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A cycle or a tunnel? A study on unemployment and low-pay dynamics in Italy

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ABSTRACT

We study the extent of persistence in unemployment and low-pay employment in Italy in the period 2014-2017, using the Italian component of the EU-SILC survey merged with administrative data. We model persistence in unemployment and low-pay employment using different dynamic random-effects models accounting for observed and latent individual heterogeneity as well as endogeneity of the initial conditions. We find evidence of true state dependence in place for both unemployment and low-pay employment. Moreover, past unemployment spells increase the probability of being low-paid, conditional on being employed, while the opposite effect is limited. For both processes the degree of reliance on the previous state is considerably greater than the magnitude of cross-effects. Thus, evidence is presented that these processes shape almost independent no-pay/low-pay tunnels leading individuals into two different traps, rather than a cycle between the two states.

1. Introduction

The working trajectories of individuals belonging to the lowest part of the income distribution, represented by unemployed and low-wage workers, provide crucial information on the state of one country's labour market. In particular, strong persistence in unemployment and/or low-pay employment raises equity concerns due to market immobility, whereas feedback effects between the two phenomena define the extent of double-level segmentation.

From a macro perspective, unemployment is socially harmful as it represents both an economic burden, for instance in terms of growth (Daveri and Tabellini, 2000) and labour productivity (Bräuninger and Pannenberg, 2002), and a fiscal cost, through unemployment benefits, and it may contribute to public finance imbalances (Liotti, 2020).[2] Furthermore, a rise in the share of low-pay workers may undermine the long-term sustainability of social security systems (Lucifora et al., 2005).

From a micro perspective, it is important to assess whether these states are persistent or transitory. Indeed, although for the majority of workers unemployment is a random event in their working lives, it is known that persistence in individual unemployment histories is a common circumstance, namely, unemployed individuals are more likely to be unemployed in the future (Arulampalam et al., 2000; Gregg, 2001). Similarly, low-paid workers are expected to remain low-paid in the following time periods (Cappellari and Jenkins, 2008). Are the causes of this persistence related to individual characteristics or does the fact that one has experienced unemployment or low-pay spells increase the likelihood of being trapped in the future? The literature distinguishes the channels using two distinct concepts: individual heterogeneity and true state dependence (Heckman, 1991). The former refers to differences in observable and unobservable characteristics between individuals, while the latter occurs if past states have a causal effect on the probability of being unemployed or low-paid in the future. Typically, the case of state dependence is associated with the presence of human capital depreciation, discouragement and social exclusion (*stigma*) from labour market participation (Biewen and Steffes, 2010; Ayllón, 2013).

Disentangling the relative importance of individual heterogeneity and true state dependence in contributing to the persistence of statuses is relevant for targeting policy measures. If state dependence is the main cause of unemployment and low-pay persistence, it may be crucial to break their vicious circles (e.g. adopting income-supporting social policies). On the other hand, effective policies should focus primarily on education, training, development of personal skills and other labour market-oriented policies if the probability of being unemployed or low paid depends on individual heterogeneity. Another critical issue is represented by the interrelated dynamics between low-pay employment

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2 For more general coverage of the topic see Layard et al. (2005) and Blanchard (2006).

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and unemployment (Stewart, 2007), that is, feedback effects that may generate low-pay/no pay cycles. The signaling effects of past states may interact and jointly affect the workers' career. For instance, workers with a history of job mobility and high unemployment incidence may be offered less secure jobs because of a lack of work experience or human capital, or because past unemployment may be perceived as a signal of low productivity. Alternatively, individuals in unemployment may lower their reservation wage and accept poorer quality jobs (Arulampalam et al., 2000).

In the last thirty years Italy has been characterized by high levels of unemployment and of low-pay employment. After the sovereign debt crisis, Southern Europe countries, including Italy, experienced a rise in unemployment larger than the EU-28 average (Boeri and Jimeno, 2016). At the same time, Italy has experienced a change in the shape of its labour income distribution (Franzini and Raitano, 2019; Hoffmann et al., 2022). An increased inequality derived from the well-known phenomenon of job polarization (Autor et al., 2003; Autor and Dorn, 2013),[3] coupled with the stunning steadiness of Italian wages,[4] has contributed to the rise of low-wage employment. The surge in the number of low-paid workers in Italy is the focus of the work of Bavaro (2022), who uses the universe of Italian private workers and shows that the incidence of low-paid workers increases from 25% in 1990 to 32% in 2017.[5] Working individuals have experienced a decline in their living standards due to the reduction in wages, the rise of part-time jobs and the decrease of the relevance of the national wage bargaining system (Cappellari, 2007).

The aim of this work is to examine the extent of state dependence in unemployment and low-pay employment in Italy. We make use of AD-SILC, a dataset integrating survey data and administrative records covering the period 2014–17 and providing information on gross labour income at the individual level, additional work related details, individual socio-demographic characteristics and other information at the household level.

Our contribution is twofold. First, we analyze the univariate processes of unemployment and low-pay employment assuming the exogeneity of employment spells, using a detailed survey dataset linked with administrative records on individual employment. This source allows us to study gross incomes as labour market outcomes, therefore avoiding incurring into redistributive effects of the household-based Italian taxation system. Secondly, we model the cross-dependencies of unemployment and low-pay employment with a bivariate probit model, relaxing the assumption of exogenous selection into employment status, to analyze their feedback effects in Italy. To our knowledge, previous analyses using Italian survey data focused on unemployment and low-pay transitions separately.

The paper is organized as follows. Section 2 summarizes the related literature. In Section 3 we formulate the models accounting for individual heterogeneity and first-order state-dependence. Section 4 includes the data description and the sample selection procedure. In Section 5 we present the main results. Finally, in Section 6 we provide concluding remarks.

2. Literature review

In this section, we highlight a non-exhaustive selection of works and frameworks relevant to our study, relating to broad definitions of unemployment and low-pay employment dynamics. Many of these studies rely on longitudinal settings and adopt different specifications of a dynamic random-effects probit model, employing discrete definitions of employment and low-pay employment.[6]

An important contribution in the study of unemployment state dependence is provided by Arulampalam et al. (2000), who make use of UK survey data and find evidence of previous employment experience affecting future labour market outcomes, consistently with the scarring theory of unemployment.[7] Baussola and Mussida (2017) provide evidence of state dependence in unemployment in Europe using EU-SILC data, highlighting some features of the analyzed labour markets (i.e., gender effects and regional differentials) including Italy. Biewen and Steffes (2010), using German survey data, suggest that a negative relation between individual unemployment persistence and the business cycle can be interpreted as evidence for stigma effects. Building on their findings, Ayllón (2013) introduces discouragement as an additional explanation of state dependence in unemployment, using the Spanish component of the European Community Household Panel.[8] Other works focus on the broader definition of non-employment persistence, as in the case of Omori (1997). Tanzi (2022) examines the non-employment scarring effects at the initial stage of the work career, providing evidence of negative effects induced by early non-employment.

In terms of low-pay dynamics, relevant contributions in the international literature are those by Stewart and Swaffield (1999) and Clark and Kanellopoulos (2013), who find positive state dependence in every considered country, and Mosthaf et al. (2014), who use German data and provide evidence of a low-pay-no-pay cycle for western German women. Cappellari (2002) uses survey data from the Bank of Italy's Survey on Household Income and Wealth (SHIW) in the period 1993–95, adopting a switching bivariate probit model, and he finds that the chance of being trapped below the low-pay threshold is sizeable, between 55 percent and 70 percent depending upon the adopted definitions. Cappellari (2007) uses SHIW data between 1993 and 2002 and focuses on two-year transitions, adopting a four-variate probit model controlling for endogenous initial conditions, earnings attrition and educational attainment. The magnitude of the estimated state dependence accounts for roughly half of the difference in transition probabilities between low- and high-paid individuals.

Strictly related to our approach, the article by Stewart (2007) provides a cross-analysis of unemployment and low-pay. The author uses UK survey data and models the two phenomena sequentially, using dynamic random-effects probit regressions controlling for endogenous initial conditions. In his findings, low-wage employment is shown to have almost as large an adverse effect as unemployment on future labour states and the difference in the two effects is found to be non-significant. Moreover, evidence is provided on low-wage jobs acting as the main conduit for repeated unemployment. The related paper by Cappellari and Jenkins (2008) investigates the low pay/no pay cycles in UK modeling the transitions jointly rather than sequentially. It confirms both the substantial persistence in the chances of being unemployed and low-paid, and the interrelationship between the two conditions. The paper by Mosthaf (2014) studies the interaction between the effects of low-wage employment and non-employment on wage prospects.

[3] See Goos et al. (2009) for a cross-country comparison in Europe and Basso (2020) for a focus on the role of demand-side changes in the Italian case.

[4] Among OECD countries, real wages decreased between 1990 and 2020 in Italy and few other countries only (OECD, 2021).

[5] For comparison, the *in-work at-risk-of-poverty* rate computed by Eurostat, using equivalized disposable income from the European Union Survey on Income and Living Conditions (EU-SILC) data, increased from 8.7% in 2006 to 11.7% in 2016.

[6] While employing discrete definitions of employment and low-pay employment induces a loss of information, compared to using continuous variables (such as the number of weeks worked and the income level), it offers the clear advantage of partitioning the population into subgroups (namely, the unemployed and the low paid) which are of significant interest from both analytical and policy perspectives.

[7] On this topic, see also Eliason and Storrie (2006) and Brandt and Hank (2014).

[8] On a similar note, Clark et al. (2001) study the negative effect of current and past unemployment on individual life satisfaction.

A connected strand of literature is the one on household poverty or low-income dynamics. The work by Cappellari and Jenkins (2004) uses UK survey data to model household low-income persistence, finding substantial state dependence. Another relevant contribution is the one by Biewen (2009), who builds on a general framework developed in Wooldridge (2000). The author uses German survey data, derives individual poverty status based on household income, and models poverty dynamics which are conditional on contemporaneous employment status. Other works focus on poverty persistence making use of household equivalized disposable income (Devicienti and Poggi, 2011; Giarda and Moroni, 2018; Fabrizi and Mussida, 2020) or different measures of financial fragilities (Loschiavo et al., 2024).

Finally, due to the recent widespread availability of administrative data, a strand of literature focuses on the dynamics of the whole income distribution, analyzing measures of income inequality, volatility, mobility, and risk. Recent examples include Arellano et al. (2022) and, for the Italian case, Hoffmann et al. (2022), among others.[9] Administrative data offer several advantages compared to surveys, including high-quality information, and complete employment spells over long horizons. On the other hand, they are often less detailed on individual demographic characteristics, and they typically do not report individuals' information at the household level (e.g. household income, wealth, etc.). We align with this body of literature in using administrative data, yet focusing on the lower tail of the income distribution (i.e. the unemployed and low paid individuals), and with the advantage of dealing with a survey-administrative linked database.

3. Methods

In this section, we overview the adopted methods providing an estimate of the causal effects of interest. First, we describe the dynamic random-effects probit model. Then, we turn to a bivariate model with feedback effects. Both models include previous states to allow for state dependence. Unobserved heterogeneity and endogenous initial conditions must be suitably accounted for to avoid overestimating the true effect of past states.

3.1. Dynamic random-effects probit model

Let y_{it} be a binary response variable equal to one if individual i is unemployed at time t, and zero otherwise. Alternatively, y_{it} may represent an indicator variable for low-pay at time t, among employed individuals. A dynamic random-effects (RE) probit model for y_{it}, $i = 1,\dots,n$, $t = 1,\dots,T$, may be written as

$$y_{it} = \mathbf{1}\{\boldsymbol{\beta}'\boldsymbol{x}_{it} + \rho y_{i,t-1} + c_i + u_{it} > 0\}, \tag{1}$$

where $\mathbf{1}\{\cdot\}$ denotes the indicator function equal to one if the argument is true. The error terms u_{it} are assumed to be i.i.d. standard normal random variables, and $\boldsymbol{x}_{it}$ is a vector of time-variant exogenous covariates, namely, they are independent of all past, current and future values of u_{it}. The parameter of interest is ρ, and c_i is the time-invariant unobserved individual effect.

If the initial conditions y_{i0} were exogenous, no particular concern was raised in terms of consistency of the standard random-effect estimator, assuming $c_i \sim N(0,\sigma_c^2)$ or accounting for the dependency of c_i on the covariates explicitly modeling the conditional mean of the unobserved effect as in Mundlak (1978) and Chamberlain (1984). However, more realistically, unless the panel dataset starts with the stochastic processes, the initial conditions cannot be considered exogenous (Akay, 2012). To deal with the endogenous initial value problem, a possible solution is adopting the methodology proposed by Wooldridge (2005), specifying a conditional density for the unobserved effect of the form[10]

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \boldsymbol{\alpha_2}'\boldsymbol{z}_i + a_i,$$

with $a_i \sim N(0,\sigma_a^2)$ and $\boldsymbol{z}_i$ is the vector including time-constant covariates (say, $\boldsymbol{q}_i$) and possibly the time-averaged time-variant covariates of Eq. (1), namely, $\bar{\boldsymbol{x}}_i$.[11] We postpone to the following section a brief discussion on the estimation procedure, as it is closely related to the bivariate extension.

As a final remark, it is worth noting that all proxies of unobserved constant factors such as talent and abilities must be included in $\boldsymbol{z}_i$. As a robustness analysis we add information on labour market histories taken from administrative records as another component of the conditional density of c_i. However, this augmented specification comes with some caveats, as discussed in Section 5.4.

3.2. Bivariate model of unemployment and low-pay employment dynamics

Standard models described in the previous section rely on the assumption of strict exogeneity of the covariates, ruling out the possibility of feedback effects from the dependent variable to future explanatory variables. In the context of low-pay employment, a similar situation is faced when sorting into employment is not exogenous, namely, when there is selection into employment status. Endogenous selection may represent the cause of an inconsistency of the parameter of interest. We deal with this issue by modeling the joint dynamics of low-pay employment and unemployment, accounting for unobserved heterogeneity and endogenous initial conditions in a Wooldridge-type setting.

Let y_{1it} be a binary response variable equal to one if individual i is unemployed at time t and $y_{2it} = 1$ if the individual is classified as low-paid. For each individual i the vectors collecting these variables, for $t = 1,\dots,T$, are defined $\boldsymbol{y}_{1i}$ and $\boldsymbol{y}_{2i}$, respectively. The model is specified as

$$y_{1it} = \mathbf{1}\{\underbrace{\boldsymbol{\beta}_0'\boldsymbol{x}_{1it} + \beta_1 y_{1i,t-1} + \beta_2 y_{2i,t-1} + \beta_3 c_i}_{=\mu_{it}} + u_{1it} > 0\}, \tag{2}$$

$$y_{2it} = \mathbf{1}\{\underbrace{\boldsymbol{\gamma}_0'\boldsymbol{x}_{2it} + \gamma_1 y_{1i,t-1} + \gamma_2 y_{2i,t-1} + c_i}_{=\lambda_{it}} + u_{2it} > 0\} \quad \text{if } y_{1it} = 0, \tag{3}$$

where the error terms (u_1, u_2) are independent standard normals and are assumed independent over time. Note that a zero correlation between u_1 and u_2 does not imply that the latent variables are residually uncorrelated, because of the presence of the unobserved common factor c_i.[12] The vectors $\boldsymbol{x}_{jit}$, $j = 1,2$, denote the sets of (possibly different) time-variant exogenous covariates, and β_3 is the loading factor allowing the unobserved heterogeneity to affect y_{1it} and y_{2it} differently. Feedback effects between the two dependent variables are captured by the parameters β_2 and γ_1. The other parameters of main interest are represented by β_1 and γ_2 and they capture the degree of state dependence of unemployment and low-pay employment. In practice, we model the joint distribution of unemployment and low-pay employment, accounting for unobserved heterogeneity. Let also $\boldsymbol{z}_i$ denote the

[9] For further examples, see the 2022 special issue of *Quantitative Economics* introducing the Global Repository of Income Dynamics.

[10] Heckman (1981), on the other hand, proposed to tackle the problem by approximating the distribution of the initial conditions conditional on c_i and a set of exogenous instruments.

[11] A convenient feature of this specification is that it can be implemented with standard random-effects probit estimation programs (e.g., `xtprobit` in `Stata`). Other possible parametrizations, less restrictive yet less parsimonious, can be found in Rabe-Hesketh and Skrondal (2013) and Skrondal and Rabe-Hesketh (2013).

[12] Stewart (2007), on the other hand, adopts a specification with two jointly normally distributed random effects. The common factor specification is adopted in Biewen (2009). Restricting the cross-processes latent correlation structure significantly reduces the model complexity and the computational burden in the estimation process.

vector of time-invariant covariates (which is assumed to be common to the two processes) and time-averaged time-variant covariates of both equations. On the basis of the adopted assumptions, the joint density of $(\boldsymbol{y}_{1i}, \boldsymbol{y}_{2i})$ conditional of $(\boldsymbol{x}_{1i}, \boldsymbol{x}_{2i}, \boldsymbol{z}_i, y_{1i0}, y_{2i0}, c_i)$ is given by

$$f(\boldsymbol{y}_{1i}, \boldsymbol{y}_{2i}|\boldsymbol{x}_{1i}, \boldsymbol{x}_{2i}, \boldsymbol{z}_i, y_{1i0}, y_{2i0}, c_i) \tag{4}$$
$$= \prod_{t=1}^{T} f(y_{1it}, y_{2it}|\boldsymbol{x}_{1it}, \boldsymbol{x}_{2it}, \boldsymbol{z}_i, y_{1i,t-1}, y_{2i,t-1}, c_i)$$
$$= \prod_{t=1}^{T} \{y_{1it}\Phi[\mu_{it}] + (1-y_{1it})\Phi[-\mu_{it}]\Phi[(2y_{2it}-1)\lambda_{it}]\}$$

where $\Phi[\cdot]$ denotes the cdf of a standard normal distribution. The likelihood function is given by

$$\ell(\boldsymbol{\theta}) = \prod_{i=1}^{n} \int_{\mathbb{R}} f(\boldsymbol{y}_{1i}, \boldsymbol{y}_{2i}|\boldsymbol{x}_{1i}, \boldsymbol{x}_{2i}, \boldsymbol{z}_i, y_{1i0}, y_{2i0}, c_i) \times \eta(c_i|\boldsymbol{z}_i, y_{1i0}, y_{2i0}) \mathrm{d}c_i, \tag{5}$$

where $\boldsymbol{\theta}$ is the vector collecting all the model parameters. Finally, one needs to specify the conditional distribution of c, which is usually taken to be normally distributed, as in

$$c_i = \alpha_0 + \alpha_1 y_{1i0} + \alpha_2 y_{2i0} + \boldsymbol{\alpha}_3' \boldsymbol{z}_i + a_i, \qquad a_i \sim N(0, \sigma_a).$$

In this case, the integral in Eq. (5) must be evaluated using a numerical method, e.g., Gauss–Hermite quadrature (Butler and Moffitt, 1982). An estimate of $\boldsymbol{\theta}$ can then be obtained maximizing $\log \ell(\boldsymbol{\theta})$ by standard conditional maximum likelihood methods.[13]

To understand the magnitudes of the state dependence and allow interpretation of the estimates, we also compute average partial effects (APEs).

4. Data and summary statistics

We make use of the AD-SILC dataset, which is built linking IT-SILC, the Italian component of the EU-SILC covering the period 2004–2017, with administrative data collected from the Italian Institute of Social Security (Istituto Nazionale di Previdenza Sociale – INPS – in Italian) recording the whole contribution histories of individuals working in Italy, up to 2019.[14] In other words, for all individuals interviewed in IT-SILC who were active in the Italian labour market, AD-SILC reports the labour and pension contributions records from the moment they entered in the labour market, encompassing gross wages, unemployment benefits, maternity and sickness allowances.

For our purposes, we focus on the last four available waves of IT-SILC, which cover the 4-year period 2014–2017. According to a rotating sampling design, a new panel of households and individuals is introduced in each wave, to replace approximately one fourth of the existing sample. The panel sample covering all the four waves consists in 2938 active individuals younger than 66. The number of observations equals 8814 that corresponds to 2938 individuals observed three times in the interval 2015–17, since 2014 is used as the baseline year for defining the initial conditions in the econometric analysis. Socio-demographic variables including age, gender, region of residence, citizenship, marital status, number of children, as well as an indicator equal to one for working partners and the household capital income are retrieved from the IT-SILC records and they are available for the entire sample.

The labour information is retrieved from the administrative records. For each year, an individual is classified as employed if she has worked at least 12 weeks in a year, including temporary layoffs, maternity and sick pays. Individuals who work less than 12 weeks are classified as unemployed, along with individuals receiving unemployment payments and those who have no administrative record for the reference year, but they report to be looking for a job (in IT-SILC). Inactive individuals (i.e., those who are neither employed nor unemployed) are excluded from the main analysis, even though they are included in a broad definition of non-employment used in Section 5.3. In alternative specifications, whose results are available in the Appendix, we employ different employment thresholds (4, 8 and 16 weeks) to assess the sensitivity of the results to the adopted threshold.

Yearly gross labour earnings are computed by summing the single earnings entries of each record in a given year.[15] For each year, we compute a low-pay threshold, which is equal to 60% of the yearly median gross earnings, among all employed individuals who are less than 65 years old, including individuals belonging to the cross-sectional dataset (i.e. not only participants to the 2014–2017 panel sample). To compute the low-pay threshold, yearly earnings are weighted with cross-sectional weights. Every individual whose yearly earnings fall below the threshold is classified as low-paid worker. In an alternative specification, which is discussed in Section 5.3, we adopt a definition of low-pay employment based on weekly gross earnings, namely, yearly earnings divided by the number of weeks worked within a given year, to account for possible within-year heterogeneity in work intensity.[16]

Employed individuals are then classified depending on the occupation they perform. We define a 3-category occupational classification composed by: private employees, public employees and a third category that includes mostly self-employed (craftsmen and tradesmen as well as professionals) and atypical workers such as collaborators. Since every worker may have more than one administrative record in each observed year, a relevant issue is constituted by the definition of the "main" occupation. We define the main occupation as the one that employs the worker for the highest number of weeks worked during the year.[17] Other information on the working conditions, such as contract characteristics (fixed term vs. open ended, part-time vs. full-time) or the province of employment, are considered with reference to the main occupation performed by an individual during the year.

Summary statistics are presented in Table 1 for the sample of active individuals younger than 66 years old in the 2014–17 time span. In Panel A, the statistics of main interest are presented for the pooled data between 2015 and 2017. Unemployed represent 8.8% of active individuals. In the 2015–17 time span, the share of low-pay employed individuals using yearly labour earnings equals 18.6% while it decreases to 12.6% when using weekly labour earnings. Panel B shows the demographic covariates taken from IT-SILC: the majority of the sample is constituted by males; the average age is around 45 years; most of the individuals are married; about half of the sample has children. In terms of education we use the highest level of education achieved in the time span, which is defined as a time-invariant variable. Almost three out of four of the observed individuals have attained at least the upper

[13] We employ a Newton–Raphson method using the R function `maxBHHH` (Henningsen and Toomet, 2011), and we evaluate the integral in Eq. (5) with a Gauss–Hermite quadrature with 10 quadrature points.

[14] For a thorough description of the dataset, see Conti et al. (2023).

[15] We correct the administrative values taken from INPS with the individual gross labour earnings from SILC in the few cases in which the information of weeks employed do not match with a positive salary (1.4% of total observations), even though the two income definitions are not perfectly comparable (SILC earnings are net of social contributions). We evaluate these cases as errors of the administrative records. Results remain unchanged if these observations are dropped from the sample.

[16] The best setting to account for heterogeneous within-year work intensity (and, at the same time, tackling directly the issue of part-timers) would have been to define a measure of low-pay employment based on hourly earnings. Unfortunately, this information is not available in our data. As a side note, assessing the working hours of the self-employed (which are included in the analysis) would not have been straightforward.

[17] In case an individual has two or more longer working spells with the same duration, we apply a secondary criterion based on earnings, and the main occupation is given by the one endowing the maximum yearly earnings. For instance, if individual i worked 16 weeks as a private employee in year t, earning 5000 euros, and 16 weeks as a self-employed, earning 10,000 euros, she is classified as self-employed.

Table 1
Descriptive statistics.
Source: Own elaborations based on AD-SILC 2014–17.

Panel A: Probabilities of unemployment and low-pay employment					
	Mean	sd		Mean	sd
Unemployment	0.088	(0.284)	Weekly low-pay	0.126	(0.332)
Yearly low-pay	0.186	(0.390)			
Panel B: Characteristics from IT-SILC					
Women	0.451	(0.498)	Educ: Primary	0.017	(0.131)
Age	45.651	(10.514)	Educ: Low-sec	0.233	(0.423)
Foreigner	0.045	(0.208)	Educ: Up-sec	0.464	(0.499)
Married	0.613	(0.487)	Educ: Tertiary	0.286	(0.452)
Children 0–15	0.507	(0.799)	Working partner	0.203	(0.403)
Household capital income	1390	(4280)			
Panel C: Labour market outcomes from social security records					
Occ: Priv employee	0.607	(0.488)	Yearly earnings	27,491	(21,521)
Occ: Pub employee	0.168	(0.374)	Weekly earnings	537	(365)
Occ: Self-employed & other workers	0.225	(0.417)	Fixed-term	0.083	(0.275)
Part-time	0.171	(0.377)			
Individuals (n)	2938		Time (T)	3	
Observations ($n \times T$)	8814				

Notes: The unemployment rate is computed conditional on being active in the labour market. Low-pay rates and other labour market outcomes in Panel C are computed conditional on being employed. The average household capital income as well as the average yearly and weekly earnings are expressed in euros.

secondary education level. From IT-SILC we also derive the working status of the partner and the level of household capital income net of imputed rents. About one in five individuals have employed partners, and the average level of household capital income in our sample is just below 1400 euros, with a large standard deviation capturing the spread of the distribution.

Panel C shows the labour variables derived from the social security records. In terms of main occupation, the majority of workers are private employees (61%), even though a significant share of the sample is composed by public employees and self-employed workers. Fixed-term and part-time contracts are significantly spread in the sample: 8.3% of workers have a fixed-term contract and 17.1% of workers are part-timers.[18]

In the final part of this section, we provide a descriptive overview of the phenomenon of persistence in the states of unemployment and low-pay. Table 2 shows the transition probabilities for the pooled sample among the three mutually exclusive labour force states (s): unemployment (U), yearly low-pay employment (LP), and higher pay employment (HP) for those workers whose wage fall above the low-pay threshold. A transition rate is computed as the frequency of individuals moving from state s_{t-1} to state s_t divided by the total number of individuals in state s_{t-1} (i.e., each row sums to one), pooled across time periods. State-dependence is evidently strong, as the row-wise highest probabilities are found along the main diagonal of the transition matrix, with the probability of remaining a higher paid worker being the highest (95.8%). Persistence is also high in the other two states characterized by low-wage and unemployment, respectively. In particular, a low-paid worker is about 25 times more likely to be a low-paid worker in the following period with respect to higher paid workers (second and third rows of the second column of Table 2), and almost 3 times more likely with respect to unemployed individuals (first row of the second column). The analysis is also replicated weighing the observations with longitudinal weights (Table A.1 in the Appendix), and these figures remain practically unchanged, indicating that hardly our regression results are affected by panel retention.

[18] These shares are computed over the whole sample, including self-employed workers.

Table 2
Labour status transition rates.
Source: Own elaborations based on AD-SILC 2014–17.

s_{t-1}	s_t		
	U	LP	HP
U	0.651	0.251	0.098
LP	0.105	0.725	0.170
HP	0.013	0.029	0.958

Notes: 8814 observations. s represents the mutually exclusive labour market states. U stands for unemployed; LP stands for low-paid workers; HP stands for higher paid workers. Each row sums to one.

5. Results

In this section we present the main results. First, we show the results of the estimated univariate models, in which the dependent variables are represented by unemployment and yearly low-pay status. Then, we account for feedback effects between unemployment and yearly low-pay condition in the bivariate framework illustrated in Section 3. We also discuss the results from a set of augmented specifications in which the unobserved heterogeneity terms include a proxy for individuals' working history. Finally, as a further analysis, we employ non-employment and weekly low-pay as dependent variables.[19]

5.1. Univariate models of unemployment and low-pay

The results of the estimated unemployment model are presented in Table 3, which shows the estimated coefficients and standard errors of a pooled probit model, and of the dynamic random-effects model described in Eq. (1) accounting for unobserved heterogeneity and endogenous initial conditions.

Being unemployed increases the unemployment probability in the next period: the lagged unemployment parameter is large and statistically significant at the 1% level in both the considered models (first row of Table 3).[20] The corresponding estimated average partial effects (APEs) are shown in the last row. The pooled probit estimator

[19] All the regressions are also replicated including longitudinal weights, and results do not change significantly.

[20] The results obtained using different unemployment thresholds are presented in Table A.2 in Appendix.

provides an APE of lagged unemployment spells of approximately 52.2 percentage points (pp). When accounting for unobserved heterogeneity and endogenous initial conditions, this figure decreases to 23.4 pp, namely, more than half of the effect is due to individual latent characteristics. No clear indications in terms of gender and country of origin effects are found, as the coefficients for women and foreigners are not significantly different from zero. However, for both these categories there is a significant relation with low-wage employment emerging in the bivariate framework discussed in the next section. There are marked regional differentials in unemployment probabilities: living in Southern and Islands regions significantly increases the probability of being unemployed in both models. As expected, lower educational attainments increase the likelihood of being unemployed as well. The effects of household circumstances on individual unemployment should not be underestimated. As shown by Baussola and Mussida (2017) in their study on European countries, marital status exerts a negative and significant impact on the probability of remaining unemployed. In our findings married individuals have a lower probability of being unemployed, and the same happens to individuals with children (between 0 and 15 years old), yet only in the pooled probit formulation. An increase in the level of household capital income reduces the probability of being unemployed, even though the magnitude of this effect is not sizeable. This covariate was included in order to account for potential voluntary unemployment (with labour income being substituted by capital income). However, the negative sign of the coefficient indicates that unemployed individuals earn less capital income, on average. Also the working partner coefficient exhibits a negative sign, although it is not statistically significant. In other words, we do not find evidence on voluntary unemployment due to intra-household sharing of duties. Instead, our findings are consistent with theories related to marital sorting, since within-couple employment is, on average, more similar.[21]

Table 3
Unemployment: univariate models.
Source: Own elaborations based on AD-SILC 2014–17.

	Probit		Dynamic RE probit	
Unemployed ($t-1$)	2.078***	(0.065)	1.421***	(0.124)
Woman	0.048	(0.050)	0.038	(0.064)
Age	−0.004	(0.002)	0.000	(0.034)
Foreigner	0.006	(0.108)	−0.026	(0.142)
Married	−0.198***	(0.060)	−0.208***	(0.078)
Children 0–15	−0.106***	(0.036)	0.175	(0.183)
North-East	0.168**	(0.080)	0.206**	(0.102)
Center	0.382***	(0.076)	0.463***	(0.102)
South	0.492***	(0.079)	0.574***	(0.108)
Islands	0.429***	(0.100)	0.512***	(0.128)
Primary	0.358*	(0.184)	0.420**	(0.209)
Low secondary	0.202***	(0.067)	0.214**	(0.091)
Upper secondary	0.115*	(0.060)	0.125	(0.078)
Capital income	−0.039***	(0.008)	−0.034	(0.022)
Working partner	−0.088	(0.080)	−0.124	(0.100)
Unemployed ($t=0$)			1.007***	(0.184)
Constant	−1.812***	(0.132)	−2.171***	(0.191)
σ_a			0.550	(0.111)
Average partial effects				
Unemployed ($t-1$)	0.522	(0.022)	0.234	(0.046)

Notes: No. of obs: 8814 (2938 individuals × 3 time periods). The baseline category of the geographical area of residence is the North-West of Italy. The baseline category of the educational attainment is tertiary education. Time-averages of the following variables are included in the random-effects model: Age, children 0–15 and capital income. Standard error in parentheses. Probit regression standard errors are clustered at the individual level.
* Significance level: $p < 0.1$.
** Significance level: $p < 0.05$.
*** Significance level: $p < 0.01$.

Table 4 shows the results on yearly low-pay employment probabilities. The sample is restricted to individuals who are always employed in the four-year time span, and the number of observations reduces to 7314 (2438 employed individuals observed three times). We adopt the same model specifications as before. The lagged low-pay condition parameter is positive and highly statistically significant at the 1% level in both specifications. The average partial effects of the lagged dependent variable is 65.9 pp in the pooled probit model and 21.1 pp in the dynamic random-effects probit model, denoting a significant role played by the unobserved heterogeneity and initial conditions in explaining the phenomenon. Differently from the findings on unemployment, women and foreign-born workers are more likely to be low-paid with respect to men and Italian-born workers. The coefficients of education and geographical area follow the same path of unemployment, namely, the more disadvantaged groups consist of individuals employed in the South and Islands regions, as well as those with lower levels of education. The role of family is crucial for low-pay employment, even more so than in unemployment: on average, married individuals tend to be less low-paid, while the opposite is observed to individuals with children. Valuable insights are offered by working-specific covariates, such as occupation, part-time and fixed-term contracts. Public employees demonstrate a lower probability of being in low-pay positions compared to private employees, while self-employed and non-standard workers exhibit a higher probability. Individuals whose primary occupation is part-time employment are significantly more likely to receive low pays.[22] Similarly, the coefficient for fixed-term contracts indicates a positive effect on the likelihood of receiving low earnings. These results are not surprising, since a reduced work intensity implies a decreased yearly wage, and they are coherent with Hoffmann et al. (2022) who identify part-time arrangements as the main driver of Italian earnings inequality in the last decades, and fixed-term contracts as drivers of earnings volatility. Finally, we observe no statistically significant coefficient associated with household capital income, suggesting the absence of substitution between labour and capital income.

5.2. Feedback effects between unemployment and low-pay employment

In this section, we discuss the role of feedback effects (i.e., cross-dependencies) between unemployment and low-pay employment to capture the potential vicious circle between the two phenomena. We take into account the possible endogenous selection issue that may cause an inconsistency of the parameters of interest, and we analyze the joint dynamics of unemployment and low-pay employment by estimating the bivariate model illustrated in Section 3.2.[23]

Results are presented in Table 5. The bivariate model provides evidence of substantial state-dependence, both for unemployment and low-pay employment, whose lagged status coefficients are statistically significant at the 1% level. Focusing on the average partial effects, we find that low-pay employment has a limited differential impact on the probability of being unemployment in the following period, compared to non-low-pay employment (3.3 pp). On the contrary, a strong state-dependence is estimated for low-pay (47.9 pp) and unemployment (38.0 pp) processes. Past unemployment also has considerable effects on future low-wage employment conditions, with an APE of 39.1 percentage points on the probability of being a low-pay worker, conditional on being employed. Results, in terms of covariates, are similar to those presented in the previous sections.

[21] Even though most of the economic literature on assortative mating focuses on educational or income outcomes, few recent works analyze the occupational choices (Schwartz et al., 2021; Mansour and McKinnish, 2018). See also Pestel (2017) who study the effect of marital sorting on earnings inequality, taking into account extensive and intensive margin labour supply choices.

[22] From our data we cannot retrieve information on whether the part-time job is voluntary or non-voluntary. However, the percentage of involuntary part-time in Italy is the highest among OECD countries (OECD, 2021).

[23] See Table A.3 in the Appendix for a comparable analysis of feedback effects using univariate models.

Table 4
Low-pay employment: univariate models for always-employed individuals.
Source: Own elaborations based on AD-SILC 2014–17.

	Probit		Dynamic RE probit	
Low-pay ($t-1$)	2.597***	(0.074)	1.523***	(0.184)
Woman	0.290***	(0.059)	0.339***	(0.095)
Age	0.006**	(0.003)	0.021	(0.043)
Foreigner	0.511***	(0.115)	0.637***	(0.170)
Married	−0.259***	(0.065)	−0.349***	(0.107)
Children 0–15	0.025	(0.035)	0.438*	(0.238)
North-East	−0.071	(0.077)	−0.115	(0.116)
Center	0.038	(0.077)	0.036	(0.119)
South	0.251**	(0.113)	0.290*	(0.162)
Islands	0.202	(0.139)	0.277	(0.199)
Educ: Primary	0.570***	(0.197)	0.636**	(0.277)
Educ: Low secondary	0.338***	(0.073)	0.345***	(0.121)
Educ: Up secondary	0.075	(0.067)	0.089	(0.101)
Capital income	−0.007	(0.008)	0.006	(0.027)
Working partner	0.121	(0.077)	0.175	(0.118)
Occ: Public employee	−0.298***	(0.112)	−0.403**	(0.170)
Occ: Self-employed	0.446***	(0.072)	0.572***	(0.112)
Part-time	0.601***	(0.075)	0.786***	(0.121)
Fixed-term	0.579***	(0.104)	0.731***	(0.137)
Unemployment (province)	0.002	(0.009)	0.001	(0.012)
Constant	−2.710***	(0.184)	−3.476***	(0.357)
Low-pay ($t=0$)			1.711***	(0.356)
σ_a			0.722	(0.164)
Average partial effects				
Low-pay ($t-1$)	0.659	(0.022)	0.211	(0.060)

Notes: No. of obs: 7314 (2438 employed individuals × 3 time periods). The baseline category of the geographical area of residence is the North-West of Italy. The baseline category of the educational attainment is tertiary education. Time-averages of the following variables are included in the random-effects model: Age, children 0–15 and capital income. Standard errors in parentheses. Probit regression standard errors are clustered at the individual level.
* Significance level: $p < 0.1$.
** Significance level: $p < 0.05$.
*** Significance level: $p < 0.01$.

Table 5
Unemployment and low-pay employment: bivariate model.
Source: Own elaborations based on AD-SILC 2014–17.

	Unemployed		Low-pay	
Unemployed ($t-1$)	1.927***	(0.132)	1.771***	(0.126)
Low-pay ($t-1$)	0.415***	(0.117)	2.051***	(0.088)
Woman	−0.094	(0.058)	0.249***	(0.066)
Age	−0.005	(0.023)	0.006	(0.027)
Married	−0.162**	(0.071)	−0.290***	(0.079)
Children 0–15	0.070	(0.111)	0.279**	(0.131)
Foreigner	−0.258*	(0.144)	0.552***	(0.118)
North-East	0.109	(0.091)	−0.015	(0.085)
Center	0.292***	(0.092)	0.062	(0.088)
South	0.296***	(0.096)	0.220*	(0.114)
Islands	0.210*	(0.112)	0.163	(0.147)
Capital income	−0.033**	(0.015)	−0.006	(0.016)
Working partner	−0.043	(0.092)	0.044	(0.091)
Occ: Public employee			−0.348***	(0.077)
Occ: Self-employed			−0.867***	(0.125)
Part-time			0.631***	(0.074)
Fixed-term			0.484***	(0.079)
Unemployment (province)			0.018*	(0.010)
	Unobserved (common) heterogeneity			
Unemployed ($t=0$)	0.792***	(0.197)		
Low-pay ($t=0$)	0.643***	(0.156)		
Educ: Primary	0.268*	(0.141)		
Educ: Low secondary	0.211**	(0.071)		
Educ: Up secondary	0.070	(0.056)		
Constant	−2.612***	(0.214)		
Loading factor	0.831	(0.090)		
σ_a	0.366	(0.116)		
Average partial effects				
Unemployed ($t-1$)	0.380	(0.051)	0.391	(0.049)
Low-pay ($t-1$)	0.033	(0.008)	0.479	(0.045)

Notes: No. of obs: 8814 (2938 individuals × 3 time periods). The baseline category of the geographical area of residence is the North-West of Italy. The baseline category of the educational attainment is tertiary education. Time-averages of the following variables are included: Age, children 0–15 and capital income. Standard errors in parentheses.
* Significance level: $p < 0.1$.
** Significance level: $p < 0.05$.
*** Significance level: $p < 0.01$.

The main results discussed so far are summarized in Table 6, which presents the estimated average partial effects of the three adopted models, for both unemployment and yearly low-pay. In the bivariate dynamic RE model, the estimated state dependence in the unemployment process falls approximately between that of the probit and univariate dynamic RE models, with the APE of past unemployment spells being almost 15 percentage points higher than that of the univariate model. This difference is likely due to the constraint imposed on the unobserved heterogeneity term, which is assumed to be common to the two processes. The estimated true state dependence in the low-pay process is also higher in the bivariate framework. This result is somewhat expected, considering that the two samples differ, as the univariate model is estimated on always-employed individuals only. Expanding the sample to include all active individuals, in the bivariate framework, to control for selection into employment, the APE of past low-pay spells more than doubles. This differential effect is likely driven by individuals who, in the 2015–2017 period, experience two subsequent periods of low-pay employment followed (or preceded) by a period of unemployment.[24]

In conclusion, the key findings can be summarized as follows. True state dependence in unemployment and low-pay employment is considerable, and the influence of past low-pay employment on current unemployment is significantly lower than the influence of past unemployment on current low-pay employment. Unobserved heterogeneity is also relevant, accounting for approximately 30 per cent of state dependence in both processes within the bivariate framework. Finally, some key explanatory variables, such as gender and birthplace, have opposite effects on unemployment and low-pay employment.

[24] By definition, these individuals contributing to higher levels of state dependence in the low-pay condition are not included in the sample consisting of always-employed individuals.

Table 6
Unemployment and low-pay employment: Average partial effects.
Source: Own elaborations based on AD-SILC 2014–17.

	s_t					
	U			LP		
	Probit	dyn RE prob	biv prob	Probit[a]	dyn RE prob[a]	biv prob
s_{t-1}						
U	0.522 (0.22)	0.234 (0.046)	0.380 (0.051)	–	–	0.391 (0.049)
LP	–	–	0.033 (0.008)	0.659 (0.022)	0.211 (0.060)	0.479 (0.045)
Obs.	8814	8814	8814	7314	7314	8814

Notes: s represents labour market states. U stands for unemployed individuals; LP stands for low-paid workers. Standard errors in parentheses.
[a] Sample consisting on always-employed individuals.

5.3. Other indicators of labour market disadvantages

In this section, we examine alternative settings considering other indicators of labour market disadvantage, in addition to unemployment and low-pay. In particular, our focus is on the persistence of

Table 7
Non-employment and low-pay employment: Average partial effects.
Source: Own elaborations based on AD-SILC 2014–17.

	s_t			
	NE			LP
	Probit	dyn RE prob	biv prob	biv prob
s_{t-1}				
NE	0.817	0.376	0.543	0.411
	(0.007)	(0.050)	(0.056)	(0.035)
LP	–	–	0.083	0.558
			(0.015)	(0.032)
Obs.	12,282	12,282	12,282	12,282

Notes: s represents labour market states. NE stands for not-employed individuals; LP stands for low-paid workers. The sample is restricted to individuals who are at least 25 years old. Standard errors in parentheses.

Table 8
Unemployment and weekly low-pay: Average partial effects.
Source: Own elaborations based on AD-SILC 2014–17.

	s_t			
	U	$W-LP$		
	biv prob	Probit[a]	dyn RE prob[a]	biv prob
s_{t-1}				
U	0.285	–	–	0.085
	(0.034)			(0.020)
$W-LP$	−0.032	0.627	0.074	0.181
	(0.012)	(0.030)	(0.023)	(0.035)
Obs.	8814	7314	7314	8814

Notes: s represents labour market states. U stands for unemployed individuals; $W-LP$ stands for (weekly) low-paid workers. Standard errors in parentheses.
[a] Sample consisting on always-employed individuals.

non-employment and of low-pay employment defined on a weekly basis.

First, we examine the degree of state dependence among non-employed individuals, including both unemployed and inactive individuals. This condition is particularly relevant in Italy, where the level of non-employment is higher than the European average.[25] To study non-employment, we restrict the sample to individuals who are at least 25 years old in order to exclude those who are still of school age. The sample consists on 12,282 observations (4094 individuals observed 3 time periods). The percentage of employed individuals is equal to 66.4%. In Table 7 we show the average partial effects of past on current non-employment state jointly with feedback effects from low-pay employment. State dependence in non-employment is substantially higher than that of unemployment, and this is due to long-term non-employed individuals. The role of past low-pay is more relevant in explaining current non-employment than current unemployment (8.3 pp). Moreover, lagged non-employment affects more markedly current low-pay status (41.1 pp) than lagged unemployment, even though this difference is not statistically significant.

Then, we measure low-pay status using weekly earnings instead of annual earnings. The former indicator does not account for the number of weeks worked in the year, namely, the unemployment risk within the year as a low-pay source. Still, there is a significant overlap between the two indicators: 98 per cent of individuals who are yearly high-paid are also weekly high-paid, while almost 62 per cent of those who are yearly low-paid are also weekly low-paid.[26] In Table 8 we present the estimated average partial effects of lagged weekly low-pay state within the different settings.

The main evidence from the use of weekly low-pay is that all the effects related to low-pay are diminished with respect to the baseline ones (with yearly low-pay). This holds true in the bivariate model for the unemployment probability (low-pay has negative sign), as well as for the univariate (RE) and bivariate model of low-pay probability. These results may be interpreted as the presence of greater mobility in the low-pay condition based on weekly labour earnings. Still, when examining the likelihood of being low-paid on a weekly basis, the difference between the average partial effects of the estimated pooled probit model (62.7 pp) and dynamic random-effects probit model (7.4 pp) is more pronounced than what stands out from the baseline model (with yearly low-pay), this means that most of the reduced state dependence in low-pay is due to the increasing role of unobserved heterogeneity. Secondly, the average partial effects of part-time arrangements (not shown) are higher with the weekly than the low-pay specification.

To wrap up, we provide evidence that non-employment state dependence is higher than that of unemployment (and low-pay), and that weekly low-pay status is less persistent than yearly low-pay.

5.4. Including labour market histories in the unobserved random effects

In this section, we perform a robustness analysis including, in each unobserved heterogeneity term, a proxy for the individuals' labour market history up to 2004.

In the previous sections, the conditional distribution of c, irrespective of the adopted specification, included the initial conditions only, namely, the dependent variable in 2014, corresponding to the first year covered by the SILC 2014–2017 panel sample. This choice aligns closely to the specifications commonly adopted in the literature addressing state dependence in the labour market, which typically relies on survey data only. However, in the current context, this specification does not fully employ all the information provided by the administrative records. Indeed, we are able to observe the complete contribution history for all individuals employed in Italy who were interviewed in the SILC.

Using administrative records on individuals' contribution histories, we are able to enhance the conditional density of the unobserved effect, including a further proxy of individual abilities, corresponding to individuals' past labour market outcomes. We focus on a maximum of ten years of individual contribution history, starting from 2004. This choice is motivated by the availability of administrative data matched with a SILC wave, whose first available wave is 2004. We recall that we employ the cross-sectional matched dataset to compute (weighted) low-pay thresholds at the national level, and to categorize individuals in the 2014–2017 longitudinal sample as either low-paid workers or not.

We emphasize that without the additional information provided by SILC, we are not able to accurately assess the labour market status of individuals in the 2014–2017 longitudinal sample, prior to 2014. For instance, we cannot exclude the possibility that an individual absent from administrative records before 2014 was inactive due to reasons such as being a student or homemaker. Similarly, we cannot rule out that such individuals were employed abroad. Given the significant proportion of inactive individuals in Italy, we are more likely to provide a better approximation of the number of years an individual is employed rather than unemployed.

Taking this caveat into consideration, for each individual, we compute, for the period 2004–2013: (i) the number of years of employment,

[25] Approximately 8 percentage points larger on average in the considered period. See Eurostat Statistics: https://ec.europa.eu/eurostat/databrowser/view/lfsi_emp_a/default/table?lang=en.

[26] Overall, as shown in Table 1, the incidence of weekly low-pay is 6 pp lower than yearly low-pay.

Table 9
Unemployment and low-pay employment including labour market history in the unobserved effect: Average partial effects.
Source: Own elaborations based on AD-SILC 2014–17.

	s_t			
	U		LP	
	dyn RE prob	biv prob	dyn RE prob[a]	biv prob
s_{t-1}				
U	0.234	0.373	–	0.351
	(0.046)	(0.043)		(0.049)
LP	–	0.026	0.194	0.398
		(0.008)	(0.054)	(0.048)
Obs.	8814	8814	7314	8814

Notes: s represents labour market states. U stands for unemployed individuals; LP stands for low-paid workers. Individual labour market history (starting from 2004) included in the unobserved heterogeneity term. Standard errors in parentheses.
[a] Sample consisting on always-employed individuals.

and (ii) the number of years of low-paid employment. In the considered period, 55 per cent of individuals were employed continuously, while almost 63 are never low-paid for the whole period. More detailed descriptive statistics are provided in the Appendix (Table A.4). These variables are included, in addition to all the other controls discussed in the previous sections, as time-invariant regressors in the univariate models of unemployment and low-paid employment, respectively, whereas they are both included in the bivariate model.

In each model, these additional controls result statistically significant (results are not reported), suggesting that we are able to better characterize households' unobserved heterogeneity. Results in terms of APEs of interest are reported in Table 9. As expected, the point estimates of the average partial effects of lagged labour market status are marginally lower compared to those of the specification that do not account for labour market histories, indicating that employment histories contribute to some degree of persistence. In particular, the estimated APEs in the unemployment equation remain largely unchanged, exhibiting, in the bivariate framework only, a 1 pp difference in the effect of lagged unemployment status, and less than one pp difference in the effect of past low-pay employment status. Slightly larger deviations are observed in the low-pay employment equation, with the effect of past low-pay employment spells decreasing by nearly 2 pp in the univariate model and by more than 8 pp in the bivariate model. Additionally, the effect of past unemployment decreases by 4 pp in the latter.

Nevertheless, the reduction in the APEs of interest is limited, from a statistical point of view, and the estimates are not different from those discussed in the previous section, as they are encompassed in the 95 per cent confidence interval of the latter. This result suggests that more recent employment history is still important in explaining labour market dynamics, even after taking into account individuals' employment history spanning up to ten years. To summarize, we complete the list of findings with the following: The inclusion of labour market history in the unobserved heterogeneity does not affect the state dependence in unemployment and it only slightly reduces state dependence in low-pay.

6. Discussion

In this paper, we examine the extent of state dependence in unemployment and low-pay employment in Italy. We make use of the AD-SILC dataset, a rich dataset merging survey data from the Italian component of EU-SILC with administrative data from the Italian Social Security Institute. First, we model unemployment and low-pay employment as univariate processes, using a pooled probit model, and a dynamic random-effects probit model accounting for observed and latent individual heterogeneity, and endogeneity of the initial conditions. Then, we adopt a bivariate specification for modeling the joint dynamics of the two phenomena including possible feedback effects.

Overall, it stands out that the Italian labour market is characterized by a significant degree of immobility, as past conditions represent important factors affecting present outcomes, even after accounting for unobserved heterogeneity. In other words, individuals in higher-paid jobs are more likely to retain their employment, whereas those who are unemployed or low-paid are more likely to remain trapped in their current conditions.

Our findings reveal a double-level segmentation in the Italian labour market. Individuals experiencing unemployment exhibit distinct characteristics compared to those experiencing low pay employment. The degree of state dependence is considerably greater than the magnitude of cross-effects. In particular, low paid individuals are more likely to have experienced prior periods of low-pay employment rather than periods of unemployment, whereas unemployed individuals are even more likely to have previously been in unemployment rather than involved in low pay employment. Individuals who manage to overcome the unemployment trap encounter the low-pay trap, with the opposite transition being less common. In this sense, the structure of the Italian labour market resembles more to a tunnel than a cycle.

Based on these findings, it becomes apparent that people who are unemployed and those with low-paying jobs have distinct needs. Addressing unemployment persistence typically requires income-supporting social policies, and policies aimed at promoting employment. On the other hand, tackling low-earnings dependence involves implementing minimum wage programs, preventing the misuse of non-standard contracts through regulation, and introducing measures that guarantee fair compensation (e.g for women and migrant workers). In both cases, it is crucial to implement policies enhancing characteristics such as higher education, serving as protective factors against unfavorable labour market conditions.

CRediT authorship contribution statement

Michele Bavaro: Conceptualization, Data curation, Formal analysis, Software, Writing – original draft, Writing – review & editing. **Federico Tullio:** Conceptualization, Data curation, Formal analysis, Software, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix

See Tables A.1–A.4.

Table A.1
Labour status weighted transition rates.
Source: Own elaborations based on AD-SILC 2014–17.

s_{t-1}	s_t		
	U	LP	HP
U	0.626	0.270	0.103
LP	0.107	0.731	0.161
HP	0.015	0.028	0.956

Notes: 8814 observations. s represents the mutually exclusive labour force states. U stands for unemployed; LP stands for low-paid workers; HP stands for higher paid workers. Each row sums to one. Weighted transition rates.

Table A.2
Unemployment based on different thresholds: (univariate) dynamic random-effects probit models.
Source: Own elaborations based on AD-SILC 2014–17.

	4 weeks		8 weeks		16 weeks	
Unemployed ($t-1$)	1.532***	(0.146)	1.501***	(0.134)	1.505***	(0.119)
Woman	−0.057	(0.072)	0.002	(0.065)	0.063	(0.060)
Age	0.008	(0.038)	0.038	(0.036)	0.001	(0.032)
Foreigner	0.091	(0.155)	0.086	(0.140)	0.034	(0.128)
Married	−0.311***	(0.089)	−0.215***	(0.079)	−0.198***	(0.074)
Children 0–15	0.082	(0.223)	0.196	(0.197)	0.068	(0.170)
North-East	0.095	(0.113)	0.122	(0.103)	0.215**	(0.096)
Center	0.399***	(0.112)	0.369***	(0.101)	0.432***	(0.097)
South	0.520***	(0.118)	0.508***	(0.108)	0.559***	(0.103)
Islands	0.501***	(0.140)	0.470***	(0.128)	0.529***	(0.121)
Educ: Primary	0.368	(0.236)	0.313	(0.212)	0.323	(0.205)
Educ: Low secondary	0.195*	(0.103)	0.185**	(0.092)	0.254***	(0.087)
Educ: Upper secondary	0.131	(0.088)	0.091	(0.079)	0.147**	(0.074)
Capital income	−0.019	(0.025)	−0.037	(0.023)	−0.026	(0.021)
Working partner	−0.080	(0.109)	−0.128	(0.101)	−0.097	(0.093)
Unemployed ($t=0$)	1.017***	(0.223)	0.951***	(0.195)	0.896***	(0.177)
Constant	−2.386***	(0.224)	−2.215***	(0.195)	−2.227***	(0.188)
σ_a	0.572	(0.131)	0.485	(0.127)	0.536	0.109
Average partial effects						
Unemployed ($t-1$)	0.225	(0.053)	0.245	(0.052)	0.277	(0.049)

Notes: The Table shows the unemployment univariate model's results when changing the unemployment thresholds. The level of unemployment equals 6.5% when the threshold is set to 4 months, 7.5% when the threshold is set to 8 months, and 10.3% when the threshold is set to 16 months. No. of obs: 8814 (2938 individuals × 3 time periods). The baseline category of the geographical area of residence is the North-West of Italy. The baseline category of the educational attainment is tertiary education. Time-averages of the following variables are included in the RE model: Age, Children 0–15 and HH capital income. Standard errors in parentheses.

* Significance level: $p < 0.1$.

** Significance level: $p < 0.05$.

*** Significance level: $p < 0.01$.

Table A.3
Unemployment and low-pay employment: Univariate dynamic random-effects probit models with feedback effects.
Source: Own elaborations based on AD-SILC 2014–17.

	Unemployment		Low-pay	
Unemployed ($t-1$)	2.089***	(0.112)	1.981***	(0.092)
Low-pay ($t-1$)	0.940***	(0.083)	2.174***	(0.108)
Woman	−0.095	(0.061)	0.243***	(0.060)
Age	0.004	(0.035)	0.010	(0.032)
Foreigner	−0.231*	(0.134)	0.498***	(0.111)
Married	−0.168**	(0.074)	−0.277***	(0.070)
Children 0–15	0.150	(0.184)	0.197	(0.164)
North-East	0.182*	(0.097)	−0.074	(0.078)
Center	0.375***	(0.096)	0.022	(0.078)
South	0.396***	(0.101)	0.189*	(0.105)
Islands	0.344***	(0.119)	0.128	(0.131)
Educ: Primary	0.049	(0.190)	0.432**	(0.187)
Educ: Low secondary	0.067	(0.087)	0.284***	(0.079)
Educ: Up secondary	0.072	(0.074)	0.058	(0.066)
Capital income	−0.042*	(0.022)	0.003	(0.020)
Working partner	−0.078	(0.096)	0.072	(0.080)
Occ: Public employee			−0.401***	(0.109)
Occ: Self-employed			0.363***	(0.072)
Part-time			0.599***	(0.076)
Fixed-term			0.484***	(0.084)
Unemployment (province)			0.012	(0.008)
Unemployed ($t=0$)	0.635***	(0.160)		
Low-pay ($t=0$)			0.686***	(0.143)
Constant	−2.519***	(0.193)	−2.530***	(0.188)
σ_a	0.472	(0.119)	0.190	(0.227)
Average partial effects				
Unemployed ($t-1$)	0.426	(0.055)	0.452	(0.029)
Low-pay ($t-1$)	0.093	(0.009)	0.456	(0.050)

(*continued on next page*)

Table A.3 (*continued*).

	Unemployment	Low-pay
No. of obs	8814	8036

Notes: The Table shows the results of the estimated dynamic random-effects probit models for unemployment and low-pay employment with the inclusion of both lagged variables as covariates. The baseline category of the geographical area of residence is the North-West of Italy. The baseline category of the educational attainment is tertiary education. Time-averages of the following variables are included in the RE model: Age, Children 0–15 and capital income. Standard errors in parentheses.

* Significance level: $p < 0.1$.

** Significance level: $p < 0.05$.

*** Significance level: $p < 0.01$.

Table A.4
Labour market history 2004–2013: descriptive statistics.
Source: Own elaborations based on AD-SILC 2004–17.

No. of years	Employment		Low-pay	
0	0.058	(0.233)	0.629	(0.483)
1–4	0.122	(0.327)	0.284	(0.451)
5–9	0.269	(0.443)	0.067	(0.250)
10	0.552	(0.497)	0.020	(0.141)

Notes: 8814 observations. For each individual we compute the number of years (between 2004 and 2013) spent in employment and in low-paid employment. Each column sums to one. Standard deviations in parentheses.

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