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Temporary Jobs and State Dependence in Italy

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Abstract

A dynamic unobserved effects probit analysis has been carried out to test the hypothesis of state dependence of temporary jobs and to understand their determinants. The econometric analysis has been conducted using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth. The results show that, firstly, jobless and unstable workers are more likely to end up in temporary contracts. Secondly, there is a significant true state dependence effect of temporary contracts that might be due to the fact that firms are systematically using temporary jobs to face demand uncertainty: loss of motivation and depreciation of human capital due to low firm-specific investments may make temporary workers less likely to jump on stabler job relationships. Moreover, the true state dependence could be related to the presence of a dual labour market, segmented into "bad" and "good" jobs. Thirdly, a significant feedback effect from past temporary jobs to recent unemployment spells has been detected.

Therefore, jobless and unstable workers are more likely to end up into temporary relationship generating a loss of human capital, affecting the workers' allocation in the whole economy, and widening the gap between possibly segmented labour markets. The policy maker might be aware of these costs associated to the widespread of temporary jobs and design policies to target those workers suffering most from the trap of temporary positions.

JEL Class.: C23, C25, J29
Keywords: temporary employment, individual heterogeneity, dynamic unobserved effects probit model, feedback effects

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1 Introduction

In the last decade the share of temporary workers has risen in almost all European countries. Indeed, temporary contracts are often seen by policy makers as a tool to increase labour market flexibility and face the high level of European unemployment. Temporary contracts may provide firms an important instrument to deal with demand uncertainty and screen the most able candidates for a long-term job-relationship.

Although temporary contracts may provide an instrument to increase labour market flexibility, they often imply important and combined disadvantages. Firstly, temporary workers are related to higher turnover and probability of unemployment (Dolado *et al.* (2002), Farber (1999)) since fixed-term contracts expire automatically at the end of the agreed period. Secondly, they seem to receive lower wages and lower investment in specific human capital than comparable permanent employees. Recent research from Britain, France, Spain, Germany, and Italy (Blanchard and Landier (2001), Brown and Session (2003), Booth *et al.* (2002a), Jimeno and Toharia (1993), Hagen (2002), and Picchio (2006a and 2006b)) has examined wages and conditions attached to fixed-term employment. In general, it has been found out that temporary workers earn significantly less than comparable permanent employees.

Another line of research has adopted a different perspective and analysed whether temporary jobs may be a "stepping stone" into longer job-relationship. Booth *et al.* (2002a) find that some temporary contracts are a "stepping stone" for a permanent job. Gagliarducci (2005), through duration techniques applied to an Italian dataset, shows that the probability of finding a permanent job after a temporary job experience is increasing in the

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duration of the temporary contract and decreasing in the number of temporary jobs and their interruptions. Ichino *et al.* (2005) focus on the role of temporary work agencies in Italy, showing that they increase the probability of finding a permanent job after 18 months.

The purpose of this paper is to understand whether temporary jobs might be a trap once we control for observable and unobservable individual heterogeneities. This means that we estimate a dynamic unobserved effects probit model to test the hypothesis of state dependence of temporary jobs, to understand the determinants of temporary jobs, and to test the exogeneity of recent unemployment events and the number of job experiences. The econometric analysis is performed using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth (SHIW), a representative survey conducted by the Bank of Italy every two years since 1989.

If we look at the raw transition probabilities of our sample, a temporary worker has a higher probability of having a temporary job 2 years later. It seems that temporary workers are more likely to experience temporary jobs in the future. Such an evidence may be due, first of all, to individual observable and unobservable characteristics that might determine the success or the failure of the worker in proving his(her) own ability during this first stage of the job relationship; then observable and unobservable characteristics affect the likelihood of having a permanent job in the future. Alternatively, it may due to a true causal effect on future type of contract (true state dependence). An example is that firms could systematically use temporary contracts to face demand uncertainty so that temporary jobs become a trap: loss of motivation and depreciation of human capital due to low firm-specific investments may make temporary workers less likely to jump on stabler job relationships. Moreover, the true state dependence could be related to the presence of a dual labour market, segmented into "bad" and "good" jobs.

Given the nature of the dataset, we estimate the probability of being a temporary worker after having had a temporary job two years before. The starting point is the estimation of a static model of the determinants of a temporary job. Different specifications and several estimators are presented, under various assumptions about the error term. We address the problem of unobserved heterogeneity following a Chamberlain's (1980) approach and we test the exogeneity of job mobility and recent unemployment spells. While we cannot reject the exogeneity of job mobility, recent unemployment spells fail the strict exogeneity requirement. It is plausible, indeed, that whether someone has a temporary job in this period has an effect on future unemployment spells. If this the case, then shocks that affect the contract type could be correlated with future unemployment events, violating strict exogeneity.

Then, we turn to the dynamic specification of the probability of having a temporary contract. This means that the probability of being a temporary worker at time t is allowed to depend on the realization at $t-1$ as well as unobserved heterogeneity. As in the static case, we propose different specifications of the model which are estimated through pooled probit estimators. Moreover, we relax the strict exogeneity of the proxy for recent unemployment spells.

The main findings are: i) a significant state dependence; ii) a higher probability of ending in temporary jobs for workers with a larger number of previous job experiences and with recent unemployment spells; iii) a significant feedback effect from past temporary experiences to recent unemployment spells that is interpreted as a significant higher probability of having an unemployment experience after a temporary job.

Finally, we estimate some dynamic linear probability models, in first-differences and in levels. Indeed, they are able to approximate the average partial effect of the lagged type of contract, fully controlling for unobserved heterogeneity and avoiding the problem of initial conditions. Therefore, the estimated coefficients of the lagged dependent variable are used to check the robustness of the results obtained through nonlinear models.

The paper is organized as follows. In Section 2 we introduce the empirical specification of a first order dynamic model for the type of contract. We discuss the econometric issues and we introduce different assumptions for alternative specifications. Section 3 describes the data and reports basic descriptive statistics of the sample used to perform the econometric analysis. In Section 4 we report the estimation results and we discuss the main findings. Finally, section 5 reports concluding remarks.

2 Model Specification and Estimation Issues

2.1 Overview

Let us define y the dummy variable denoting the occurrence of an event. Here y shows whether an employee has a temporary job or a permanent one. Thus, the scalar dependent y_{it} is a binary variable such that

$$y_{it} = \begin{cases} 1 & \text{if individual } i \text{ has a temporary job at time } t \\ 0 & \text{if individual } i \text{ has a permanent job at time } t. \end{cases}$$

The empirical specification of the dynamic probability model for contract type is

$$y_{it} = 1[\mathbf{x}'_{it}\boldsymbol{\beta} + y_{it-1}\rho + \varepsilon_{it} > 0], \quad (i = 1, \ldots, N;\ t = 1, \ldots, T), \qquad (1)$$

where $1[\cdot]$ is the indicator function, ε_{it} captures the effect of unobserved components, $\mathbf{x}_{it}$ is a K-vector of skill, family, labour, and individual structure variables that may explain the type of contract, and $\boldsymbol{\beta}$ and ρ are K-dimensional and scalar parameters, respectively. More in details, $\mathbf{x}_{it}$ contains time-variant and time-invariant variables. The latter category includes the constant, education (4 dummies), geographical area of residence (4 dummies) and gender. The time-variant variables are experience, its quadratic form, household position, marital status, spouse's working status, presence of pre-scholar children, time intercepts, and, in some specifications, two potentially endogenous dummy variables controlling for employment history: the first one has been built on the basis of the number of previous job experiences, whereas the second one is a proxy for recent unemployment spells.[1] The error term ε_{it} can be decomposed into a possibly serially correlated idiosyncratic component, u_{it}, and a time-invariant individual heterogeneity, c_i, so that

$$\varepsilon_{it} = c_i + u_{it}.$$

Throughout the analysis u_{it} is supposed to be normally distributed with zero mean and variance equal to one. Nevertheless, we are going to state different assumptions about the serial correlation of u_{it}, the presence of the individual-specific component c_i, and ρ.

Equation (1) is the most general setting of our model and it makes the distinction between the sources of persistence conditional on the observed covariates $\mathbf{x}_{it}$. Indeed, persistence of temporary contracts may be due to unobserved heterogeneity c_i and to true state dependence $y_{it-1}\rho$. Distinguishing between these sources of state dependences could be important in drawing policy implications of the expansion of temporary contracts. For instance, firms could use systematically temporary contracts to face demand uncertainty and have low firing costs so that temporary jobs become a trap: loss of motivation and depreciation of human capital due to low firm-specific investments may make temporary workers less likely to jump on stabler job relationships. This suggests that temporary jobs may show true state dependence: having a temporary contract today might increase the probability of having a temporary contract next period. On the other hand, some employees are more likely to have a temporary contract because of unobservable individual characteristics (for example, bad signals and ability), corresponding to the individual-specific component c_i in equation (1).

[1] We have also included, in order to capture the heterogeneity of occupations, dummy variables for qualification (white collar and manager, while blue collar is the reference), firm size (6 dummies), and sector (8 dummies). Since they turned out to be always jointly not significant, we removed them from the specification of the model.

In this section we study the assumptions under which the parameters of static and dynamic nonlinear models can be consistently estimated;[2] we introduce some econometric models and the corresponding estimators, in order to provide some guidelines and to make clear how the results reported in section 4 have been obtained.

2.2 Static Nonlinear Models

Under the assumption that the dynamics do not matter or simply if we are not interested in the dynamics, we can rewrite equation (1) setting $\rho = 0$, yielding

$$y_{it} = 1[\mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} > 0], \quad (i = 1, \ldots, N;\ t = 1, 2), \tag{2}$$

where $t = 1$ corresponds to 2002 and $t = 2$ corresponds to 2004. Assume that the error term ε_{it} is normally distributed with zero mean and variance equal to one. Then, we can write the static model in terms of response probabilities

$$P(y_{it} = 1|\mathbf{x}_{it}) = \Phi(\mathbf{x}'_{it}\boldsymbol{\beta}), \quad (i = 1, \ldots, N;\ t = 1, 2), \tag{3}$$

where $\Phi(\cdot)$ is the Gaussian cumulative distribution function. Under these assumptions, which are quite strong assumptions because we are assuming that we do not even have neglected heterogeneity, we can consistently estimate $\boldsymbol{\beta}$ maximizing the partial log-likelihood function of the response probability model in equation (3); this means that we can perform a simple pooled probit estimate using a robust variance-covariance matrix estimator if serial correlation in the scores across t is likely to be present. The estimation results presented in the first three columns of table 2 have been obtained via pooled probit estimator under zero correlation in the scores across t.

Now, we relax the assumptions about the composite error term ε_{it} and we focus on the individual-specific component c_i. We assume that

$$P(y_{it} = 1|\mathbf{X}_i, c_i) = P(y_{it} = 1|\mathbf{x}_{it}, c_i) = \Phi(\mathbf{x}'_{it}\boldsymbol{\beta} + c_i), \tag{4}$$
$$(i = 1, \ldots, N;\ t = 1, 2),$$

where $\mathbf{X}_i$ is the $T \times K$ matrix of the covariates for individual i across all time periods. The first equality is the strong assumption because it says that, conditional on individual heterogeneity, $\mathbf{x}_{it}$ is strictly exogenous. Moreover, assume that

$$y_{i1}, y_{i2} \text{ are independent conditional on } (\mathbf{X}_i, c_i) \text{ and} \tag{5}$$
$$c_i \mid \mathbf{X}_i \sim \mathrm{N}(0, \sigma_c^2). \tag{6}$$

[2] Or a scaled version of the originals parameters.

Under assumptions (4), (5), and (6) we are in a random effects probit framework and $\boldsymbol{\beta}$ and σ_c^2 can be estimated by maximum likelihood integrating out c_i; we integrate out c_i through an approximation based on 20-point Gauss-Hermite quadrature.[3] Therefore, the estimation results displayed in the central columns of table 2 have been obtained through the random effects probit estimator.

Finally, we relax both assumptions (5) and (6) estimating a Chamberlain's random effect probit model. Especially, assumption (6) is quite strong because it implies that c_i and $\mathbf{X}_i$ are independent and uncorrelated. Thus, we relax it adopting the Chamberlain's (1980) assumption about the individual-specific component

$$c_i \mid \mathbf{X}_i \sim \mathrm{N}(\psi + \mathbf{X}_i\boldsymbol{\xi}, \sigma_a^2). \tag{7}$$

The individual heterogeneity is still normally distributed conditional on $\mathbf{X}_i$, but now the conditional mean depends on the covariates. Assumption (7) allows for some correlation between the unobserved individual component and the observed covariates and we can rewrite the probit model as

$$P(y_{it} = 1|\mathbf{X}_i) = \Phi(\mathbf{x}_{it}'\boldsymbol{\beta} + \psi + \mathbf{X}_i\boldsymbol{\xi} + a_i), \tag{8}$$

where $a_i|\mathbf{X}_i \sim \mathrm{N}(0, \sigma_a^2)$. In this kind of models we loose the identification of the coefficients of time-invariant variables in $\mathbf{x}_{it}$ and the constant becomes undistinguishable from ψ. However, even if we cannot identify the causal effects of time-invariant explanatory variables, we can include them in the model in order to explicitly control for some observed individual heterogeneity.

We could estimate model (8) via random effects probit estimator (integrating out a_i), but we are also relaxing assumption (5) so that we estimate a scaled version of our parameters (the scaling factor is $(1+\sigma_a^2)^{-1/2}$) by a simple pooled probit estimator and by a generalized estimating equations (GEE) approach (Zeger *et al.*, 1988) with standard errors robust to arbitrary serial correlation.[4] The last three columns of table 2 report the estimation results of model (8) via GEE estimator, while table 3 displays estimation results of model (8) via pooled probit estimator using different sets of time-varying explanatory variables. Indeed, the basic assumption for the consistency of these estimators is strict exogeneity of the covariates. Since strict exogeneity is likely to fail for the explanatory variables "Mobility"[5] and "Unemployment benefits", we introduce them only in specifications (2) and (3) of table 3.

[3] See Butler and Moffitt (1982).

[4] More details can be found, e.g., in Wooldridge (2002), pp. 483–490.

[5] The variable "Mobility" is a dummy variable equal to 1 if the employee has already had 2 or more job experiences

Since both the GEE approach and pooled probit estimator are consistent (they consistently estimate the scaled coefficients) under the assumptions of the Chamberlain's random effects probit model, we solely present the pooled probit results of specifications (2) and (3).[6]

2.3 Dynamic Nonlinear Models

2.3.1 A Dynamic Unobserved Effects Probit Model under Strict Exogeneity

In order to estimate the dynamic nonlinear model (1) accounting for unobserved heterogeneity, we follow Wooldridge (2005) who proposed a simple way to deal with the problem of initial conditions. We can rewrite model (1) in terms of response probabilities as

$$P(y_{it} = 1 | y_{it-1}, \ldots, y_{i0}, \mathbf{X}_i, c_i) = \Phi(\mathbf{x}'_{it}\boldsymbol{\beta} + y_{it-1}\rho + c_i), \tag{9}$$

which implies that the explanatory variables are supposed to be strictly exogenous conditional on individual heterogeneity and that the probability of having a temporary contract at time t is allowed to depend on the realization at time $t-1$ and on an individual-specific component, c_i. The test for state dependence is H_0: $\rho = 0$, after controlling for individual heterogeneity, c_i.

The contribution to the likelihood of individual i can be written as

$$f(y_{i1}, y_{i2} | y_{i0}, \mathbf{X}_i, c_i; \boldsymbol{\delta}) = \prod_{t=1}^{2} \Phi\big[(2y_{it} - 1)(\mathbf{x}'_{it}\boldsymbol{\beta} + y_{it-1}\rho + c_i)\big], \tag{10}$$

showing that its estimation arises the problem of an appropriate treatment of the initial value, y_{i0}, where $t = 0$ corresponds to 2000. The possibility of treating the initial observation as a nonstochastic initial condition may not be easily accepted in this framework. Indeed, it would be difficult to argue that the type of contract in 2000 ($t = 0$) and unobservable characteristics (like ability or/and bad signals) are independent. As mentioned before, a simple way to deal with the problem of initial condition has been proposed by Wooldridge (2005). The idea is to obtain $f(y_{i1}, y_{i2} | y_{i0}, \mathbf{X}_i)$ postulating a density for c_i given $(y_{i0}, \mathbf{X}_i)$, ending up with a procedure that is very close to the Chamberlain's (1980) approach. A convenient choice for a density of the individual heterogeneity is the Gaussian density. Indeed we may specify the individual heterogeneity as follows:

$$c_i = \psi + y_{i0}\xi_0 + \mathbf{X}_i\boldsymbol{\xi} + a_i, \quad a_i \sim \mathrm{N}(0, \sigma_a^2), \quad a_i \perp (y_{i0}, \mathbf{X}_i).$$

[6] The GEE estimates of specifications (2) and (3) are available on demand from the author.

Under these assumptions we can rewrite equation (1) and we get the following dynamic unobserved effects probit model

$$y_{it} = 1[\mathbf{x}_{it}'\boldsymbol{\beta} + y_{it-1}\rho + \psi + y_{i0}\xi_0 + \mathbf{X}_i\boldsymbol{\xi} + a_i + u_{it} > 0]. \tag{11}$$

This model can be estimated in the RE framework, it is just a matter of controlling for the initial condition and for lagged and forward realizations of the time-variant variables at each time period. The introduction of the initial observations and the linear approximation of individual heterogeneity allow us to distinguish between spurious state dependence (state dependence generated by the unobservable individual-specific component) and true state dependence. Following the same estimation criteria of the static nonlinear model, we estimate a scaled version of our parameters by a simple pooled probit estimator with standard errors robust to arbitrary serial correlation.[7] In this way we get the estimation results collected in table 4.

The estimation method presented in this subsection hinges on the strict exogeneity of the explanatory variables, conditional on c_i. Now we are going to relax the strict exogeneity for one of the explanatory variables allowing for feedback effects from the dependent variable to future realizations of this covariate. Specifically, the variable which is supposed to violate strict exogeneity is "Unemployment benefits", a dummy indicator equal to 1 if the worker has received some unemployment benefits in the interview year. It is a proxy for recent unemployment spells that is likely to increase the probability of having a temporary contract.[8] On the other hand, it is plausible that having a contract type increases the probability of future unemployment spells, invalidating strict exogeneity. In the next subsection we develop an econometric model which takes into account the possible feedback effect from the type of contract to future unemployment benefits. We follow Wooldridge (2000) and two empirical applications by Blindum (2003) and Biewen (2004).

2.3.2 A Dynamic Unobserved Effects Probit Model with Feedback Effects

Let w_{it} denote the unemployment benefits indicator and $\mathbf{z}_{it}$ the $(K-1)$-vector of exogenous explanatory variables, so that $[\mathbf{z}_{it}', w_{it}]' \equiv \mathbf{x}_{it}$. If there are feedback effects from y_{it} to w_{it} we can write the conditional response

[7] Indeed, applying a pooled probit approach does not allow the identification of σ_a^2 and we are also able to estimate the scaled parameters with a scaling factor equal to $(1+\sigma_a^2)^{-1/2}$.

[8] Indeed, an unemployment spell may be interpreted as a bad signal by the employer who is, therefore, more willing to propose a temporary job.

probability of y_{it} as

$$P(y_{it} = 1 \mid \mathbf{Z}_i, w_{it}, w_{it-1}, \dots, w_{i0}, y_{it-1}, \dots, y_{i0}, c_i; \boldsymbol{\delta}, \rho)$$
$$= \Phi(\mathbf{z}'_{it}\boldsymbol{\delta}_1 + w_{it}\delta_2 + w_{it-1}\delta_3 + y_{it-1}\rho + c_i), \tag{12}$$

and the response probability of w_{it} as

$$P(w_{it} = 1 \mid \mathbf{Z}_i, w_{it-1}, \dots, w_{i0}, y_{it-1}, \dots, y_{i0}, c_i; \boldsymbol{\theta})$$
$$= \Phi(\mathbf{z}'_{it}\boldsymbol{\theta}_1 + w_{it-1}\theta_2 + y_{it-1}\theta_3 + c_i\theta_4), \tag{13}$$

where, in order to address the problem of initial conditions, the individual-specific component is assumed to be

$$c_i = \psi + y_{i0}\xi_0 + w_{i0}\xi_1 + \mathbf{Z}_i\boldsymbol{\xi}_2 + a_i, \quad a_i \sim \mathrm{N}(0, \sigma_a^2), \quad a_i \perp (y_{i0}, w_{i0}, \mathbf{Z}_i).$$

Then, the individual i's contribution to the likelihood function can be written as

$$f(y_{i1}, y_{i2}, w_{i1}, w_{i2} \mid y_{i0}, w_{i0}, \mathbf{Z}_i, c_i; \boldsymbol{\delta}, \rho, \boldsymbol{\theta}) \tag{14}$$
$$= \prod_{t=1}^{2} f(y_{it} \mid \mathbf{z}_{it}, w_{it}, y_{it-1}, w_{it-1}, c_i; \boldsymbol{\delta}, \rho)$$
$$\cdot \prod_{t=1}^{2} f(w_{it} \mid \mathbf{z}_{it}, y_{it-1}, w_{it-1}, c_i; \boldsymbol{\theta})$$
$$= \prod_{t=1}^{2} \Phi\big[(2y_{it} - 1)(\mathbf{z}'_{it}\boldsymbol{\delta}_1 + w_{it}\delta_2 + w_{it-1}\delta_3 + y_{it-1}\rho + c_i)\big] \tag{15}$$
$$\cdot \prod_{t=1}^{2} \Phi\big[(2w_{it} - 1)(\mathbf{z}'_{it}\boldsymbol{\theta}_1 + w_{it-1}\theta_2 + y_{it-1}\theta_3 + c_i\theta_4)\big] \tag{16}$$

Equation (16), which is the additional equation for the proxy of recent unemployment spells, contains lagged contract type so that we are able to control for possible feedback effects from contract type at time $t-1$ to unemployment spells at time t. Moreover, both in equation (15) and in equation (16) we control for individual heterogeneity and for possible correlation among the initial realizations of unemployment benefits and contract type and the individual-specific component. The coefficient θ_4 in the equation for unemployment benefits allows some flexibility of the impact of the unobserved time-invariant determinants of contract type, c_i, on the probability of having unemployment benefits.

At this point, we can write down the log-likelihood and we could maximize it integrating out a_i, as if we were in a RE probit framework. However, since we are interested in computing average partial effects (APEs) and in order to allow for serial correlation in the idiosyncratic error term, we simply estimate model (15)-(16) by pooled probit. This implies that we get an estimate of the true scaled parameters, $(\boldsymbol{\delta}'_a, \rho_a, \boldsymbol{\theta}'_a)$, where the a subscript means that we have multiplied each parameter by $(1+\sigma_a^2)^{-1/2}$. As pointed out by Blindum (2003), if we are interested in the estimation of the average partial effects (APEs) we need a consistent estimate of the true scaled parameters $(\boldsymbol{\delta}'_a, \rho_a, \boldsymbol{\theta}'_a)$, that is exactly what a simple pooled probit approach provides.

Finally, identification of the joint model requires some exclusions restrictions otherwise identification comes only through distributional assumptions. Thus, we included the dummy indicator for marital status into the unemployment benefits equation and we excluded it from the equation for the type of contract: we are assuming that marital status is strictly exogenous and that it is not able to affect directly the type of contract. Following the procedure that we have described in this subsection, we obtain the estimation results depicted in table 6.

2.4 Dynamic Linear Probability Models

We adopt the following dynamic linear probability model specification for (1):

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + y_{it-1}\rho + c_i + u_{it}, \quad (i = 1, \ldots, N;\ t = 0, 1, 2). \qquad (17)$$

First differencing is a simple way to get rid of individual heterogeneity, yielding

$$\Delta y_{it} = \boldsymbol{\Delta}\mathbf{x}'_{it}\boldsymbol{\beta} + \Delta y_{it-1}\rho + \Delta u_{it},\ (i = 1, \ldots, N;\ t = 1, 2). \qquad (18)$$

Since Δy_{it-1} is correlated to Δu_{it}, this model can be consistently estimated using y_{i0} and noncontemporaneous realizations of the explanatory variables as valid excluded instruments. Thus, we are able to solve the problem of individual heterogeneity and to avoid the complication of initial conditions. Therefore, the estimated results displayed in table 9 are used to assess the robustness of our dynamic nonlinear models in approximating the unobserved heterogeneity and its correlation with initial values.

3 Data and Sample

The empirical analysis has been conducted using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth (SHIW).[9]

[9]The Survey and further details are available on the Web-server of the Bank of Italy (http://www.bancaditalia.it/statistiche/consultazione).

The SHIW is a nationally representative survey conducted by the Bank of Italy every two years since 1989. As the question about the contract type was introduced in 2000,[10] we cannot use for this empirical analysis previous surveys.

We take individuals into the range 15–65 years of age in 2000 and we removed individuals who were not employees in one of the three waves. Finally, we excluded observations with missing values for some of the variables used in the specification of the probability model, ending up with a sample of 1,381 employees. Since the heart of this paper is the estimation of a dynamic nonlinear probability model, we loose the first time period, which is exploited only for the initial values. In order to make the results of the static nonlinear probability models comparable to the ones of the dynamic nonlinear probability models, we estimate the static models using only the 2002 and 2004 waves; thus, we have a sample of 2,762 observations, corresponding to 1,381 employees. The dynamic linear probability models are instead estimated using 1,381 observations, since we loose one time period for first-differencing, and a further time period to correct the endogeneity of the lagged first difference of the dependent variable.

The dependent variable is a dummy indicator for the type of contract, y_{it}: it is equal to 0 if the individual is a permanent worker and equal to 1 if the individual is a fixed-term worker or a worker for a temporary work agency. The data allows us to distinguish between two types of temporary workers: fixed-term contracts and workers for temporary work agencies. The small sample size of workers for temporary work agencies forces us to aggregate temporary workers in a unique category.[11] Over 2000–2004, the average percentage of workers with a temporary job is 5.43%; more in details, it is equal to 6.66% in 2000, 5.36% in 2002, and 4.27% in 2004.

As concern the covariates, we deepen our attention into two dummy variables, "Mobility" and "Unemployment benefits". They have been introduced in the specification of the probability model to capture a possible bad signal for the employer and recent unemployment spells, respectively. Indeed, "Mobility" is a dummy variable which is equal to one if the employee has had three or more different job experiences, zero otherwise; "Unemployment benefits" is also a dummy indicator equal to one if the employee has received some unemployment benefits during the interview year. These are the reasons why the latter will be interpreted as a proxy for recent unemployment spells and the former as previous employment spells.

[10] Annex B1, question 1 of the SHIW questionnaire.

[11] The fraction of temporary workers for temporary work agencies is 0.29% over the full sample and 5.3% over the temporary workers' subsample, corresponding to 12 observations.

Table 1: Sample Characteristics

	Full Sample	Always Permanent	Temporary only in 2004	Temporary only in 2002	Always Temporary
Experience	22.930	23.282	19.879	19.208	16.423
	(10.20)	(9.90)	(13.08)	(13.12)	(10.38)
None or Elementary	0.064	0.064	0.121	0.146	0.192
	(.24)	(.24)	(.33)	(.35)	(.40)
Middle school	0.300	0.299	0.333	0.313	0.269
	(.46)	(.46)	(.47)	(.47)	(.45)
Professional school	0.085	0.083	0.182	0.104	0.000
	(.28)	(.28)	(.39)	(.31)	(.00)
High school	0.413	0.422	0.273	0.333	0.308
	(.49)	(.49)	(.45)	(.47)	(.47)
University degree or +	0.133	0.133	0.091	0.104	0.231
	(.34)	(.34)	(.29)	(.31)	(.43)
North-East	0.241	0.249	0.121	0.188	0.115
	(.43)	(.43)	(.33)	(.39)	(.32)
North-West	0.256	0.261	0.212	0.167	0.192
	(.44)	(.44)	(.41)	(.37)	(.40)
Centre	0.241	0.245	0.212	0.188	0.192
	(.43)	(.43)	(.41)	(.39)	(.40)
South	0.167	0.155	0.364	0.271	0.269
	(.37)	(.36)	(.48)	(.45)	(.45)
Islands	0.096	0.089	0.091	0.188	0.231
	(.29)	(.29)	(.29)	(.39)	(.43)
Female	0.415	0.409	0.424	0.458	0.615
	(.49)	(.49)	(.50)	(.50)	(.49)
Head of household	0.484	0.499	0.364	0.323	0.173
	(.50)	(.50)	(.48)	(.47)	(.38)
Spouse not working	0.225	0.220	0.303	0.313	0.212
	(.42)	(.41)	(.46)	(.47)	(.41)
Married	0.712	0.726	0.500	0.615	0.442
	(.45)	(.45)	(.50)	(.49)	(0.50)
Children<6	0.105	0.106	0.091	0.083	0.096
	(.31)	(.31)	(.29)	(.28)	(.30)
Mobility	0.349	0.346	0.500	0.313	0.365
	(.48)	(.48)	(.50)	(.47)	(.49)
Unemployment benefits	0.016	0.013	0.030	0.021	0.154
	(.12)	(.11)	(.17)	(.14)	(.36)
Sample size	1,381	1,274	33	48	26

Source: SHIW - Bank of Italy, 2002 and 2004.
Notes: Standard errors in parentheses.

Since we loose the first time-period for initial values, we can observe in our sample four possible contract type sequences: "always permanent", "permanent-temporary", "temporary-permanent", and "always temporary". Table 1 presents summary statistics of the variables used in the econometric analysis by sequences. The observed frequencies show that employees who are always permanent workers have better human capital factors: they are more experienced and better educated. Employees who had at least one fixed-term job relationship are more likely to live in the South of Italy, to have no children in pre-scholar age, and not to be head of household and married. Furthermore, people characterized by sequence "always temporary" are more likely to have had recent unemployment spells, consistent with the idea that unemployment events may convey bad signals.

4 Estimation Results

Tables 2 and 3 present estimation results of some static nonlinear probability models. These estimation results are discussed in subsection 4.1. Table 4 shows the estimates via pooled probit of three specifications of a dynamic unobserved effects probit model under the strict exogeneity of the explanatory variables, conditional on unobserved heterogeneity; table 5 contains the corresponding estimated APEs. These findings are discussed in subsection 4.2. Tables 6 and 7 display estimation results and APEs of a dynamic unobserved effects probit model with feedback effects from contract type to the proxy for recent unemployment spells; these results are commented in subsection 4.2.2. Table 8, showing the correct predictions, focuses on the goodness of fit of our dynamic nonlinear models. Finally, in subsection 4.2.4 we assess the robustness of the state dependence effect through the estimation of dynamic linear probability models and the estimation results are displayed in table 9.

4.1 Static Probit Models Estimation Results

Tables 2 and 3 contain results that focus on the determinants of temporary jobs ignoring dynamic effects of past contract types on current positions.

The first three columns of table 2 present the estimation results of a pooled probit model. The estimated coefficients of variables capturing the skill structure are significant, showing that the probability of having a temporary contract decreases with experience at an increasing rate and that lower educated employees are more likely to have a temporary job. The geographical dummies, which capture labour market heterogeneity, tell us that the probability of a temporary contract is higher in the South of Italy: living in the South increases the probability of having a temporary job by 6.4 percentage points, while the effect of living in the Island (Sicily and Sardinia) is about 6.8 percentage points. Also gender matters, and female employees have a significantly higher probability (2.3 percentage points) of receiving a temporary job than the comparable male worker. Household characteristics affect the choice of the contract: if the employee's spouse is not working the probability of having a temporary contract is significantly higher (around 3 percentage points), while if we are talking about married employees, the probability is significantly lower (2.7 percentage points). It seems that the higher the employee's household responsibility, the higher the worker's probability of accepting a temporary job.

The central columns of table 2 report the results from a random effects (RE) probit model, estimated by MLE using a Gauss-Hermite quadrature procedure with 20 quadrature points. The unobserved heterogeneity, which is assumed to be independent on the explanatory variables, accounts for about 40% of the unexplained variance of the composite disturbance $\varepsilon_{it} = c_i + u_{it}$, and it allows to improve the fit of the model measured by the log-likelihood. The estimated response probability effects decline to 1% for women, married individuals, and employees whose spouse is not working. The estimated effect of living in the South (including Sicily and Sardinia) declines by about 50%.

The last three columns of table 2 and the first three columns of table 3 present the estimation results of a Chamberlain's (1980) random effects probit model via GEE estimator and pooled probit estimator, respectively. The unobserved heterogeneity is allowed to be correlated to the explanatory variables but, as we have seen in subsection 2.2, we cannot identify the causal effects of time-invariant explanatory variables, even if we can include them in the model in order to explicitly control for observable individual heterogeneity.

Allowing the individual heterogeneity to be correlated to the explanatory variables, we find that the fraction of the unexplained variance of the composite error term $a_i + u_{it}$ due to a residual unobserved heterogeneity a_i is about 27%. Focusing on the GEE approach, the estimated coefficient of getting married is no more significant and the coefficient of the dummy for the spouse's employment status is now negative and different from zero only at a 10% significance level. The household position is estimated to have a significant effect on contract type and being head of household increases the probability of having a temporary contract of 6.6 percentage points. The presence of children in pre-scholar age does not affect the choice of contract. Similar results are obtained through a pooled probit estimation of the Chamberlain's (1980) random effects model. Note that, since the null hypothesis H_0: $\boldsymbol{\xi} = 0$ is rejected, we can infer that controlling for the correlation be-

Table 2: Pooled Probit, Random Effects Probit, and Correlated GEE Probit Estimates of the Static Model of Contract Type

	Pooled Probit			RE Probit			Correlated GEE Probit		
Variable	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.[†]	
Experience	-0.060	0.016	***	-0.081	0.022	***	-0.059	0.019	***
Experience^2/100	0.001	0.000	**	0.001	0.000	**	0.001	0.000	**
Education - Reference:None or Elementary									
Middle school	-0.529	0.166	***	-0.664	0.232	***	-0.530	0.197	***
Professional school	-0.558	0.216	***	-0.668	0.297	**	-0.551	0.225	**
High school	-0.834	0.175	***	-1.058	0.246	***	-0.828	0.214	***
University degree or +	-0.560	0.196	***	-0.739	0.276	***	-0.551	0.232	**
Area - Reference: North East									
North-West	0.153	0.145		0.198	0.199		0.145	0.160	
Centre	0.160	0.146		0.209	0.200		0.160	0.163	
South	0.621	0.145	***	0.814	0.201	***	0.610	0.151	***
Islands	0.616	0.161	***	0.795	0.225	***	0.605	0.177	***
Female	0.341	0.101	***	0.439	0.140	***	0.321	0.110	***
Head of household	-0.162	0.106		-0.160	0.144		0.634	0.213	***
Spouse not working	0.348	0.132	***	0.424	0.178	**	-0.345	0.201	*
Married	-0.342	0.126	***	-0.425	0.173	**	-0.596	0.490	
Children$<$6	0.122	0.158		0.160	0.213		0.434	0.340	
D2000	-0.071	0.090		-0.094	0.107		-0.060	0.078	
Constant	-0.865	0.270	***	-1.133	0.374	***	-0.834	0.274	***
Random effect: time-variant variables in all time periods									
Head of household$_1$							-0.405	0.168	**
Head of household$_2$							-0.486	0.211	**
Spouse not working$_1$							0.169	0.262	
Spouse not working$_2$							0.586	0.248	**
Married$_1$							0.555	0.292	*
Married$_2$							-0.277	0.539	
Children$<6_1$							-0.461	0.406	
Children$<6_2$							0.169	0.320	
Wald Stat. for H_0: $\boldsymbol{\xi}$=0							χ^2_8=25.8 p-value=0.001		
Observations		2,762			2,762			2,762	
Pseudo R^2		0.126			0.101			0.114[(a)]	
Wald χ^2		134.6			93.5			108.8	
Log-likelihood		-465.9			-445.5				
$\sigma^2_{c(a)}$					0.654			0.375	

Source: SHIW - Bank of Italy, 2002 and 2004.
Notes: Number of observations: N=1,381 employees across T=2 years. The simple pooled probit model assumes that the composite error term ε_{it} is iid across i and t. Its varince is normalized to 1. The RE probit model is estimated by MLE using a Gauss-Hermite quadrature procedure.
* Significant at 10%; ** significant at 5%; *** significant at 1%.
[†]Standard errors robust to serial correlation have been computed.
[(a)] The sum of squared residuals measure is reported.

Table 3: Correlated Pooled Probit Estimates of the Static Model of Contract Type

Model specification	(1)			(2)			(3)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.†	
Experience	-0.058	0.018	***	-0.064	0.018	***	-0.065	0.018	***
Experience^2/100	0.001	0.000	**	0.001	0.000	**	0.001	0.000	**
Education - Reference:None or Elementary									
Middle school	-0.528	0.192	***	-0.520	0.191	***	-0.446	0.178	**
Professional school	-0.546	0.223	**	-0.570	0.224	**	-0.521	0.224	**
High school	-0.827	0.209	***	-0.817	0.210	***	-0.710	0.197	***
University degree or +	-0.552	0.227	**	-0.515	0.231	**	-0.372	0.218	*
Area - Reference: North East									
North-West	0.146	0.159		0.124	0.161		0.038	0.168	
Centre	0.157	0.160		0.162	0.163		0.078	0.162	
South	0.604	0.148	***	0.678	0.157	***	0.620	0.156	***
Islands	0.603	0.175	***	0.649	0.179	***	0.627	0.180	***
Female	0.321	0.110	***	0.356	0.110	***	0.326	0.109	***
Head of household	0.602	0.238	**	0.617	0.244	**	0.628	0.261	**
Spouse not working	-0.335	0.215		-0.401	0.228	*	-0.395	0.232	*
Married	-0.626	0.458		-0.575	0.474		-0.619	0.500	
Children<6	0.408	0.338		0.453	0.349		0.459	0.353	
D2000	-0.062	0.078		-0.110	0.080		-0.124	0.084	
Mobility				1.061	0.398	***	1.053	0.404	***
Unemp. benefits							0.394	0.217	*
Constant	-0.837	0.273	***	-0.932	0.287	***	-0.924	0.290	***
Random effect: time-variant variables in all time periods									
Head of household$_1$	-0.398	0.178	**	-0.382	0.170	**	-0.400	0.181	**
Head of household$_2$	-0.462	0.215	**	-0.540	0.234	**	-0.568	0.247	**
Spouse not working$_1$	0.172	0.275		0.200	0.270		0.237	0.290	
Spouse not working$_2$	0.579	0.260	**	0.633	0.259	**	0.652	0.257	**
Married$_1$	0.588	0.313	*	0.566	0.315	*	0.617	0.323	*
Married$_2$	-0.286	0.483		-0.318	0.515		-0.361	0.542	
Children<6$_1$	-0.442	0.392		-0.488	0.383		-0.458	0.394	
Children<6$_2$	0.183	0.311		0.213	0.318		0.184	0.319	
Mobility$_1$				-0.129	0.239		-0.147	0.250	
Mobility$_2$				-0.561	0.433		-0.565	0.441	
Unemp. benefits$_1$							0.434	0.349	
Unemp. benefits$_2$							0.905	0.289	***
Wald Stat. for H_0: $\boldsymbol{\xi}$=0	χ^2_8=22.1	p-value=0.005		χ^2_{10}=26.2	p-value=0.004		χ^2_{12}=38.2	p-value=0.000	
Observations		2,762			2,762			2,762	
Pseudo R^2		0.138			0.155			0.185	
Wald χ^2		103.5			127.8			153.1	
Log-pseudolikelihood		-459.7			-450.6			-434.7	
Strict exogeneity test:[(a)]	χ^2_4=5.29	p-value=0.259		χ^2_5=6.36	p-value=0.273		χ^2_6=15.8	p-value=0.015	
Specification test:[(b)]	χ^2_3=0.68	p-value=0.878		χ^2_3=0.81	p-value=0.848		χ^2_3=4.36	p-value=0.225	

Source: SHIW - Bank of Italy, 2002 and 2004.
Notes: Number of observations: N=1,381 employees across T=2 years. * Significant at 10%; ** significant at 5%; *** significant at 1%.
†Standard errors robust to serial correlation have been computed.
[(a)]This test has been performed including the forward of time-variant variables as additional set of covariates and then jointly testing their significance.
[(b)]This test follows Wooldridge (2005) and it has been performed through a two step procedure: i) we estimate the basic model and compute $\mathbf{X}_i\widehat{\boldsymbol{\xi}}$; ii) we include this term up to the fourth power in the basic model and we test their joint significance.

tween unobserved heterogeneity and explanatory variables is important and that the RE probit model estimates are biased due to the failure of the standars RE probit assumptions.

In the last columns of table 3 we include two new explanatory variables that should control for employment history and provide employers with bad signals. Specifically, estimation results that include a dummy variable equal to one if the worker had in the past 2 or more job experiences are displayed in the central columns. This variable is an indicator of the worker's instability. The last three columns present estimation results of the specification including also a dummy variable equal to one if the worker had unemployment benefits during the interview year. This indicator is a proxy for recent unemployment events. As a matter of fact, both of them increase the probability of having a temporary contract but the strict exogeneity assumption, conditional on the individual-specific component, is likely to fail. Indeed, there could be some feedback effects from the type of contract to future realizations of these variables. If temporary contracts increase the probability of higher job-turnover and/or of unemployment, then, having a temporary contract at time t increases the probability of having an unemployment event or an unstable job-position at time $t+1$, invalidating the strict exogeneity requirement. For this reason, we have performed a strict exogeneity test as suggested by Wooldridge (2002). While we cannot reject the null hypothesis of strict exogeneity of the job-mobility indicator, there is evidence of endogeneity for the proxy for recent unemployment spells, most likely due to a feedback effect. Thus, the estimation results reported in the last three columns of table 3 loose in credibility and we will face this problem in a dynamic setting.

4.2 Dynamic Probit Models Estimation Results

4.2.1 Estimation Results under Strict Exogeneity

We now present the estimation results of three different specifications of a dynamic unobserved effects probit model for contract type under the strict exogeneity assumption of the explanatory variables, conditional on individual heterogeneity. The starting point is a model in which we exclude the variables controlling for employees' employment history (specification (1)); then, we introduce the job-mobility indicator (specification (2)); finally, we include also the proxy for recent unemployment spells (specification (3)) that is supposed to violate the strict exogeneity assumption. These estimation results are reported in table 4 and, as we have seen in subsection 2.3.1, they have been obtained through a pooled probit estimator.

Table 4: Correlated Pooled Probit Estimates of the Dynamic Model of Contract Type

Model specification	(1)			(2)			(3)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.†	
y_{t-1}	0.967	0.184	***	0.984	0.182	***	0.929	0.185	***
Experience	-0.031	0.017	*	-0.038	0.016	**	-0.040	0.017	**
Experience^2/100	0.000	0.000		0.000	0.000		0.001	0.000	
Education - Reference:None or Elementary									
Middle school	-0.462	0.177	***	-0.442	0.177	**	-0.409	0.178	**
Professional school	-0.370	0.205	*	-0.393	0.205		-0.374	0.213	*
High school	-0.642	0.191	***	-0.626	0.193	***	-0.575	0.197	***
University degree or +	-0.391	0.203	*	-0.346	0.207	*	-0.267	0.210	
Area - Reference: North East									
North-West	0.111	0.155		0.094	0.157		0.043	0.161	
Centre	0.091	0.150		0.089	0.153		0.035	0.156	
South	0.418	0.143	***	0.472	0.151	***	0.447	0.153	***
Islands	0.309	0.172	*	0.342	0.176	*	0.337	0.175	*
Female	0.228	0.105	**	0.261	0.104	**	0.246	0.106	**
Head of household	0.693	0.313	**	0.690	0.317	**	0.681	0.328	**
Spouse not working	-0.458	0.274	*	-0.542	0.284	*	-0.547	0.284	*
Married	-0.620	0.566		-0.553	0.589		-0.591	0.595	
Children<6	0.632	0.383	*	0.677	0.384	*	0.676	0.380	*
D2000	-0.042	0.096		-0.099	0.100		-0.115	0.101	
Mobility				1.164	0.495	**	1.148	0.492	***
Unemp. benefits							0.426	0.285	
Constant	-1.277	0.274	***	-1.353	0.283	***	-1.311	0.285	***
Random effect: initial condition and time-variant variables in all time periods									
y_0	0.447	0.187	**	0.408	0.184	**	0.410	0.192	**
Head of household$_1$	-0.508	0.190	***	-0.471	0.174	***	-0.459	0.184	**
Head of household$_2$	-0.434	0.266		-0.496	0.284	*	-0.522	0.294	*
Spouse not working$_1$	0.305	0.237		0.360	0.236		0.387	0.250	
Spouse not working$_2$	0.580	0.249	**	0.626	0.253	**	0.651	0.256	**
Married$_1$	0.452	0.274	*	0.407	0.280		0.456	0.288	
Married$_2$	-0.192	0.530		-0.214	0.556		-0.251	0.569	
Children<6$_1$	-0.525	0.381		-0.562	0.366		-0.543	0.374	
Children<6$_2$	0.103	0.346		0.120	0.350		0.098	0.346	
Mobility$_1$				-0.334	0.232		-0.321	0.243	
Mobility$_2$				-0.549	0.503		-0.565	0.502	
Unemp. benefits$_1$							0.003	0.323	
Unemp. benefits$_2$							0.771	0.278	***
Wald Stat. for H_0: $\boldsymbol{\xi}$=0	χ^2_8=21.6 p-value=0.006			χ^2_{10}=25.4 p-value=0.005			χ^2_{12}=32.1 p-value=0.001		
Observations		2,762			2,762			2,762	
Pseudo R^2		0.246			0.258			0.274	
Wald χ^2		264.5			275.4			294.4	
Log-pseudolikelihood		-402.1			-395.6			-387.1	
Specification test:[a]	χ^2_3=0.38 p-value=0.945			χ^2_3=6.17 p-value=0.104			χ^2_3=4.65 p-value=0.199		

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.

Notes: Number of observations: N=1,381 employees across T=2 years. * Significant at 10%; ** significant at 5%; *** significant at 1%.

†Standard errors robust to serial correlation have been computed.

[a]This test follows Wooldridge (2005) and it has been performed through a two step procedure: i) we estimate the basic model and compute $(y_{i0}\widehat{\xi}_0 + \mathbf{X}_i\widehat{\boldsymbol{\xi}})$; ii) we include this term up to the fourth power in the basic model and we test their joint significance.

Table 5: Average Partial Effects of the Dynamic Probit Models of Contract Type

Model specification	(1)		(2)		(3)	
Variable	APE		APE		APE	
y_{t-1}	0.133	***	0.134	***	0.120	***
Head of household$_t$	0.064	*	0.062	*	0.061	*
Spouse not working$_t$	-0.031	*	-0.036	**	-0.036	**
Married$_t$	-0.057		-0.048		-0.051	
Children$<6_t$	0.069		0.074		0.072	
Mobility$_t$	–		0.129		0.125	
Unemployment benefits$_t$	–		–		0.041	
Raw transition probabilities						
y_{t-1}					0.326[(a)]	

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: * significant at 10%; ** significant at 5%; *** significant at 1%.
(a) It is given by $P(y_{it} = 1|y_{it-1} = 1) - P(y_{it} = 1|y_{it-1} = 0)$

The covariate effects are generally close to those in the static Chamberlain's (1980) random effects model. The coefficient of the dummy indicator for the presence of children in pre-scholar age is now different from zero at a 10% level and since it is positive there is some evidence that children are an incentive to accept a temporary job. Moreover, the coefficient of the proxy for recent unemployment spells is still positive but no longer significant, even if there could be an important bias due to its plausible endogeneity. Let us now focus on the dynamic because the coefficient of lagged contract type is always positive and highly significant. Therefore, even if we control for unobserved heterogeneity and we remove spurious state dependende, there is a significant amount of true and positive state dependence, meaning that the probability of having a temporary job is significantly higher if the employee was a temporary worker 2 years before, *ceteris paribus*. Table 5 displays the estimated APEs and they give a measure of the state dependence effect in terms of percentage points: the state dependence effect is around 13% and a bit lower and equal to 12% when we introduce the proxy for recent unemployment spells.

If we compute the matrix of transition probabilities from raw data, we notice that the persistence is much higher and equal to 32.6%.[12] This means that it is possible to explain most of the persistence of temporary contracts by spurious state dependence, i.e. the persistence due to observed and unobserved heterogeneity. However, even if the persistence due to observed and unobserved heterogeneity can almost explain 60% of the persistence from the

[12]Table A-1 reports the matrix of transition probabilities from raw data.

raw data, there is evidence of a significant and positive true state dependence of temporary contracts. Finally, note that the initial type of contract is also very important, and implies that there is substantial correlation between unobserved heterogeneity and the initial condition.

4.2.2 Estimation Results with Feedback Effects

As we have seen, the dummy indicator for unemployment benefits is likely to be endogenous and indeed it failed the strict exogeneity test in a static framework. However, we can note that the estimated APEs of the lagged contract type are quite robust to the introduction of possible endogenous variables. The point is that we have a bias in the estimated coefficient of the endogenous variable and it could be of some interest, from the policy viewpoint, both to have a consistent estimate of the coefficient of the proxy for recent unemployment spells and to model the dynamic of recent unemployment spells to evaluate the magnitude of the feedback effect.

Table 6 displays the estimation results of a dynamic unobserved effects probit model relaxing the strict exogeneity for the proxy of recent unemployment events and jointly estimating the dynamic of contract type and unemployment benefits.[13] In the first three columns the estimation results of the equation of the contract type are reported, while the last three columns focus on the equation of unemployment benefits. Table 7 contains the estimated APEs.

The results suggest that, even after controlling for the endogeneity of unemployment benefits, there is a significant and positive state dependence for temporary contracts. The estimated state dependence effect is in line with those obtained before and employees who had a temporary job in the past are more likely to have a current temporary contract (+12.5% percentage points). The covariate effects are, once again, generally close to those obtained both in the static and dynamic framework under the strict exogenity of unemployment benefits. A first important finding is that the coefficient of the proxy for recent unemployment spells is now highly significant and positive, meaning that recent unemployment spells are a bad signal for employers, increasing the probability of finding a job with a fixed duration by about 11 percentage points. The initial type of contract is also very important, and implies that there is substantial correlation between the unobserved heterogeneity and the initial condition.

[13] In order to have identification of the joint model, we remove marital status from the set of covariates explaining contract type and we include it in the set of covariates explaining unemployment benefits.

Table 6: Joint Dynamic Model of Contract Type and Unemployment Benefits

Dependent variable	Contract Type			Unemployment benefits		
Variable	Coeff.	S.E.†		Coeff.	S.E.†	
Endogenous variable						
Unemployment Benefits	0.845	0.220	***			
Lagged endogenous variable						
y_{t-1}	0.942	0.186	***	0.727	0.176	***
Unemployment benefits$_{t-1}$	0.081	0.200		0.865	0.258	***
Experience	-0.055	0.015	***	-0.029	0.024	
Experience^2/100	0.001	0.000	**	0.001	0.000	
Education - Reference:None or Elementary						
Middle school	-0.439	0.182	**	-0.208	0.216	
Professional school	-0.407	0.214	*	-0.130	0.263	
High school	-0.617	0.202	***	-0.463	0.215	**
University degree or +	-0.347	0.216		-0.868	0.435	**
Area - Reference: North East						
North-West	0.067	0.160		0.541	0.195	***
Centre	0.034	0.153		0.418	0.212	**
South	0.450	0.151	***	0.118	0.241	
Islands	0.331	0.178	*	0.180	0.300	
Female	0.212	0.106	**	0.086	0.157	
Head of household	0.706	0.316	**	0.128	0.156	
Spouse not working	-0.507	0.271	*	-0.165	0.186	
Married				0.419	0.175	**
Children<6	0.631	0.373	*	-0.189	0.238	
D2000	-0.084	0.100		0.137	0.134	
Mobility	1.115	0.495	**	0.318	0.130	**
Constant	-1.212	0.286	***	-2.671	0.424	***
Random effect: initial conditions and time-variant variables in all time periods						
y_0	0.391	0.193	**			
Unemployment Benefits$_0$	0.167	0.336				
Head of Household$_1$	-0.534	0.196	***			
Head of Household$_2$	-0.467	0.293				
Spouse not working$_1$	0.320	0.226				
Spouse not working$_2$	0.521	0.254	**			
Children<6$_1$	-0.669	0.365	*			
Children<6$_2$	0.130	0.358				
Mobility$_1$	-0.315	0.234				
Mobility$_2$	-0.527	0.508				
θ_4				-0.000	0.000	***
Wald Statistics for H_0: $\boldsymbol{\xi_2}$=0	χ^2_8=23.2 p-value=0.003					
Observations					2762	
Pseudo R^2					0.230	
Wald χ^2_{29}					120.5	
Log-pseudolikelihood					-584.7	

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: Number of observations: N=1,381 employees across T=2 years.
* Significant at 10%; ** significant at 5%; *** significant at 1%.
†Standard errors robust to serial correlation have been computed.

Table 7: Average Partial Effects of the Joint Dynamic Model of Contract Type and Unemployment Benefits

Dependent variable	Contract Type		Unemp. benefits	
Variable	APE		APE	
y_{t-1}	0.125	***	0.045	**
Unemployment benefits$_t$	0.109	**	–	
Unemployment benefits$_{t-1}$	0.006		0.065	*
Head of household$_t$	0.065	*	0.004	
Spouse not working$_t$	-0.034	**	-0.005	
Married$_t$	–		0.012	***
Children$<6_t$	0.067		-0.006	
Mobility$_t$	0.121		0.011	**
Raw transition probability				
y_{t-1}	0.326[(a)]			

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: *significant at 10%; **significant at 5%; ***significant at 1%.
[(a)] It is given by $P(y_{it} = 1|y_{it-1} = 1) - P(y_{it} = 1|y_{it-1} = 0)$

If we focus now on the estimation results of the equation for unemployment benefits, a second important finding arises. The lagged contract type is able to explain the current proxy for recent unemployment spells: the associated coefficient is indeed highly significant and positive.[14] This evidence may be interpreted as a rejection of the "stepping stone" theory, because it seems that a temporary job today increases the probability of having an unemployment event in the future. However, if we look at the estimated feedback effect, the probability of having an unemployment spell increases by about 4.5 percentage points if the employee had a temporary job in the past; even if this estimated APE is significantly different from zero, the magnitude is not so large. Finally, a significant state dependence of the proxy for recent unemployment spells has been found out, meaning that, conditional on individual heterogeneity, an unemployment event at time t leads to an higher unemployment probability at time $t + 1$ by about 6.5 percentage points.

4.2.3 Predicted Contract Types and Predicted Contract Type Sequences

In order to provide a descriptive evaluation of the goodness of the fit of the dynamic nonlinear models estimated in this paper, we report in table 8 the percent correctly predicted contract types and the percent correct predicted contract type sequences. We follow the usual rule according to which we

[14]This is the feedback effect from contract type to unemployment that confirm our suspicion about the strict exogeneity of unemployment benefits.

predict, for each i and t, y_{it} to be unity when the estimated probability is larger than or equal to 0.5, i.e. $\widehat{\Phi}_{it} \geq 0.5$. If $\widehat{\Phi}_{it} < 0.5$, y_{it} is predicted to be zero. The percentages reported in table 8 are the percentages of times the predicted y_{it} matches the actual y_{it}. If we are talking about predicted sequences, then we refer to the percentages of time the predicted sequence matches the actual sequence $\{y_{it}, y_{it-1}\}$.

In column (1) we report the correct predictions of the dynamic model in which there are no covariates controlling for employment history; column (2) displays the correct predictions when we introduce the job-mobility covariate, while column (3) refers to the model in which we have also introduced the proxy for recent unemployment spells. Finally, the last column reports the correct prediction percentages of the dynamic model with feedback effects from contract type to unemployment benefits.

Table 8: Correct Predicted Contract Types and Correct Predicted Contract Type Sequences from Dynamic Probit Models

	(1)	(2)	(3)	Joint model
Correct predicted contract types				
Permanent	99.58%	99.51%	99.73%	99.62%
Temporary	11.28%	14.29%	16.54%	12.78%
Overall	95.33%	95.40%	95.73%	95.44%
Correct predicted contract type sequences				
Always permanent	99.37%	99.37%	99.61%	99.37%
From permanent to temporary	0.00%	0.00%	0.00%	0.00%
From temporary to permanent	4.17%	10.42%	10.42%	12.50%
Always temporary	11.54%	15.38%	23.08%	15.38%
Overall	92.03%	92.32%	92.69%	92.40%

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.

As regard the correct predicted contract type realizations, we can see that the overall percent correctly predicted is always quite high and, indeed, we are able to correctly predict more than 95% of the time. Nevertheless, if we focus on this measure for each outcome, we realize that the model is able to predict almost without mistakes employees with a permanent job (more than 99.5% of the time), but it is correct only about 11.3%–16.5% of the time for temporary workers. This means that we are not able to well predict the outcome we would most like to predict. Note that, as soon as we introduce in the specification of the probability model the variables controlling for employment history (columns (2) and (3)), the percent correctly predicted for temporary jobs increases. The performance of the dynamic model with feedback effects in terms of correct predicted contract types is in line with the other dynamic models.

We now turn to the correct predicted contract type sequences. If we look at the overall results, we could argue that the dynamic model is really able to predict the transitions, since it correctly predicts sequences more than 92% of the time. But, looking for each possible sequence, we realize that the model cannot well predict sequences like temporary-permanent or temporary-temporary, which are of primary interest. While the dynamic models correctly predict more than 99.3% of the time permanent-permanent sequences, they are never able to predict permanent-temporary transitions, and they have low performances in predicting temporary-permanent (4.2%–12.5%) and temporary-temporary (11.5%–23.1%) sequences. We can note that the goodness of the models in predicting temporary-permanent sequences considerably increases when we introduce in the model specifications the two covariates controlling for employment history; the dynamic model with feedback effects is the best in predicting this sort of sequence (12.5% of the time)

4.2.4 Robustness Check: Dynamic Linear Probability Models

Table 9 presents the estimation results from dynamic linear probability models corresponding to equations (17) and (18). The aim is to assess the robustness of the state dependent effects derived through dynamic nonlinear probability models. Indeed first-differencing the linear specification of model (1) allows us to fully remove individual heterogeneity which is instead only approximated through a Chamberlain's (1980) approach. Moreover, it is well-known that linear probability models seem to provide good estimates of partial effects. The state dependence effects we have found out in the previous subsections could be indeed generated by some unobserved heterogeneity that we are not able to capture through the Chamberlain's (1980) approach. For instance, durations of temporary contracts longer than 2 years could matter, so that we may observe a state dependence simply generated by the fact that temporary contracts have not been expired yet. If it is so, we can remove this time-invariant unobserved individual characteristic using the first-difference of the linear probability model.

The first row of table 9 displays OLS estimates of the lagged contract type coefficient for the model in first-differences and in levels: the estimates are -0.381 and 0.300, respectively. The former estimate is biased downwards due to negative correlation between Δy_{it-1} and Δu_{it}: this is the common problem of endogeneity in first-differences dynamic linear models. The latter estimate is biased upward due to the correlation between y_{it-1} and individual heterogeneity.

The second row reports estimation results using the initial value of the dependent variable, y_{i0}, as instrument for Δy_{it-1} in the first-differences specification and Δy_{it-2} as instrument for y_{it-1} in the levels specification. The estimated lagged dependent variable coefficients are 0.149 and 0.106, meaning that they are converging; note that the estimated state dependence effects from the dynamic nonlinear models always lie between these two values. The F statistics from the first-stage regressions indicate that we do not have problems of weak instruments.

Table 9: Dynamic Linear Probability Models of Contract Type

	First Difference Specification			Level Specification		
	ρ	Instruments	Tests	ρ	Instruments	Tests
(1)	-0.381	–	–	0.300	–	–
	(.047)			(.055)		
(2)	0.149	y_{i0}	185.7[(a)]	0.106	Δy_{it-2}	114.4[(a)]
	(.087)		(.000)	(.090)		(.000)
(3)	0.157	y_{i0}, $\mathbf{x}_{i0}$	2.46[(b)]	0.157	Δy_{it-2}, $\mathbf{x}_{i0}$	4.97[(b)]
	(.082)		(.873)	(.077)		(.548)
Unemployment benefits in the specification of the linear probability model						
(4)	-0.384	–	–	0.289	–	–
	(.047)			(.053)		
(5)	0.146	y_{i0}	185.3[(a)]	0.098	Δy_{it-2}	112.4[(a)]
	(.086)		(.000)	(.090)		(.000)
(6)	0.149	y_{i0}, $\mathbf{x}_{i0}$	3.07[(c)]	0.145	Δy_{it-2}, $\mathbf{x}_{i0}$	5.24[(c)]
	(.081)		(.879)	(.077)		(.631)
Observations			1,318			1,318

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: Number of observations: N=1,381 employees. White (1980) robust standard errors have been computed. The full set of estimation results are reported in appendix, tables A-2, A-3, and A-4. Row (3) and (6) reports efficient GMM estimation results.
[(a)]First-stage F-statistic for the power of the excluded instrument, conditional on the included exogenous variables.
[(b)]Hansen J over-identification statistic, with 6 degrees of freedom.
[(c)]Hansen J over-identification statistic, with 7 degrees of freedom.

In the third row we introduce, as further instruments, the initial values of the time-variant explanatory variables, $\mathbf{x}_{i0}$ and we estimate the model via efficient GMM estimator. In this way we are able both to increase the efficiency of the estimates and to test the validity of the instruments. We can see that the estimated lagged dependent variable coefficients converge to the same value, 0.157, which is different from zero at a 10% significance level in the first-differences specifications and at a 5% significance level in the specification in levels. The results of the over-identification tests do not reject the null hypothesis, meaning that the instruments seem to be valid. If we include, as further explanatory variable, the proxy for recent unemployment spells, we draw the same conclusions.

Therefore, fully controlling for unobserved heterogeneity and avoiding the problem of initial values through dynamic linear probability models result in estimated state dependence effects which are very close to those from dynamic unobserved effects probit models. This finding gives robustness to the estimated results presented and commented in the previous subsections.

5 Concluding Remarks and Policy Suggestions

In this paper we have estimated a dynamic unobserved effects probit model to test the hypothesis of state dependence of temporary jobs, to understand the determinants of temporary jobs, and to test the exogeneity of recent unemployment events and job-mobility. The econometric analysis has been performed using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth (SHIW), a representative survey conducted by the Bank of Italy every two years since 1989.

Given the specification of our dynamic unobserved effects probit model we can distinguish between two sources of state dependences conditional on the observed covariates: persistence of temporary contracts due to unobserved heterogeneity and due to true state dependence. For instance, firms could use systematically temporary contracts to face demand uncertainty and have low firing costs so that temporary jobs become a trap: loss of motivation and depreciation of human capital due to low firm-specific investments may make temporary workers less likely to jump on stabler job relationships. This suggests that temporary jobs may show true state dependence: having a temporary contract today should arise the probability of having a temporary contract next period. On the other hand, some employees are more likely to have a temporary contract because of their individual characteristics (for example, bad signals and ability), corresponding to individual heterogeneity.

The starting point has been the estimation of a static model of the determinants of a temporary job. Addressing the problem of unobserved heterogeneity through a Chamberlain's (1980) approach we have found out that employment history is important in explaining the probability of having a temporary contract. Employees with an unstable job-career or with recent unemployment spells are more likely to find a temporary job. While we cannot reject the exogeneity of job mobility, recent unemployment spells have failed the strict exogeneity requirement. This finding has been interpreted as a possible feedback effect: a temporary job in this period has an effect on future unemployment spells. If this the case, shocks affecting the contract type could be correlated with future unemployment events, violating strict exogeneity.

Then, we have turned to the dynamic specification of the probability of having a temporary contract. This means that the probability of being a temporary worker at time t has been allowed to depend on the realization in $t-1$ as well as unobserved heterogeneity. We have proposed different specifications of the model which have been estimated through pooled probit estimators. Moreover, we have relaxed the strict exogeneity of the proxy for recent unemployment spells. The main findings are:

- A significant true state dependence of temporary contracts. We have computed the matrix of transition probabilities from raw data and we have noticed that the raw persistence is much higher. Thus, it is possible to explain most of the persistence of temporary contracts by spurious state dependence, i.e. the persistence due to observed and unobserved heterogeneity. However, even if the persistence due to observed and unobserved heterogeneity can almost explain 60% of the persistence from the raw data, there is evidence of a significant and positive true state dependence of temporary contracts.

- A higher probability of ending in a temporary job for workers with higher job-mobility and with recent unemployment spells, likely to be interpreted as bad signals by employers.

- A significant feedback effect from past temporary job experiences to recent unemployment spells that has been interpreted as a significant higher probability of having an unemployment experience after a temporary job.

Finally, we have estimated some dynamic linear probability models, in first-differences and in levels. Indeed, they are able to approximate the average partial effect of the lagged type of contract, fully controlling for unobserved heterogeneity and avoiding the problem of initial conditions. Therefore, the estimated coefficients of the lagged dependent variable have been used to check the robustness of the results obtained through nonlinear models. We have seen that the estimated state dependence effects from dynamic nonlinear and linear models are very close to each other.

These empirical findings might be of some interests from the policy viewpoint. First, we have seen that jobless and unstable workers are more likely to end up in temporary contracts. Secondly, the significant true state dependence effect of temporary contracts might be due to the fact that firms are systematically using temporary jobs to face demand uncertainty: loss of motivation and depreciation of human capital due to low firm-specific investments may make temporary workers less likely to jump on stabler job relationships. Moreover, the true state dependence could be related to the presence of a dual labour market, segmented into "bad" and "good" jobs. Therefore, jobless and unstable workers are more likely to end up into temporary relationship generating a loss of human capital, affecting the workers' allocation in the whole economy, and widening the gap between possibly segmented labour markets. The policy maker might be aware of these costs associated to the widespread of temporary jobs and design policies to target those workers suffering most from the trap of temporary positions.

Appendix

This appendix adds details of the definition and construction of variables used in the econometric analysis, illustrates how we have estimated average partial effects, and reports estimation results not presented in the text.

A-1 Data Appendix

Temporary and Permanent Contracts

The dummy variable y_{it} has been built using question 1, section "CONTRATT" of the annex B1 (information on the activity of employees) of the SHIW questionnaire. The question requires to indicate your contract choosing between permanent, fixed-term, and worker for temporary job agency. Thus, the dummy variable for the contract type is equal to 0 when the employee answers to have a permanent contract, it is equal to 1 if the worker replies to belong to the last two categories.

Table A-1 reports the transition probabilities using 2002 and 2004 data. The raw state dependence effect is 32.6%, meaning that the probability of having a temporary contract is higher by about 32.6 percentage points if the worker had a temporary job two years before.

Table A-1: Transition Probabilities

	Permanent in t	Temporary in t
Permanent in $t-1$	97.48%	2.52%
Temporary in $t-1$	64.86%	35.14%
State dependence	-32.62%	32.62%

Source: SHIW - Bank of Italy, 2002 and 2004.

Work Experience

Work experience has been computed using age information and answers to question B07 of the SHIW questionnaire: "How old were you when you began to work?". Work experience is in years and, furthermore, it is a potential experience since we do not know if there have been any unemployment spells between the working starting date and the interview time.

The information used to calculate work experience is affected by measurement errors: they have been detected because of inconsistency in answering to the same question in 2000, 2002, 2004.[15] Thus, we decided to introduce some assumptions and correct the detected inconsistencies for the 1,381 employees in our sample.

We assume that the 2000 answer to question B07 about the age at which the individual began to work is more reliable, since the worker was temporally closer to his (her) life moment in which (s)he started working (and so the worker should have a lower probability of wrongly answering to question B07). Therefore, we corrected the 2002 and 2004 answers to question B07, using the 2000 answer and adding 2 years in 2002 and 4 years in 2004.

Job-Mobility

"Mobility" is an indicator which is equal to one when the employee has already had in the past 2 or more different job experiences. This information comes from question B05 of the SHIW questionnaire: "Consider all activities, including temporary ones, performed up to 31.12.2000/2002/2004: how many activities had you performed, including the one, if any, being performed at 31.12.2000/2002/2004?"

Unemployment Benefits

This variable is equal to one when the worker has received some unemployment benefits during the interview year. The information about the unemployment benefits can be found in section B6, questions b2–b4.

A-2 Estimating Average Partial Effects

We are also interested in estimating the effects of some covariates on the response probabilities. Since we are assuming the presence of an unobserved individual heterogeneity, we have to average across the distribution of the individual-specific component and then compute the change in the response probabilities for some interesting values of the covariates. This mean that we need to define the APEs in the context of a dynamic unobserved effects probit model with and without feedback effects.

First, let us derive APEs in the simplest framework, assuming that the explanatory variables are strictly exogenous. As described by Wooldridge (2005), under strict exogeneity conditional on $c_i = \psi + y_{i0}\xi_0 + \mathbf{X}_i\boldsymbol{\xi} + a_i$, the average partial effects are based on

$$\mathrm{E}\big[\Phi(\mathbf{x}'_{it}\boldsymbol{\beta} + y_{it-1}\rho + \psi + y_{i0}\xi_0 + \mathbf{X}_i\boldsymbol{\xi} + a_i)\big], \tag{A-1}$$

where the expectation is with respect to $(y_{i0}, \mathbf{X}_i, a_i)$. Wooldridge (2005) shows that, applying iterated expectations, expression (A-1) can be rewritten as

$$\mathrm{E}\big[\Phi(\mathbf{x}'_{it}\boldsymbol{\beta}_a + y_{it-1}\rho_a + \psi_a + y_{i0}\xi_{a0} + \mathbf{X}_i\boldsymbol{\xi}_a)\big], \tag{A-2}$$

where the a subscript indicates that the original parameters have been multiplied by the scaling factor $(1+\sigma_a^2)^{-1/2}$, and the expectation is now with respect to $(y_{i0}, \mathbf{X}_i)$.

[15]For instance, the same worker gives two different answers to question B07 in 2002 and 2004, when we would expect the same answer in both years since the date at which the worker began her first job activity is time-invariant.

Then, the APE of the lagged contract type (the state dependence effect) is defined as

$$\begin{aligned} \mathrm{APE}_{y_{it-1}} &= \mathrm{E}\big[\Phi(\mathbf{x}'_{it}\boldsymbol{\beta}_a + \rho_a + \psi_a + y_{i0}\xi_{a0} + \mathbf{X}_i\boldsymbol{\xi}_a)\big] \\ &- \mathrm{E}\big[\Phi(\mathbf{x}'_{it}\boldsymbol{\beta}_a + \psi_a + y_{i0}\xi_{a0} + \mathbf{X}_i\boldsymbol{\xi}_a)\big], \end{aligned} \tag{A-3}$$

since $y_{it-1} = \{0, 1\}$. In a similar way we can define the APEs for other dummy variables. A consistent estimator of $\mathrm{APE}_{y_{it-1}}$ is

$$\begin{aligned} \widehat{\mathrm{APE}}_{y_{it-1}} &= \sum_{i=1}^{N} \big[\Phi(\mathbf{x}'_{it}\widehat{\boldsymbol{\beta}}_a + \widehat{\rho}_a + \widehat{\psi}_a + y_{i0}\widehat{\xi}_{a0} + \mathbf{X}_i\widehat{\boldsymbol{\xi}}_a)\big] \\ &- \sum_{i=1}^{N} \big[\Phi(\mathbf{x}'_{it}\widehat{\boldsymbol{\beta}}_a + \widehat{\psi}_a + y_{i0}\widehat{\xi}_{a0} + \mathbf{X}_i\widehat{\boldsymbol{\xi}}_a)\big], \end{aligned} \tag{A-4}$$

where the a subscript refers now to multiplication by the scaling factor $(1+\widehat{\sigma}_a^2)^{-1/2}$. Since the pooled probit estimator of our dynamic unobserved effects model is consistent for the scaled version of the original parameters, in order to compute the estimator in equation (A-4), we simply need to plug in the coefficients estimated via pooled probit. The APEs reported in table 5 have been estimated following this approach.

As concern the dynamic unobserved effects probit model with feedback effects, the average partial effect of lagged contract type is given by

$$\begin{aligned} \mathrm{APE}_{y_{it-1}} &= \mathrm{E}\big[\Phi(\mathbf{z}'_{it}\boldsymbol{\delta}_{a1} + w_{it}\delta_{a2} + w_{it-1}\delta_{a3} + \rho_a + \psi_a \\ &+ y_{i0}\xi_{a0} + w_{i0}\xi_{a1} + \mathbf{Z}_i\boldsymbol{\xi}_{a2})\big] \\ &- \mathrm{E}\big[\Phi(\mathbf{z}'_{it}\boldsymbol{\delta}_{a1} + w_{it}\delta_{a2} + w_{it-1}\delta_{a3} + \psi_a \\ &+ y_{i0}\xi_{a0} + w_{i0}\xi_{a1} + \mathbf{Z}_i\boldsymbol{\xi}_{a2})\big], \end{aligned} \tag{A-5}$$

where, as pointed out by Biewen (2004), the expectation is over all characteristics indexed by i. A consistent estimator is

$$\begin{aligned} \widehat{\mathrm{APE}}_{y_{it-1}} &= \sum_{i=1}^{N} \big[\Phi(\mathbf{z}'_{it}\widehat{\boldsymbol{\delta}}_{a1} + w_{it}\widehat{\delta}_{a2} + w_{it-1}\widehat{\delta}_{a3} + \widehat{\rho}_a + \widehat{\psi}_a \\ &+ y_{i0}\widehat{\xi}_{a0} + w_{i0}\widehat{\xi}_{a1} + \mathbf{Z}_i\widehat{\boldsymbol{\xi}}_{a2})\big] \\ &- \sum_{i=1}^{N} \big[\Phi(\mathbf{z}'_{it}\widehat{\boldsymbol{\delta}}_{a1} + w_{it}\widehat{\delta}_{a2} + w_{it-1}\widehat{\delta}_{a3} + \widehat{\psi}_a \\ &+ y_{i0}\widehat{\xi}_{a0} + w_{i0}\widehat{\xi}_{a1} + \mathbf{Z}_i\widehat{\boldsymbol{\xi}}_{a2})\big]. \end{aligned} \tag{A-6}$$

Taking into account this procedure, we have estimated APEs also for the other equation of the joint model (the equation of unemployment benefits). Table 7 displays APEs estimated according to expression (A-6). Concluding, asymptotic standard errors of expressions (A-4) and (A-6) have been computed by the delta method.

A-3 Full Set of Estimation Results for the Dynamic Linear Probability Models

Tables A-2, A-3, and A-4 are integral parts of table 9, but they are not reported in the text for sake of brevity. Table A-2 displays the full set of estimation results of the first-differences specifications of the dynamic linear probability models. The column numbers correspond to the row numbers of table 9. Tables A-3 and A-4 are the level specifications counterparts.

Table A-2: First Difference Specifications of the Dynamic Linear Probability Model of Contract Type

	(1)			(2)			(3)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.	
Δy_{t-1}	-0.381	0.047	***	0.149	0.087	*	0.157	0.082	*
ΔExperience^2	0.000	0.000		0.000	0.000		0.000	0.000	
ΔHead of Household	0.047	0.017	***	0.050	0.023	**	0.044	0.022	**
ΔSpouse not working	-0.041	0.025	*	-0.054	0.032	*	-0.042	0.030	
ΔMarried	-0.046	0.034		-0.063	0.052		-0.057	0.052	
ΔChildren<6	0.006	0.016		0.023	0.023		0.024	0.022	
ΔMobility	0.070	0.028	**	0.084	0.029	***	0.088	0.029	***
Constant	-0.043	0.021	**	-0.026	0.023		-0.026	0.022	
Observations		1,381			1,381			1,381	
F-test exc. Instruments		–			$F(1,1373)$=185.7			$F(7,1367)$=28.74	
		–			p-value=0.000			p-value=0.000	
Hansen J statistics		–			–			χ^2_6=2.459	
		–			–			p-value=0.873	
Instruments		–			y_{i0}			y_{i0}, $\mathbf{x}_{i0}$	

Unemployment Benefits in the specification of the linear probability model

	(4)			(5)			(6)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.	
Δy_{t-1}	-0.384	0.047	***	0.146	0.086	*	0.149	0.081	*
ΔExperience^2	0.000	0.000		0.000	0.000		0.000	0.000	
ΔHead of household	0.043	0.017	***	0.048	0.022	**	0.044	0.022	**
ΔSpouse not working	-0.037	0.023	*	-0.051	0.031	*	-0.044	0.029	
ΔMarried	-0.047	0.034		-0.063	0.052		-0.057	0.051	
ΔChildren<6	0.007	0.016		0.024	0.023		0.025	0.022	
ΔMobility	0.064	0.028	**	0.079	0.029	***	0.085	0.029	***
ΔUnemp. Benefits	0.116	0.051	**	0.086	0.050	*	0.063	0.044	
Constant	-0.042	0.020	**	-0.025	0.023		-0.028	0.021	
Observations		1,381			1,381			1,381	
F-test exc. instruments		–			$F(1,1372)$=185.3			$F(7,1367)$=26.38	
		–			p-value=0.000			p-value=0.000	
Hansen J statistic		–			–			χ^2_7=3.067	
		–			–			p-value=0.879	
Instruments		–			y_{i0}			y_{i0}, $\mathbf{x}_{i0}$	

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: †White (1980) robust standard errors have been computed. See notes of table 9.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A-3: Level Specifications of the Dynamic Linear Probability Model of Contract Type

	(1)			(2)			(3)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.	
y_{t-1}	0.300	0.055	***	0.106	0.090		0.157	0.077	**
Experience^2	-0.000	0.000		-0.000	0.000	**	-0.000	0.000	*
Education - Reference:None or Elementary									
Middle school	-0.038	0.029		-0.055	0.032	*	-0.048	0.030	
Professional school	-0.028	0.033		-0.047	0.035		-0.047	0.034	
High school	-0.052	0.028	*	-0.072	0.032	**	-0.065	0.031	**
University degree or +	-0.029	0.031		-0.045	0.034		-0.046	0.033	
Area - Reference: North East									
North-West	0.010	0.012		0.010	0.012		0.006	0.011	
Centre	0.014	0.012		0.015	0.013		0.008	0.012	
South	0.056	0.019	***	0.066	0.020	***	0.061	0.019	***
Islands	0.024	0.020		0.037	0.022	*	0.027	0.020	
Female	0.017	0.011		0.021	0.012	*	0.019	0.011	*
Head of household	-0.009	0.011		-0.016	0.011		-0.015	0.011	
Spouse not working	0.018	0.013		0.025	0.013	*	0.024	0.012	**
Married	-0.045	0.013	***	-0.052	0.013	***	-0.044	0.012	***
Children$<$6	0.019	0.019		0.018	0.020		0.017	0.017	
Mobility	0.035	0.012	***	0.038	0.012	***	0.033	0.012	***
Constant	0.054	0.033		0.084	0.037	**	0.073	0.034	**
Observations		1,381			1,381			1,381	
F-test exc. instruments		–			$F(1,1364)=$ 114.4			$F(7,1358)$=18.94	
		–			p-value=0.000			p-value=0.000	
Hansen J statistic		–			–			χ^2_6=4.970	
		–			–			p-value=0.548	
Instruments		–			Δy_{it-2}			Δy_{it-2}, $\mathbf{x}_{i0}$	

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: †White (1980) robust standard errors have been computed. See notes of table 9.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table A-4: Level Specifications of the Dynamic Linear Probability Model of Contract Type Including Unemployment Benefits

	(4)			(5)			(6)		
Variable	Coeff.	S.E.†		Coeff.	S.E.†		Coeff.	S.E.	
y_{t-1}	0.289	0.053	***	0.098	0.090		0.145	0.077	*
Experience^2	-0.000	0.000		-0.000	0.000	**	-0.000	0.000	**
Education - Reference:None or Elementary									
Middle school	-0.034	0.028		-0.049	0.030	*	-0.041	0.029	
Professional school	-0.025	0.033		-0.043	0.033		-0.041	0.033	
High school	-0.044	0.027		-0.063	0.030	**	-0.056	0.029	*
University degree or +	-0.021	0.030		-0.036	0.032		-0.034	0.031	
Area - Reference: North East									
North-West	0.008	0.012		0.007	0.012		0.004	0.011	
Centre	0.010	0.012		0.010	0.012		0.004	0.012	
South	0.054	0.019	***	0.064	0.020	***	0.059	0.019	***
Islands	0.024	0.020		0.038	0.022	*	0.032	0.020	*
Female	0.015	0.011		0.019	0.012		0.017	0.011	
Head of household	-0.010	0.011		-0.016	0.011		-0.016	0.010	
Spouse not working	0.021	0.012	*	0.028	0.013	**	0.027	0.012	**
Married	-0.048	0.013	***	-0.055	0.013	***	-0.048	0.012	***
Children<6	0.018	0.019		0.017	0.020		0.016	0.016	
Mobility	0.032	0.012	***	0.034	0.012	***	0.031	0.012	***
Unemp. benefits	0.195	0.071	***	0.225	0.081	***	0.211	0.078	***
Constant	0.053	0.033		0.082	0.036	**	0.072	0.034	**
Observations		1,381			1,381			1,381	
F-test exc. instruments		–			$F(1,1363)$= 112.4			$F(8,1356)$=16.40	
		–			p-value=0.000			p-value=0.000	
Hansen J statistic		–			–			χ^2_7=5.237	
		–			–			p-value=0.631	
Instruments		–			Δy_{it-2}			Δy_{it-2}, $\mathbf{x}_{i0}$	

Source: SHIW - Bank of Italy, 2000, 2002, and 2004.
Notes: †White (1980) robust standard errors have been computed. See notes of table 9.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

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