State Dependence in Welfare Benefits in a Non-Welfare Context

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Abstract

This study investigates state dependence in social assistance benefit receipt in Turkey where benefit receipt and persistence rates have witnessed a significant increase over the last decade. We estimate state dependence through dynamic random effects probit models, controlling for observed and unobserved heterogeneity, and endogenous initial conditions. Particularly, we employ Wooldridge's (2005) estimator to achieve consistent and correct estimates of state dependence, and compare the results with the estimates from Heckman's (1981) reduced form approach as a sensitivity check. Both estimators enable us to deal with the potential bias due to the short panel length. Our results suggest that the benefit receipt of the last year increases the likelihood of benefit receipt in the current year by 17 to 21 percentage points. The high level of state dependence in Turkey can be explained by the inefficiencies in the benefit allocation system rather than the generosity of the benefits, as opposed to the welfare states.

JEL classifications: I30, I38, J18, C23

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1 Introduction

There is an ongoing debate in the welfare economics literature on benefit dependency. The discussions revolve around countries with generous social assistance schemes, such as Canada, Germany, the United Kingdom and Scandinavian countries. The question central to this literature is whether the generosity of the social assistance system causes dependence in benefit receipt; in other words, whether benefit receipt in the current period makes the beneficiary more likely to receive future benefits. In technical terms, it makes an attempt to ascertain *state dependence* in benefit receipt. Empirical evidence suggests a considerable level of state dependence in the aforementioned countries that are considered for discussion in this matter (see Andren and Andren, 2013; Cappellari and Jenkins, 2014; Hansen et al., 2014; Königs, 2014), with an exception of Riphahn and Wunder (2016).

The related literature from developing countries, mostly from Latin America and Africa, mainly focuses on the evaluation of anti-poverty social transfer programs (*e.g.*, Baird et al., 2011; Duflo, 2003; Edmonds and Schady, 2012; Manacorda et al., 2009). To the best of our knowledge, none of the studies in this small literature have attempted to investigate the dynamics of social assistance benefits. This could be partly because state dependence is not expected to be an issue in developing countries, given a short spell of the benefits, and partly because of the unavailability of longitudinal data. The current study contributes to the literature by analyzing the dynamics of social assistance benefits within the state dependence framework, in a developing country context. It employs a novel panel dataset from Turkey, where the role of social assistance benefits in the welfare and political arena has witnessed an increase over the last decade.[1] This period corresponds to a new term of government, led by a

[1] The existing literature in Turkey also focuses on the poverty alleviation role of social assistance benefits. In a qualitative analysis of social policies in Turkey, Buğra (2009) considers social assistance benefits as an essential tool for poverty alleviation. In an empirical work, Şeker and Dayıoğlu (2015) point to the poor and modest levels of social assistance in Turkey, and relate the comparable rates of exit from poverty with European averages to the large size of the informal economy. Aytaç (2014), on the other hand, draws attention to the political preferences in allocating the social transfers across multiple electoral districts. In relation to this, in their empirical analysis on the identification of target groups, Karagöl et al. (2013) discuss the need for revisions in eligibility criteria for benefit

single party that came into power in November 2002, after a domestically-originated economic crisis.[2]

Having experienced noticeable changes in the field of social assistance, both in quantitative and qualitative terms, Turkey assumes an interesting position in relation to the investigation of dynamics of social assistance benefits. According to the Ministry of Finance records, social expenditures financed by public sources increased fifteen-fold since 2002 and reached 32.9 billion Turkish Liras (about 10.1 billion Euro) in 2014. The share of social assistance expenditures in GDP rose to 1.73 percent in 2014, while it was only 0.5 percent in 2002.[3] Currently, 3 million households, accounting for 15.6 percent of total number of households, receive some type of social transfers.[4] Moreover, we observed a steady increase in the welfare participation rate in Turkey, contrary to the downward trend in developed countries such as Canada, the United Kingdom and the United States.[5] The increase in the welfare participation rate in the 2005-2012 period is associated with a remarkably high rate of persistence (of around 80 percent), despite a relatively low level of and constant trend in the entry rate (see Figure 4). This study seeks to determine the extent of the high observed persistence rate in Turkey that can be explained by state dependence.

This question is of particular importance from a policy-making perspective, especially in a country like Turkey that lacks a well-targeted and well-designed social safety net. The absence of nationwide rules set for benefit allocation leaves a large room for discretionary policies. The drawbacks in the system might potentially explain for the high rate of persistence in benefit receipt. On the other hand, the high persistence rate can be due to the observed and unobserved characteristics of the individual factors. If this is the case, then policies may be less effective in inducing exits from

receipt.

[2]Justice and Development Party (AKP) has recently, the fourth time, won the general elections held on November 1st, 2015 as a single government for a four-year period.

[3]Nevertheless, the ratio of social expenditures to GDP is still below the EU and OECD average, 2.5 and 2.3 percent, respectively (OECD, 2014).

[4]See the link for the reference: `http://www.maliye.gov.tr/KonusmaSunumlari/SunumMerkezi/index.html?ktp=2015YBSK`, retrieved on 24 November 2015.

[5]See Figure 1 for Turkey and Hansen et al. (2014); Cappellari and Jenkins (2008); Scholz et al. (2009) for above-mentioned countries.

social assistance and in subsequently reducing persistence and state dependence. The study, therefore, emphasizes on the need to disentangle the so-called *structural* state dependence from the spurious components that emerge from individual heterogeneity.

To accomplish this, we employ a series of dynamic random effects probit models that facilitate the control for unobserved heterogeneity. We use annual panel data from the 'Survey of Income and Living Conditions', for the period 2006-2012. Identification of structural state dependence emphasizes on the need to handle endogenous initial conditions, which if undetected could lead to a bias in parameter estimates. We deal with this problem through the employment of two empirical methods proposed by Wooldridge (2005) and Heckman (1981). We also implement an alternative specification of the Wooldridge's estimator suggested by Rabe-Hesketh and Skrondal (2013) and test whether our results are biased due to the short time span of panel.

Our results suggest that failure to control for the endogenous initial conditions leads to a serious overestimate of the state dependence. We find significant evidence of state dependence in social assistance benefit receipt, even after controlling for unobserved heterogeneity and endogenous initial conditions. The results are quite consistent among different specifications. This consistency ensures the feasibility of a state dependence analysis, based on a short panel, which is particularly important for developing countries that lack long panel data. It is found that benefit receipt in previous year increases the likelihood of receiving benefits in the current year on average by 17 to 21 percentage points. This finding is at least 3 percentage points larger than the results reported for the United Kingdom and Germany (Cappellari and Jenkins, 2014; Königs, 2014). The persistence rate is also estimated as higher, whereas the study finds a substantially lower entry rate in Turkey relative to these countries. Taken together, the strong evidence of structural state dependence in benefit receipt points out a high potential for a successful policy reform that would result in a reduction in the persistence rate.

The rest of the paper is organized as follows. Section 2 presents the data and provides descriptive statistics for trends in benefit receipt and transition rates. Section

3 introduces the empirical models before discussing the results in Section 4. Section 5 concludes the study. Appendix A provides an institutional background about the social assistance system in Turkey.

2 Data

For the analysis of state dependence in social assistance benefit receipt, the data are obtained from the 'Survey on Income and Living Conditions (SILC)', a representative longitudinal survey of households in Turkey. The panel was initiated in 2006, and the latest survey was made available in 2012. SILC is the first of its kind of panel survey that has been attempted in Turkey. The survey is designed as a rotating panel in which the sample of households and corresponding individuals are traced annually for four consecutive years. The structure design of the panel facilitates replacement of one-fourth of the sample by a new one in each year, thus three-fourths of the sample remains unchanged with respect to the previous year.

SILC involves detailed information on demographic (*e.g.*, age, education, marital status), labor force (*e.g.*, employment status, previous work information, income) and household characteristics. In a sampled household, all members are individually interviewed and one of the household members (*reference person*) fills an additional questionnaire regarding the household characteristics. This household-level survey provides relevant information related to social assistance benefits. We conduct an individual level analysis based on the reference persons, extracting the benefit receipt information from the household's recipient status. Households are used as the unit of analysis in comparable studies by Hansen et al. (2014) and Riphahn and Wunder (2016).

The outcome variable of our interest indicates whether the reference person within a household is in benefit receipt or not. In this study we focus on social assistance schemes aiming at income maintenance rather than income replacement. In particular, we exclude the contribution-based social assistance schemes such as unemployment benefits, maternal benefits, sickness allowance and retirement pension from the analysis. Therefore, to construct the outcome variable we examine the questions regarding non-contributory social transfers received by households, including family and child allowances, housing benefits, and other social benefits in cash and kind.[6]

Given the household-based eligibility criteria, we might expect that changes in the household composition and size affect the benefit recipient status. We might also expect that individual characteristics of household members are important drivers of the probability of receiving social assistance benefits. An individual level analysis –based on reference persons– allows us to control for both respondent's and partner's characteristics, as well as to deal with the compositional changes within households through divorce, repartnering, or the entry to adulthood of a dependent child (Cappellari and Jenkins, 2014; Königs, 2014).

The panel used for our analysis, beginning from the year 2006, consists of seven waves. However, as mentioned above, every individual can at the most be observed for four consecutive years. As a focus on the state dependence analysis, the study examines reference persons who were observed for at least two consecutive years during the sample period.[7] The sample is restricted to working age population (aged 15 to 64) for ruling out complications regarding the entry into the labor market and old-age pension scheme. The analysis also excludes individuals in full-time education and deletes observations with missing information on one or more control variables. We end up with a final sample of 3,450 individuals (10,239 observations) in the balanced panel and 14,383 individuals (25,222 observations) in the unbalanced panel.

2.1 Descriptive Statistics

In this subsection, we first present the trend in the share of recipients in total working age population for the period 2005-2012. Figure 1 illustrates a steady increase in the

[6]See Appendix A for the types of social assistance schemes, eligibility criteria for being in receipt and institutional structure.

[7]The sample will further be restricted to individuals observed over the entire panel period (*i.e.*, four years) as the main regression analysis relies on balanced sample. This issue is elaborated in Section 4.

rate of social assistance benefit receipt until 2009, and a relatively constant trend since then (denoted by solid line). It reaches its peak value of 18.8 percent just after the global economic crisis year of 2008, and does not fall significantly in the post-crisis period.[8]

A breakdown of different social assistance schemes is shown in the same graph. The first category is *child benefits* comprising cash and in-kind maternity allowances and conditional cash transfers related to children's health care and education (denoted by long dashed line). The second one is *housing benefits*, which involve cash allowances related to repairment and reconstruction (denoted by long dashed-dotted line). These benefits play a significant role in certain cases such as earthquake, food disaster or mining accidents. The number of respondents reporting the housing benefits receipt are negligible in our sample (less than 1 percent). The last category comprises all *other social assistance benefits* in cash and in kind, financed by public and/or private resources (denoted by dashed line). The incidence of other social assistance benefits is clearly the highest of all the social assistance schemes. However, we observe a slight decrease in the recipient rate of these transfers after 2009, which is associated with a proportional increase in the rate of child benefits recipients.

The rates of benefit receipt by household type are presented in Figure 2. While there is an upward trend for the households with dependent children (aged less than 16), those without dependent children and single-person households exhibit a relatively smooth trend with a lower rate. This implies that the rise in the overall benefit receipt shown in Figure 1 is primarily driven by the households with dependent children, which is consistent with the upward trend in child and family allowances. On the other hand, women and men seem to equally benefit from social assistance and exhibit similar patterns over the observation period, as seen in Figure 3. This is plausible, given that the recipient units are the households, not individuals –also noted by Königs, 2014.

[8] It is worthy to note that the period denoting an upward trend in benefit receipt coincides with positive economic growth, except for the year of 2009.

Examining the summary statistics presented in Table 1, one may notice the substantial variation in the amount of annual social transfers across households, ranging from 15 to 20,520 Turkish Liras. The ratio of social transfers to net household income is about 10% on average with a remarkable standard deviation. Household size and number of children in the household are notably higher among the benefit recipients than the non-recipients. The personal characteristics of benefit recipients and non-recipients also differ significantly. Female and non-employed household heads are more likely to receive social transfers. In line with expectations, the educational level of household heads and their spouses' are lower among the recipient households relative to the non-recipients. The share of individuals whose daily life is restricted due to health problems constitutes about 39% of the recipients, while it is only 22% among the non-recipients.

Lastly, we discuss the annual transition rates into and out of benefit receipts. Figure 4 displays an opposite trend in the entry and exit rates over the period. The pattern is more apparent during the recovery period of the 2008 crisis. That is, a decline in the entry rate is accompanied by an increase in the exit rate after 2009. The observed transition rates provide evidence about 'raw' state dependence in social assistance receipt –namely, the difference between persistence and entry rate (i.e., 1− exit rate). The persistence rate of around 80 percent together with the entry rate of around 5 percent indicates that every three out of four recipients in a given year continue to receive the benefits in the next year.

The raw state dependence may be due to some observed and unobserved characteristics as well as structural features of the social assistance system. The main objective of this paper is to analyze the extent to which the raw state dependence is structural. In this regard, a regression analysis is conducted in the following section to disentangle the structural state dependence from its spurious components.

3 Empirical Method

A dynamic random-effects probit model, which is largely cited in the recent empirical work, is employed to analyze state dependence in social assistance benefit (*e.g.*, Andren and Andren, 2013; Cappellari and Jenkins, 2014; Hansen et al., 2014; Königs, 2014). The model has also been applied to other binary outcomes such as poverty, labor force participation and unemployment (*e.g.*, Arulampalam and Stewart, 2009; Biewen, 2009; Chay and Hyslop, 2014; Stewart, 2007).[9] This section introduces the model mainly on the basis of these cited studies.

The latent equation for the binary outcome variable of being in receipt of social assistance is specified as:

$$\begin{aligned} y_{it} &= 1\{y^*_{it} > 0\} \\ &= 1\{\beta_0 + \beta_1 y_{it-1} + X'_{it}\Omega + \alpha_i + u_{it} > 0\} \quad \text{for (i=1,..., N; t=2,...,T)} \end{aligned} \tag{1}$$

where y_{it} is the observed binary outcome variable indicating whether the individual is in benefit receipt. $\mathbf{1}(.)$ is an indicator function equal to one if the latent variable $y^*_{it} > 0$, and zero otherwise. In other words, each individual i is observed to be in receipt in year t if the indicator function is equal to one, and to be not in receipt if it is zero. The latent variable, to be interpreted as the potential utility from receiving social assistance, depends on the lagged dependent variable (y_{it-1}), observable characteristics (X_{it}), unobserved individual-specific random effects (α_i) and a white-noise error term (u_{it}). The vector X_{it} includes the reference person's characteristics such as gender, age, age square, completed years of schooling, health problems and employment status, the spouse's educational attainment, as well as the number of children and household size.

The white-noise error term is assumed to be serially uncorrelated[10], independent

[9] An alternative estimation method might be a dynamic logit model with random effects, as implemented by Riphahn and Wunder (2016). Particularly, they use a dynamic multinomial logit model to estimate transitions between three labor market states (inactivity, employment, and welfare receipt). Given the focus of this study is not to analyze multi-state transitions, we take advantage of probit models in interpreting the results –in stead of dealing with the log odds of the outcome variable.

[10] Following the previous studies using a similar method, we assume the error term is not correlated

of X_{it} and y_{it-1}, and normally distributed. Even if the errors u_{it} are assumed serially uncorrelated, the composite error term, $v_{it} = \alpha_i + u_{it}$, would be correlated over time due to the individual-specific time-invariant α_i terms. The correlation between the composite error terms from any two different periods t and s is assumed to be the same: $\rho = Corr(v_{is}.v_{it}) = \sigma^2_\alpha/(\sigma^2_\alpha + 1)$ for $t, s = 2, ..., T; t \neq s$ and $\sigma^2_u = 1$. It is further assumed that the two error components, v_{it} and u_{it}, have zero mean and are uncorrelated with each other, the dynamic structure of benefit receipt is approximated by a first-order Markov model, and the covariates (X_{it}) are strictly exogenous.

Under these conditions, the probability that the individual i receives social assistance at time t (t>1), conditional on y_{it-1}, X_{it} and α_i, is given by:

$$Pr(y_{it} = 1|y_{it-1}, X_{it}, \alpha_i) = \Phi(\beta_0 + \beta_1 y_{it-1} + X'_{it}\Omega + \alpha_i) \tag{2}$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

The standard random effects model assumes α_i to be uncorrelated with X_{it}. Alternatively, the *Mundlak-Chamberlain* approach is employed, which allows for correlation between the unobserved individual-specific effect α_i and observed characteristics X_{it} in the model. This correlation is achieved by supposing a relationship between α_i and either time-averaged characteristics, also known as Mundlak-averages, or a combination of the variables' lags and leads. Several of the aforementioned studies, such as Cappellari and Jenkins (2008) and Königs (2014), use time-averages $(\bar{X}_i)$, describing $\alpha_i = \bar{X}'_i a + \zeta_i$ where $\zeta_i \sim N(0, \sigma^2_\zeta)$. The individual characteristics that are left in ζ_i are supposed to be independent of X_{it} and u_{it} for all i, t.

The coefficient estimate of the lagged dependent variable β_1 is the parameter of interest. To achieve the *structural* also known as *genuine* state dependence one must distinguish it from the spurious components that are induced by observed and unob-

with its past values (Cappellari and Jenkins, 2014;Königs, 2014;Hansen et al., 2014; Hansen and Lofstrom, 2009) There have also been extensions of the model that release this assumption.Stewart (2007), assumes that the error term is autocorrelated and follows an AR(1) process. He uses a Maximum Simulated Likelihood estimator to address the issue. Hyslop (1999) also assumes a serially correlated error term. He concludes that the magnitude of the correlation is found to be small.

served characteristics. The failure to control for the unobserved heterogeneity, such as unobserved labor market ability or individualistic preferences, might lead to a spuriously high level of state dependence (namely, the over estimation of β_1) (Königs, 2014). The implementation of controls for the observed and unobserved heterogeneity (via X_i and α_i, respectively) eliminates the spurious components and provides with structural state dependence.

Estimation of the structural state dependence requires an additional assumption about the initial conditions. It implies the need to specify the relationship between the individual specific effect α_i and the dependent variable in the initial period y_{i1} that typically cannot be treated as exogenous. Unless the start of the process coincides with the start of the observation period for each individual —and this is not the case— there exists a correlation between α_i and y_{i1}. This would induce the lagged dependent variable correlated with the composite error term, leading to a bias in parameter estimates. In particular, the estimator of a standard random effects probit model that assumes the absence of correlation between the initial conditions and the α_i will be inconsistent, which also leads to the overestimation of β_1 in Equation(1) (Stewart, 2007).

We deal with the problem of endogenous initial conditions using the Conditional Maximum Likelihood (CML) estimator suggested by Wooldridge (2005). We also employ an alternative specification of his estimator proposed by Rabe-Hesketh and Skrondal (2013) to deal with the potential bias in the initial conditions due to the short panel length. We compare the results with those from Heckman's (1981) reduced form approach as a sensitivity check. Heckman's estimator is introduced prior to the discussion of Wooldridge's estimator to facilitate the understanding of the empirical discussion.

3.1 Heckman's Estimator

Heckman (1981) specifies a linearized approximation to the reduced form equation for the initial value of the latent variable. Specifically, the latent variable in the initial year y_{i1}^* can be written as:

$$y_{i1}^* = \pi_0 + Z_{i1}'\pi_1 + \theta_1\alpha_i + u_{i1} \qquad (i = 1, ...N) \tag{3}$$

where Z_{i1} represents a vector of exogenous covariates including explanatory variables observed in the first wave (X_{i1}) and pre-sample characteristics that are deemed as “instruments". The explanatory variables in the vector X_{i1} include the same observed characteristics considered in the baseline regression (Equation 1). The pre-sample characteristics, on the other hand, are considered as a proxy for poverty and include the ability to afford the bills, rent and credit card payments, and unemployment status over the past year, prior to the initial sample period.

The study assumes the composite error term, $v_{i1} = \theta\alpha_i + u_{i1}$, to be correlated with α_i, but uncorrelated with u_{it} for $t \geq 2$.[11] The standard assumptions regarding the distributions of the u_{it} and α_i that they are normally distributed, the former with variance 1, the latter with variance σ_α^2 are considered, as before. Given these normalizations, the model can be estimated with maximum likelihood techniques (Stewart, 2007).

Equations (1) and (3) together specify a complete model for $(y_1, ..., y_T)$. In this model, the contribution to the likelihood function for individual i is given by: [12]

$$L_i = \int \left\{ \Phi[(Z_{i1}'\pi_1 + \theta_1\alpha)(2y_{i1} - 1)] \prod_{t=2}^{T_i} \Phi[\beta_1 y_{it-1} + X_{it}'\Omega_1 + \theta_t\alpha)(2y_{it} - 1)] \right\} g(\alpha) d\alpha$$

where $\theta_T = 1$ for identification (of σ_α^2), $g(\alpha)$ is the probability density function of the unobserved individual-specific effect, and Φ is the standard normal cumulative distribution function. The covariates are considered the same as described above. Longitudinal averages of time-varying variables $\bar{X}_i$ (*i.e.*, number of children, household size, health and employment status) are also included in the regression analysis to

[11] A test of $\theta = 0$ provides a test of exogeneity of the initial condition in this model.

[12] To simplify notation, the intercepts β_0 and π_0 in Equations (1) and (3) are not explicitly shown in the likelihood function.

allow the correlation between the observed characteristics and unobserved individual heterogeneity. For sake of brevity, $\bar{X}_i$ is subsumed in X_{it}. As in the common practice, the integral is evaluated using Gaussian-Hermite quadrature based on the assumption that α is normally distributed (Arulampalam and Stewart, 2009).

3.2 Wooldridge's Estimator

Wooldridge (2005) proposes a CML estimator in which one does not need to find the density of $(y_{i1}, ..., y_{iT})$ given the exogenous variables. Specifically, he specifies an approximation for the density of α_i conditional on the initial observation y_{i1}, and either the set of explanatory variables $X_i = (X_{i2}, ..., X_{iT})$ or averages of the X-variables over t as regressors in the model.

Wooldridge's estimator has practical advantages over Heckman's estimator that the initial dependent variable does not need to be jointly modeled with the subsequent dependent variables and that estimation can be achieved using standard random effects probit software. On the other hand, a recent study by Akay (2012) claims that the parameter estimates from the Wooldridge's estimator might be biased in applications which rely on panel data containing a small number of time periods. As a response to this concern, Rabe-Hesketh and Skrondal (2013) suggest including initial period explanatory variables in the auxiliary model (for the individual-specific effect) as additional regressors –besides the longitudinal averages and the lagged dependent variable.[13] Rabe-Hesketh and Skrondal (2013) also reveal that the Wooldridge's original auxiliary model, in which the individual-specific effect is conditioned on the lagged dependent variable and explanatory variables at periods $t = 2, ..., T$, serves as a favorable outcome. Following their proposal, we exclude the initial-period characteristics from the covariates and from their longitudinal averages, but include them only as

[13] Rabe-Hesketh and Skrondal (2013) indicate the problem with the "overly-constrained model" suggested by Akay (2012) that he includes initial period explanatory variables in the longitudinal averages. Since the conditional distribution of the unobserved effect depends more directly on the initial-period explanatory variables than on the explanatory variables at the other periods, the coefficients of the initial-period explanatory variables should not be constrained to equal the coefficients at the other periods.

additional regressors in our last specification, in Equation (6).

We begin the analysis with the Wooldridge's original model and assume the following auxiliary model:

$$\alpha_i = \varsigma_0 + \varsigma_1 y_{i1} + X_i' \varsigma_2 + a_i \tag{4}$$

where $X_i' = (X_{i2}', ..., X_{iT}')$. The correlation between y_{i1} and α_i is handled by the use of Equation (4), providing another unobservable individual-specific heterogeneity term a_i that is uncorrelated with the initial observation y_{i1}. Here and henceforth a_i is assumed to be normally distributed with mean 0 and variance σ_a^2, given the covariates in each specification.

Secondly, we employ a specification for the individual specific effect following the Mundlak-Chamberlain approach described above:

$$\alpha_i = \varsigma_0 + \varsigma_1 y_{i1} + \bar{X}_i' \varsigma_2 + a_i \tag{5}$$

where $\bar{X}_i = \frac{1}{T-1} \sum_{t=2}^{T} X_{it}$ includes time varying explanatory variables that are correlated with the unobservable α_i.

In the last specification, we add the initial-period explanatory variables (X_{i1}) to the auxiliary model as suggested by Rabe-Hesketh and Skrondal (2013). The new specification for the individual-specific effect α_i can be written as:

$$\alpha_i = \varsigma_0 + \varsigma_1 y_{i1} + \bar{X}_i' \varsigma_2 + X_{i1}' \varsigma_3 + a_i \tag{6}$$

where X_{i1} is a vector of explanatory variables in the initial year, and all other variables are as considered in Equation (5).

The probability of benefit receipt is achieved by substituting each of these three auxiliary models into Equation (2), separately. To illustrate, as for Equation (5) the probability of benefit receipt becomes:

$$Pr(y_{it} = 1 | a_i, y_{i1}) = \Phi[\beta_0 + \beta_1 y_{it-1} + \varsigma_1 y_{i1} + \bar{X}_i' \varsigma_2 + X_{it}' \Omega + a_i], \qquad (t = 2, ..., T)$$

where the constant term ς_0 is subsumed into β_0. In this model, the contribution to the likelihood function for individual i is given by:

$$L_i = \int \left\{ \prod_{t=2}^{T} \Phi[(\beta_0 + \beta_1 y_{it-1} + \varsigma_1 y_{i1} + \bar{X}_i' \varsigma_2 + X_{it}' \Omega + a)(2y_{it} - 1)] \right\} g(a) da$$

where $g(a)$ is the normal probability density function of the new unobserved individual-specific effect a_i, specified in Equation (5). The likelihood function is maximized evaluating the integral over a, using Gaussian-Hermite quadrature, which is based on the assumption that a is normally distributed.

4 Results

This section presents estimation results from the specifications described in the previous section. Given the non-linearity of the models, the magnitudes of the coefficient estimates provide little information about the size of the effects of the observable characteristics, and hence the degree of state dependence. The level of state dependence is assessed through the measure of average partial effect of benefit receipt. The next subsection elaborates on this issue.

Given the concern that sample drop out is not random, the unobservable determinants of non-response or panel attrition might be correlated with the unobservables determining benefit receipt. We therefore rely on a balanced sample analysis in which only individuals tracked over the entire panel period are kept in the operational sample. In fact, many of the previous studies use balanced panel to avoid the potential attrition bias.[14] Only a few studies rely on an unbalanced panel or a weakly balanced sample mainly due to a huge drop in the number of observations in balanced panel.[15] However, this is not a worrying issue for our analysis because a relatively shorter panel is employed for the study. Hence, the sample size remains sufficiently

[14] See Andren and Andren, 2013; Biewen, 2009; Hansen et al., 2014; Stewart, 2007.

[15] Königs (2014) deals with the attrition bias problem constructing a weakly balanced panel, while Cappellari and Jenkins (2014) rely on the finding that the impact of attrition is small in their sample, previously reported by Cappellari and Jenkins (2008).

large in the balanced panel. Hereby, the results from the Wooldridge estimator based on a balanced sample are discussed prior to comparing them with the results from the Heckman estimator.[16]

Estimation results of the dynamic random effects probit model based on the Wooldridge estimator are presented in Table 2. The first column of the table provides estimates assuming that initial conditions are exogenous, and columns 2 to 4 display the results obtained from the specifications indicated in Equations (4), (5) and (6), respectively. The coefficient estimate of the lagged recipient status, namely state dependence, lie in the narrow range between 1.37 and 1.32, and all are strongly statistically significant. This range is according to the three specifications that allow for endogenous initial conditions. The magnitude of the coefficient estimate decreases as the longitudinal averages (of time varying variables) and the initial-period explanatory variables are added to the regression.

On the other hand, the failure to account for endogenous initial conditions doubles the coefficient estimate of the lagged dependent variable (first row of column 1). The reduction in the coefficient estimate after controlling for endogenous initial conditions coincides with an increase in the estimated standard deviation of the individual-specific effect (σ_α), which is reported at the bottom of Table 2. σ_α is estimated as about 1, which translates into a cross-period correlation (ρ) in the composite error term of around 0.5. This implies that half of the variance in the composite error term comes from the permanent individual unobserved heterogeneity. As presented in the second row of Table 2, the coefficient estimate of the control for the receipt status in the initial period ($t = 1$) is positive and statistically significant. This points out that individuals who have received social assistance benefit in the initial period have a higher probability of receiving benefit in following periods. Taken together, our

[16] Conducting a similar analysis on an unbalanced panel, we find noticeably higher coefficient estimates (as well as higher average partial effects) which can be interpreted as evidence of the attrition bias leading to an overestimate of state dependence. The results from the Wooldridge's estimator and the corresponding predicted probabilities are presented in the appendix, in Table B.1 and Table B.2, respectively. We use STATA programming '*redprob*' written by Stewart (2006) for producing results of the Heckman's estimator, which is applicable only to balanced panels.

results support the evidence that the estimates based on the exogeneity assumption suffer from initial conditions bias, and this bias has the potential to overestimate the degree of state dependence.[17]

Table 3 shows the main estimation results from the Heckman's approach. Each column of the table belongs to a separate specification using different subsets of instruments to estimate the initial conditions equation. The estimates of the initial conditions regression, indicated in Equation (3), are reported in Table 4. Models 1 to 3 use various pre-sample characteristics, separately or together, as instruments, while model 4 only includes first-wave characteristics in the estimation of the initial condition equation. The pre-sample characteristics involve the information about the past unemployment status (one year prior to the first wave), and past ability to afford bills, rent and credit card payments. The coefficient estimate of the lagged dependent variable, fluctuating around 1.5, is slightly higher than the results obtained from the Wooldridge estimator. The magnitude of the coefficient estimate is not sensitive to the choice of instrument, changing the coefficients only in small margins (first row of Table 3). The consistency in the estimation results between the Wooldridge's and Heckman's approaches suggests the robustness of the results. Moreover, the lower coefficient estimates (and average partial effect) from the Wooldridge's estimator relative to the Heckmans' implies that the Wooldridge estimates are unlikely to suffer from an upward bias due to using a short panel.

The models presented in Table 2 and Table 3 consist of covariates including the reference person's characteristics (*i.e.*, sex, age, age square, marital status, own and spouse's education, health restriction, employment status), household characteristics (*i.e.*, number of children, household size) and year dummies. The relations between the personal characteristics and the likelihood of being in receipt are generally in the expected direction. The signs of the estimates of the explanatory variables derived from the Wooldridge estimator do not differ from the Heckman estimator. The prob-

[17]Furthermore, the hypothesis $\theta = 0$, exogeneity of the initial condition, is strongly rejected in the Heckman's reduced form model, in Equation (3). Rather, the estimate of θ is around 1, as reported in Table 3.

ability of receiving social assistance benefit decreases with an increase in age, though the estimate is either at the borderline significance or statistically insignificant. As one would expect, both the respondent's and the spouse's educational attainment are negatively and strongly associated with benefit receipt. On the other hand, having a restrictive health condition makes people more likely to receive benefit. Surprisingly, gender and employment status do not seem to be related with the benefit receipt. This finding is, however, consistent with very similar trends in the benefit receipt rate for women and men, illustrated in Figure 3. As stated by Königs (2014), this could be explained by the definition of the beneficiary unit, whereupon our analysis relies on. Women and men who live in the same household are treated equally as recipients, since we have defined benefit receipt at household level. Similarly, the null impact of employment status could be linked to the fact that the regression analysis conditions on the personal characteristics of the household heads (reference persons) who are more likely to be employed (as seen in Table 1), and possibly ineligible for being recipient, whereas the beneficiary unit is the household so that any (other) member of the household could be the eligible recipient.

The household characteristics, such as the number of dependent children and household size are not strongly associated with benefit receipt, which could be related with the insufficient time variation in those variables over the period. The time-averages of these variables, particularly the coefficient estimate of the number of children, are rather statistically significant (see Table 2 and Table 3). As illustrated in Figure 2, child allowances account for a considerable share among the social assistance schemes, and in relation to this a household having dependent children increases its likelihood of being in receipt. Overall, the time-averages play an important role in the models. In particular, they help to control for the potential correlation between the unobserved individual heterogeneity and the observed characteristics. Most of the coefficients on the time-averaged variables are statistically significant, and their signs are the same as the corresponding variables. The model also captures time trends in benefit receipt during the observation period, using year dummy variables as covariates –although not presented in tables for the sake of brevity. We find positive and statistically significant coefficient estimates for the 2008-2011 period. This is consistent with the increasing rate of benefit receipt over most of the sample period, shown in Figure 1.

4.1 Degree of State Dependence

Estimation results from the dynamic random effects probit model presented in Table 2 and Table 3 suggest considerable state dependence in social assistance benefit receipt in Turkey. The coefficient estimates of the lagged benefit receipt is always positive and statistically significant regardless of the specification relied on. Lastly, we discuss the average partial effect (APE) of benefit receipt to assess the level of state dependence. The APE simply equals to the difference in average predicted probabilities of social assistance receipt across individuals over time conditional on benefit receipt and non-receipt in the previous period (*i.e.*, the difference between predicted persistence and entry probabilities) (Stewart, 2007).

Table 5 displays the estimated transition rates (of entry and exit) and average partial effects calculated based on the Wooldridge's estimates presented in Table 2. In the case of the Wooldridge's original specification, Equation (4), the average probability of benefit receipt at t conditional on receipt at $t-1$ is predicted to be 21 percent (*persistence rate*), and the average probability of benefit receipt at t conditional on non-receipt at $t-1$ is predicted to be 1.5 percent (*entry rate*). The APE is thus calculated to be 19.5 percentage points, which decreases to 18.1 percentage points when the study relies on the model specified in Equation (5) (Table 5, column 3). This model facilitates addition of longitudinal averages of time varying explanatory variables to the regression. The inclusion of additional control variables of first-wave characteristics, as in the case of Equation (6), lowers the APE by 17.2 percentage points (Table 5, column 4). In line with the higher coefficient estimates from the Heckman's approach, we find a higher APE ranging between 20 to 25 percentage points depending on the subset of instruments used to estimate the initial conditions equation.[18]

[18] For the sake of brevity, these results are not presented here, but available upon request from the

Furthermore, we examine the heterogeneity in state dependence across subgroups of the population. Table 6 breaks down the results presented in Table 5 by educational attainment, number of children and employment status. All the models displayed in columns 1 to 3 assume endogenous initial conditions, specified in Equations (4), (5) and (6), respectively. The covariates other than the one(s) of interest are evaluated at mean while calculating the marginal effects. An inspection of the table makes it clear that an increase in educational attainment substantially decreases the level of state dependence. For instance, the APE is about 38 percentage points among those who have no schooling degree, while it is 5.7 percentage points among university graduates (16 years of schooling) (see column 1). The number of children creates even a larger difference in the level of state dependence. The APE among families with five children is 46 percentage points which is more than five times that of the families without children. As previously discussed, the employment status does not play such a key role in determining state dependence in benefit receipt. The difference in the APE between the households with non-employed and employed heads is not remarkable, nonetheless it is higher among the non-employed. The bottom panel of the table presents the predicted probabilities of entry and persistence in benefit receipt particularly for a vulnerable group –in terms of these three dimensions. For a household with three children and a non-employed and low-educated head, past receipt is associated with an about 38-percentage points higher probability of being in receipt in the current period, compared to the case of no receipt in the last period.

While the structural state dependence of around 17 to 21 percentage points is substantial, the value is considerably lower than the difference between the observed persistence and entry rates of about 75 percent, illustrated in Figure 4. This implies that most of the observed state dependence is due to the observed and unobserved heterogeneity across individuals (Hansen et al., 2014; Königs, 2014; Riphahn and Wunder, 2016). The average partial effects estimated for Turkey are at least 3 percentage points higher than those reported by Cappellari and Jenkins (2008) for the United Kingdom

authors.

(of 14.4 percentage points) and by Königs (2014) for Germany (of 14.1 percentage points). While the estimated persistence rate is comparable to these countries, the entry rate is around 4 percentage points lower in Turkey. The divergence in the degree of state dependence in benefit receipt could be related to distinctive institutional structuring in different countries and/or different definitions of social assistance benefits adopted by studies. Similar to the latter explanation,(Riphahn and Wunder, 2016) explain the reason of the substantial divergence between their findings from Germany and those reported by Königs (2014) by the potential difference in types of benefits and different transition patterns of subsamples that the two studies rely on.

Our results suggest that state dependence in social assistance might also be a relevant phenomenon for developing countries. Contrary to developed countries, the generosity of the welfare system cannot be considered as a responsible for the high level of state dependence in Turkey. The situation in Turkey rather addresses the poorly-designed social assistance schemes and dysfunction in monitoring mechanisms (see Appendix A). As stated in Eder (2010), the public organizations of Turkish welfare regime keep their populist strategies with their re-election concerns and vastly expand social assistance programs for political purposes. Political arbitrage and clientelism appear as distinctive characteristics of the social assistance system in Turkey (Eder, 2010). Given this, we consider ambiguous criteria in receiving social transfers and patronage in redistribution mechanisms as one of the potential channels explaining the high degree of state dependence shown in our results. Within a welfare regime lacking in an effective monitoring mechanism, there is no incentive for beneficiaries to exit from the scheme. It is therefore reasonable to expect such a high rate of persistence in benefit receipt in the case of Turkey. This strong evidence of structural state dependence leaves a large room for policy implications in reducing the high persistence rate in benefit receipt. The policies could attempt to promote exits from benefits, and hence to reduce the persistence rate, as well as to allow for new entries in the system. The latter is at least as important as reducing the persistence rate for developing countries that suffer from high level of poverty, given the key role of social assistance in poverty alleviation.

5 Conclusion

The empirical evidence on the evaluation of dynamics of social assistance benefits has thus far been limited to the developed economies, despite the existence of social transfers in many developing countries. The current study examined this issue in Turkey, over the last decade, within the state dependence framework. This is the first empirical study to explore state dependence in social assistance benefit receipt, in context of a developing country.

Based on annual panel data for the 2006-2012 period, dynamic random effects probit model was employed for controlling unobserved heterogeneity and initial conditions. In order to model initial conditions and check for sensitivity, the results from Heckman's two step estimator were compared with the results from Wooldridge's estimator. We also implement an alternative specification of Wooldridge's estimator suggested by (Rabe-Hesketh and Skrondal, 2013) to test whether the results are biased due to the usage of a short panel. The methodological contribution of the current study highlights the feasibility of a state dependence analysis using a short panel, which is of particular importance for developing countries, where it is difficult to find and employ long-panel datasets. The results are quite consistent across different specifications and suggest strong evidence of state dependence in social assistance benefit receipt. It was found that social assistance benefit receipt in previous year increases the probability of being in receipt in current year by 17 to 21 percentage points, after controlling observed and unobserved characteristics, and endogenous initial conditions.

Turkey is far from having a generous welfare benefit system. The high degree of structural state dependence comparable to the welfare countries is thus not attributable to the generosity of the system but, arguably, to the inefficiencies in the benefit allocation system. Lack of a well-defined poverty-scoring formula and a nationwide standard eligibility criteria leave a large room for discretionary implementations and political preferences, particularly in allocating the benefits by local authorities. Assessment of the impact of political preferences on benefit receipt is out the scope of this study. We leave it for future research upon the availability of data. However, one can suggest that more transparent and clear eligibility criteria along with better enforcement and monitoring mechanisms might reduce the current level of state dependence, thereby bringing about a more efficient welfare system.

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Figures and Tables

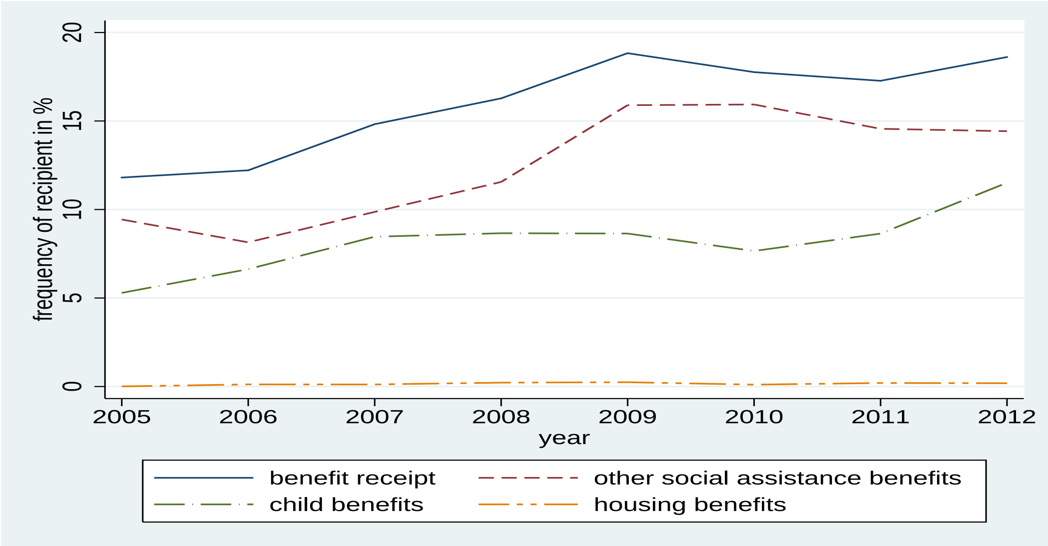

Figure 1: Rate of benefit receipt of the working age population (age 15-64)

Note: Benefit receipt rate refers to the share of working age individuals from a benefit receiving household. It is calculated using individual sampling weights based on micro data from SILC.

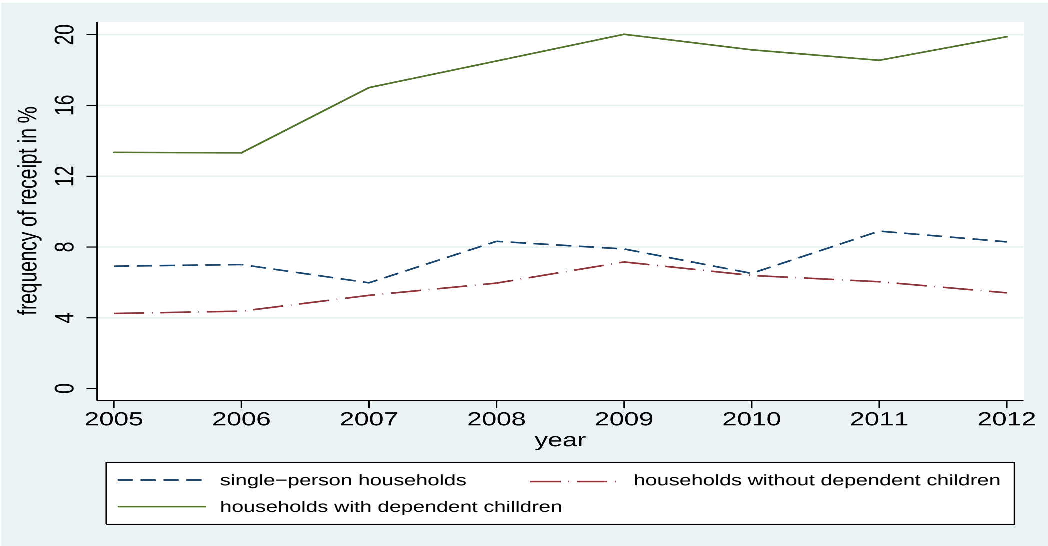

Figure 2: Rates of benefit receipt by household type

Note: Benefit receipt rate refers to the share of benefit receiving households of the given type. It is calculated using household sampling weights based on micro data from SILC.

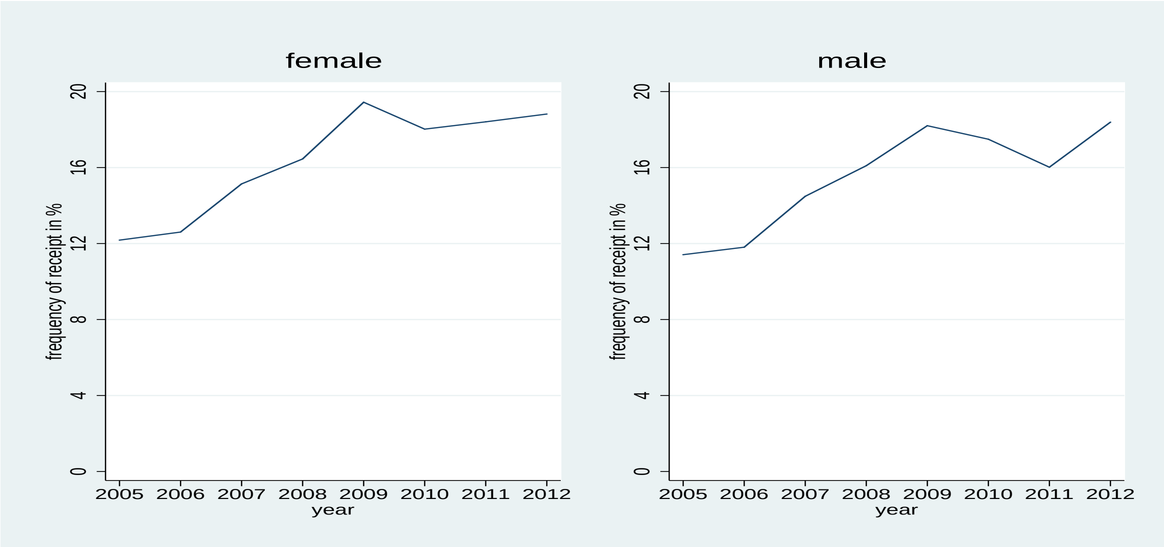

Figure 3: Rates of benefit receipt by gender

Note: Benefit receipt rate refers to the share of working age females (males) who are members of benefit receiving households. It is calculated using individual sampling weights based on micro data from SILC.

Figure 4: Benefit transition rates of of the working age population (age 15-64)

Note: *Entry rate* is defined as the number of recipients at time t among those who were not in receipt at time *t-1* divided by the total number of individuals not in receipt at *t-1*. *Exit rate* is the number of non-recipients at t among those who were in receipt at time *t-1* divided by the total number of individuals in receipt at *t-1*. *Persistence rate* is equal to one minus the exit rate. All rates are expressed as a percentage and are calculated using individual sampling weights based on micro data from SILC.

Table 1: Summary statistics of social assistance benefit (SAB) recipients and non-recipients

	(1) mean	(2) st. dev.	(3) min.	(4) max.	(5) obs.
SAB recipient rate	0.18	0.38	0	1	15,351
Annual SAB in Turkish Liras (at HH level)	644	943	15	20,520	2,758
SAB share in net HH income	0.10	0.22	0	5.96	2,758
Individual characteristics of SAB recipients					
Age	44.2	9.36	19	64	2,758
Female	0.12	0.33	0	1	2,758
Married	0.89	0.31	0	1	2,758
Completed years of education	4.46	3.34	0	16	2,750
Spouse's education	2.65	3.10	0	16	2,390
Household size	5.57	2.45	1	19	2,758
Number of children in HH	2.75	1.94	0	12	2,758
Health restriction	0.39	0.49	0	1	2,750
Non-employed	0.28	0.45	0	1	2,758
Individual characteristics of non-recipients					
Age	45.5	9.72	19	64	12,593
Female	0.08	0.28	0	1	12,593
Married	0.91	0.29	0	1	12,593
Completed years of education	7.98	4.53	0	16	12,586
Spouse's education	5.90	4.48	0	16	11,285
Household size	4.07	1.74	1	19	12,593
Number of children in HH	1.32	1.31	0	11	12,593
Health restriction	0.22	0.43	0	1	12,593
Non-employed	0.24	0.43	0	1	12,593

Source: Authors' own calculations based on the appended sample of two balanced panels of 2006-2009 and 2009-2012. *SAB recipient rate* refers to the share of social assistance beneficiaries in the working age population (aged 15-64). *Net HH income* refers to the total household (HH) income minus social assistance benefits. Individual characteristics belong to reference persons in households.

Table 2: Dynamic Random Effects Probit Model :
Wooldridge's Estimator

Balanced Sample

	(1)	(2)	(3)	(4)
Benefit receipt at $t-1$	2.318***	1.371***	1.344***	1.317***
	(0.053)	(0.119)	(0.119)	(0.119)
Benefit receipt at $t=1$		1.751***	1.783***	1.840***
		(0.230)	(0.230)	(0.233)
Personal characteristics				
Age	-0.031	-0.058*	-0.054	0.163
	(0.019)	(0.033)	(0.034)	(0.159)
Age square	0.023	0.048	0.043	-0.159
	(0.022)	(0.038)	(0.039)	(0.172)
Female	-0.044	-0.084	-0.189	-0.212
	(0.205)	(0.322)	(0.330)	(0.412)
Years of schooling	-0.055***	-0.089***	-0.089***	-0.052
	(0.008)	(0.012)	(0.013)	(0.071)
Spouse's education	-0.048***	-0.072***	-0.071***	-0.066
	(0.007)	(0.013)	(0.013)	(0.056)
No. children	0.061	0.306***	0.103	0.068
	(0.080)	(0.044)	(0.096)	(0.099)
Household size	0.060	-0.031	0.071	0.091
	(0.067)	(0.032)	(0.083)	(0.084)
Health restriction	0.096	0.227***	0.133	0.142*
	(0.069)	(0.067)	(0.086)	(0.086)
Non-employed	-0.132	0.052	-0.134	-0.112
	(0.099)	(0.083)	(0.122)	(0.123)
Time-averages				
Avg: no. children	0.151*		0.250**	0.260
	(0.085)		(0.106)	(0.159)
Avg: household size	-0.098		-0.126	-0.179
	(0.069)		(0.089)	(0.123)
Avg: health restriction	0.182*		0.244*	0.299*
	(0.094)		(0.140)	(0.177)
Avg: non-employed	0.217*		0.317*	0.490**
	(0.118)		(0.162)	(0.225)
First-wave characteristics				
Fst: age				-0.228
				(0.159)
Fst: age square				0.221
				(0.177)
Fst: years of schooling				-0.037
				(0.071)
Fst: spouse's education				-0.006
				(0.057)

Fst: no. children				0.042
				(0.138)
Fst: household size				0.023
				(0.107)
Fst: health restriction				-0.041
				(0.118)
Fst: non-employed				-0.230
				(0.166)
Constant	-0.599	-0.517	-0.644	-0.519
	(0.410)	(0.699)	(0.711)	(0.754)
Year dummies	Yes	Yes	Yes	Yes
No. observations	10,239	10,239	10,239	10,156
No. individuals	3,450	3,450	3,450	3,400
σ_α	0.001	1.010	1.037	1.059
	(30.009)	(0.108)	(0.109)	(0.110)
ρ	0.000	0.505	0.518	0.529
	(0.070)	(0.054)	(0.052)	(0.052)
Log likelihood	-2135.379	-2089.754	-2062.051	

Note: Estimation is based on the appended sample of two balanced panels of 2006-2009 and 2009-2012. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Dynamic Random Effects Probit Model :
Heckman's Estimator

Balanced Sample

	(1)	(2)	(3)	(4)
Benefit receipt at $t-1$	1.543***	1.543***	1.573***	1.504***
	(0.097)	(0.096)	(0.099)	(0.093)
Personal characteristics				
Age	-0.032	-0.031	-0.031	-0.032
	(0.032)	(0.033)	(0.032)	(0.033)
Age square	0.016	0.014	0.015	0.015
	(0.037)	(0.037)	(0.036)	(0.038)
Female	-0.040	-0.055	-0.042	-0.115
	(0.471)	(0.481)	(0.468)	(0.455)
Years of schooling	-0.109***	-0.109***	-0.107***	-0.112***
	(0.014)	(0.014)	(0.014)	(0.014)
Spouse's education	-0.085***	-0.084***	-0.083***	-0.087***
	(0.013)	(0.013)	(0.013)	(0.013)
No. children	0.112	0.111	0.111	0.112
	(0.093)	(0.093)	(0.092)	(0.093)
Household size	0.060	0.060	0.058	0.063
	(0.077)	(0.077)	(0.076)	(0.078)
Poor health	0.119	0.121	0.119	0.121
	(0.081)	(0.081)	(0.081)	(0.082)
Non-employed	-0.091	-0.089	-0.090	-0.090
	(0.119)	(0.119)	(0.118)	(0.120)
Time-averages				
Avg: no. children	0.327***	0.327***	0.315***	0.342***
	(0.106)	(0.106)	(0.105)	(0.107)
Avg: household size	-0.145*	-0.144*	-0.140*	-0.150*
	(0.084)	(0.084)	(0.083)	(0.084)
Avg: poor health	0.383***	0.385***	0.375***	0.395***
	(0.135)	(0.135)	(0.133)	(0.137)
Avg: non-employed	0.295*	0.309*	0.290*	0.321*
	(0.162)	(0.162)	(0.160)	(0.164)
Constant	-0.300	-0.332	-0.328	-0.300
	(0.691)	(0.692)	(0.677)	(0.710)
ρ	0.505	0.504	0.487	0.525
	(0.059)	(0.059)	(0.063)	(0.054)
θ	1.131	1.146	1.161	1.117
	(0.159)	(0.163)	(0.172)	(0.149)
Log likelihood	-3201.488	-3194.233	-3190.143	-3207.502
Observations	15,352	15,352	15,352	15,352

Note: Estimation is based on the appended sample of two balanced panels of 2006-2009 and 2009-2012. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Heckman's initial condition equation estimation

	(1)	(2)	(3)	(4)
Personal characteristics				
Age	0.008	0.013	0.004	
	(0.044)	(0.045)	(0.044)	
Age square	-0.000	-0.000	-0.000	
	(0.001)	(0.001)	(0.001)	
Female	0.395	0.156	0.293	
	(0.609)	(0.614)	(0.609)	
Years of schooling	-0.127***	-0.123***	-0.123***	
	(0.016)	(0.016)	(0.016)	
Spouse's education	-0.083***	-0.088***	-0.084***	
	(0.016)	(0.016)	(0.016)	
No. children	0.442***	0.444***	0.437***	
	(0.062)	(0.062)	(0.062)	
Household size	-0.109**	-0.108**	-0.109**	
	(0.045)	(0.046)	(0.046)	
Poor health	0.500***	0.446***	0.463***	
	(0.099)	(0.100)	(0.100)	
Non-employed	-0.108	0.187	-0.070	
	(0.150)	(0.119)	(0.150)	
Pre-sample characteristics				
Pre: unemployed	0.738***		0.619***	
	(0.215)		(0.217)	
Pre: poverty1		0.016	0.010	
		(0.127)	(0.126)	
Pre: poverty2		0.209**	0.190**	
		(0.092)	(0.092)	
Pre: poverty3		0.325***	0.307***	
		(0.096)	(0.096)	
First-wave characteristics				
Fst: age				0.020
				(0.046)
Fst: age square				-0.050
				(0.054)
Fst: years of schooling				-0.128***
				(0.016)
Fst: spouse's education				-0.086***
				(0.016)
Fst: no. children				0.451***
				(0.062)
Fst: household size				-0.109**
				(0.046)
Fst: poor health				0.485***
				(0.100)
Fst: nonemployed				0.201*
				(0.119)
Constant	-0.682	-0.942	-0.798	-0.861
	(0.889)	(0.902)	(0.891)	(0.948)
Observations	15,352	15,352	15,352	15,352

Note: Estimation is based on the appended sample of two balanced panels of 2006-2009 and 2009-2012. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Predicted probabilities from the Wooldridge estimator

Balanced Sample

	(1)	(2)	(3)	(4)
Entry	0.038***	0.015***	0.014***	0.013***
	(0.005)	(0.003)	(0.003)	(0.003)
Persistence	0.708***	0.210***	0.195***	0.185***
	(0.025)	(0.053)	(0.051)	(0.050)
APE (%)	67.0	19.5	18.1	17.2
Observations	10,239	10,239	10,239	10,156

Note: Prediction is based on the estimates presented in Table 2, using the appended sample of two balanced panels of 2006-2009 and 2009-2012. Covariates are evaluated at mean in calculating the marginal effects. APE refers to the average partial effect, indicating the difference between persistence and entry rates. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Heterogeneity across subgroups:
Predicted probabilities from the Wooldridge estimator

Balanced Sample

	(1)	(2)	(3)
by Educational attainment			
Entry			
No education	0.066***	0.063***	0.034
	(0.012)	(0.012)	(0.041)
5 years	0.025***	0.024***	0.019**
	(0.005)	(0.005)	(0.009)
8 years	0.013***	0.012***	0.013***
	(0.003)	(0.003)	(0.003)
12 years	0.005***	0.005***	0.007
	(0.002)	(0.002)	(0.007)
16 years	0.002*	0.002*	0.004
	(0.001)	(0.001)	(0.007)
Persistence			
No education	0.446***	0.423***	0.308
	(0.065)	(0.065)	(0.197)
5 years	0.280***	0.262***	0.222***
	(0.058)	(0.056)	(0.076)
8 years	0.198***	0.183***	0.178***
	(0.052)	(0.050)	(0.050)
12 years	0.114***	0.104***	0.129
	(0.042)	(0.039)	(0.079)
16 years	0.059**	0.053*	0.090
	(0.030)	(0.027)	(0.104)
by Number of children			
Entry			
No kid	0.004**	0.009*	0.010*
	(0.001)	(0.005)	(0.005)
3 kids	0.038***	0.020***	0.017***
	(0.007)	(0.007)	(0.006)
5 kids	0.123***	0.032	0.024
	(0.029)	(0.023)	(0.019)
Persistence			
No kid	0.093**	0.150**	0.155**
	(0.037)	(0.061)	(0.063)
3 kids	0.343***	0.235***	0.211***
	(0.064)	(0.064)	(0.062)
5 kids	0.583***	0.305**	0.254**
	(0.074)	(0.121)	(0.114)
by Employment status			
Entry			
Employed	0.014***	0.015***	0.014***
	(0.003)	(0.004)	(0.004)
Nonemployed	0.016***	0.011***	0.011***
	(0.005)	(0.004)	(0.004)
Persistence			
Employed	0.207***	0.202***	0.191***
	(0.053)	(0.053)	(0.052)
Nonemployed	0.223***	0.167***	0.162***
	(0.057)	(0.050)	(0.050)
5-year education, 3 children, nonemployed			
Entry	0.066***	0.026**	0.019
	(0.013)	(0.011)	(0.012)
Persistence	0.445***	0.272***	0.223***
	(0.067)	(0.072)	(0.085)
Observations	10,239	10,239	10,156

Note: Prediction is based on the estimates presented in Table 2, using the appended sample of two balanced panels of 2006-2009 and 2009-2012. Covariates are evaluated at mean in calculating the marginal effects. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix A Institutional Background

Social assistance schemes in Turkey are mainly coordinated by the central government, local authorities appointed by the central government, or municipalities. The key governmental institution responsible for this coordination is the Social Assistance and Solidarity Fund (SASF). Although SASF has been legally existent for nearly thirty years to assist people in absolute poverty, Turkey in fact lacks in a well-targeted and well-designed social safety net (Ahmed et al., 2007). On the other hand, the country has recently experienced noticeable changes in the field of social assistance. An increase in the number of beneficiaries and in the share of government budgets allocated to social assistance schemes, indicated in Section 1, were associated with substantial institutional changes.

As an outcome of a new regulation introduced in 2004, the institutional structure of the Fund (previously structured as a General Secretariat) has been strengthened by reorganizing it as a General Directorate of the Prime Ministry. The General Directorate was affiliated to the newly established Ministry of Family and Social Policies in 2011. The SASF was established to work in conjunction with regional associations that are located in each sub-province. There are currently 973 local associations that receive a regular monthly budget from the SASF (Aytaç, 2014; Metin, 2011). The selection of beneficiaries is under the responsibility of these associations. The benefits are allocated on the basis of 'neediness', which is determined through a proxy-means test. The details of the proxy-means test (namely, poverty-scoring formula) are not disclosed by the SASF. Individual criteria are applied by every association to determine the neediness of beneficiaries. The executive committees formed under every association of the sub-province execute their decisions independently. The autonomy exercised by centrally appointed bureaucrats of the local executive committees leaves an ample room for discretion, particularly for political preferences, in determining eligibility of the benefits (Aytaç, 2014; Adaman et al., 2007).

While these committees do not adhere to the norms in determining the neediness of beneficiaries, the law provides a tacit definition for the term 'needy'. The individuals who are not covered by any social security institution and do not have monthly income, or those with per capita income lower than one third of net minimum wage are considered as needy (Law, 3294). This threshold is *de jure* the eligibility criteria for free health care beneficiaries (namely, green card holders). However, a nationalized and binding poverty-scoring formula based on a settled threshold does not exist for other social transfers. While applicants with scores below a certain threshold (determined by local committees) become officially eligible, applicants with poverty scores above the threshold are not automatically excluded from consideration, and they can still be regarded eligible at the discretion of the executive committee (Aytaç, 2014).

The benefits allocated by the SASF through the local Associations might be classified in four categories. First category focuses on the health benefits, which is provided by the Fund. It provides health-related equipment for individuals who are not covered by any social security institution, while the medicine and treatment costs are covered by the Green Card programme. The second category is concerned with the education benefits in kind, and includes contribution of school clothes and stationery supplies for the poor households with primary and secondary school children. The third category involves family allowances such as food stamps, fuel, support for repair and maintenance of households, and other housing benefits that are provided in cash. Last category aims at meeting the basic needs of the people suffering from natural disasters and providing aid for public food-banks.

Even though the bulk of the social assistance schemes is administered by the central governments or local authorities (municipalities), there are still non-negligible number of social assistance and social service programs provided by non-governmental, private and charity organizations. They do not qualitatively differ from the governmental programs described above (Adaman et al., 2007).

Appendix B Tables

Table B.1: Dynamic Random Effects Probit Model :
Wooldridge's Estimator

Unbalanced Sample

	(1)	(2)	(3)	(4)
Benefit receipt at $t-1$	2.295***	1.560***	1.551***	1.410***
	(0.038)	(0.088)	(0.089)	(0.097)
Benefit receipt at $t=1$		1.342***	1.357***	1.690***
		(0.170)	(0.172)	(0.205)
Personal characteristics				
Age	-0.043***	-0.058***	-0.058***	0.072
	(0.012)	(0.016)	(0.017)	(0.110)
Age square	0.032**	0.045**	0.043**	-0.050
	(0.014)	(0.019)	(0.019)	(0.122)
Female	-0.016	-0.024	-0.060	-0.199
	(0.105)	(0.142)	(0.144)	(0.177)
Years of schooling	-0.051***	-0.068***	-0.067***	-0.083
	(0.005)	(0.007)	(0.007)	(0.061)
Spouse's education	-0.045***	-0.058***	-0.058***	-0.029
	(0.005)	(0.007)	(0.007)	(0.046)
No. children	0.099	0.197***	0.132*	0.105
	(0.063)	(0.024)	(0.073)	(0.081)
Household size	0.022	-0.005	0.057	0.100
	(0.048)	(0.017)	(0.056)	(0.067)
Health restriction	0.063	0.231***	0.089	0.094
	(0.056)	(0.040)	(0.065)	(0.068)
Non-employed	-0.097	0.117**	-0.091	-0.068
	(0.078)	(0.046)	(0.091)	(0.095)
Time-averages				
Avg: no. children	0.051		0.072	0.063
	(0.064)		(0.076)	(0.123)
Avg: household size	-0.029		-0.067	-0.049
	(0.049)		(0.058)	(0.097)
Avg: health restriction	0.186***		0.223***	0.299**
	(0.067)		(0.082)	(0.122)
Avg: non-employed	0.227***		0.269**	0.305*
	(0.087)		(0.105)	(0.161)
First-wave characteristics				
Fst: age				-0.148
				(0.110)
Fst: age square				0.114
				(0.123)
Fst: years of schooling				0.007
				(0.061)

Fst: spouse's education				-0.033
				(0.046)
Fst: no. children				0.065
				(0.102)
Fst: household size				-0.073
				(0.081)
Fst: health restriction				-0.063
				(0.088)
Fst: non-employed				-0.030
				(0.122)
Constant	-0.322	-0.381	-0.396	-0.073
	(0.249)	(0.344)	(0.346)	(0.407)
Year dummies	Yes	Yes	Yes	Yes
No. observations	25,222	25,222	25,222	24,645
No. individuals	14,383	14,383	14,383	13,931
σ_α	0.001	0.801	0.811	0.945
	(16.953)	(0.083)	(0.084)	(0.092)
ρ	0.000	0.391	0.397	0.472
	(0.433)	(0.049)	(0.050)	(0.048)
Log likelihood	-5280.686	-5225.342	-5217.612	-5051.059

Note: Estimation is based on the appended sample of two unbalanced panels of 2006-2009 and 2009-2012. Clustered robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table B.2: Predicted probabilities from the Wooldridge estimator

Unbalanced Sample

	(1)	(2)	(3)	(4)
Entry	0.038***	0.020***	0.020***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Persistence	0.697***	0.313***	0.307***	0.229***
	(0.011)	(0.047)	(0.048)	(0.047)
APE (%)	65.6	29.3	28.7	21.3
Observations	25,222	25,222	25,222	24,645

Note: Prediction is based on the estimates presented in Table B.1, using the appended sample of two unbalanced panels of 2006-2009 and 2009-2012. Covariates are evaluated at mean in calculating the marginal effects. APE refers to the average partial effect, indicating the difference between persistence and entry rates. Clustered robust standard errors in parentheses.***p<0.01,**p<0.05,*p<0.1.