Università Politecnica delle Marche
DIPARTIMENTO DI ECONOMIA

The Dynamics of Unemployment, Temporary and Permanent Employment in Italy

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QUADERNI DI RICERCA n. 286

May 2007

Abstract

This paper evaluates whether and on the extent to which temporary jobs have been a springboard to regular jobs in Italy. Using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth several dynamic unobserved effects probit models for the probability of having a permanent job are estimated. The main results show that a temporary position, rather than being unemployed, significantly increases the probability of having a permanent job 2 years later of about 13.5–16 percentage points. The robustness of this stepping stone effect is then assessed relaxing the parametric assumptions on unobserved individual heterogeneity.

JEL Class.: C23, C25, C35, J29
Keywords: temporary employment, unemployment, stepping stone, individual heterogeneity, dynamic unobserved effects probit model

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1 Introduction

In recent years temporary employment has risen in almost all European countries and this sort of contract has been used as an instrument to get labour market flexibility and as a response to the high level of European unemployment rate. The Italian employees' standard arrangement has traditionally been full-time, permanent, and characterized by high degree of employment protection. But, some newly labour market reforms[1] have changed the institutional set-up and atypical employment forms, among which temporary contracts, have been growing in importance.

Researchers have extensively debated on advantages and disadvantages attached to temporary contracts. Indeed, temporary jobs may increase labour market flexibility, provide firms with an instrument to face demand uncertainty, and be a "stepping stone" into longer employment relationships (Booth et al. 2002, Hagen 2003, Zijl et al. 2004, Ichino et al. 2005); from the other side, it is has been pointed out that temporary workers face higher turnover and probability of unemployment (Dolado, García-Serrano and Jimeno 2002, Farber 1999) and suffer wage penalties (Blanchard and Landier 2002, Booth et al. 2002, Brown and Session 2003, Jimeno and Toharia 1993, Hagen 2002, Picchio 2006).

The purpose of this paper is to provide empirical evidence to that branch of the literature that is trying to assess whether temporary jobs may be a springboard toward regular employment or a dead end position. Indeed, temporary job experiences may provide the unemployed with the opportunity to gain skills, knowledge, and avoid the deterioration of human capital and bad

**Preliminary. Comments are welcome. As a part of my PhD thesis, this study has been financed by the Marche Polytechnic University doctoral fellowship.*

[1] The labour market reforms which have extended and generalized the discipline of temporary jobs are the "Treu package" (Law No. 196/1997), Legislative Decree No. 368/2001, and the "Biagi law" (Law No. 30/2003).

signals attached to unemployment. But, if firms exploit this tool of labour market flexibility for systematically facing demand uncertainty without investing in temporary employees, temporary job experience may become a trap. Temporary workers may not gain in terms of human capital and come back to the unemployment pool without any advantage with respect to the unemployed. It could be focal in a welfare evaluation of the widespread of temporary contracts to assess whether in Italy temporary contracts have had a stepping stone effect into permanent positions. Therefore, the aim is to understand whether having today a temporary job, rather than being unemployed, increases or decreases the probability of having a permanent job within few years, once we control for individual observables and unobservables characteristics.

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. Raw probabilities of permanent employment conditional on the past working status highlight that a temporary position, rather than unemployment, increases the probability of having a regular job two years later by about 28.4 percentage points. It seems that temporary contracts provide a stepping stone into permanent jobs but such a raw evidence may be spurious. There could be indeed some individual characteristics determining both the current working status and the future transition into a permanent job. For example, more able individuals might be more willing to accept a temporary job as an alternative to unemployment and, at the same time, might be the ones with an higher hazard rate toward a permanent job. Then, the stepping stone effect from raw data might entirely reflect the higher ability of the stock of temporary workers.

In order to remove the spurious component from the stepping stone effect we estimate dynamic unobserved effects probit models for the probability of permanent employment; the model is dynamic because we introduce the lagged working status among the covariates. Unobserved heterogeneity is linearly approximated following the Chamberlain's (1980) approach, whereas the problem of initial conditions is faced by both the Heckman's (1981) method and the Wooldridge's (2005) conditional maximum likelihood estimator.

The main finding is that, *ceteris paribus*, having a temporary contract today rather than being unemployed increases the probability of having a permanent position two years later of about 13.5–16 percentage points. This finding is interpreted as a stepping stone effect, since it comes from the estimate of a counter-factual outcome probability.

Finally, we assess the robustness of the stepping stone result relaxing the parametric assumptions about the individual heterogeneity. We estimate: i) Dynamic linear probability models which are able to approximate the average partial effects, by fully controlling for unobserved heterogeneity and avoiding the problem of initial conditions; ii) Dynamic non-linear probability models where unobserved heterogeneity is randomly drawn from a discrete distribution with a finite number of support points.

This paper is organized as follows. In section 2 we describe the data and report descriptive statistics of the sample used in the econometric analysis. Section 3 presents the econometric specification of dynamic nonlinear models for the probability of permanent employment and displays estimation results. In section 4 we check the robustness of the results relaxing the parametric assumptions about individual heterogeneity. Finally, section 5 concludes.

2 Data and Sample

The empirical investigation is performed using the 2000, 2002, and 2004 waves of the Survey of Italian Households' Income and Wealth (SHIW).[2] The SHIW is a nationally representative survey conducted by the Bank of Italy every two years since 1989. As the question about the type of contract was introduced in 2000, the longitudinal dimension of the sample is restrained to the period 2000–2004.

We take all the individuals who belong to the panel dimension of the SHIW from 2000 until 2004 and are either unemployed or employees. We exclude individuals out of the range 15–64 years of age in 2000 and observations with missing values for some of the variables used in the specification of the econometric models. We end up with a balanced panel of 1,677 individuals, observed over 3 time periods. Since we estimate dynamic nonlinear models of order one, we loose the first time period, which is only exploited for the initial values.

The dependent variable is a dummy indicator, y_{1it}, equal to 1 if individual i is a permanent worker at time t and 0 otherwise. The dynamic will be captured by the lag of this indicator and by the lag of the unemployment indicator y_{2it}, which is equal to 1 if individual i is unemployed at time t. Over 2000–2004, the average composition of the labour force is as follows: 9.8% unemployed, 6.3% temporary workers, 83.9 permanent workers.[3]

[2]The SHIW and further details about the dataset are available on the web-server of the Bank of Italy: http://www.bancaditalia.it/statistiche/indcamp/bilfait.

[3]An individual is unemployed if she declares to be either a first-job seeker or unemployed in section B (Employment and Incomes) question "APQUAL" of the SHIW questionnaire. The information about the employees' contract type comes from the answer to question

Table 1 displays relative frequencies of permanent jobs, conditional on past labour market state, by some individual characteristics. Looking at the first row of the table, we note that there is a raw positive effect of temporary jobs. A temporary worker is more than twice as likely to find a stable job position two years later as someone who is currently unemployed. Having a temporary job today, rather than being unemployed, increases the raw probability of having a permanent job in the future by about 28.4 percentage points. This shows that in the raw data there is a substantial stepping stone effect of temporary contracts. The relative frequencies of permanent employment are lower for men, the youth, and the less educated. People living in the South of Italy or in regions with a higher unemployment rate are less likely to have a permanent job.

Table 1: Unconditional and Conditional Relative Frequencies of Permanent Employment by Individual Characteristics

	Unconditional	Permanent at $t-1$	Unemployed at $t-1$	Temporary at $t-1$	Stepping stone effect
All	0.850	0.951	0.232	0.516	0.284
Male	0.839	0.947	0.224	0.515	0.291
Female	0.866	0.958	0.250	0.517	0.267
Age≥40	0.923	0.966	0.260	0.588	0.328
Age<40	0.737	0.922	0.225	0.467	0.242
Potential experience≥20	0.923	0.965	0.250	0.554	0.304
Potential experience<20	0.748	0.926	0.228	0.490	0.262
High school or more	0.901	0.968	0.310	0.573	0.263
Up to professional school	0.797	0.932	0.188	0.481	0.293
North-Centre	0.920	0.968	0.296	0.574	0.278
South	0.702	0.902	0.203	0.462	0.259
Regional unemp≥median	0.782	0.933	0.213	0.481	0.268
Regional unemp<median	0.926	0.969	0.328	0.574	0.246
Married	0.718	0.918	0.207	0.455	0.248
Not-married	0.921	0.965	0.321	0.573	0.252
Head of household	0.924	0.968	0.297	0.559	0.262
Other household position	0.791	0.935	0.218	0.500	0.282
Spouse not working	0.870	0.940	0.321	0.534	0.213
Spouse working/no spouse	0.844	0.954	0.216	0.510	0.294
Children<6 years	0.872	0.932	0.294	0.632	0.338
No children<6 years	0.848	0.953	0.223	0.506	0.283
Observations	3,354	2,783	349	252	–

Table 2 reports summary statistics of the explanatory variables used in the econometric analysis. Table 3 displays the observed transitions between labour market positions and, as expected, most of the individuals show a strong persistence in permanent jobs. The identification of the effects we are

"CONTRATT" of annex B1 (information about the employees' job).

Table 2: Sample Characteristics

	Mean	Standard Deviation	Minimum	Maximum
Unemployed	0.098	0.298	0	1
Permanent employed	0.839	0.368	0	1
Temporary employed	0.062	0.242	0	1
Age	40.73	10.42	15	67
Potential experience	20.25	11.46	0	58
Female	0.393	0.488	0	1
Education				
None or Elementary	0.082	0.275	0	1
Middle school	0.324	0.468	0	1
Professional school	0.083	0.277	0	1
High school	0.392	0.488	0	1
University degree or more	0.118	0.323	0	1
Geographical Area				
North-East	0.221	0.415	0	1
North-West	0.228	0.419	0	1
Centre	0.230	0.421	0	1
South	0.199	0.399	0	1
Islands	0.123	0.328	0	1
Regional unemployment rate	0.130	0.106	0	0.384
Permanent income[(a)]	1,119	5,691	-23,252	45,622
Transitory income[(b)]	0.000	8,145	-75,513	59,038
Married	0.650	0.477	0	1
Head of Household	0.440	0.496	0	1
Spouse not working	0.217	0.412	0	1
Children<6 years	0.104	0.306	0	1
Observations				5,031

Notes: Pooled data for SHIW waves (2000–2004).
[(a)] The permanent income is the within-individual mean across the period 2000–2004 of the individual nonlabour income.
[(b)] The transitory income is defined as the deviation from the individual permanent income.

Table 3: Observed Transitions between Labour Market Positions

	Destination state			
Origin state	Unemployment	Temporary job	Permanent job	Total
Unemployment	226	42	81	349
	6.7%	1.3%	2.4%	10.4%
Temporary job	25	75	123	223
	0.7%	2.2%	3.7%	6.6%
Permanent job	54	82	2,646	2,782
	1.6%	2.4%	78.9%	82.9%
Total	305	199	2,850	3,354
	9.1%	5.9%	85.0%	100.0%

looking for comes from observations out off the diagonal of this transition matrix.

3 Econometric Modelling and Estimation Results

In this section we discuss and present the econometric models for permanent employment, whose estimation results are displayed in table 4. The starting point (subsection 3.1) is a bivariate dynamic unobserved effects probit model for permanent employment, which is the most general specification we present and takes into account the endogeneity of the previous labour market state. Then, in subsection 3.2, we move on to a univariate framework, whereas subsection 3.3 and table 5 deal with the goodness of fit of the estimated dynamic nonlinear models.

3.1 Bivariate Unobserved Effects Probit Model

Let us define y_{1it} and y_{2it} the scalar indicator variables denoting the occurrence at time t of a permanent job and unemployment, respectively. The dynamic probability model for permanent employment is empirically specified using a bivariate unobserved effects probit model:

$$y_{1it} = 1[y_{1it-1}\rho_{11} + y_{2it-1}\rho_{12} + \mathbf{x}'_{1it}\boldsymbol{\beta}_1 + c_{1i} + u_{1it} > 0] \quad (1)$$
$$y_{2it} = 1[y_{1it-1}\rho_{21} + y_{2it-1}\rho_{22} + \mathbf{x}'_{2it}\boldsymbol{\beta}_2 + c_{2i} + u_{2it} > 0] \text{ if } y_{1it} = 0, \quad (2)$$

where $1[\cdot]$ is the indicator function, $\mathbf{x}_{1it}$ and $\mathbf{x}_{2it}$ are vectors of skill, family, and individual structure variables that may explain the working status, c_{1i} and c_{2i} are time-invariant individual heterogeneities. Finally, (u_{1it}, u_{2it}) is the idiosyncratic error term which is assumed to be bivariate standard normal with covariance ρ_u. Such a model is a modified version of that of Alessie et al. (2004) and follows the Stewart's (2007) model to investigate the inter-related dynamics of unemployment and low-wage employment.

The model is bivariate in order to allow y_{2it} to be endogenous in equation (1). The coefficient of primary interest is ρ_{12}; indeed it captures the effect of past unemployment, rather than temporary employment (the reference category), on the current probability of having a permanent job. Therefore it conveys whether having a temporary job today, rather than being unemployed, reduces or increases the future probability of having a permanent position.

The regressors vector $\mathbf{x}_{1it}$ 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 potential experience, its quadratic form, household position, marital status, spouse's working status, presence of pre-scholar children, time intercept, and nonlabour income. Following Hyslop (1999) the nonlabor income is decomposed into a permanent component h_i^p, which is estimated by the within-individual mean across the sample period 2000–2004, and a transitory component h_{it}^m estimated by the deviation from the permanent component. The idea is that permanent income captures the total effect of income expectations on the likelihood of having a permanent job, whereas the transitory component has a direct income effect on it. The regressors vector $\mathbf{x}_{2it}$ contains $\mathbf{x}_{1it}$ and age and squared age.

Correlation between unobserved heterogeneity, c_{ji} with $j \in \{1, 2\}$, and observed characteristics is allowed by adopting a correlated random-effects specification (Chamberlain 1980):

$$c_{ji} = \sum_{s=0}^{T} \boldsymbol{\delta}_{j1s} \mathbf{w}_{jis} + \sum_{s=0}^{T-1} \delta_{j2s} h_{jis}^m + a_{ji} \tag{3}$$

where $\mathbf{w}_{jis}$ is a 3-dimensional vector containing marital status, spouse's working status, and presence of pre-scholar children and $a_{ji} \sim iid\ N(0, \sigma_{a_j}^2)$ and independent of $\mathbf{x}_{jit}$.

In order to distinguish between spurious and true stepping stone effect, we have also to make assumptions about the relationship between the initial observations of the dependent variables and individual heterogeneity. At this stage we apply the Wooldridge's (2005) conditional maximum likelihood approach to the initial condition problem; therefore we model the density conditional on initial values, which enter the linear approximation of unobserved heterogeneity.

The likelihood function to be maximized is given by

$$\mathscr{L} = \prod_{i=1}^{N} \prod_{t=1}^{T} \Big\{ y_{1it} \Phi(y_{1it}^*) + (1 - y_{1it}) \Phi_2 \big[-y_{1it}^*, (2y_{2it} - 1) y_{2it}^*; -(2y_{2it} - 1) \rho_u \big] \Big\}, \tag{4}$$

where Φ_2 is the cumulative bivariate normal distribution function and $y_{jit}^* = y_{1it-1}\rho_{j1} + y_{2it-1}\rho_{j2} + \mathbf{x}_{jit}' \boldsymbol{\beta}_j + c_{ji}$ for $j = 1, 2$ and $t = 1, \ldots, T$.

The estimation results of the bivariate model are reported in the first three columns of table 4. The coefficient of the lagged permanent position is positive and highly significant. Since the lagged temporary working status is the reference group, having a permanent job today, rather than a temporary contract, significantly increases the probability of having a permanent job in the future.

This is an expected results, whereas what we wish to understand is whether a temporary position as an alternative to unemployment is able to increase the chances to get a permanent job in the future. This is conveyed by the coefficient of the lagged unemployment status which is negative and highly significant: having been unemployed at time $t-1$, rather than temporary employed, decreases the likelihood of having a permanent position at time t. In other words, an individual who accepts a temporary job today, rather than unemployment, has a significantly higher probability of being a permanent worker in two years: this is the stepping stone effect, since, *ceteris paribus*, a temporary job provides an opportunity to jump into regular employment.

Looking at the estimated coefficients of the other explanatory variables, we note that the higher the potential experience of the worker, the higher the probability of having a permanent job. This finding is coherent with the human capital theory and job-search explanations. Women and less educated individuals are less likely to have a permanent job. The higher the permanent and transitory incomes, the lower the probability of having a permanent position. An explanation might be found in the job-search theory: when nonlabour income increases or is constantly high, the individual has less incentives to look for and/or accept a stable job. Finally, individuals that are head of the household or married are more likely to have a permanent job. It seems that the higher the employee's household responsibility, the higher the probability of having a stable position.

Note that a Wald test for significance of the coefficients of the linear approximation of the unobserved heterogeneity rejects the null hypothesis. Performing the analysis without introducing time-variant variables in all the time periods would generate biased results due to their correlation with unobserved heterogeneity. Furthermore, the coefficient of the initial employment status is highly significant and this finding definitively rejects a simpler bivariate probit not accounting for unobserved heterogeneity and initial conditions problem.

The log-likelihood ratio (LR) test for independent equations does not instead reject the null hypothesis, meaning that we are meeting a special case of the bivariate model: since the error terms are not correlated, we can estimate equation (1) in a univariate framework.

Table 4: Dynamic Probit Models for Permanent Employment

	Bivariate model			Wooldridge's model			Heckman's model		
Variable	Coeff.	S.E.[(a)]		Coeff.	S.E.[(a)]		Coeff.	S.E.	
Permanent job$_{t-1}$	0.968	0.143	***	0.967	0.143	***	0.780	0.203	***
Unemployed$_{t-1}$	-0.503	0.173	***	-0.504	0.173	***	-0.547	0.137	***
Experience	0.035	0.012	***	0.035	0.012	***	0.070	0.021	***
Experience^2/100	-0.064	0.026	**	-0.064	0.026	**	-0.124	0.041	***
Female	-0.080	0.079		-0.078	0.078		-0.130	0.098	
Education - Reference: None or Elementary									
Middle school	0.338	0.120	***	0.336	0.120	***	0.431	0.153	***
Professional school	0.356	0.157	**	0.356	0.157	**	0.486	0.207	**
High school	0.768	0.133	***	0.767	0.133	***	0.999	0.207	***
University degree or +	0.648	0.171	***	0.647	0.171	***	0.851	0.229	***
Area - Reference: North-East									
North-West	0.085	0.129		0.084	0.129		0.077	0.148	
Centre	0.003	0.115		0.002	0.115		-0.019	0.139	
South	-0.337	0.190	*	-0.337	0.190	*	-0.463	0.230	**
Islands	-0.318	0.175	*	-0.320	0.174	*	-0.497	0.218	**
Head of household	0.391	0.098	***	0.392	0.098	***	0.432	0.116	***
Unemployment rate	-0.818	0.726		-0.817	0.726		-1.247	0.850	
Permanent income	-0.036	0.008	***	-0.036	0.008	***	-0.046	0.011	***
Transitory income	-0.023	0.012	*	-0.023	0.012	*	-0.026	0.012	**
Spouse not working	0.277	0.314		0.272	0.312		0.302	0.241	
Married	1.149	0.564	**	1.150	0.564	**	1.271	0.575	**
Children<6	-0.207	0.285		-0.208	0.286		-0.206	0.294	
D2004	0.033	0.073		0.034	0.073		0.028	0.080	
Constant	-0.580	0.200	***	-0.580	0.200	***	-0.369	0.234	
Random Effect: Initial condition and time-variant variables in all time periods									
Permanent job$_0$	0.419	0.146	***	0.420	0.146	***			
Unemployed$_0$	0.003	0.173		0.005	0.173				
Transitory income$_0$	0.015	0.009	*	0.015	0.009	*	0.012	0.010	
Transitory income$_1$	0.036	0.010	***	0.036	0.010	***	0.040	0.014	***
Spouse not working$_0$	0.015	0.151		0.017	0.150		-0.006	0.151	
Spouse not working$_1$	-0.252	0.238		-0.251	0.238		-0.266	0.202	
Spouse not working$_2$	-0.283	0.193		-0.280	0.193		-0.313	0.198	
Married$_0$	0.122	0.342		0.121	0.343		0.176	0.466	
Married$_1$	-1.000	0.472	**	-0.999	0.472	**	-1.058	0.619	*
Married$_2$	0.135	0.487		0.134	0.487		0.094	0.413	
Children<6$_0$	0.151	0.184		0.150	0.184		0.159	0.228	
Children<6$_1$	-0.341	0.259		-0.343	0.260		-0.405	0.312	
Children<6$_2$	0.236	0.271		0.240	0.270		0.272	0.280	
H_0:[$\boldsymbol{\delta}_{11}, \boldsymbol{\delta}_{12}$]=0	χ^2_{11}=27.8	p-value=0.00		χ^2_{11}=27.1	p-value=0.00		χ^2_{11}=18.4	p-value=0.07	
Observations		3,354			3,354			5,031	
Pseudo R^2		0.436			0.453			0.245	
Wald χ^2		955.6			957.3			418.6	
Log-likelihood		-990.4			-776.5			-1284.8	
LR test of indep. equat.	χ^2_1=0.05	p-value=0.830							
Average Partial Effects									
APE$_U^T$ [(b)]		0.161			0.162			0.137	
APE$_U^P$ [(c)]		0.348			0.340			0.267	
APE$_T^P$ [(d)]		0.186			0.181			0.130	

Notes: Number of individuals: N=1,677. *Significant at 10%;**significant at 5%;***significant at 1%.
[(a)] Standard errors robust to serial correlation.
[(b)] APE$_U^T$ is the marginal effect of a past Temporary job (the hyperscript T) instead of Unemployment (the subscript U).
[(c)] APE$_U^P$ is the APE of a past Permanent job (the hyperscript P) instead of unemployment.
[(d)] APE$_T^P$ is the APE of a past permanent position instead of a past temporary contract.

3.2 Univariate Models for the Probability of Permanent Employment

Given the result of the LR test of independent equations, we replicate the analysis in a univariate framework by solving the initial conditions problem following the Wooldridge's (2005) approach and the Heckman's (1981) methodology.

As we have already mentioned, Wooldridge (2005) suggested to face the initial conditions problem modelling the density of $(y_{1i1}, \ldots, y_{1iT})$ conditional on initial conditions and explanatory variables. Under the linear approximation assumption of individual heterogeneity, we therefore have

$$
\begin{aligned}
& c_{1i} = \psi + y_{1i0}\xi_{10} + y_{2i0}\xi_{20} + \sum_{s=0}^{T} \boldsymbol{\delta}_{11s}\mathbf{w}_{1is} + \sum_{s=0}^{T-1} \delta_{12s} h_{1is}^{m} + a_{1i}, \\
& a_{1i} \sim \mathrm{N}(0, \sigma_{a_1}^2), \;\; a_{1i} \perp (y_{1i0}, y_{2i0}, \mathbf{x}_{1i}).
\end{aligned}
\tag{5}
$$

Then, model (1) can be rewritten as

$$
\begin{aligned}
y_{1it} &= 1\Big[y_{1it-1}\rho_{11} + y_{2it-1}\rho_{12} + \mathbf{x}_{1it}'\boldsymbol{\beta}_1 + \psi_1 + y_{1i0}\xi_{10} + y_{2i0}\xi_{20} \\
&+ \sum_{s=0}^{T} \boldsymbol{\delta}_{11s}\mathbf{w}_{1is} + \sum_{s=0}^{T-1} \delta_{12s} h_{1is}^{m} + a_{1i} + u_{it} > 0 \Big],
\end{aligned}
\tag{6}
$$

and estimated using standard random effects probit program integrating out a_i. In order to relax the implicit assumption of zero serial correlation of the score, we use simple pooled probit estimator with standard errors robust to arbitrary serial correlation. What we have to pay is a loss in terms of efficiency and that we obtain a scaled version of our parameters, where the scaling factor is given by $(1 + \sigma_{a_1}^2)^{-1/2}$.[4]

The approach proposed by Heckman (1981) consists instead in specifying a latent variable model for the initial realization of the dependent variable:

$$
y_{1i0}^{*} = \mathbf{z}_{i0}'\boldsymbol{\gamma} + \theta c_{1i} + u_{i0}. \tag{7}
$$

This equation is a linearized approximation to the reduced form equation for the initial value of the latent variable, where $\mathbf{z}_{i0}$ is a vector of exogenous variables (including $\mathbf{x}_{1i0}$ and a set of parental dummies)[5] and u_{i0} is independent

[4]The scaled estimates of the parameters is what is needed to estimate the average partial effects. See e.g. Wooldridge (2002), pp. 495, for further details.

[5]The parental dummies are: 4 dummies indicating the parents' maximum attained educational level and one dummy indicating whether one of the parents is a public employee.

on c_{1i}. This reduced form equation is jointly estimated with the dynamic probability model (1). Let us define $\lambda \equiv \frac{\sigma^2_{c_1}}{\sigma^2_{c_1}+\sigma^2_u}$ the autocorrelation of the composite error term between two time periods; then, the the likelihood to be maximized is given by

$$\begin{aligned} \mathscr{L} = \prod_{i=1}^{N} \int_{c^*} \Big\{ & \Phi\left[(\mathbf{z}'_{i0}\boldsymbol{\gamma} + \theta\sigma_{c_1}c^*)(2y_{1i0}-1)\right] \\ \times & \prod_{t=1}^{T} \Phi\left[(y_{1it-1}\rho_{11} + y_{2it-1}\rho_{12} + \mathbf{x}'_{1it}\boldsymbol{\beta}_1 + \sigma_{c_1}c^*)(2y_{1it}-1)\right]\Big\} d\Phi(c^*), \end{aligned} \tag{8}$$

where $c^* = c_1/\sigma_c$ and, following from the implicit normalization $\sigma^2_u = 1$, $\sigma_{c_1} = \sqrt{\lambda/(1-\lambda)}$. Since c_{1i} is unobservable, in equation (8) we integrate it out under the assumption that c_{1i} is normally distributed. The integral over c_{1i} is evaluated using Gaussian-Hermite quadrature with 20 points.

The estimation results of these univariate models are reported in the last columns of table 4. Coherently with the outcome of the independent equations LR test, the estimation results of the single equation models are in line with those of the bivariate model. There is still a highly significant stepping stone effect of temporary jobs into permanent positions.

In order to provide a quantitative evaluation of the stepping stone effect, we estimate, following Stewart (2007), average partial effects (APEs hereafter) at the sample means, $\bar{\mathbf{x}}_1$.[6] The idea is to predict the probabilities of having a permanent job conditional on different past labour market positions, so that we can compare counter-factual outcome probabilities. The estimated APEs are reported at the bottom of table 4. Using the Wooldridge's estimator we find a stepping stone effect of about 16.2 percentage points: if an individual accepts today a temporary job as an alternative to unemployment, her probability of having a permanent position in two years increases of about 16 percentage points. The stepping stone effect from the Heckman's estimator is lower and equal to 13.7 percentage points.

Given these estimation results, let us summarize the main findings. We have seen that estimating dynamic unobserved effects probit models for the probability of permanent employment depicts temporary jobs as a channel out of unemployment and a springboard toward a stable job. Indeed, looking at the estimated counter-factual probabilities evaluated at the sample means and the corresponding average partial effects, we can affirm that, given observable and unobservable characteristics, an individual accepting a temporary job today, rather than unemployment, increases her own proba-

[6]See appendix A-1 for more details about the definition and the estimation of the APEs.

bility of having a permanent job in two years of about 13.7–16 percentage points.

Finally, we have tried to understand the direction of the biases if we do not take into account the presence of the unobservable and unobservable individual heterogeneity. We have seen in table 1 that the the raw stepping stone effect is of about 28 percentage points. If we estimated the APEs of a dynamic probit model with no unobserved heterogeneity, we would find a stepping stone effect of temporary jobs of about 20 percentage points.[7] Therefore, one fourth of the initial stepping stone effect is spurious because of observable heterogeneity $\mathbf{x}_1$. When we move on to unobserved effects models and we explicitly take into account the possible presence of the unobservable heterogeneity we get an even lower estimated APE. These findings suggest that: i) About one half of the raw stepping stone effect is spurious and due to the presence of observable and unobservable individual characteristics; ii) The estimated marginal effect of a temporary job is upward biased if we do not consider the presence of the individual heterogeneity. If we assume that more able workers are more likely to make a transition from a temporary to a permanent contract, then this implies that more able unemployed workers are more likely to accept a temporary position instead of a further period of job-seeking. Such a self-selection of the more able workers into temporary contracts is predicted by the Loh's (1994) theoretical model: temporary contracts can be viewed as a probationary period and firms' sorting mechanism; then, firms can attract more able workers by paying a low wage during the probationary period, but promising higher wages in the future.

3.3 Goodness of Fit

In order to provide a descriptive evaluation of the goodness of the fit of the dynamic nonlinear models, we report in table 5 the percent correctly predicted employment status and the percent correctly predicted sequences. We follow the usual rule according to which we predict, for each i and t, y_{1it} 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_{1it} is predicted to be zero. The percentages reported in table 5 are the percentages of times the predicted y_{1it} matches the actual y_{1it}. By predicted sequences, we refer to the percentages of time the predicted sequence matches the actual sequence $\{y_{1it}, y_{1it-1}\}$.

In the first column we report the correct predictions of the bivariate dynamic model, whereas the last two columns display the correct predic-

[7]The estimation results of a simple dynamic pooled probit model are available from the author but not reported for sake of brevity.

tions when we estimate single equation dynamic probit models using the Wooldridge's (2005) and the Heckman's (1981) estimator, respectively.

The three different estimation techniques are very close to each other in terms of goodness of fit. Permanent employment is very well predicted, more than 96% of the time. As concern the correct predicted unemployment or temporary employment realizations, the models are correct more than 50% of the time.

Table 5: Correct Predicted Status and Sequences

	Bivariate model	Wooldridge's model	Heckman's model
Correct predicted permanent employed status			
Permanent employed	96.42%	96.31%	97.40%
Temporary employed or unemployed	59.72%	60.20%	50.20%
Overall	90.91%	90.82%	90.31%
Correct predicted permanent-temporary employment or unemployment sequences			
Always PC	97.02%	96.87%	97.91%
From TC or U to PC	10.10%	7.07%	9.09%
From PC to TC or U	0.00%	0.00%	0.00%
Always TC or U	69.05%	69.05%	56.55%
Overall	85.09%	84.79%	84.50%

Note: The acronyms PC, TC, and U respectively refer to permanent contract, temporary contract, and unemployment.

We now move on to the correct predicted permanent employment sequences. If we look at the overall results, we could argue that the dynamic models are really able to predict the transitions, since they correctly predict sequences more than 85% of the time. But, looking at each possible sequence, we realize that our models cannot predict permanent/unemployment-temporary job sequences and poorly perform in predicting unemployment-temporary job/permanent sequences (around 10% of the time). Conversely, the dynamic models well perform in predicting time-invariant sequences.

4 Robustness Analysis

In this section we assess the robustness of the stepping stone effect relaxing the parametric assumptions about the individual heterogeneity. Therefore, in subsection 4.1 we replicate the Heckman's procedure for initial conditions but the residual a_{1i} of the linear approximation of the unobserved heterogeneity c_{1i} is assumed to have a discrete mass point distribution.

In subsection 4.2 we instead focus on dynamic linear probability models for permanent employment, since they provide satisfactory estimates of average partial effects near the center of the distribution of the covariates:

first-differencing is a straightforward way to fully remove the time persistent individual heterogeneity and to avoid any problem of initial conditions. As pointed out by Stewart (2007), since we do not need any particular parametric assumption about unobserved heterogeneity, this approach may be considered as a semi-parametric method compared to the dynamic nonlinear models we have seen so far.

4.1 Discrete Distribution of the Individual Heterogeneity

We provide an alternative specification of the unobserved heterogeneity to the ones that characterize the Heckman's and Wooldridge's estimators. Instead of imposing normality, the distribution of a_{1i} is assumed to be discrete with mass point a_1^d, $d \in \{1, \ldots, D\}$, and corresponding probability p_d. We specify probabilities p_1 to p_D using a multinomial logit model:

$$p_d = \frac{\exp \lambda_d}{\sum_{j=i}^{D} \exp \lambda_j}, \ \ \lambda_D = 0, \ \ d = 1, \ldots, D. \tag{9}$$

Therefore, we maximize the following discrete mixture likelihood function:

$$\begin{aligned}
\mathscr{L} &= \prod_{i=1}^{N} \Bigg\{ \sum_{d=1}^{D} p_d \Big[\Phi \big[(\mathbf{z}'_{i0} \boldsymbol{\gamma} + \theta a_1^d)(2y_{1i0} - 1) \big] \\
&\cdot \prod_{t=1}^{T} \Phi \big[(y_{1it-1}\rho_{11} + y_{2it-1}\rho_{12} + \mathbf{x}'_{1it}\boldsymbol{\beta}_1 \\
&+ \sum_{s=0}^{T} \boldsymbol{\delta}_{j1s}\mathbf{w}_{jis} + \sum_{s=0}^{T-1} \delta_{j2s} h_{jis}^{m} + a_1^d)(2y_{1it} - 1) \big] \Big] \Bigg\},
\end{aligned} \tag{10}$$

where D is chosen according to the Akaike Information Criterion (AIC).

The estimation results of the discrete mixture probability model are reported in table 6. According to the AIC the unobserved heterogeneity seems to be important but only two points of support are detected: the first one has 16.8% probability mass, whereas the second one 83.2%. The estimated coefficient of the lagged unemployment indicator is significantly negative and close to those presented before. Once again, a temporary job today, rather than unemployment, significantly increases the probability of having a permanent position in two years. The marginal effect of a temporary contract instead of unemployment is in line with those obtained before and it lies between the estimates of the APEs from the Heckman's and Wooldridge's approaches. This finding assesses the robustness of the results obtained under the parametric assumption about the individual heteregeneity.

Table 6: Discrete Mixture Dynamic Model for Permanent Employment

Variable	Coeff.	S. E.	
Permanent job$_{t-1}$	0.654	0.170	***
Unemployed$_{t-1}$	-0.643	0.133	***
Experience	0.080	0.020	***
Experience^2/100	-0.147	0.041	***
Female	-0.102	0.103	
Education - Reference: None or Elementary			
Middle school	0.492	0.161	***
Professional school	0.492	0.233	**
High school	1.036	0.203	***
University degree or more	0.809	0.222	***
Area - Reference: North-East			
North-West	0.033	0.177	
Centre	-0.082	0.166	
South	-0.535	0.251	**
Islands	-0.548	0.232	**
Head of household	0.407	0.126	***
Unemployment rate	-1.360	0.865	
Permanent income	-0.044	0.012	***
Transitory income	-0.018	0.010	*
Spouse not working	-0.060	0.196	
Married	0.938	0.457	**
Children<6	-0.158	0.325	
D2004	-0.076	0.118	
Unobserved heterogeneity[(a)]			
θ	1.705	0.524	***
a_1^1	-1.347	0.315	***
a_1^2	-0.040	0.206	
λ_1	-1.598	0.298	***
p_1	0.168		
p_2	0.832		
Average Partial Effects			
APE$_U^T$		0.153	
APE$_U^P$		0.240	
APE$_T^P$		0.086	
AIC		1.607	
Observations		5,031	
Log-likelihood		-1,283.3	

(a) The estimated coefficients of the time-variant variables in all time periods are not reported for sake of brevity.

4.2 Dynamic Linear Probability Models

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

$$y_{1it} = y_{1it-1}\rho_{11} + y_{2it-1}\rho_{12} + \mathbf{x}'_{1it}\boldsymbol{\beta}_1 + c_{1i} + u_{1it}, \quad (i = 1, \ldots, N;\ t = 0, 1, 2). \tag{11}$$

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

$$\Delta y_{1it} = \Delta y_{1it-1}\rho_{11} + \Delta y_{2it-1}\rho_{12} + \boldsymbol{\Delta}\mathbf{x}'_{1it}\boldsymbol{\beta}_1 + \Delta u_{1it}, \ (i = 1, \ldots, N;\ t = 1, 2). \tag{12}$$

Since Δy_{1it-1} and Δy_{2it-1} are possibly correlated to Δu_{1it}, this model can be consistently estimated by using y_{1i0}, y_{2i0}, and noncontemporaneous realizations of the explanatory variables as valid excluded instruments.

The estimation results of dynamic linear probability model are displayed in table 7. The upper panel reports ordinary least squares (OLS), instrumental variables (IV), and efficient generalized method of moments (GMM) estimates of the first-differenced dynamic model, whereas in the lower panel the dynamic model is in level. The coefficients of primary interest are the ones associated to the lagged unemployment status and, since their reference is lagged temporary employment, they directly provide an approximation of the average partial effect.

The OLS estimates from the model in first-differences and the model in levels are -0.089 and -0.258, respectively. The former is biased upward due to positive correlation between Δy_{2it-1} and Δu_{1it}, while the latter is biased downward due to negative correlation between y_{2it-1} and the unobservable heterogeneity.

The central columns report IV estimation results using: y_{1i0} and y_{2i0} as instruments for Δy_{1it-1} and Δy_{2it-1} in the first-differences specification; Δy_{1it-1} and Δy_{2it-1} as instruments for y_{1it-1} and y_{2it-1} in the level specification. The estimated lagged unemployment status coefficients are now -0.105 and -0.138: they are converging to each other. The F-tests for excluded instruments as suggested by Staiger and Stock (1997) show no sign of weakness of the instruments.

Finally in the last three columns we report the efficient GMM estimation results, introducing as further instruments the initial values of time-varying explanatory variables. In this way we gain in terms of efficiency and test the validity of the instruments with a standard over-identification test. The over-identification tests do not reject the null hypothesis, so that the instruments seem to be valid. The stepping stone effect is between 13-15.8 percentage points. Therefore, fully controlling for the unobserved heterogeneity

Table 7: Dynamic Linear Probability Models Estimation Results

	OLS			IV			Efficient GMM		
Variable	Coeff.	S.E.[(a)]		Coeff.	S.E.[(a)]		Coeff.	S.E.	
First-difference specification									
ΔPermanent job$_{t-1}$	-0.392	0.042	***	0.254	0.086	***	0.215	0.083	**
ΔUnemployed$_{t-1}$	-0.089	0.060		-0.105	0.109		-0.130	0.106	
ΔExperience^2	-0.076	0.019	***	-0.038	0.023	*	-0.040	0.022	*
ΔHead of household	-0.066	0.025	***	-0.063	0.032	*	-0.069	0.030	**
ΔUnemployment rate	-0.141	0.290		-0.176	0.356		-0.094	0.343	
ΔTransitory income	-0.002	0.001	**	-0.002	0.001	**	-0.003	0.001	**
ΔSpouse not working	0.054	0.055		0.059	0.063		0.042	0.061	
ΔMarried	0.063	0.039		0.108	0.068		0.100	0.067	
ΔChildren$<$6	0.003	0.026		-0.025	0.038		-0.023	0.038	
Constant	0.090	0.020	***	0.040	0.024	*	0.041	0.023	*
Observations		1,677			1,677			1,677	
F-test exc. instruments:		–		$F(2,1667)$=115.4			$F(11,1658)$=23.3		
ΔPermanent job$_{t-1}$		–		p-value=0.000			p-value=0.000		
F-test exc. instruments:		–		$F(2,1667)$=67.9			$F(11,1658)$=14.8		
ΔUnemployed$_{t-1}$		–		p-value=0.000			p-value=0.000		
Hansen J statistics		–			–		χ^2_9=7.577		
		–			–		p-value=0.577		
Level specification[(b)]									
Permanent job$_{t-1}$	0.346	0.033	***	0.180	0.077	**	0.197	0.075	***
Unemployed$_{t-1}$	-0.258	0.041	***	-0.138	0.109		-0.158	0.104	
Experience	0.008	0.002	***	0.016	0.004	***	0.015	0.004	***
Experience^2	-0.014	0.005	***	-0.029	0.009	***	-0.027	0.008	***
Head of household	0.020	0.010	*	0.019	0.015		0.017	0.014	
Unemployment rate	-0.189	0.119		-0.361	0.197	*	-0.333	0.188	*
Transitory income	-0.001	0.001		-0.000	0.001		-0.000	0.001	
Spouse not working	0.003	0.013		0.011	0.019		0.006	0.016	
Married	0.042	0.012	***	0.069	0.018	***	0.065	0.018	***
Children$<$6	-0.021	0.019		-0.014	0.034		-0.006	0.033	
Constant	0.445	0.044	***	0.472	0.081	***	0.473	0.080	***
Observations		1,677			1,677			1,677	
F-test exc. instruments:		–		$F(2,1657)$=229.8			$F(9,1650)$=52.8		
Permanent job$_{t-1}$		–		p-value=0.000			p-value=0.000		
F-test exc. instruments:		–		$F(2,1657)$=150.0			$F(9,1650)$=34.9		
Unemployed$_{t-1}$		–		p-value=0.000			p-value=0.000		
Hansen J statistics		–			–		χ^2_7=5.566		
		–			–		p-value=0.591		

(a) White (1980) robust standard errors have been computed.

(b) Gender, educational, and geographical dummies have been included in the level specification but not reported for sake of brevity. In the overidentified case we used as excluded instruments age, its square, and the initial values of the regional unemployment rate, the dummies for marital status, spouse's working status, household position, and presence of prescholar children.

and avoiding the initial conditions problem indicate that having a temporary job, rather than being unemployed, increases of about 13-15.8 percentage points the future probability of having a permanent position. This is a further finding which gives robustness to the conclusions coming from dynamic nonlinear probability models.

5 Concluding Remarks

In this paper we assess whether and on the extent to which temporary jobs have been a springboard toward regular employment or a dead end position in Italy using the 2000, 2002, and 2004 waves of the SHIW. The sample is made up of individuals who have been unemployed, permanent employed, and temporary employed in 2000, 2002, and 2004.

We have estimated a bivariate dynamic unobserved effects probit model to predict the probability of having a permanent position given the lagged labour market state. The main finding is that, *ceteris paribus*, having a temporary contract today, rather than being unemployed, increases the probability of having a permanent job 2 years later of about 13.7–16.2 percentage points.

This evidence suggests that, given observable and unobservable characteristics, temporary contracts in Italy are a stepping stone into permanent jobs. They allow individuals to leave unemployment giving them the opportunity to acquire generic (and possibly) specific skills and making them permanent employable afterwards.

Finally, we have estimated dynamic discrete mixture and linear probability models to assess the robustness of the stepping stone effect to the parametric assumptions about the individual heterogeneity. The estimated average partial effects following these two approaches, which are nonparametric in the specification of the unobserved heterogeneity, are in line with those obtained through dynamic nonlinear unobserved effects probit models.

Appendix

A-1 Estimation of the Average Partial Effects

In this analysis the APEs, or marginal effects, are estimated following Stewart (2007): we estimate the counter-factual outcome probabilities evaluated at the sample means, $\bar{\mathbf{x}}_1$.

Let us call p_U, p_P, and p_T the probability of permanent employment given, respectively, unemployment, permanent employment, and temporary employment at time $t-1$. Then, when we perform the Wooldridge's analysis we have that

$$\widehat{p}_P = \frac{1}{N}\sum_{i=1}^{N}\Phi\big[\bar{\mathbf{x}}_1'\widehat{\boldsymbol{\beta}}_1 + \widehat{\rho}_{11} + \widehat{c}_{1i}\big],\ \widehat{p}_U = \frac{1}{N}\sum_{i=1}^{N}\Phi\big[\bar{\mathbf{x}}_1'\widehat{\boldsymbol{\beta}}_1 + \widehat{\rho}_{12} + \widehat{c}_{1i}\big],\ \text{and}$$

$$\widehat{p}_T = \frac{1}{N}\sum_{i=1}^{N}\Phi\big[\bar{\mathbf{x}}_1'\widehat{\boldsymbol{\beta}}_1 + \widehat{c}_{1i}\big],$$

where $\widehat{c}_{1i}$ is the estimated linear approximation (5) of unobserved heterogeneity. When we adopt the Heckman's estimator, the outcome probabilities must be rescaled because of a different normalisation, so that the arguments of the standard normal c.d.f is multiplied by $(1-\widehat{\lambda})^{1/2}$; moreover $\widehat{c}_{1i}$ is, in this case, the estimated correlated random effect according to specification (3).

Hence, the estimated APEs are defined as $\widehat{APE}_H^J = \widehat{p}_J - \widehat{p}_H$ with $J, H = U, P, T$. For example, $\widehat{APE}_U^T$ is the effect of a temporary job at time $t-1$, rather than unemployment, on the probability of being a permanent worker at time t.

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