
Center	-0.004	0.03	0.176	2.36
South	0.294	3.00	0.664	12.24
Constant	0.257	0.49	-0.730	1.60
ρ_1	-0.005	0.28		
ρ_2	-0.396	5.21		
ρ_3	0.297	1.76		
Log-likelihood	-122,353.37			
Number of observations	105,809			
Number of individuals	60,364			
Number of households	26,994			
Model χ^2(d.f.=124)	4966.14	($p < 0.000$)		

Table 1.5: Trivariate probit model with endogenous switching. Equation for current poverty status. Regression include year dummies (reference year is 1998). Reference categories for dummy variables are: male, HH male, HH married, HH education less than high school, HH pensioner or other, household with no children or elderly individuals, living in the North of Italy.

Covariate (measured at $t-2$)	Base year poverty	
	Coefficient	|t-ratio|
Individual characteristics		
Female	0.10	0.66
Age	-0.005	0.73
Age squared	-0.00008	0.80
Head of Household characteristics		
Female	0.075	1.42
Age	-0.013	1.01
Age squared	0.0001	0.76
Single	-0.078	0.96
Separated or divorced	0.198	1.47
Widowed	-0.255	2.50
High educated	-0.560	11.63
Employee	-0.268	4.22
Self employed	-0.173	2.16
Unemployed	0.943	10.34
Household characteristics		
Number if income earners	-0.649	15.43
Children aged 0-2	0.337	4.34
Children aged 3-5	0.155	2.40
Children aged 6-13	0.186	3.75
Children aged 14-18	0.467	9.59
Adult aged 65-75	-0.014	0.20
Adult aged 76+	0.236	2.22
Center	0.075	0.98
South	0.882	17.63
Exclusion restrictions		
HH father years of education	-0.034	1.97
HH father years of education- squared	0.0003	0.25
HH mother years of education	-0.082	4.71
HH mother years of education- squared	0.003	2.50
Constant	1.023	2.95
Log-likelihood	-31,457.958	
Number of observations	53,798	
Number of individuals	21,874	
Number of households	9,709	
Model χ^2(d.f.=91)	2556.08	($p < 0.000$)

Table 1.6: Bivariate probit model with endogenous switching. Equation for base year poverty status. Regression include year dummies (reference year is 1998). Reference categories for dummy variables are: male, HH male, HH married, HH education less than high school, HH pensioner or other, household with no children or elderly individuals, living in the North of Italy.

Covariate (measured at t-2)	Base year poverty		Retention	
	Coefficient	|t-ratio|	Coefficient	|t-ratio|
Individual characteristics				
Female	0.21	1.91	0.008	0.98
Age	-0.014	3.18	-0.007	2.21
Age squared	0.00005	0.83	0.0002	4.03
Head of Household characteristics				
Female	0.052	1.43	-0.014	0.55
Age	-0.016	1.96	0.032	5.16
Age squared	0.0001	1.21	-0.0003	4.98
Single	-0.051	1.02	-0.145	4.03
Separated or divorced	0.182	2.40	-0.109	2.67
Widowed	-0.126	1.97	-0.03	0.64
High educated	-0.561	16.74	0.038	1.71
Employee	-0.278	6.48	0.035	1.28
Self employed	-0.213	4.03	-0.041	1.18
Unemployed	0.891	13.79	0.01	0.20
Household characteristics				
Number if income earners	-0.613	22.28	0.007	0.52
Children aged 0-2	0.327	6.48	-0.066	1.69
Children aged 3-5	0.191	4.36	0.060	1.80
Children aged 6-13	0.266	7.93	0.075	3.07
Children aged 14-18	0.468	13.91	0.035	1.39
Adult aged 65-75	0.078	1.49	0.006	0.20
Adult aged 76+	0.182	2.40	0.078	1.70
Center	0.129	2.70	-0.103	3.64
South	0.878	26.97	0.112	4.51
Exclusion restrictions				
HH father years of education	-0.022	1.84		
HH father years of education- squared	0.0002	0.32		
HH mother years of education	-0.093	7.53		
HH mother years of education- squared	0.004	4.63		
Climate 2			0.237	2.05
Climate 3			0.354	3.57
Climate 4			0.555	5.73
Climate 5			0.674	6.99
Constant	1.213	5.63	-1.407	7.29
Log-likelihood	-122,353			
Number of observations	105,809			
Number of individuals	60,364			
Number of households	26,994			
Model χ^2(d.f.=124)	4966.14	($p < 0.000$)		

Table 1.7: Trivariate probit model with endogenous switching. Equations for current poverty status and panel retention. Regression include year dummies (reference year is 1998). Reference categories for dummy variables are: male, HH male, HH married, HH education less than high school, HH pensioner or other, household with no children or elderly individuals, living in the North of Italy.

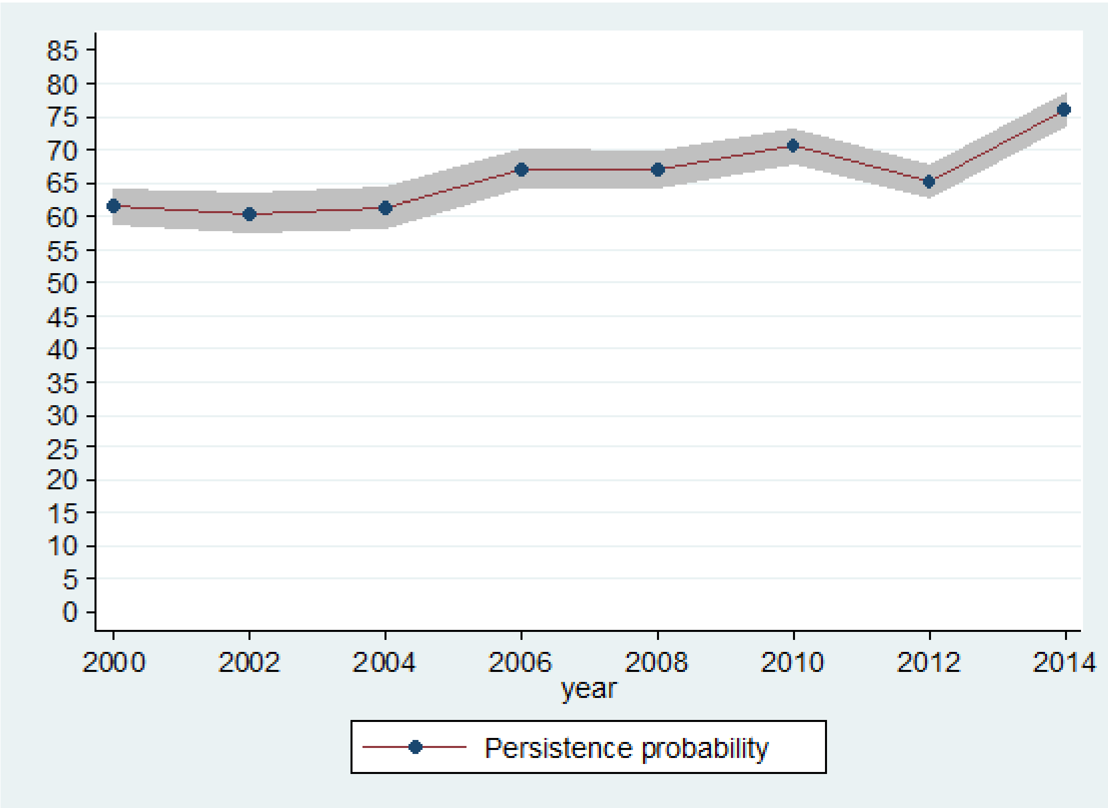

Figure 1.1: Conditional probability of being poor in period t given being poor in period $t-2$ (persistence probability) - SHIW waves 1998 to 2014. Poverty line set at the 60% of the median contemporary equivalised household income. Analytical weights assumed - 95% confidence interval.

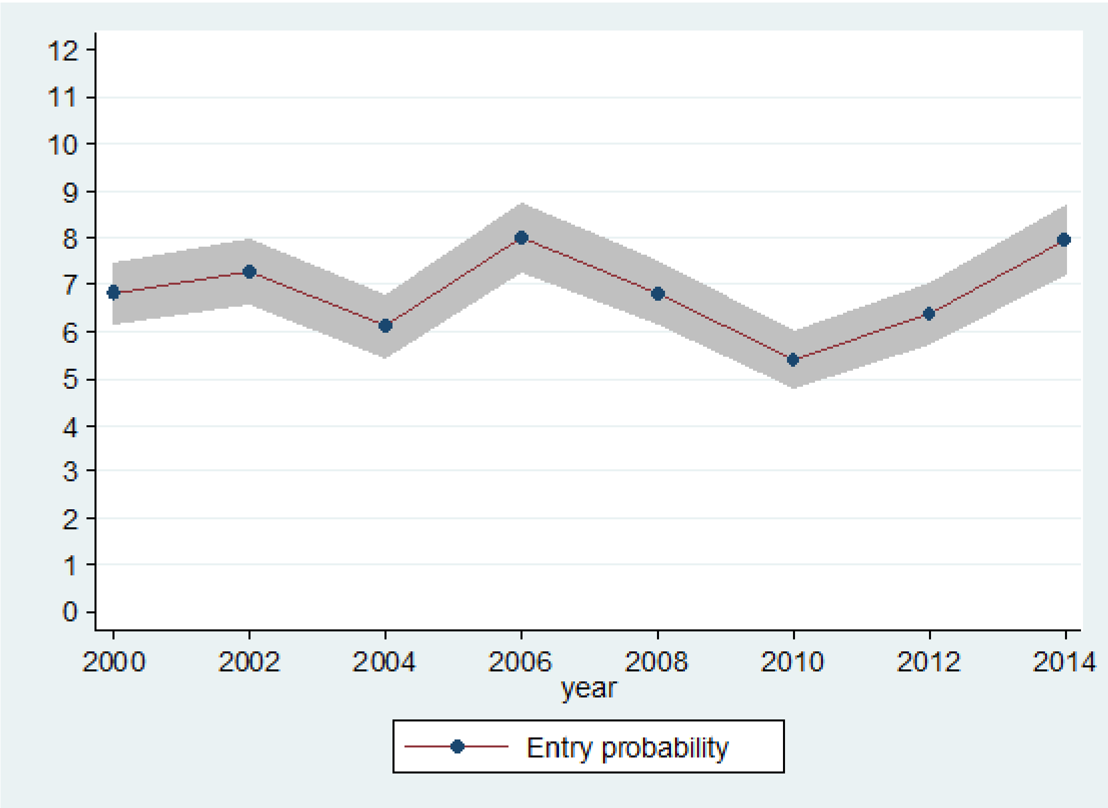

Figure 1.2: Conditional probability of being poor in period t given being not poor in period $t-2$ (entry probability) - SHIW waves 1998 to 2014. Poverty line set at the 60% of the median contemporary equivalised household income. Analytical weights assumed - 95% confidence interval.

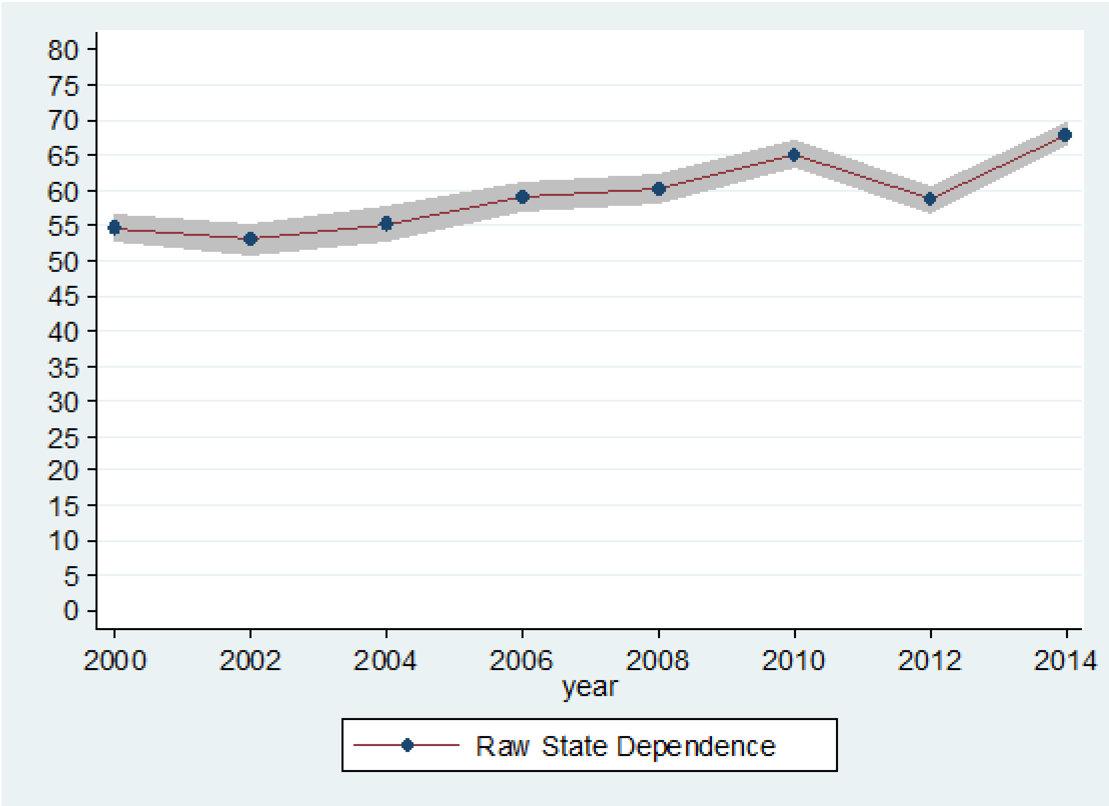

Figure 1.3: Raw State Dependence - SHIW waves 1998 to 2014. Poverty line set at the 60% of the median contemporary equivalised household income. Analytical weights assumed - 95% confidence interval.

Chapter 2

Do Tax Rebates Affect Perceived Economic Hardship? Evidence from Italy

2.1 Introduction

In this chapter we investigate the causal effect of fiscal policy on perception of households regarding their own economic situation. To do this, we examine a national massive tax rebate introduced in Italy in 2014 using data from the Bank of Italy Survey on Household Income and Wealth (SHIW). Our analysis relies on a difference-in-differences (DD) methodology and shows that households who benefited from the policy experienced an improvement of their ability to make ends meet and a reduction in perceived economic hardship.

Past literature has mainly focused on the causal impact of fiscal stimulus on household consumption responses. In this work, we approach this subject taking one step back and showing that economic policy has, *per se*, an impact on households perception. We argue that investigating this effect is relevant for, at least, three reasons. First, it could lead to a better comprehension of the structural mechanism through which fiscal policy impacts on behavior. If households are not liquidity constrained, only those who experience an improvement of their perceived financial situation may respond in terms of consumption. At the same time, the magnitude of this effect may vary according to individual perception, which may act as a consumption multiplier for fiscal policy. We think that these mechanisms may be key to understand the success of the economic policy. Second, considering that self-assessed financial situation is often used as a welfare or standard of living indicator, analyzing the mechanism through which economic policy affects individual perception has important implications for households well-being. Third, considering the specific time setting of the tax rebate under investigation (two months after the appointment of a new Government and one month before the 2014 European elections), our work could be linked to the literature analyzing political business cycles.

This chapter is organized as follows. Section 2 presents the policy under investigation. Section 3 reviews the literature concerning the effects of income changes due to public policy on consumption responses and that analyzing the dynamics of perceived financial difficulties. Section 4 introduces the dataset and analyzes the specific elements concerning the tax bonus in the 2014 SHIW survey. Section 5 presents the econometric strategy, illustrates the results and deals with the robustness checks of our analysis. Finally, section 6 concludes.

2.2 The tax bonus

The result of the primary election of the main majority party led to the formation of a new Government in February 2014. One of the first proposals of the new appointed Prime Minister, Matteo Renzi, was to introduce a monetary transfer with the aim of counteracting the effects of the economic crisis by increasing household consumption. This proposal was formally announced to the press the 12th of March and licensed by the Government as a tax bonus with the Decree Law 66/2014 the 24th of April. Finally, the policy effectively came into force in May 2014. Considering the amount of the bonus and the surname of the Italian prime minister, the tax bonus is also known in the Italian public debate as "Renzi bonus" or "80 euro". Bonus recipients were individuals, employed, with a total gross annual income between €8,145 and €26,000. The bonus resulted, in the standard case, in an increase in the individual's salary of €80 per month, directly provided in the individual's pay check at the end of each month. Individuals who earned between €24,000 and €26,000 received a decreasing amount of the bonus according to the formula: Bonus=80*(26,000-gross income)/2,000 €. Therefore, eligibility was determined by individual total gross income and a household could have had none, one or more than one bonus recipient. Moreover, the delivery mechanism was completely automatic, consisting in a reduction of the tax withheld on behalf of the employee by the employer. In 2015 the measure became permanent.

Several factors contributed to the design of the allocation rule. First, employees were chosen as recipients to pay the bonus directly in their pay check. Second, the minimum threshold was set to avoid the withholding agent to pay the transfer out of pocket to individuals who earned so little that they do not pay taxes.

Third, the reduction after €24,000 and the upper income limit were set for equity reasons. According to the official statistics of the Italian Ministry of Economy and Finance, 11.6 million individuals received the tax credit in 2014, resulting in a transfer of €6 billion. Moreover, 1.4 million individuals had to return the bonus back when filing the 2015 income tax return, between April and June. This may have happened for two reasons. The first one is that the bonus was based on 2014 gross income, precisely known only at the end of 2014. Secondly, the bonus was calculated according to the months spent as employee (e.g. if an individual worked for 9 months she was entitled to receive only two thirds of the bonus). Another information known at the end of the fiscal year.

2.3 Literature review

The general framework of our work is the literature analyzing the response of consumption to changes in income, for a review see Jappelli and Pistaferri (2010). More in detail, our work is related to the literature using survey data to test whether changes in household income induced by fiscal policy affect household consumption expenditure. This literature can be divided into two branches (Neri et al. (2017)). One of them directly exploits questions on how the respondents declared of having used, or are planning to use, the extra funds received from the rebate. Using this information, the marginal propensity to consume (MPC) from the rebate is estimated. Examples of this approach are Shapiro and Slemrod (2003a), Shapiro and Slemrod (2003b), Shapiro and Slemrod (2009) and Sahm et al. (2010). These papers analyze the effects of the 2001 and 2008 tax cuts in the US using questions added to the University of Michigan Survey of Consumers.

They estimate the MPC from the tax rebate being about one-third. Leigh (2012) studies the impact of the 2009 Australian fiscal stimulus, showing that 40% of respondents declared having spent the household stimulus payment, with a resulting MPC of about 0.42. Graziani et al. (2013) analyze an Internet sample of workers to estimate the effects of a tax cut. They find that 35% of individuals have spent the majority of the amount received from the tax cut, with a resulting average MPC of about 36%. Kan et al. (2017) study the 2009 Taiwan Shopping Voucher Program using survey data and finding that the MPC is about 25%. A different branch of the literature uses directly information on expenditure contained in micro data to estimate household spending response to rebates. Johnson et al. (2006) and Parker et al. (2013) analyze, respectively, the impact of the 2001 and 2008 fiscal stimulus packages introduced in the US on consumption expenditures using the Consumer Expenditure Survey (CE). Johnson et al. (2006) find that household spent from 20% to 40% of their rebates on nondurable goods during the three months period in which their rebates arrived and the 66% considering also the following three months period. Moreover, they find stronger responses for low liquid wealth or low income households. Parker et al. (2013) report that households spent from 12% to 30% of their payments on nondurables during the three-month period of payment receipt, and a significant larger amount on durables, estimating a total response from 50% to 90% of the payment.

For what concerns the perception of economic hardship, Fusco (2016) investigates the issue of state dependence in perceived financial difficulties using an endogenous switching trivariate probit model and data from Luxembourg for the period 2003-2009. Ayllón and Fusco (2017) analyze the interrelated dynamics of income poverty and poverty perceptions using Luxembourg survey data. Both papers exploit the survey make ends meet question to measure subjective financial hardship. This chapter is also linked to the literature on the relationship between public policy and well-being (Layard (1980); Layard (2006); Frey and Stutzer (2000)).

There are several working papers that analyze the Renzi bonus. Gagliarducci and Guiso (2015) study the effect of the bonus on consumption expenditure, adopting an RDD strategy and ISTAT data on consumption matched with fiscal data to detect bonus recipients. An additional contribution on the specialized press is provided by Pinotti (2015). Andini et al. (2017) are working on machine learning targeting of the bonus using SHIW data. In Neri et al. (2017), the authors exploit a propensity score matching difference-in-differences strategy, finding effects of the bonus on food consumption and expenditure on means of transportation.

2.4 Data and summary statistics

We use data from the Bank of Italy Survey on Income Household and Wealth (SHIW). The SHIW is one of the main sources of microeconomic data in Italy, providing detailed information on household demographics, income, consumption, labor supply, real and financial wealth. It is administered on a biannual basis and contains a longitudinal component of roughly half of the households surveyed in a given wave (i.e. in 2014 8,156 households were surveyed but only 4,459 of them were surveyed also in 2012). Moreover, the 2014 wave contains specific items on the Renzi bonus in the questionnaire module devoted to household consumption. We use the panel component from waves 2012 and 2014 to estimate the causal effect of the tax rebate on households perception of financial hardship in a difference -in-differences framework. In order to test the common trend hypothesis, we also exploit previous SHIW waves up to 2002.

2.4.1 Dependent variable

We use as our outcome variable the survey element on self-assessed household general economic situation. The question directly asks: *"Is your household's income sufficient to see you through to the end of the month? 1. with great difficulty; 2. with difficulty; 3. with some difficulty; 4. fairly easily; 5. easily; 6. very easily."* This information is available since 2002, the answer is given at the household level and it is possible to know by which household member (i.e. the respondent may not be the head of household). Table 2.1, Panel A shows the distribution of the make ends meet question ($memq$) for the balanced 2012-2014 household panel component. The distribution of perceived economic status seems not to vary so much by years but, to show that some variation across categories of perceptions do exists, we build a transition matrix reported in Table 2.1, Panel B. To sum up, our dependent variable is a categorical variable that indicates household's ability to make ends meet, it ranges from 1(lowest ability) to 6(highest ability) and has been collected in the SHIW since 2002. In the further analysis, we introduce a second outcome variable through a dichotomization of the aforementioned make ends meet question. We do this for two reasons. First, to focus on needier households and second, in order to have a simpler interpretation of our results through the use of dichotomous outcome probability models. We thus generate an indicator for financial hardship as a dummy variable which equals one if an household makes ends meet with great difficulty ($memq = 1$) or with difficulty ($memq = 2$) and 0 otherwise ($memq > 2$). Summary statistics and the corresponding transition matrix for this financial hardship indicator are reported in Table 2.2.

2.4.2 The tax bonus in the SHIW

The 2014 SHIW wave contains specific questions on the Renzi bonus in the questionnaire section devoted to household consumption. All interviews have been conducted between January and July 2015 and refer to 2014 information. In this section we introduce and present summary statistics for these survey items. *Bonus* is a dummy indicating if anyone in the household has benefited from the tax rebate in 2014. $Numbonus$ contains information on the number of individuals within the household who have received the bonus. *Ammbonus* is a continuous variable indicating how much (in terms of euros) the household has received overall each month. $Comebonus1$, $Comebonus2$ and $Comebonus3$ shows, in percentage terms, which fraction of the overall bonus has been devoted to, respectively, consumption, savings and debt repayment. *Anbonus* is a variable specifying for how many years the respondent (the question is asked both to recipients and non-recipients) expects the bonus will be paid. $Anbonus1$ is a dummy for the expected remaining on force of the bonus and equals one if the respondent expects that the bonus is a permanent measure.

In our dataset, we have 1,514 households in which there is at least one member who has received the bonus, corresponding to 21.87% of the Italian households. Of the households who received the bonus (treated households), 84.28% have one member who received the bonus, 14.46% two members, 0.92% three members, 0.26% four members and 0.07% five members. These figures do not match with those reported by the Ministry of Finance in 2015 and based on tax declarations.

Even if we consider that roughly 1/6 of treated households have more than one individual entitled to receive the bonus, the corresponding number of recipients does not reach 11.3 million individuals reported by official statistics. Data clearly suffer from under-reporting. Several features of the bonus recipients distribution could be compared with official tax return data in order to exclude a non-random under-reporting. Considering that we have treated individuals in the control group (i.e. individuals who benefit from the bonus but did not report this information to the interviewer), our estimates will represent a lower bound of the true effect. As far as the amount of the bonus, obviously we found a probability mass in its distribution at €80 (67.57%). Considering that the bonus is given on an individual basis, that the household can have more than one bonus perceiver and that the amount of the bonus linearly decreases between €24,000 and €26,000, other values are possible apart from €80. Regarding the way in which the respondents reported to having used the bonus, households devoted, overall, 87% to consumption, 10% to savings and 3% to the repayment of debt. Concerning the expected remaining in force , 50.31% of households expect the measure to be permanent. The remaining households think that the bonus will be paid just for one year (1.80%), for two years (14.90%), for three years (16.18%), for four years (10.05%) or for more than four years (6.74%).

Table 2.3 provides further evidence on the relation between household income and the tax bonus for year 2014. Row (1) shows the percentage of households with at least one bonus recipient by quintiles of the equivalised household income distribution. This percentage is, for the first and the fifth quintile, quite similar (17%) and smaller than those of the other quintiles; this fact can be explained by the design of the bonus that excluded individual incomes below €8,145 and above €26,000. At the same time, the percentage of recipient households increases from the second (24.2%) to the fourth (32.8%) quintile, where we find the highest percentage of bonus recipients. Rows (2) and (3) display the mean household and equivalised household income by income quintile. Rows (4) and (5) present the mean of our dependent variables. As expected, the make ends meet question shows an increasing pattern by income quintile, while the percentage of households in perceived financial hardship is a decreasing function of income quintile. Row (6) computes the percentage increase in household income implied by the bonus. Recipients households in the first quintile observed an increase in their annual income of 4.2% , this percentage is decreasing by quintile and reaches 1.3% for the fifth quintile. Finally, in row (7), we calculate the monthly amount of the bonus for recipients households by income quintile. The monthly amount increases from the first to the fourth quintile, passing from €79.5 to 91 €and turning back to €86.4 for the fifth quintile. This figure can be explained by the fact that the probability of having more than one employee increases in household income. The monthly amount is smaller in the fifth quintile because of the upper threshold prescribed by the design of the policy. Finally, in row (8), we show the percentage of the bonus amount spent for consumption by quintile as declared by bonus recipients. A clear pattern does not emerge, however, while the three bottom quintiles of the distribution declared of having spent a percentage greater or equal than 90%, the remaining two quintiles declared a substantial smaller percentage (78.2% for the fourth and 83.3% for the fifth).

2.4.3 Control variables

In some model specifications, which will be introduced in the following section, we add variables to control for observed individual and household characteristics. Individual characteristics refer to the household head and are age (and its square), gender, civil status (single, separated, widowed, reference is married), educational level (dummy for education higher than lower middle school) and job market status (employee, self-employee, unemployed, pensioner, reference is inactive in the labour market). Household level variables are the number of children between 0 and 3 years, 4 and 10 years and 11 and 17 years; the number of individuals between 18 and 59 years, 60 and 74 years and with more than 74 years; the area of residence (Center and South and Islands, reference is North of Italy); the quintile of the yearly equivalised household income distribution and the number of income perceivers. Summary statistics for these controls, along with those for two outcome variables, are reported in Table 2.4.

2.5 Econometric strategy

In order to estimate the causal effect of the tax bonus on household perceived economic situation, we exploit a difference-in-differences (DD) approach and OLS:

$$memq_{it} = \alpha + \lambda post_t + \gamma treat_i + \beta post_t * treat_i + x_{it}^{'}\delta + \varepsilon_{it} \tag{2.1}$$

where $memq_{it}$ is the categorical variable ranging from 1 to 6 and indicating the household's self-assessed economic situation, α is a constant term, $post_t$ is a dummy variable equal to one if year is 2014 and 0 otherwise, $treat_i$ is a dummy variable equal to one if the household has at least one member who received the bonus and zero otherwise, $post_t * treat_i$ is their interaction and x_{it} is a set of control variables. Moreover, to validate our analysis, we estimate an ordered probit model (OP) in a DD framework using the same variables of specification 2.1. The resulting model is:

$$memq^*_{it} = \lambda post_t + \gamma treat_i + \beta post_t * treat_i + x^{'}_{it}\delta + \varepsilon_{it} \tag{2.2}$$

where, differently from equation 2.1, $memq^*_{it}$ indicates the latent process and $memq_{it} = j$ if $\eta_{j-1} < memq^*_{it} \leq \eta_j$ with $j = 1, ..., 6$.

Then, we focus on the probability of being in financial hardship, dichotomizing the categorical variable $memq_{it}$ and, analogously with the previous analysis, estimating both a linear probability model (OLS) and a probit model:

$$hardship_{it} = \alpha + \lambda post_t + \gamma treat_i + \beta post_t * treat_i + x^{'}_{it}\delta + \varepsilon_{it} \tag{2.3}$$

$$hardship^*_{it} = \alpha + \lambda post_t + \gamma treat_i + \beta post_t * treat_i + x^{'}_{it}\delta + \varepsilon_{it} \tag{2.4}$$

Differently from the previous specifications, the dependent variable is now a dummy variable which equals one if household i, at time t, makes ends meet with great difficulty or difficulty and zero otherwise.

In all our regressions, our parameter of interest is β and, under the assumption that in the absence of the program the trend of the perceived financial hardship would not have been systematically different between treated and non-treated households, it represents the causal effect of the tax bonus on perceived financial hardship.

2.5.1 Results

We estimate our models on a balanced panel of 4,459 households of which 864 received the bonus in 2014. We observe households in 2012 and 2014, for a total of 8,918 household-year observations. Results for the parameter of interest from the DD estimations for models 2.1 and 2.2 are reported in Table 2.5, panel A. The first two columns present the results of the OLS. Column (1) shows that, when considering no control variables in the specification, the parameter of interest is 0.222 and statistically significant at the 1% level. When we add covariates, the parameter decreases to 0.141 and is still statistically significant at the 1% level. These numbers can be interpreted as changes in the make ends meet indicator. As a consequence, we find that the tax bonus increased, according to the econometric specification, from 0.222 to 0.141 points household's self-assessed economic situation on the indicator ranging from 1 to 6. Columns (3) and (4) report the estimates for the ordered probit (OP) model. The β estimate for the baseline specification is 0.181, while it decreases to 0.170 in the specification with controls. Both parameters are statistically significant at the 1% level. These estimates are not comparable with those from the OLS model and refer to the latent process that drives households in each of the six categories of the make ends meet indicator. In order to have a more clear interpretation of our estimates, the computation of marginal probabilities is required. Table 2.6, Panel A reports marginal effects for each of the six categories of the outcome. Columns (1) and (2) refer to the baseline

specification, while columns (3) and (4) consider the model with covariates. As pointed out by Puhani (2012), attention must be paid when estimating interaction terms in nonlinear model. Consequently, along with marginal effects computed in the standard way (Std. ME), we also compute those considering the cross difference of the observed outcome minus the cross difference of the potential non-treatment outcome (Adj. ME). In the following discussion, for the sake of brevity, and also considering that the two types of marginal effects are not so different, we refer to marginal effects computed à la Puhani (Columns (2) and (4)). Following baseline specification results, the bonus decreased of 5.2% the probability of making ends meet with great difficulty and of 1.8% that of making ends meet with difficulty. The sign for the remaining four categories, and the corresponding marginal effects, turns into positive and, remarkably, the policy increases the probability of making ends meet fairly easily of 3.9%. When adding covariates in the model the marginal effects for all the six categories are smaller but preserve the same sign pattern and are still statistically significant. In particular, the marginal effect on making ends meet with great difficulty and fairly easily is, respectively, -3.3% and +2.2%.
Table 2.8 and 2.9 illustrate full estimates for all the four models having the make ends meet variable as their outcome. Education, employment status and the ranking in the income distribution positively affect household's make ends meet ability. On the other hand, an head of household single, separated or widowed, unemployed and living in the South or Center of Italy are negatively correlated with the answer to the make ends meet question.
Results for the DD of the binary outcome on the binary treatment (models (3) and (4)) are reported in Table 2.7, panel A. Columns (1) and (2) show the results for the linear probability model. In the baseline specification the parameter of in-

terest is -0.078 and is statistically different from zero at the 1% level of confidence. Adding covariates its value decreases to -0.052 but it remains significant at the 5% level. These coefficients can be directly interpreted as the causal effect of the bonus on the probability of being in perceived economic hardship. Overall, we find that the bonus reduced from 7.8% to 5.2% the probability of being in perceived economic hardship. Columns (3) and (4) report the corresponding estimates for the probit model. Also in this case, the parameters have not a direct interpretation and we have to refer to marginal probabilities, reported in Table 2.6, Panel B. Our estimates substantially confirm the results of the linear probability model, indicating that the bonus reduced from 7.8% to 5.0% the probability of being in economic hardship. Tables 2.10 and 2.11 illustrate full estimates for the OLS and Probit models. An head of household separated or divorced, widowed, living in the South of Italy and unemployed are positively correlated with perceived financial hardship, while being high educated, self-employee, pensioner or in higher income quintiles negatively affect the probability of being in hardship.

2.5.2 Robustness checks

In this subsection we show the robustness of our results in two ways. First, we perform a placebo test running the DD estimations on the balanced panel of households observed in years 2010 and 2012 assigning the treatment status in 2012, one time period before the introduction of the reform. Treated (and non treated) households are identified through the bonus question included in wave 2014 and the treatment is assigned to those household who effectively received the bonus in 2014. Because of the survey design, we are not able to observe all the 2012 and 2014 panel households also in the period 2010-2012. As a consequence, the number of observations decreases from 8,918 to 5,788 household year-observations and the estimates of our placebo test are not performed on the same sample of the result shown in Table 2.5 and Table 2.7, panel A. Considering that the real treatment occurred in 2014, we expect the β coefficients of our estimates being not statistically significant. Results for this placebo test are reported in Table 2.5, Panel B for the make ends meet question and in Table 2.7, panel B for the financial hardship dummy. In all the resulting estimates, the casual parameters of interest are not statistically different from zero significant at any level of confidence. This results strongly supports our estimates of the causal effects of the bonus. Second, as already mentioned, considering that we are not able to follow all the 2014 households in past SHIW waves, we (re)estimate the DD models on the new placebo sample composed of 5,788 household year-observations for the period 2012-2014 and assigning the treatment in 2014. Now we expect the coefficient being statistically significant and indicating, again, the casual effect of the bonus. Results for this counter-placebo test (i.e. DD on the placebo sample for the period 2012-2014) are reported in Tables 2.5 and 2.7, Panel C. Also if, in some cases, the significance of the β parameters decreases (in particular for the models with controls), the causal effect of the bonus (re)appears in our results. The smaller statistical significance can be due to the fact that, in performing this exercise, we loose a substantial amount of observations, reducing, accordingly, the precision of our estimates.

2.5.3 Common trend assumption

The identification assumption of our models strongly relies on the fact that, in the absence of the tax reform, the trend of perceived financial hardship would not have been systematically different between treated and non-treated households. In this subsection we provide evidence that this hypothesis seems to be realistic in our data. It is important to remember that, given the sample design, we are not able to go back in time with the same observations of the estimation sample. For this reason, we test the common trend in two different ways. First, we use all information from 2002 (the first wave in which the make ends meet question is available) up to 2014 and, for each wave, we keep only those households also surveyed in 2014. The treatment status is assigned, in all time periods, on the basis of having received the bonus in 2014. Figure 2.1 illustrates the trend in the make ends meet ability for treated (blue line) and non-treated (red line) households for the period 2002 to 2014. The figure shows that the two groups have the same pattern for waves previous to 2014, when we observe a re-ranking in average self-assessed perception between treated and control groups. Second, considering that the pattern of Figure 2.1 is computed on time-varying samples, we aggregate observations for years 2010, 2012 and 2014 creating a balanced panel for the households continuously observed from 2010 onwards. It is important to notice that this sample is the same used to estimate the results reported in Table 2.5 and Table 2.7, panels B and C. The results of this exercise are illustrated in Figure 2.2. Also in this case, the common trend hypothesis seems to hold, the pattern is parallel for the period 2010-2012 and the overtaking of the period 2012-2014 is more pronounced.

We proceed analogously for the dichotomized outcome variable for perceived financial hardship. Considering the way in which this variable has been created, it represent the percentage of households in financial hardship in each time period. As a consequence, differently from the make ends meet indicator, an increasing pattern for average financial hardship translates in a worsening of household perceptions. Results for the longer period are shown in Figure 2.3. In this case, in particular before 2010, the validity of the common trend hypothesis from a graphical inspection appears with less evidence. From 2002 to 2004 the pattern shows the same sign but is steeper for treated household, from 2006 to 2010, conversely, the pattern is diverging. Considering the shorter period (2010-2014) Figure 2.4 shows that, in this case, the parallel trend hypothesis holds.

2.5.4 Heterogeneity analysis

We perform an heterogeneity analysis of the causal effect of the bonus exploiting the survey items on individual's beliefs about the persistence of the policy (*Anbonus* and *Anbonus1*) and the declared use of the tax credit (*Comebonus1-3*) contained in the 2014 SHIW wave. Regarding the expectation about the remaining in force of the policy, we divide treated households in two groups: the first group (*treat1*) includes households in which the respondents expect that the bonus is a permanent measure, while the second one (*treat2*) is composed by households who believe that the policy has a limited duration. Analogously, concerning the use that households made with the amount of the tax rebate, we differentiate treated households in two groups: the first group (*treat1*) is for households who spent only part of the bonus for consumption, using the remaining amount for saving or debt repayment, the second one (*treat2*) concerns households who devoted all the bonus amount to consumption.

The resulting models to estimate such heterogeneous effects on the ability to make ends meet are, also in this case, an OLS:

$$\begin{aligned} memq_{it} = \alpha + \lambda post_t + \gamma_1 treat1_i + \gamma_2 treat2_i + \beta_1 post_t * treat1_i \\ + \beta_2 post_t * treat2_i + x'_{it}\delta + \varepsilon_{it}; \end{aligned} \tag{2.5}$$

and an Ordered probit model:

$$\begin{aligned} memq^*_{it} = \lambda post_t + \gamma_1 treat1_i + \gamma_2 treat2_i + \beta_1 post_t * treat1_i \\ + \beta_2 post_t * treat2_i + x'_{it}\delta + \varepsilon_{it} \end{aligned} \tag{2.6}$$

Results for these models are reported in Table 2.12. Panel A illustrates the estimates related to the expected duration of the bonus. The baseline OLS specification shows that individuals who perceived the bonus as non-permanent measure experienced a larger increase in the ability to make ends meet. The coefficient associated with them, β_2=0.251, is in fact larger than that associated with treated households who expect the measure to be permanent (β_2=0.194). However, adding control variables, the causal effect becomes identical for the two groups (0.140). A similar result is obtained using the Ordered probit model, also if, in this case, the specification with controls shows a slightly larger magnitude for the group who expects the policy to be permanent ($\beta_1 = 0.178 > 0.161 = \beta_2$). Panel B reports the results for the percentage of the bonus spent for consumption. These estimates show a more clear pattern, illustrating that households who spent the whole amount of the rebate for consumption experienced a smaller increase in the ability to make ends meet with respect to households who were able to allocate a part of the bonus also to savings or debt repayment. This conclusion ($\beta_2 < \beta_1$) is robust to model specification and the inclusion of covariates in the regressions.

In the same spirit of the previous analysis, we also perform DD regressions on the dummy variable for financial hardship, by means of an OLS:

$$\begin{aligned} hardship_{it} = \alpha + \lambda post_t + \gamma_1 treat1_i + \gamma_2 treat2_i + \beta_1 post_t * treat1_i \\ + \beta_2 post_t * treat2_i + x'_{it}\delta + \varepsilon_{it}; \end{aligned} \tag{2.7}$$

and a Probit model:

$$\begin{aligned} hardship^*_{it} = \alpha + \lambda post_t + \gamma_1 treat1_i + \gamma_2 treat2_i + \beta_1 post_t * treat1_i + \\ \beta_2 post_t * treat1_i + x'_{it}\delta + \varepsilon_{it} \end{aligned} \tag{2.8}$$

The results of this analysis are reported in Table 2.13. Concerning the remaining in force of the bonus (Panel A), the magnitude of the effect on perceived economic hardship seems to be larger for those households who perceived the policy as non-permanent. Moreover, considering that the β_1 coefficient is never statistically significant at any confidence level, we find a causal and negative effect of the bonus only for this sub-group of households. Finally, analyzing the results for the use of the bonus (Panel B), we learn that those households who were able to devote only a fraction of the bonus to consumption experienced a sensible larger increase, with respect to households who spent all the bonus for consumption, of their perceived economic situation ($\beta_1 > \beta_2$ in all the specifications).

2.6 Conclusion

In this chapter we examined the effects of a massive tax rebate on household's self-assessed financial hardship. We relied on DD estimations, using data from the Bank of Italy Survey on Household Income and Wealth (SHIW). Results for self-assessed make ends meet indicate that the bonus had a positive and statistically significant effect on household perception. Using OLS, this effect ranges from 0.222 (for the baseline model) to 0.141 (model with controls) points on the *memq* indicator. Using an Ordered probit model, we calculated that the bonus decreased of 5.2% the probability of make ends meet great difficult and increased of 3.9% the corresponding probability for the category *fairly easily*. Adding covariates, this effects are, respectively, -3.3% and +2.2%. After that, we focused on the probability of being in financial hardship, dichotomizing the make ends meet question. Overall, we find that, according to the econometric specification, the bonus decreased from 5% to 7.8% the probability of perceive financial difficulties. Placebo tests, that exploit information from 2010 and assign the treatment status in 2012, do not show, for all of the econometric specifications and as expected, statistically significant coefficients for the causal effect of interest. Moreover, as an additional robustness check, we performed DD estimations on the sample used for the placebo test. The result of this test shows that the causal effect of interest is -again- statistically different from zero. We attribute the lower statistical significance of these estimates to the loss of information implied by the survey design. Graphical tests on the common trend assumption show that the patterns of the means of the outcome variables for treated and non treated households seems to be parallel. The latter evidence is less clear when considering the binary variable for economic hardship. Then, we studied if the causal effect differs according to household's expected beliefs about the persistence of the policy and considering the bonus allocation. Regarding the latter point, households who were able to allocate only a part of the bonus to consumption experienced a larger increase in their perceived ability to make ends meet. The descriptive evidence suggest that wealthier households who received the bonus devoted a smaller fraction to consumption. As a consequence, when receiving the bonus, they had the chance to choice how to allocate it, receiving higher benefits from the policy. At the same time, these recipients may have seen the bonus as an unexpected source of income, altering their reaction to the policy. This evidence could also explain the re-ranking observed in Figure 2.1 and suggests that the policy has not been well targeted. Concerning the expected remaining in force of the policy, the evidence is less clear and does not allow to infer that the bonus had a different impact for the two groups.

This work can be improved, and extended, in several directions. First, the issues related to the miss-reporting of the bonus could be better understood using the SHIW-HFCS 2014, a SHIW complementary survey that allows to use information on gross incomes, and microsimulation models. Second, the common trend hypothesis could be tested more rigorously using an event study approach. Third, with the availability of the new SHIW 2016 wave, we will be able to track treated individuals for one more point in time, thus improving our analysis. Finally, electoral data could be used to investigate if there is a causal link between the bonus and the electoral consensus obtained by the incumbent party.

Panel A: distribution

year	with great difficulty	with difficulty	with some difficulty	fairly easily	easily	very easily	Total
2012	18.92	17.89	29.49	25.79	5.67	2.23	100.00
2014	19.98	17.86	29.96	24.08	6.46	1.66	100.00
Total	19.45	17.87	29.72	24.94	6.06	1.95	100.00

Panel B: transition matrix

			make ends meet 2014				
make ends meet 2012	with great difficulty	with difficulty	with some difficulty	fairly easily	easily	very easily	Total
with great difficulty	57.62	25.81	14.08	2.20	0.26	0.02	100
with difficulty	27.07	35.91	30.29	5.35	1.02	0.35	100
with some difficulty	8.54	17.41	49.95	22.57	1.42	0.12	100
fairly easily	1.36	5.64	24.99	54.66	11.41	1.95	100
easily	0.66	3.00	14.76	40.20	34.34	7.03	100
very easily	1.62	0.00	0.00	24.78	42.30	31.30	100
Total	18.69	18.07	30.10	24.96	6.48	1.70	100

Table 2.1: Distribution of the self-assessed household ability to make ends meet and transition matrix. Percentages. Balanced panel sample composed of 8,918 household-year observations. Analytical weights assumed.

	Panel A: mean	
year	hardship	
2012	36.8	
2014	37.8	
Total	37.3	

	Panel B: transition matrix	
	2014	
	non hardship	hardship
2012		
non hardship	84.65	15.35
hardship	26.5	73.5
total	63.25	36.75

Table 2.2: Summary statistics for the dummy variable indicating household financial hardship and transition matrix. Balanced panel sample composed of 8,918 household-year observations. Percentages. Analytical weights assumed.

Quintile of the equivalised household income distribution	(1st)	(2nd)	(3rd)	(4th)	(5th)	total
(1) Bonus recipients	0.170	0.244	0.282	0.328	0.166	0.236
	(0.376)	(0.430)	(0.450)	(0.470)	(0.372)	(0.425)
(2) Household income	12270.4	20592.5	26901.3	36014.4	62036.7	30870.6
	(6496.3)	(7642.4)	(9359.4)	(12508.7)	(35117.3)	(24474.9)
(3) Eq. household income	6572.8	12159.7	16805.0	22132.4	38297.5	18745.6
	(2701.8)	(1363.5)	(1312.0)	(1768.5)	(17977.1)	(13546.1)
(4) memq	1.615	2.343	2.919	3.433	4.120	2.842
	(0.812)	(0.953)	(0.960)	(0.897)	(0.973)	(1.266)
(5) hardship	0.825	0.520	0.296	0.121	0.051	0.378
	(0.380)	(0.500)	(0.457)	(0.327)	(0.220)	(0.485)
(6) Delta income	0.042	0.029	0.026	0.020	0.013	0.026
	(0.016)	(0.011)	(0.011)	(0.009)	(0.006)	(0.014)
(7) Monthly bonus amount	79.5	83.1	86.3	91.8	86.4	85.9
	(19.3)	(29.0)	(33.3)	(36.3)	(32.7)	(31.5)
(8) Consumption	0.900	0.934	0.905	0.782	0.833	0.870
	(0.281)	(0.209)	(0.262)	(0.380)	(0.353)	(0.307)

Table 2.3: Descriptive statistics for the relation between income, make ends meet, financial hardship and the tax bonus (by equivalised household income quintile). Year 2014. Estimation sample. Standard deviations in parenthesis. Analytical weights assumed.

Variable	Obs	Mean	Std. Dev.	Min	Max
make ends meet	8918	2.8616	1.2670	1	6
hardship	8918	0.3732	0.4837	0	1
age	8918	56.3698	16.1378	19	101
female	8918	0.4618	0.4986	0	1
single	8918	0.1553	0.3622	0	1
separated or divorced	8918	0.0839	0.2773	0	1
widowed	8918	0.1599	0.3665	0	1
high educated	8918	0.4872	0.4999	0	1
children aged 0-3	8918	0.0697	0.2843	0	3
children aged 4-10	8918	0.1801	0.4766	0	4
children aged 11-17	8918	0.1986	0.4908	0	4
adults aged 18-59	8918	1.4021	1.1921	0	6
adults aged 60-74	8918	0.4283	0.6922	0	3
adults aged 75+	8918	0.2420	0.5119	0	4
number of income earners	8918	1.5888	0.7065	1	5
north	8918	0.4513	0.4978	0	1
center	8918	0.1731	0.3784	0	1
south	8918	0.3755	0.4843	0	1
employee	8918	0.3926	0.4884	0	1
self-employee	8918	0.0916	0.2885	0	1
unemployed	8918	0.0529	0.2239	0	1
pensioner	8918	0.2853	0.4516	0	1
income quintile	8918	2.9733	1.4223	1	5
household income	8918	31022.69	23780.45	-20000	440199.1
equivalised household income	8918	18777.60	13038.97	-13333.33	220099.6

Table 2.4: Summary statistics for dependent and control variables. Years 2012 and 2014 pooled. Balanced sample composed of 8,918 household-year observations Analytical weights assumed.

make ends meet	(1) OLS	(2) OLS	(3) OP	(4) OP
Panel A: DD estimations				
$post_t * treat_i$	0.2222***	0.1410***	0.1809***	0.1698***
	(0.0536)	(0.0506)	(0.0442)	(0.0741)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.0016	0.4994	0.0002	0.2138
Panel B: placebo test				
$post_t * treat_i$	0.0188	0.0355	0.0191	0.0473
	(0.0712)	(0.0690)	(0.0588)	(0.0829)
Controls	NO	YES	NO	YES
Observations	5,788	5,788	5,788	5,788
Households	2,894	2,894	2,894	2,894
R-squared	0.0042	0.4734	0.0009	0.1998
Panel C: DD on placebo sample				
$post_t * treat_i$	0.1924***	0.0978*	0.1534***	0.1222*
	(0.0636)	(0.0581)	(0.0524)	(0.0715)
Controls	NO	YES	NO	YES
Observations	5,788	5,788	5,788	5,788
Households	2,894	2,894	2,894	2,894
R-squared	0.0011	0.5188	0.0003	0.2266

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Difference-in-differences estimations. Dependent variable is self-assessed ability to make ends meet. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Panel A: balanced panel for years 2012 and 2014, 8,918 household-year observations. Panels B and C: balanced panel for years 2010, 2012 and 2014, 5,788 household-year observations. Analytical weights assumed.

	(1) Std. ME	(2) Adj. ME	(3) Std. ME	(4) Adj. ME
Panel A: Ordered probit model				
with great difficulty	-0.0497	-0.0519	-0.0323	-0.0330
	(0.0122)	(0.0130)	(0.0116)	(0.0120)
with difficulty	-0.0187	-0.0176	-0.0096	-0.0092
	(0.0047)	(0.0043)	(0.0035)	(0.0033)
with some difficulty	0.0030	0.0055	0.0012	0.0019
	(0.0013)	(0.0026)	(0.0006)	(0.0011)
fairly easily	0.0385	0.0388	0.0218	0.0223
	(0.0095)	(0.0095)	(0.0079)	(0.0081)
easily	0.0183	0.0173	0.0125	0.0121
	(0.0045)	(0.0042)	(0.0045)	(0.0043)
very easily	0.0086	0.0077	0.0064	0.0059
	(0.0023)	(0.0020)	(0.0024)	(0.0021)
Controls	NO	NO	YES	YES
Panel B: Probit model				
hardship	-0.0785	-0.0778	-0.0497	-0.0495
	(0.0253)	(0.0253)	(0.0222)	(0.0222)
Controls	NO	NO	YES	YES

Table 2.6: Marginal effects. Panel A: ordered probit model. Panel B: Probit model. Column (1) standard marginal effects for the baseline specification, column (2) adjusted marginal effects for the baseline specification, column (3) standard marginal effects for the specification with controls, column (4) adjusted marginal effects for the specification with controls. Standard errors in parenthesis.

hardship	(1) OLS	(2) OLS	(3) Probit	(4) Probit
Panel A: DD estimations				
$post_t * treat_i$	-0.0776***	-0.0516**	-0.2078***	-0.1961**
	(0.0250)	(0.0233)	(0.0672)	(0.0876)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.002	0.3632	0.0016	0.3182
Panel B: placebo test				
$post_t * treat_i$	0.0092	0.0028	0.0234	-0.0416
	(0.0333)	(0.0318)	(0.0912)	(0.1213)
Controls	NO	YES	NO	YES
Observations	5,788	5,788	5,788	5,788
Households	2,894	2,894	2,894	2,894
R-squared	0.0027	0.3393	0.0021	0.3102
Panel C: DD on placebo sample				
$post_t * treat_i$	-0.085***	-0.0557**	-0.2304***	-0.2018*
	(0.0301)	(0.0280)	(0.0816)	(0.1080)
Controls	NO	YES	NO	YES
Observations	5,788	5,788	5,788	5,788
Households	2,894	2,894	2,894	2,894
R-squared	0.0022	0.3762	0.0017	0.3365

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Difference-in-differences estimation. Dependent variable is a binary indicator for financial hardship that equals one if household makes ends meet with difficulty or with some difficulty. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Panel A: balanced panel for years 2012 and 2014, 8,918 household-year observations. Panels B and C: balanced panel for years 2010, 2012 and 2014, 5,788 household-year observations. Analytical weights assumed.

make ends meet	(1) OLS		(2) OLS with controls	
	Coefficient	SE	Coefficient	SE
post ∗ treat	0.222***	-0.0536	0.140***	-0.0506
treat	-0.124**	-0.0613	-0.116**	-0.0484
post	-0.0887***	-0.025	-0.00542	-0.0229
Individual characteristics				
age			-0.0155*	-0.00854
age2			0.000136*	-0.0000756
female			-0.0169	-0.0361
single			-0.0953*	-0.0558
separated or divorced			-0.314***	-0.0618
widowed			-0.201***	-0.0562
high educated			0.151***	-0.0354
Household characteristics				
children aged 0-3			-0.0762	-0.0544
children aged 4-10			0.0528	-0.0357
children aged 11-17			0.0982***	-0.0333
adult aged 18-59			-0.00128	-0.0248
adult aged 60-74			0.0245	-0.0399
adult aged 75+			0.116**	-0.0502
number of income earners			0.0121	-0.0296
center			-0.0733*	-0.0434
south			-0.279***	-0.0385
employee			0.0437	-0.0569
self-employee			0.227***	-0.0697
unemployed			-0.328***	-0.0743
pensioner			0.145***	-0.0532
income quintile			0.529***	-0.0145
constant	2.907***	-0.0306	1.691***	-0.258
R-squared	0.002		0.3632	
N	8918		8918	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: DD regression results from the OLS model. Full estimates. Dependent variable is self-assessed ability to make ends meet. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Column (1) baseline regression, column (2), specification with controls. Analytical weights assumed.

make ends meet	(1) OP		(2) OP with controls	
	Coefficient	SE	Coefficient	SE
post ∗ treat	0.181***	-0.0442	0.170***	-0.0609
treat	-0.106**	-0.0501	-0.142**	-0.0585
post	-0.0727***	-0.0206	-0.00775	-0.0278
Individual characteristics				
age			-0.0200*	-0.0103
age2			0.000175*	-0.0000908
female			-0.019	-0.0432
single			-0.11	-0.0675
separated or divorced			-0.399***	-0.0775
widowed			-0.243***	-0.0683
high educated			0.183***	-0.0424
Household characteristics				
children aged 0-3			-0.106	-0.0672
children aged 4-10			0.0622	-0.0435
children aged 11-17			0.114***	-0.0404
adult aged 18-59			0.00144	-0.0312
adult aged 60-74			0.0354	-0.0494
adult aged 75+			0.138**	-0.0613
number of income earners			0.0134	-0.0365
center			-0.0895*	-0.0511
south			-0.336***	-0.0459
employee			0.054	-0.0687
self-employee			0.264***	-0.083
unemployed			-0.516***	-0.112
pensioner			0.170***	-0.0634
income quintile			0.616***	-0.0188
Pseudo R-squared	0.0016		0.3182	
N	8918		8918	

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.9: DD regression results from the Ordered probit model. Full estimates. Dependent variable is self-assessed ability to make ends meet. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Column (1) baseline regression, column (2), specification with controls. Analytical weights assumed.

hardship	(1) OLS		(2) OLS with controls	
	Coefficient	SE	Coefficient	SE
post ∗ treat	-0.0776***	-0.025	-0.0516**	-0.0233
treat	0.0068	-0.026	0.0041	-0.0222
post	0.0285***	-0.0107	0.00142	-0.0103
Individual characteristics				
age			0.00325	-0.00369
age2			-0.0000282	-0.0000328
female			-0.00177	-0.0159
single			0.0359	-0.0242
separated or divorced			0.0942***	-0.0281
widowed			0.0617**	-0.0258
high educated			-0.0281*	-0.0163
Household characteristics				
children aged 0-3			-0.0064	-0.0259
children aged 4-10			-0.00211	-0.0169
children aged 11-17			-0.0311**	-0.0155
adult aged 18-59			0.0129	-0.0107
adult aged 60-74			0.0253	-0.0164
adult aged 75+			-0.0293	-0.0222
number of income earners			-0.0103	-0.0135
center			0.00146	-0.0175
south			0.102***	-0.0176
employee			-0.0356	-0.0262
self-employee			-0.0906***	-0.03
unemployed			0.118***	-0.0338
pensioner			-0.0843***	-0.0236
income quintile			-0.167***	-0.00622
constant	0.367***	-0.0118	0.783***	-0.111
R-squared	0.002		0.3632	
N	8918		8918	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.10: DD regression results from the OLS model. Full estimates. Dependent variable is a dummy indicator for financial hardship. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Column (1) baseline regression, column (2), specification with controls. Analytical weights assumed.

hardship	(1) Probit		(2) Probit with controls	
$post * treat$	-0.208***	-0.0672	-0.196**	-0.0876
treat	0.018	-0.0687	0.0564	-0.0821
post	0.0747***	-0.0282	0.0122	-0.0411
Individual characteristics				
age			0.00955	-0.0133
age2			-0.0000743	-0.000119
female			0.022	-0.0625
single			0.15	-0.0945
separated or divorced			0.386***	-0.105
widowed			0.222**	-0.0962
high educated			-0.145**	-0.0605
Household characteristics				
children aged 0-3			-0.000585	-0.0926
children aged 4-10			-0.000346	-0.0617
children aged 11-17			-0.115**	-0.0567
adult aged 18-59			0.0359	-0.0389
adult aged 60-74			0.0738	-0.0647
adult aged 75+			-0.142	-0.0876
number of income earners			-0.0354	-0.0509
center			0.0216	-0.0731
south			0.354***	-0.0595
employee			-0.0602	-0.0928
self-employee			-0.337***	-0.121
unemployed			0.448***	-0.137
pensioner			-0.225***	-0.0828
income quintile			-0.576***	-0.0244
constant	-0.341***	-0.0313	0.919**	-0.395
Pseudo R-squared	0.0016		0.3182	
N	8918		8918	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11: DD regression results from the Probit model. Full estimates. Dependent variable is a dummy indicator for financial hardship. Treatment is a binary indicator that equals one if at least one individual in the household received the bonus. Column (1) baseline regression, column (2), specification with controls. Analytical weights assumed.

make ends meet	(1) OLS	(2) OLS	(3) OP	(4) OP
Panel A: expected duration of the bonus				
$post_t * treat1_i$	0.1938***	0.1403**	0.1597***	0.1777**
	(0.0706)	(0.0671)	(0.0577)	(0.0813)
$post_t * treat2_i$	0.2512***	0.1402**	0.2023***	0.1612**
	(0.0728)	(0.0687)	(0.0605)	(0.0819)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.0019	0.4970	0.0006	0.2138
Panel B: % of the bonus spent for consumption				
$post_t * treat1_i$	0.3892***	0.2815***	0.3100***	0.3199***
	(0.1132)	(0.1014)	(0.0914)	(0.1155)
$post_t * treat2_i$	0.1890***	0.1116**	0.1555***	0.1393**
	(0.0580)	(0.0554)	(0.0481)	(0.0673)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.0058	0.4977	0.0018	0.2142

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.12: Heterogeneity analysis - DD estimations. Dependent variable is self-assessed ability to make ends meet. Analytical weights assumed.

hardship	(1) OLS	(2) OLS	(3) Probit	(4) Probit
Panel A: expected duration of the bonus				
$post_t * treat1_i$	-0.0580	-0.0416	-0.1553	-0.1612
	(0.0354)	(0.0320)	(0.0961)	(0.1200)
$post_t * treat2_i$	-0.0981***	-0.0621**	-0.2616***	-0.2322**
	(0.0316)	(0.0305)	(0.0845)	(0.1137)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.0062	0.3619	0.0052	0.3176
Panel B: % of the bonus spent for consumption				
$post_t * treat1_i$	-0.1541***	-0.1200**	-0.5175***	-0.5700**
	(0.0521)	(0.0518)	(0.1723)	(0.2231)
$post_t * treat2_i$	-0.0622**	-0.0376	-0.1636**	-0.1422
	(0.0272)	(0.0251)	(0.0716)	(0.0924)
Controls	NO	YES	NO	YES
Observations	8,918	8,918	8,918	8,918
Households	4,459	4,459	4,459	4,459
R-squared	0.0062	0.3619	0.0052	0.3176

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.13: Heterogeneity analysis - Difference-in-differences estimations. Dependent variable is a dummy indicator for financial hardship. Analytical weights assumed.

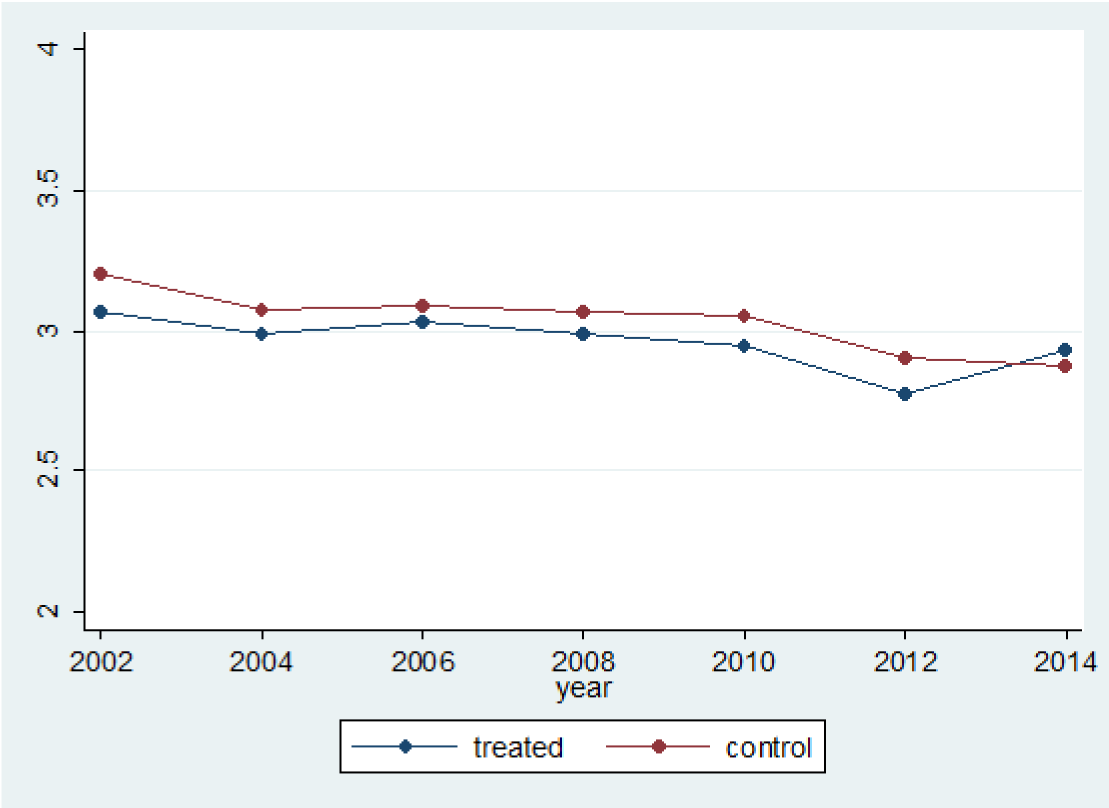

Figure 2.1: Common trend hypothesis for self-assessed make ends meet. Unbalanced panel for years 2002-2014 composed of 1,025 households in 2002 (184 treated and 841 non treated), 1,420 in 2004 (254 treated and 1,166 non treated), 1,834 in 2006 (337 treated and 1,497 non treated) 2,315 in 2008 (1,879 treated and 436 non treated), 2,894 in 2010 (552 treated and 2,342 non treated), 4,459 in 2012 (864 treated and 3,595 non treated) and 8,156 in 2014 (1,514 treated and 6,642 non treated). Analytical weights assumed.

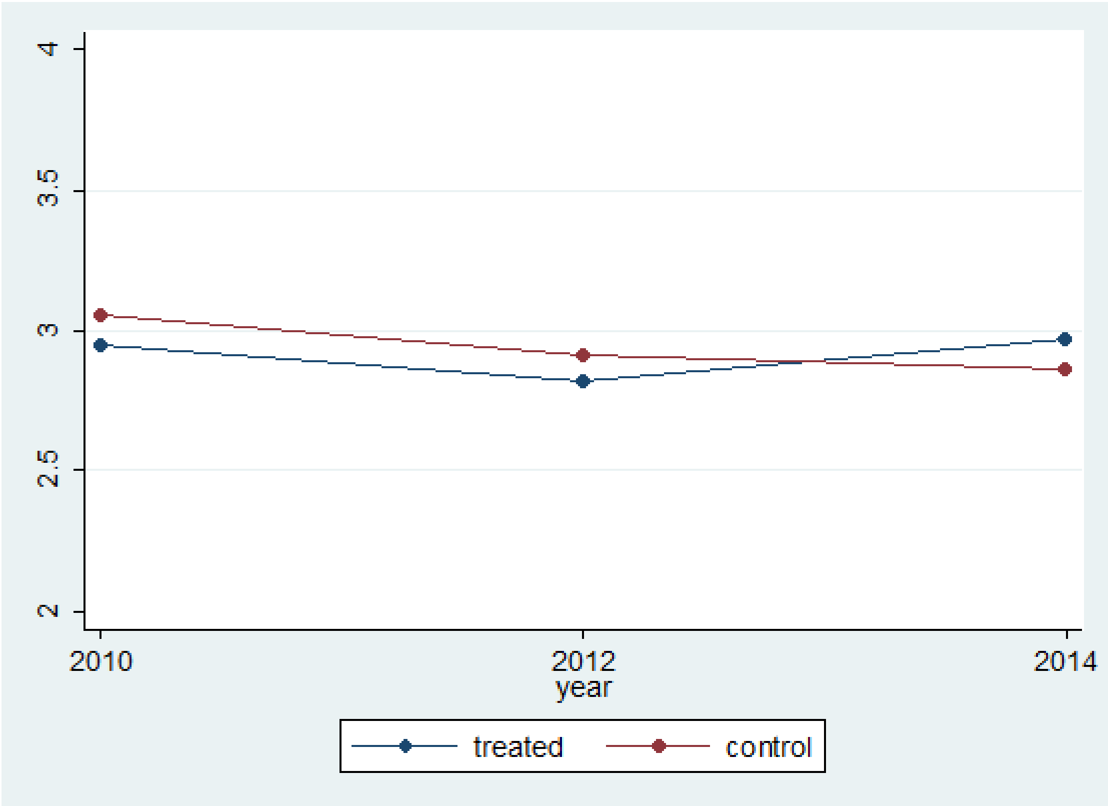

Figure 2.2: Common trend hypothesis for self-assessed make ends meet. Balanced panel for years 2010-2014 composed of 2,894 households of which 552 received the bonus and 2,342 did not receive the bonus in 2014. Analytical weights assumed.

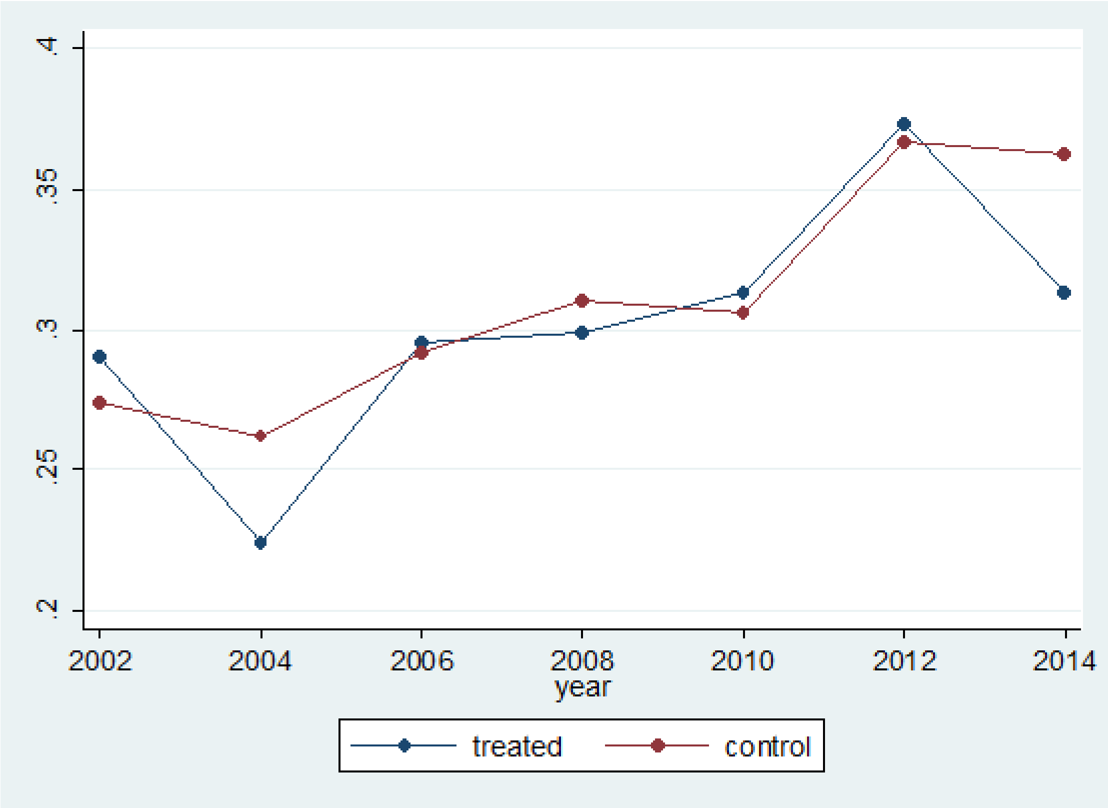

Figure 2.3: Common trend hypothesis for household perceived financial difficulty. Unbalanced panel for years 2002-2014 composed of 1,025 households in 2002 (184 treated and 841 non treated), 1,420 in 2004 (254 treated and 1,166 non treated), 1,834 in 2006 (337 treated and 1,497 non treated) 2,315 in 2008 (1,879 treated and 436 non treated), 2,894 in 2010 (552 treated and 2,342 non treated), 4,459 in 2012 (864 treated and 3,595 non treated) and 8,156 in 2014 (1,514 treated and 6,642 non treated). Analytical weights assumed.

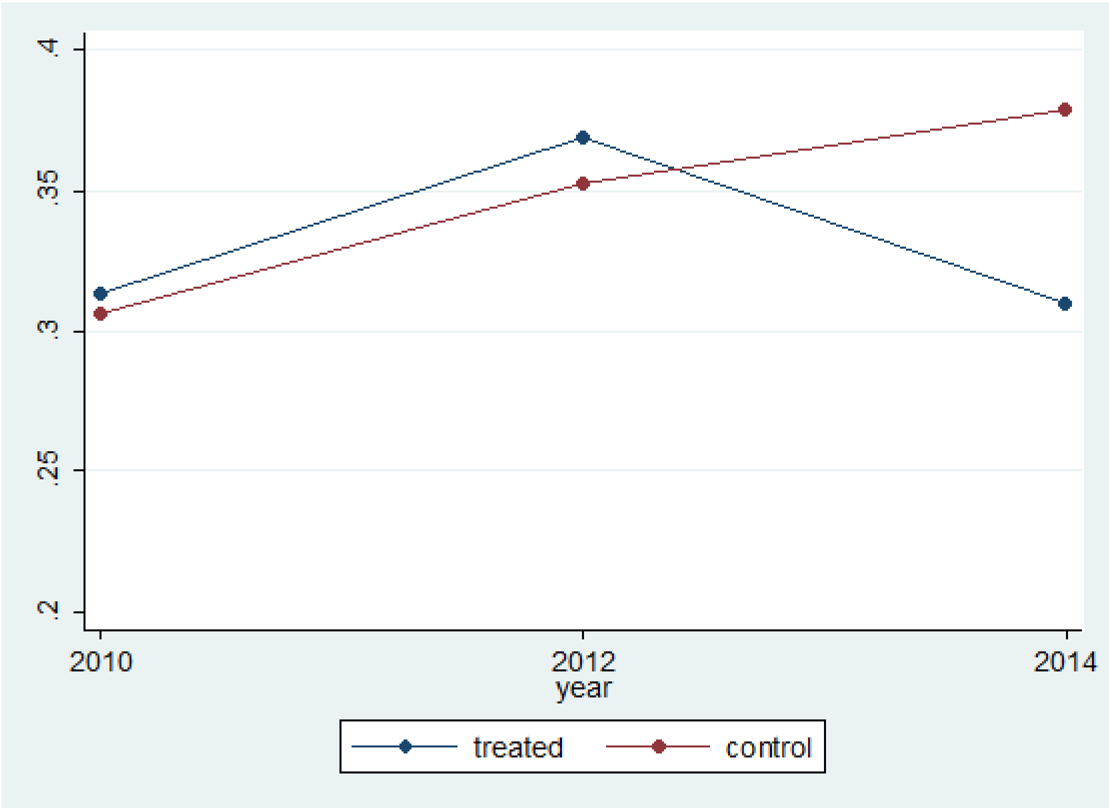

Figure 2.4: Common trend hypothesis for household perceived financial difficulty. Balanced panel for years 2010-2014 composed of 2,894 households of which 552 received the bonus and 2,342 did not receive the bonus in 2014. Analytical weights assumed.

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