Young people between education and the labour market during the COVID-19 pandemic in Italy

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Abstract

Purpose – The aim is to study the impact of the COVID-19 pandemic on the careers of different groups of young individuals, based on transition probabilities.

Design/methodology/approach – The authors analyse the evolution of individual shares and flows between different types of employment (self-employment, temporary, and permanent), unemployment, education, and other types of inactivity of individuals aged 20–29 in Italy.

Findings – The authors find that the pandemic worsened an already concerning situation of higher inactivity rates, compared to other EU countries. In quarters III and IV of 2020, mainly females and non-Italian citizens were less in (permanent and temporary) employment and more in the NLFET (neither in the labour force nor in education or training) state compared to the same quarters one year before. The authors also find evidence of a temporary but not persistent return to education among 20–24 years old individuals, particularly females. These changes are suggestive of a prolongation of the time needed to achieve temporary and permanent employment, mostly for females and non-Italian citizens.

Originality/value – The contribution lies in the provision of a rigorous estimation and analysis of the impact of COVID-19 on the careers of young individuals in Italy.

Keywords Labour market flows, Transition probabilities, First passage time, Young workers' careers, NLFET (neither in the labour force nor in education or training) state

Paper type Research paper

1. Introduction

The devastating economic impact of the COVID-19 pandemic has been shown to differ widely among demographic and socioeconomic groups (Chetty *et al.*, 2020). Although the issue of young individuals being one of the categories hit the most has been vocally raised in Europe (Eurofound, 2020) and extensively acknowledged in the literature (Lee *et al.*, 2021; Alon *et al.*, 2021; Bluedorn *et al.*, 2021; Adams-Prassl *et al.*, 2020; Blustein *et al.*, 2020), there are few specific quantitative studies on the topic. In this paper, we investigate how the COVID-19 pandemic has affected the careers of different groups of young individuals aged 20–29 in Italy, on the basis of transition probabilities between different labour market and education states. Specifically, we focus on the way the expected enlarged outflow into the NLFET (Neither in the Labour Force nor in Education or Training) state and the expected increased return to schooling caused by the pandemic may have extended the time it takes for young individuals to find a job. We investigate how these two channels have evolved across the age groups 20–24 and 25–29, and we explore heterogeneous effects by gender, citizenship, geographical area and education [1].

JEL Classification — C18, C53, E32, E24, J6.

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Young individuals in Europe tend to take quite a long time to progress from the end of their studies to the attainment of a job (Pastore, 2015). Although there is large heterogeneity across countries, young individuals in Mediterranean countries perform particularly poorly and Italy generally ranks last in Europe for the time young take to complete their transition from school to work. In 2017, on average, Italian students are reported to take 2.88 years to transit to a job which is at least six month long, compared to a European average of 1.47 years; moreover, for individuals with compulsory education, the duration increases up to 5.18 years (Pastore *et al.*, 2021). Many reasons have been identified in explaining these alarming statistics. From a macroeconomics perspective, a longer transition correlates with GDP growth, the spread of temporary employment and the quality of institutions directly affecting the ability of entrants into the labour market to smoothly complete the transition, namely, the educational system, the legal labour market arrangements, and active labour market policies (Pastore, 2015; Dietrich and Möller, 2016; Pastore *et al.*, 2020; O'Higgins, 2012). From a microeconomic point of view, being a female and an immigrant have been shown to be the main risk factors for the delayed transition (Struffolino and Borgna, 2021; Pastore *et al.*, 2020). We expect the disruption in the access to education and employment opportunities caused by the COVID-19 pandemic to put the young generation on a much more volatile trajectory in finding and maintaining quality jobs and income (OECD, 2020). The 2008 financial crisis had already led the number of young people not in employment, education or training (NEET) to rise significantly in Europe and the number of unemployed young people to increase by 20% (Eurostat, 2012), with long-lasting negative effects on their career paths and future earnings (Heckman and Borjas, 1980) [2]. The economic effects of the pandemic are exacerbating the existing vulnerability of young people in labour markets, as they are more likely to be on non-standard employment, such as temporary or part-time work, facing a higher risk of job and income loss (OECD, 2019; Quaranta *et al.*, 2020). Moreover, young people are over-represented in sectors that were shut down during the lockdown and are mainly employed in sectors that are structurally changed by the distancing measure (Bank of Italy, 2021). In the first two-quarters of 2020 a large number of young individuals lost their jobs or got furloughed because of the severe drop in GDP and the deterioration of the labour market conditions. As a consequence, they may have decided to delay the transition to the labour market by staying longer in schooling, or to go back to studying. Most worryingly, they might have also got discouraged and fallen into the NLFET state. As these decisions are heavily dependent on individual characteristics, the impact of COVID-19 is likely to have been asymmetric across groups of workers.

We propose a methodology for the estimation of the careers of different groups of young individuals based on transition probabilities across seven states (self employment, permanent employment, temporary employment, unemployment, education, furlough scheme, and NLFET). We use longitudinal quarterly labour force data for the period 2013–2020 for Italy to illustrate how the actual shares of individuals aged 20–29 have changed across these seven states before, during the outburst and in the quarters following the COVID-19 shock. Italy was the first country in Europe to be hit by the COVID-19 pandemic and to implement a national lockdown in the beginning of March 2020. We then analyse the way the transition probabilities across these states have changed in the same time period. With this information, we compute the first passage time (FPT) from education to permanent/temporary employment, i.e. the probability distribution of quarters which an individual takes to achieve for the first time permanent/temporary employment, starting from the education state. Then, we compute the expected first passage time (EFPT) from education to permanent/temporary employment, i.e. the expected number of years it takes for individuals to transit from education to permanent/temporary employment for the first time (Lieberman and Hillier, 2001, p. 818). The EFPT is an alternative quantification of the school-to-work transition (STWT) duration, traditionally measured in the literature as the time elapsed from the termination of schooling to the starting of the first job (Manacorda *et al.*, 2017; Pastore *et al.*, 2021). While this latter approach is viable if the exact dates of termination of education and starting of the first job are known, its main challenge regards how to treat individuals that at the time of data termination or collection have finished education, haven't had their first job yet and are either unemployed or inactive (incomplete transitions). The usual approach is either to restrict the analysis to individuals with complete transitions or to set the starting of the first job at the end of the observation period. The estimation of the EFPT is suitable whenever the dates of termination of education and starting of the first job are not observed. Moreover, the EFPT offers a sophisticated method to deal with individuals with incomplete transitions, i.e. individuals who are in education in the previous quarter and either unemployed or inactive in the current quarter, by providing an estimation of the time needed to achieve employment on the basis of the transition matrix. The EFPT, however, is subject to a measurement error, due to the approximation of the exact dates of termination of education and starting of the first job at quarter level, with the additional caveat that individuals might not be at their first work experience; moreover, it is based on the assumption that the transitions are well represented by a first-order Markovian process. Additional details about pros and cons of the two methodologies are discussed in Section 6.

Following the literature which provides evidence of longer transitions for low-educated, immigrant, females and resident in the South of Italy (Pastore, 2015), we also calculate the FPT and EFPT for specific groups of individuals identified on the basis of gender, citizenship, education and geographical area of residence. In quarters III and IV of 2020 we find significantly lower shares of young individuals in permanent and temporary employment and higher shares in the NLFET state, compared to the same quarters one year earlier (just before the outburst of the pandemic). We consistently find increased transition probabilities towards the NLFET state and lower transition probabilities towards temporary and permanent employment, in the same time period. These shifts have been particularly large among females and non-Italian citizens. Such changes provide suggestive evidence of longer FPT and EFPT to temporary and permanent employment, particularly among females and non-Italian citizens.

The paper is organized as follows. Section 2 discusses the literature on the topic, while Section 3 presents the institutional background. Section 4 illustrates the data. Section 5 shows evidence of the sudden and the persistent impacts of the COVID-19 shock on shares and transition probabilities, while Section 6 discusses the changes in the time needed for young individuals to achieve employment. Section 7 contains some concluding remarks.

2. Literature review

Strong similarities have been found between school-to-work transitions in the United States and in Europe (Quintini and Manfredi, 2009). However, pathways in the United States are much more dynamic than in Europe and school-to-work transitions involve much less time spent in unemployment. Although Eurostat (2012) estimated extremely short and smooth durations of the transitions to work across all EU countries, this result might be biased by the widespread diffusion in Southern European countries of temporary work arrangements, which have shortened the average unemployment duration, but not the transition duration to a "stable" job [3]. In fact, for the case of Italy, Quintini *et al.* (2007) reports a duration of the transition to a permanent job almost four times higher than the one estimated by Eurostat [4]. By reducing employment opportunities for young people, the 2008 financial crisis accelerated pre-existing trends towards prolonged education participation and precarious employment and exacerbated considerable pre-existing cross-country differences in the transition duration in Europe (Schoon and Bynner, 2019). Specifically, countries which created bridges between education and employment experienced lower levels of youth unemployment, while young people in less-proactive states suffered higher levels of youth unemployment, temporary employment and NEET rates (Kogan, 2019; Helms Jørgensen *et al.*, 2019; Pastore, 2019).

From a microeconomic perspective, economic recessions have been shown to affect disproportionately more individuals who were already economically disadvantaged, such as non-natives, young workers, and low-educated (Hoynes *et al.*, 2012; Montenovo *et al.*, 2020). In line with this research, Churchill (2021), Nunes *et al.* (2021), Economic Observatory (2021) show that the COVID-19 pandemic has aggravated the labour market situation of young workers, who have been impacted by COVID-19 significantly more compared to older workers. Young women, especially those in their 20s, seem to have been particularly exposed to the economic fallout. There are also studies showing that a large number of people between the age of 15 and 24 have dropped out of the labour market entirely (Jackson, 2020; Mayhew and Anand, 2020). However, some studies also show that although younger workers lost more jobs initially, no systematic difference remains in the pandemic's employment impact across age groups later on (Lee *et al.*, 2021). For instance, in the USA by November 2020, the unemployment effect of the pandemic was fairly similar across all age groups, except for the youngest group's non-participation rate which had still not fully recovered.

Finally, there is a relatively long tradition in labour economics looking at the question of whether unemployment and inactivity are behaviourally different states, which is directly linked to the definitions of NEET and NLFET (O'Higgins and Stimolo, 2015). NEET, an acronym for "Not in Education, Employment, or Training", refers to a person who is unemployed and not receiving an education or vocational training. The NEET category includes the unemployed (individuals without a job and seeking one), as well as individuals outside the labour force (without a job and not seeking one) and it is usually age-bounded to exclude people in old-age retirement (ILO, 2020). NLFET, a definition coined in the 2013 report on Global Employment Trends for Youth by the International Labour Organization, stands for "neither in the labour force nor in education or training". It is similar to NEET but it excludes the unemployed youth (who are part of the labour force). While early work on labour market transitions suggested that unemployment and NLFET were not substantively different states (Clark *et al.*, 1979), Flinn and Heckman (1983) in their seminal work, and more recently Battistin *et al.* (2007), provide evidence of different behavioral equations governing transitions from out of the labor force to employment and from unemployment to employment, supporting the need for a clear distinction between the two states.

3. Institutional background of analysis

In the analysis of the effect of the COVID-19 pandemic on the careers of young individuals, several institutional factors play a major role. Among these, the features of the Italian schooling system, which creates strong delays in the achievement of a university degree, and the policies adopted during the pandemic crisis in the labour market. In the following section, we will discuss both in some details.

3.1 The Italian schooling system

Education in Italy is compulsory from 6 to 16 years of age. It is illegal for students below the age of 16 to drop out of school. The educational system is organized in two cycles of comprehensive and compulsory schooling. Pupils enter primary school at age six and conclude the five-year cycle at age eleven. In this first compulsory cycle the educational curriculum is the same for all pupils. Secondary education in Italy lasts 8 years and is divided into two stages: junior high school and high school. Junior high school lasts three years (roughly from age 11 to 14), and high school lasts five years (roughly from age 14 to 19). Every tier involves an exam at the end of the final year, required to gain a degree and have access to further education. There are three types of high school: lyceum, technical institutes and professional institutes. The education received in a lyceum is mostly theoretical, while technical institutes offer both a wide theoretical education and a specialization in a specific field of studies [5]. Finally, professional institutes offer a form of secondary education focused on practical subjects (engineering, agriculture, gastronomy, technical assistance, handcrafts); although the duration of the studies is five years, some schools also offer a diploma after the first three years. Since 1969, access to university has been liberalized: independent on the type of high school chosen, any individual with a five-year high school diploma can enroll in university. The majority of university studies are organized in two levels: the first, which lasts three years, provides a bachelor's degree, while the second, which includes additional two years, provides a master's degree. Students stopping after the first three years should be 22 years old, while those completing the whole cycle should be 24 years old. Unfortunately, in practice students take much longer to complete their degrees: in 2018 the average age of students completing their bachelor's (master's) degree was 24.6 (27.3), with large heterogeneity according to the field of study (AlmaLaurea, 2019, p. 11). This evidence supports our choice of focusing our analysis on the 20–29 years old individuals (Section 5).

3.2 Labour market policies during the COVID-19 pandemic in Italy

The first cases of COVID-19 in Italy were registered on January 31, 2020, but the virus began to spread exponentially in the second half of February. On March 10, the whole country went into a full *lockdown*. Subsequently, on March 11 the government prohibited nearly all commercial activity except for supermarkets and pharmacies and on March 21 it restricted movement of people and closed all non-essential businesses and industries [6].

On March 17 the Italian government implemented two new labor market policies in support of workers: (1) a COVID furlough scheme and (2) a ban on layoffs. The former was implemented for an initial duration of 9 weeks, and it applied retroactively starting from February 23. The furlough scheme existed in Italy before the outburst of the pandemic, however it was not relevant before the pandemic as it absorbed only 0.05% of the working age population in quarter IV of 2019 (and 0.02% of the 20–24 and 25–29 groups). It became more important during the pandemic as it collected approximately 1.9% of the working age population (and 1.2 and 2.6% of the 20–24 and 25–29 groups) in quarter IV of 2020. The new measure represented an extension of the pre-existing furlough scheme to all firms, independently on size and to all employees, independently on the tenure within the firm [7]. This measure was introduced with the aim of preserving employment and allowing firms to cut labor costs during the lockdown period, by reducing hours of work thanks to a wage subsidy granted by the government. Firms using the COVID furlough scheme could also renew temporary contracts, waiving to the norms of the standard regulation. This means that we could observe flows both from permanent and temporary employment to the furlough scheme (but not from self-employment). Also the suspension of the regulations regarding the renewals of temporary contracts could have increased the persistence into temporary employment.

The second measure introduced by the government, i.e. the ban on layoffs, prevented firms to fire workers for an initial period of five months, starting from March 17; this ban could be applied retroactively to pending, but already validated layoffs from February 23. This implies that in the period considered we might observe fewer transitions from permanent and temporary employment to unemployment. As the transition to permanent employment often includes spells of temporary employment and unemployment, the two measures implemented during the pandemic might have further prolonged the time needed to achieve (permanent or temporary) employment. Two decrees extended the validity of these measures, which were then terminated in June 2021 for most sectors, except for the textile, shoes and fashion industries, for which the measures will end in October 2021. We expect to identify the first impact of the pandemic in quarter I of 2020, and a much more pronounced effect in the following quarter (quarter II), when the lockdown was fully in place (Section 5.1).

Quarters III and IV of 2020 should reflect the relaxation of the lockdown measures and the persistent incidence of the pandemic (Section 5.2).

4. Data and methodology

We use Italian quarterly longitudinal labour force data as provided by the Italian Institute of Statistics (ISTAT) for the period 2013 (quarter I) to 2020 (quarter IV) [8]. The Italian Labour Force Survey (LFS) follows a simple rotating sample design, where households participate for two consecutive quarters, exit for the following two-quarters, and come back in the sample for other two consecutive quarters. As a result, 50% of the households, interviewed in a quarter, are re-interviewed after three months, 50% after twelve months, 25% after nine and fifteen months. This rotation scheme allows to obtain 3 months longitudinal data, which include almost 50% of the original sample [9]. On average approximately 70.000 individuals are interviewed each quarter, of which 45.000 are part of the working age population. Per each interviewee we observe a large number of individual and labour market characteristics at the time of the interview and three months before. The drawback of these data is the point-in-time measurement of the individuals' state, which fails to capture the transitions within the period (quarter) and the lack of precise information about the dates of termination of education and the starting of the first job.

The dynamics of the labour market can be efficiently described by Markov Chains with discrete states in discrete time. Our dataset allows to consider quarters as unit of time and to define seven labour market states: permanent (PE), temporary (TE), self-employment (SE), unemployment (U), the furlough scheme (FS), education (EDU) and inactivity (NLFET). The NLFET state collects the working age individuals who are not in the labour force, in education or in training, therefore representing an accurate measure of inactivity (Ose and Jensen, 2017). The dynamics are therefore represented through a Transition Probability Matrix (TPM), which shows both permanence in each labour market state and the probability of transition from one state to another in a given period of time, and fully characterizes the dynamics of the shares of the whole population in each state. In particular, the shares of individuals in different states provide a picture of the long-term trends, as they take longer to react to shocks, while the transition probabilities inform about the sudden impact of the (pandemic) shock. Taking into account the structure of the available database, we compute the labour market flows by calculating the quarter-on-quarter transitions made by individuals between different labour market states. In the analysis we take the first quarter of 2020, which marks the time of the initial spread of the virus, as the period when the dynamics of the Italian labour market are expected to change. The inferential analysis on the shares and transition probabilities is computed via bootstrap using 1,000 draws from the original sample. To assess the way the pandemic has affected the transition probabilities across labour market states, we compare the actual data with the counterfactual scenario of no pandemic shock, i.e. the quarterly transition probabilities for the different categories of individuals against the forecasted quarterly transition probabilities during the pandemic, i.e. from quarter I of 2020 to quarter IV of 2020. The forecasted transition probabilities are computed using a combination of four forecasting models (ETS, TSLM, THETAF, and ARIMA) [10] in the period 2013 (quarter I)- 2019 (quarter IV). Using different forecasting methods on the same time series and averaging them has been shown to improve accuracy significantly: the combination approach is almost always close or better than the best component method (Hyndman and Athanasopoulos, 2021, Section 12.4).

5. The impact of the COVID-19 pandemic on young individuals

Although in our data we observe four age groups of young individuals potentially still interested in education (15–19, 20–24, 25–29 and 30–34), we mainly focus on the two central categories: age 20–24 and age 25–29 [11].

The seven different labour market states chosen for our analysis represent important steps in the career trajectory of young individuals from school to a stable job. Specifically, it has been shown that young people in Italy tend to go through several cycles of temporary employment and unemployment before landing into a more long-term job position (Gagliarducci, 2005). Moreover, self-employment could represent a form of "franchise working" by means of which many firms seek to bypass the costs and rigidities of the permanent contract (Barbieri, 2001; Barbieri and Scherer, 2008). The COVID-19 outbreak and the implementation of the lockdown could have significantly changed young individuals' choices by pushing them into the NFLET state, if discouraged by the recession, or back into education, as a consequence of the lower opportunity cost of being in education. The time needed to find a job could have also been affected by the extension of the furlough scheme to include all workers, including those on temporary employment, during the pandemic (see Section 3.2). Finally, within the two age groups we look at heterogeneous effects as different types of young individuals could have reacted differently to the pandemic shock. Specifically, we focus on differences by gender, education, geographical area and citizenship.

Section 5.1 documents how the shares of individuals in the seven states and the transition probabilities across states have been deeply affected by the pandemic shock in quarters I and II of 2020, while Section 5.2 illustrates the strong persistence of the pandemic shock in quarters III and IV of 2020. Section 5.2.1 compares the changes in the shares of young individuals in different labour market states in quarters III and IV of 2020 with the same quarters one year before and, finally, 5.2.2 discusses how the changes in transition probabilities between states in quarters III and IV of 2020 provide key information on the dynamics of the labour market, in particular on the changes in the transition probabilities from education to work.

5.1 The sudden impact of the COVID-19 shock

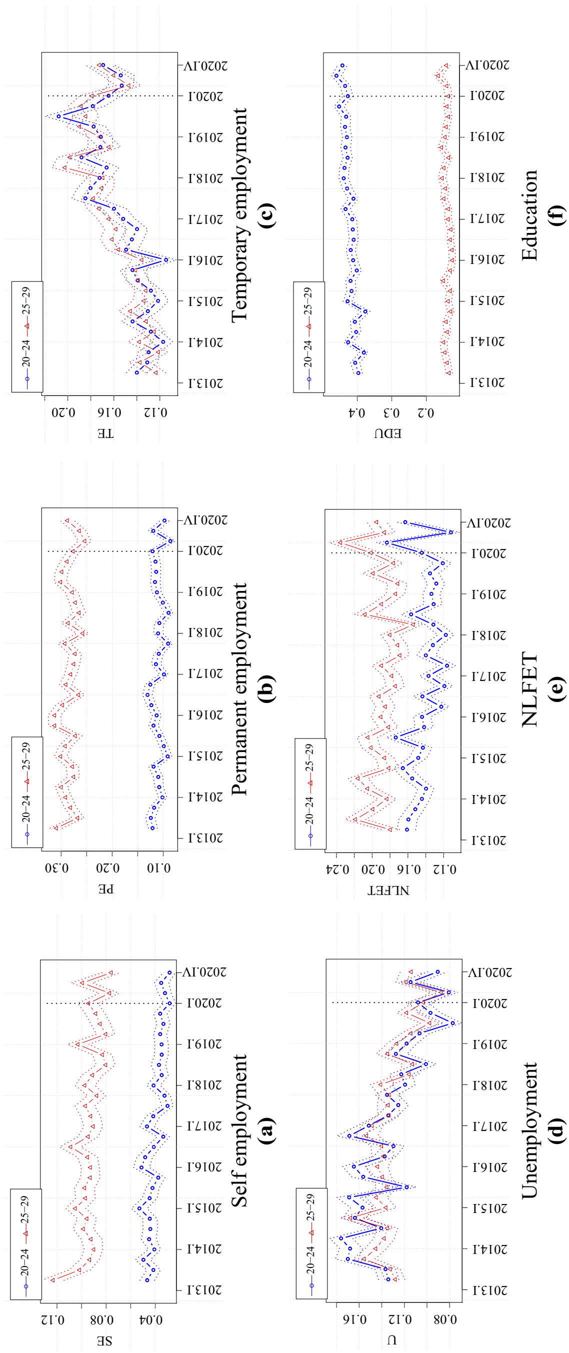
Figure 1 documents a decline in the shares of permanent employment, mostly in quarter II (the one with the strictest lockdown), and a dramatic drop in the shares of temporary employment in quarters I and II of 2020 for both the 20–24 and 25–29 age groups. While the shares of individuals in unemployment did not increase substantially, there are signs of an interruption of the declining trend started in 2017 for both age categories. While we do not find substantial changes in the education shares, we observe a large increase in the NLFET shares for both age categories in both quarters. Looking at the time series of the transition probabilities from education to different states for the age group 20–24 (Figure 2), we confirm a large increase in the transition probability from education to the NLFET state and a decline in the transitions from education to temporary employment [12].

We also detect some anomalies in the data which may derive from distorted individual choices coming from financial incentives introduced to support the income of individuals who were active on the labour market. Specifically, we observe in quarter I of 2020 for the 20–24 age group an increase in permanent employment and unemployment and a decrease in education. These anomalies are confirmed in the time series of the transition probabilities from education to different states for the 20–24 years old age group (Figure 2) [13].

In what follows, we are interested in looking at the persistence of the pandemic effects in the medium-term to understand how they may have impacted the transition duration. We focus on quarters III and IV of 2020, in which we are expecting to observe some economic adjustments following the shock.

5.2 The persistence of the COVID-19 shock

Given the high seasonality present in the data, we compare quarters III and IV of 2020 with the same quarters one year earlier, before the pandemic outburst. In the quarters just before



Note(s): Confidence intervals at 90% are computed using 1000 bootstraps
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure 1.
Shares of individuals aged 20–24 and 25–29 in the state self-employment, permanent employment, temporary employment, unemployment, NLFET, education, and furlough scheme

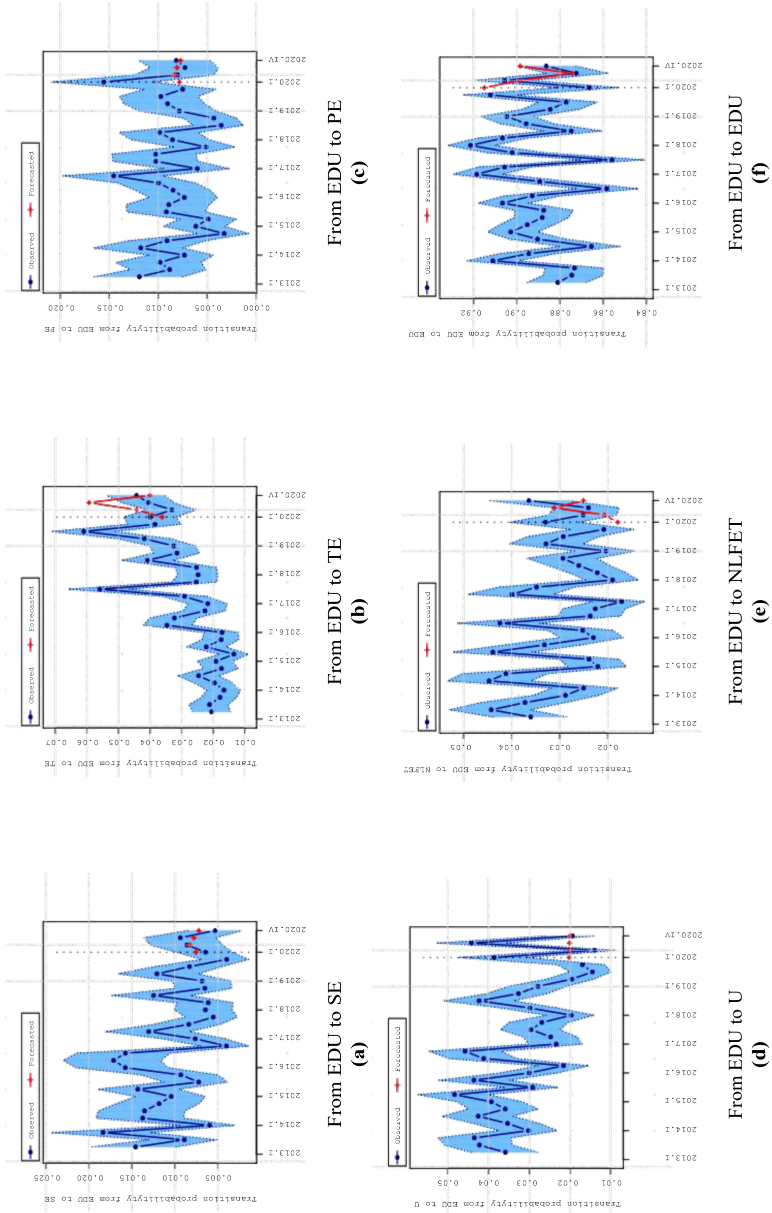


Figure 2.
Transition probabilities from education for individuals aged 20–24 and forecasted transition probabilities for quarters I-IV of 2020

Note(s): The forecasted transition probabilities are computed using a combination of four forecasting models (ETS, TSLM, THETAF, and ARIMA) (Hyndman and Athanasopoulos, 2021) in the period 2013 (quarter I)- 2019 (quarter IV). Confidence intervals at 90% are computed using 1000 bootstraps and reported in parenthesis. EDU refers to education, TE to temporary employment, PE to permanent employment, U to unemployment

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

the pandemic approximately 43% of young people in the 20–24 age group were in education, 11% in permanent employment, 19% in temporary employment, 4% in self-employment, 9% in unemployment and 13% in the NLFET state (Table A1 in Appendix 2). As expected, among 25–29 young individuals, the share in education was smaller (approximately 14 versus 43%), while the share in employment was larger (19 versus 11% in permanent employment, 30 versus 19% in temporary employment, 8 versus 4% in self-employment). The share of 25–29 young people in unemployment was comparable to the share of 20–24 (10% approximately), while a larger share of 25–29 years old individuals was in the NLFET state (19 versus 13%).

5.2.1 Changes in the shares in different labour market states. Table 1 reports the changes in the shares of young individuals in different labour market states in quarters III and IV of 2020 compared to the same quarters one year before. We report a significant increase in the shares of individuals in the furlough scheme and in the NFLET state and a decline in the share of individuals in permanent and temporary employment across all age groups in both quarters. The decline in temporary employment is particularly large among the 20–24 age group, while among the 25–29 age group we observe a strong decrease in both temporary and permanent employment. The share of individuals in education did not persistently change during the pandemic. Among females, we observe similar patterns, but larger magnitudes (Table A2 in Appendix 5). Moreover, for the 20–24 age group we also detect an increase in the share in education in both quarters. Among non-citizens (Table A4 in Appendix 5), we observe a sharper decline in temporary and permanent employment and a higher increase in the NFLET share. We also report a large and significant decrease in education among the 25–29 age group in both quarters [14].

5.2.2 Changes in the transition probabilities across labour market states. In this section we report the changes in the transition probabilities across states between the quarters III and IV of 2019 and 2020 for the age groups 20–24 and 25–29. Specifically, we focus on the transitions from and to education.

5.2.2.1 Transitions from education to employment. Among 20–24 years old individuals in quarter III of 2020 (compared to quarter III of 2019) an increase in the probability to move from education to unemployment and a decrease in the transition to temporary unemployment are observed (Table 2, row 6). In quarter IV of 2020, we observe less persistence in the education state and an increased outflow towards the NFLET state (Table 2, row 12). Among 25–29 years old individuals we report in quarter III of 2020 a decrease in persistence in the education state and increased outflows towards self-employment and unemployment (Table 3, row 6). However, these changes are not persistent in quarter IV (Table 3, row 12).

5.2.2.2 Transitions into the NLFET state. We observe a decrease in the persistence in the NLFET state among 20–24 years old individuals in quarter III of 2020 paired with increased outflows towards unemployment and education (Table 2, row 5). However, this is compensated by an increased persistence in the NLFET state in quarter IV (Table 2, row 10) and increased inflows back into the NLFET state coming from education and unemployment (Table 2, column 5). Among 25–29 years old individuals we observe in quarter III of 2020 a decrease in the persistence in the NLFET state and increased outflows towards unemployment and education (Table 3, row 5). However, in quarter IV we find higher probabilities to transit from unemployment back to the NLFET state (Table 3, row 8).

5.2.2.3 Transitions back to schooling. In quarter III of 2020, we observe an increased flow from the NFLET state towards education for 20–24 years old (Table 2, row 5), while, in quarter IV a lower persistence in education and decreased transitions to education from self-employment and the NLFET state (Table 2, column 6). In quarter III of 2020, increased flows to education among the 25–29 years old from self-employment, unemployment and the NLFET state are observed (Table 3, column 6); however, in quarter IV no changes appear to

Table 1. Changes in the shares of individuals in different labour market states

	SE	TE	PE	U	NLFET	EDU	FS
2019.III vs 2020.III							
All (15–64)	−0.002** (0.027)	−0.007*** (0.000)	−0.011*** (0.000)	−0.006*** (0.000)	*0.009**** (0.000)	0.002* (0.054)	0.016*** (0.000)
20–24	−0.002 (0.205)	*−0.020**** (0.000)	−0.0004 (0.455)	−0.007** (0.025)	*0.008*** (0.041)	0.011** (0.034)	0.010*** (0.000)
25–29	0.002 (0.275)	*−0.009*** (0.018)	*−0.017**** (0.000)	−0.012*** (0.000)	*0.016**** (0.000)	0.001 0.409)	0.018*** (0.000)
2019.IV vs 2020.IV							
All (15–64)	−0.003*** (0.000)	−0.009*** (0.000)	−0.014*** (0.000)	−0.007*** (0.000)	*0.013**** (0.000)	0.002* (0.082)	0.018*** (0.000)
20–24	−0.004** (0.025)	*−0.024**** (0.000)	*−0.008**** (0.005)	−0.001 (0.361)	*0.021**** (0.000)	0.004 (0.256)	0.012*** (0.000)
25–29	−0.002 (0.237)	*−0.019**** (0.000)	*−0.021**** (0.000)	−0.008*** (0.006)	*0.024**** (0.000)	0.005 0.139)	0.021*** (0.000)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal shares in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Table 2. Changes in the transition probabilities between quarters III and IV in 2020 and 2019 for individuals aged 20–24

	SE	TE	PE	U	NLFET	EDU	FS
Quarter III							
SE	0.026 (0.284)	0.050* (0.077)	−0.019 (0.152)	−0.001 (0.434)	−0.011 (0.297)	*−0.045* (0.151)	0.000 ( )
TE	0.004 (0.146)	0.003 (0.481)	−0.010 (0.254)	0.009 (0.219)	−0.017* (0.082)	*0.011* (0.248)	0.000 ( )
PE	0.009* (0.081)	0.010 (0.295)	−0.042* (0.052)	0.008 (0.219)	0.008 (0.198)	*−0.013* (0.169)	0.021*** (0.001)
U	0.008 (0.244)	−0.050** (0.035)	0.006 (0.248)	0.052 (0.101)	0.007 (0.395)	*−0.024* (0.168)	0.000 ( )
NLFET	−0.015** (0.021)	0.032* (0.051)	−0.023** (0.020)	*0.162**** (0.000)	*−0.220**** (0.000)	*0.063** (0.000)	0.000 ( )
EDU	0.001 (0.354)	*−0.021**** (0.002)	−0.002 (0.211)	*0.030**** (0.000)	−0.005 (0.187)	*−0.005* (0.354)	0.002** (0.031)
FS	−0.143*** (0.000)	−0.107*** (0.000)	0.607*** (0.000)	−0.095*** (0.000)	−0.078*** (0.000)	−0.120*** (0.000)	−0.063** (0.026)
Quarter IV							
SE	0.029 (0.289)	0.029 (0.120)	0.045* (0.099)	−0.031* (0.094)	0.002 (0.454)	*−0.073**** (0.009)	0.000 ( )
TE	0.006 (0.154)	0.002 (0.444)	−0.031*** (0.006)	−0.004 (0.398)	0.010 (0.289)	−0.014 (0.211)	0.032*** (0.000)
PE	0.004 (0.313)	−0.001 (0.471)	−0.036 (0.114)	0.002 (0.379)	0.004 (0.386)	0.007 (0.294)	0.020*** (0.003)
U	−0.003 (0.262)	−0.010 (0.349)	0.001 (0.444)	−0.016 (0.325)	*0.060*** (0.039)	−0.032 (0.113)	0.000 ( )
NLFET	−0.030*** (0.000)	−0.002 (0.457)	0.006 (0.138)	*−0.066**** (0.001)	*0.133**** (0.000)	*−0.041*** (0.023)	0.001 (0.106)
EDU	0.001 (0.304)	0.006 (0.213)	0.001 (0.395)	0.002 (0.320)	*0.016**** (0.002)	*−0.026**** (0.001)	0.000 ( )
FS	−0.143*** (0.000)	0.072 (0.235)	−0.143*** (0.000)	−0.143*** (0.000)	0.091 (0.198)	0.098 (0.199)	0.168* (0.084)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal transition probabilities in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Table 3. Changes in the transition probabilities between quarters III in 2020 and 2019 for 25–29 years old individuals

	SE	TE	PE	U	NLFET	EDU	FS
Quarter III							
SE	−0.007 (0.383)	−0.011 (0.185)	0.025*** (0.008)	−0.011 (0.243)	−0.019* (0.066)	*0.024*** (0.033)	0 ( )
TE	0.009* (0.078)	−0.007 (0.411)	−0.030 (0.019)	0.008 (0.273)	0.017 (0.167)	0.003 (0.354)	0 ( )
PE	0.005 (0.191)	−0.010* (0.062)	−0.0003 (0.495)	0.002 (0.283)	−0.007* (0.086)	0.002 (0.209)	0.009*** (0.001)
U	0.008 (0.202)	−0.031* (0.088)	−0.016** (0.037)	0.061** (0.047)	−0.089*** (0.000)	*0.067**** (0.000)	0.000*** (0.000)
NLFET	−0.013*** (0.004)	−0.007 (0.328)	0.008** (0.082)	*0.045*** (0.013)	*−0.057**** (0.008)	*0.019** (0.052)	0.004** (0.041)
EDU	*0.021**** (0.002)	−0.005 (0.350)	0.002 (0.358)	*0.057**** (0.000)	−0.016 (0.148)	*−0.059**** (0.004)	0 ( )
FS	−0.143*** (0.000)	−0.042* (0.052)	0.617*** (0.000)	−0.130*** (0.000)	−0.090*** (0.000)	−0.143*** (0.000)	−0.069*** (0.000)
Quarter IV							
SE	−0.037* (0.095)	−0.013 (0.169)	−0.001 (0.475)	0.011 (0.194)	0.030** (0.034)	0.010 (0.191)	0 ( )
TE	−0.003 (0.289)	0.022 (0.184)	0.011 (0.246)	−0.014 (0.183)	0.003 (0.413)	*−0.036**** (0.000)	0.016*** (0.000)
PE	−0.006** (0.048)	0.004 (0.295)	−0.031*** (0.006)	0.018*** (0.000)	−0.003 (0.358)	0.002 (0.309)	0.015*** (0.000)
U	0.007 (0.215)	−0.003 (0.468)	−0.006 (0.312)	−0.041 (0.149)	*0.069*** (0.012)	−0.030* (0.065)	0.004 (0.146)
NLFET	−0.009* (0.062)	0.018* (0.098)	0.002 (0.385)	−0.053*** (0.003)	0.027 (0.151)	0.014 (0.125)	0 ( )
EDU	0.002 (0.428)	−0.002 (0.404)	0.002 (0.401)	0.010 (0.248)	−0.001 (0.497)	*−0.011* (0.328)	0 ( )
FS	0 (0.824)	0.109 (0.128)	−0.715* (0.087)	0.095 (0.173)	0.013 (0.286)	0 (0.815)	0.498*** (0.000)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal transition probabilities in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

be relevant except for a lower inflow from temporary employment to education (Table 3, column 6).

Combining the changes in the share of individuals aged 20–24 in education in quarter III of 2020 (Table 1) with the transition probabilities (Table 2), we observe the same persistence in education across the two-quarters (quarters III of 2019 and 2020), but an increased outflow from education to unemployment. However, the increased inflow from the NLFET state to education has over-compensated the outflows, leading to a raise in the share of individuals in the education state (+1.1% points). In quarter IV the share in education is constant: while the inflows to education decreased both from self-employment and the NLFET state, the persistence in the state decreased as well and the outflow to the NLFET state increased.Among individuals aged 25–29, in quarter III a decrease persistence in the education state and increased outflows towards unemployment and self-employment are observed. On the other hand, we also find an increase in the inflows towards education from self-employment, unemployment and the NLFET state. As the inflows and outflows from education turn out to be similar in size, the share in education is unchanged. In quarter IV, we only observe a decrease in the inflows to education from temporary employment and unemployment, but no significant changes in the outflows and in the share in the education state.

6. The duration of the transition from education to employment

In our approach based on transition probabilities, the impact of the pandemic on the time needed to achieve (permanent or temporary) employment is measured by the *first passage time* (FPT), i.e. the probability distribution of quarters which an individual takes to arrive for the first time at state j, i.e. permanent or temporary employment, starting from state i, i.e. education [15]. We also compute the *expected first passage time* (EFPT), i.e. the expected number of years it takes to move from the education state to the employment state (permanent or temporary) for the first time (Lieberman and Hillier, 2001, p. 818; see Appendix 6 for technical details).

This approach differs from the one commonly used in the literature (Manacorda *et al.*, 2017; Pastore *et al.*, 2021). When individual longitudinal data are available (administrative records, cross-section sample survey with retrospective questions, panel and cohort surveys) and the exact dates of termination of education and starting of the first job are known, a measure of the duration of the school-to-work transition (STWT) is computed as the time elapsed until individuals who have terminated schooling *exit* to a job. The main drawback of this approach regards individuals that at the time of data termination or collection have finished education, but have not had their first job and are either unemployed or inactive (incomplete transitions). The share of young individuals with incomplete transitions might be large among specific categories; this could have a non-negligible impact on the estimated STWT duration. For example, Table 1 in Pastore *et al.* (2020) shows large differences in the estimated Italian STWT duration when based on complete versus incomplete transitions, where in the latter the *exit* time to a job is set equal to the time of data termination or collection. This issue should impose a general downward bias in the estimated STWT duration and poses a potential problem for cross-country comparisons, caused by the heterogeneity in youth inactivity and unemployment rates across countries. Moreover, time series comparisons could also be problematic, as this downward bias could depend on the business cycle, i.e. on the fluctuating share of young individuals who are inactive or unemployed at the time of data termination or collection.

The estimation of the EFPT is suitable whenever exact dates of termination of education and starting of the first job are not observed. Moreover, in comparison with the STWT duration estimation, the EFPT offers a sophisticated method to deal with individuals with incomplete transitions, i.e. individuals who are in education in the previous quarter and either unemployed or inactive in the current quarter, by providing an estimation of the time needed to achieve employment on the basis of the transition matrix. However, the EFPT approach suffers from two main drawbacks: (1) a measurement error, due to the approximation of the exact dates of termination of education and starting of the first job at quarter level, with the additional caveat that individuals might not be at their first work experience and (2) the assumption that the transitions are well represented by a first-order Markovian process. A final less crucial disadvantage regards the possibility for a limited investigation of some explaining factors (e.g. gender and education).

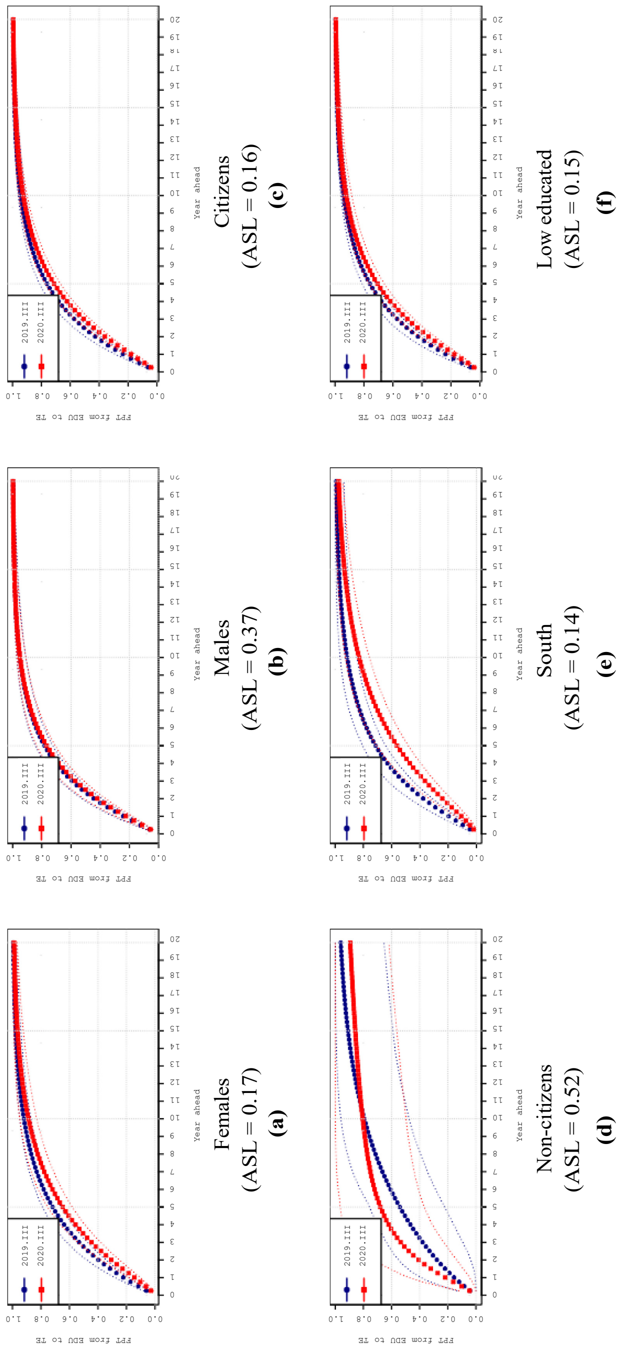
6.1 First passage time

Figure 3 reports the FPT from education to temporary employment for individuals aged 20–24. In particular, the FPT in quarter III of 2019 is calculated taking the estimated transition probabilities for that quarter and applying the procedure described in Appendix 6 [16]; the same technique is used to compute the FPT in quarter III of 2020. We take the distance between the two curves as a measure of the pandemic impact.

Before the pandemic, females and individuals living in the South were the categories for which the FPT to temporary employment was longer, in line with the findings of Pastore (2015). In particular, in quarter III of 2019 after 5 years from graduation approximately 71.8% of females and 54.1% of non-citizens were employed for the first time with a temporary contract, compared to approximately 80% of males, citizens and low-educated individuals (Figure 3). In quarter III of 2020, the situation only slightly deteriorated for males, citizens and low-educated, while it affected more severely females and individuals living in the South. Among females the percentage in temporary employment after 5 years from graduation dropped by 7% points to 64.7%; among individuals living in the South the percentage fell from 71.3% to 63.3%. Although only some of the changes are statistically significant at 15% level, the overall picture suggests that the effects have been highly asymmetric by gender and geographical area.

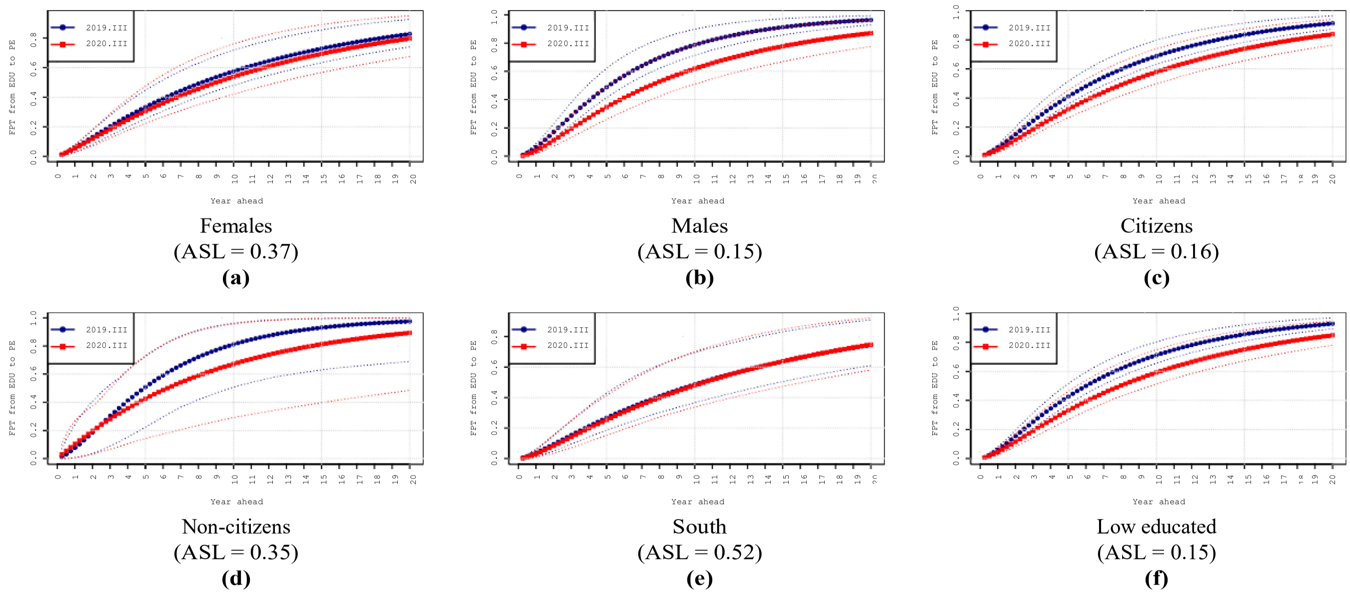
The FPT to permanent employment of 20–24 years old before the pandemic was highest among males and non-citizens (Figure 4): after five years from graduation, 50% of them were on a permanent contract for the first time, while approximately 40% of citizens and low-educated had a permanent contract. However, these percentages were down to 33.3% among females and to 26.6% for individuals living in the South. The impact of the pandemic has also been highly asymmetric: males are the category among whom the FPT to permanent employment dropped the most from 48.7% to 34.6%. Among low-educated individuals the percentage dropped from 42.6% to 33.1%, among citizens from 41% to 32.2%, while negligible changes are observed among females and individuals living in the South. Again, only some of the changes are statistically significant at 15% level, but the overall picture is suggestive of important changes happening in the labour market.

Before the pandemic, 25–29 years old individuals living in the South were the ones for whom the FPT to temporary employment was longer (Figure 5) [17]. In particular, while on average 25–29 years old in education in quarter III of 2019 had almost 80% probability to have been at least once in temporary employment after 5 years, this probability was down to approximately 65% for individuals living in the South. The pandemic extended the FPT to temporary employment mostly among high-educated individuals: after 5 years the FPT fell from 71.2 to 52.8%. Among females the percentage fell from 75.5 to 66.8%, while among males and non-citizens the decline has been minimal. The small number of 25–29 years old individuals still in education explains why the high educated category is the only one for which these changes are statistically significant at 15% level, while it is lower for all other groups.



Note(s): Joint confidence intervals at 90% are computed using 1000 bootstraps, taking as measure of distance between distributions the Kolmogorov–Smirnov statistic (see Appendix 8). The attained significant level (ASL) of the null hypothesis of equal FPT in the two quarters is the result of the one-side Kolmogorov–Smirnov test using a bootstrap procedure (see Appendix 8). The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The low educated category includes individuals with a primary or secondary level of education
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure 3.
First passage time (FPT) to temporary employment (TE) from education (EDU) for individuals aged 20–24



Note(s): Joint confidence intervals at 90% are computed using 1000 bootstraps, taking as measure of distance between distributions the Kolmogorov–Smirnov statistic (see Appendix 8). The attained significant level (ASL) of the null hypothesis of equal FPT in the two quarters is the result of the one-side Kolmogorov–Smirnov test using a bootstrap procedure (see Appendix 8). The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The low educated category includes individuals with a primary or secondary level of education
Source(s): LFS3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure 4.
First passage time (FPT) to permanent employment (PE) from education (EDU) for individuals aged 20–24

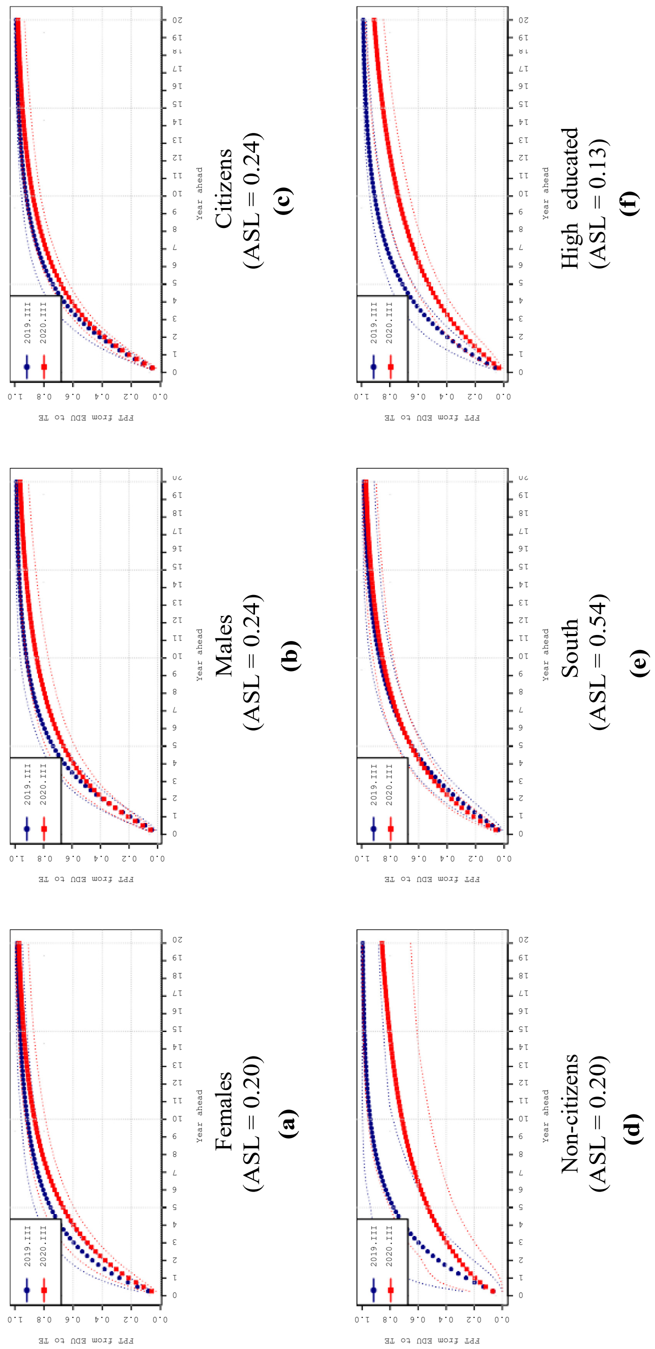


Figure 5.
First passage time (FPT) to temporary employment (TE) from education (EDU) for individuals aged 25–29

Note(s): Joint confidence intervals at 90% are computed using 1000 bootstraps, taking as measure of distance between distributions the Kolmogorov–Smirnov statistic (see Appendix 8). The attained significant level (ASL) of the null hypothesis of equal FPT in the two quarters is the result of the one-side Kolmogorov–Smirnov test using a bootstrap procedure (see Appendix 8). The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The high educated category includes individuals with a tertiary level of education

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

6.2 Expected first passage time

In order to eliminate the presence of seasonality in the quarter EFPT, we calculate the (annual) EFPT for each quarter as the mean of the same quarter and the three-quarters before EFPTs, which we report in Figures 6–8 and in Appendix 7. For the 20–24 age category, overall, the most recent years before the COVID-19 outburst show a declining trend in EFPT, which is abruptly overturned in the second quarter of 2020. Specifically, the EFPT to temporary employment increased as a consequence of the pandemic across all groups of individuals, except for males (Figure 6). The effect is particularly striking for females, among whom the EFPT increased from 5 years in quarters III and IV of 2019 to remain persistently higher at 5.7 years in the last two-quarters of 2020. Among low-educated, citizens and individuals living in the South, the EFPT increased of approximately six months in quarters II and III of 2020, but returned to lower levels in quarter IV of 2020. The same pattern is observed for the EFPT estimates to permanent employment (Figure 7), where the declining trend in the years before the COVID-19 outburst is overturned in the second quarter of 2020. The effect is particularly dramatic among non-citizens, for whom the EFPT went from an average of 8.2 years in quarters III and IV of 2019 to an average of 10 years in quarters III and IV of 2020.

For the 25–29 age group, the EFPT to temporary employment increased across all groups of workers (Figure 8) [18]. The EFPT for males, citizens and individuals living in the South was showing a declining trend in the quarters before the pandemic, but the shock overturned that trend. Among females and high-educated individuals, the trend was constant in 2019 but the pandemic led to an increase in the EFPT from an average of 5.2 and 6 years in quarters three and four of 2019 to an average of 5.6 and 6.4 years in the last two-quarters of 2020, respectively. The largest increase concerns non-citizens, for whom the expected time to temporary employment raised from 5.8 years in the last two-quarters of 2019 to 9.9 years in quarters III and IV of 2020.

Although, we adopt a different methodology with respect to the ones commonly used in the literature, our findings on the time it takes for young individuals to transit from education to employment in Italy agree with some contributions on the issue in terms of duration and its heterogeneity across different groups. As in Pastore *et al.* (2021), the time is longer for females, who are more likely to fail in job searching and tend to carry major family responsibilities (Kleven *et al.*, 2019); moreover, similarly to (Pastore *et al.*, 2020), the time it takes to achieve both permanent and temporary employment is much longer for residents in the South and low-educated individuals, due to lower job opportunities in the Southern regions and for low-skill workers (Struffolino and Borgna, 2021). However, contrary to Pastore *et al.* (2021), the time to both permanent and temporary employment for non-citizens is shorter compared to citizens. Non-citizens usually have a lower reservation wage and are willing to accept any job offer, which implies a higher effort in job seeking and a higher job finding rate, although at the cost of accepting worse working conditions (Fullin, 2011).

7. Concluding remarks

The time it takes for young individuals to find a job when they finish education in Italy is extremely long, and our results suggest that it might have been further prolonged by the COVID-19 pandemic. On overage, an individual in the 20–24 age group in education was expected to find a permanent job after 11.5 years or a temporary job after 5 years before the pandemic (i.e. in quarters III and IV of 2019). Within the same age category, females would take 12.9 years and 5 years to find a permanent or temporary job, respectively. Residents in the South would take 16.3 years and 8 years, respectively. Our findings are suggestive of a worse situation after the outburst of the pandemic. Specifically, we provide evidence of increased probabilities in quarters III and IV of 2020 to enter into the NLFET (Neither in the

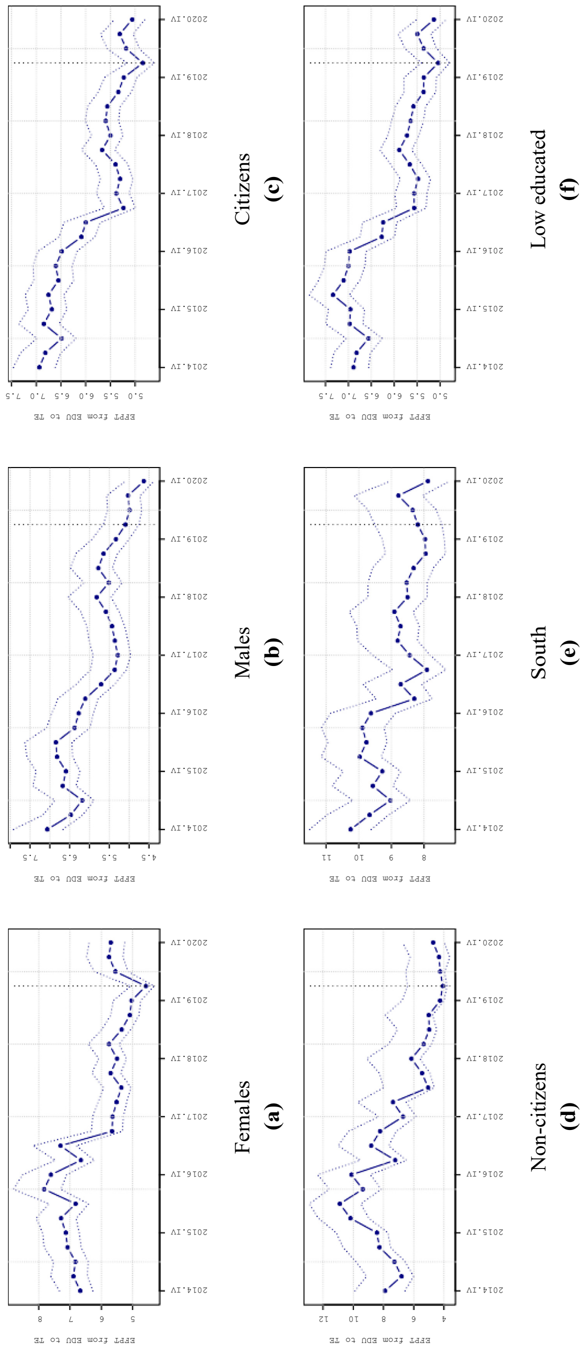


Figure 6.
Expected first passage time (FPT) to temporary employment (TE) from education (EDU) for individuals aged 20–24

Note(s): Confidence intervals at 90% are computed using 1000 bootstraps. The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The low educated category includes individuals with a primary or secondary level of education
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

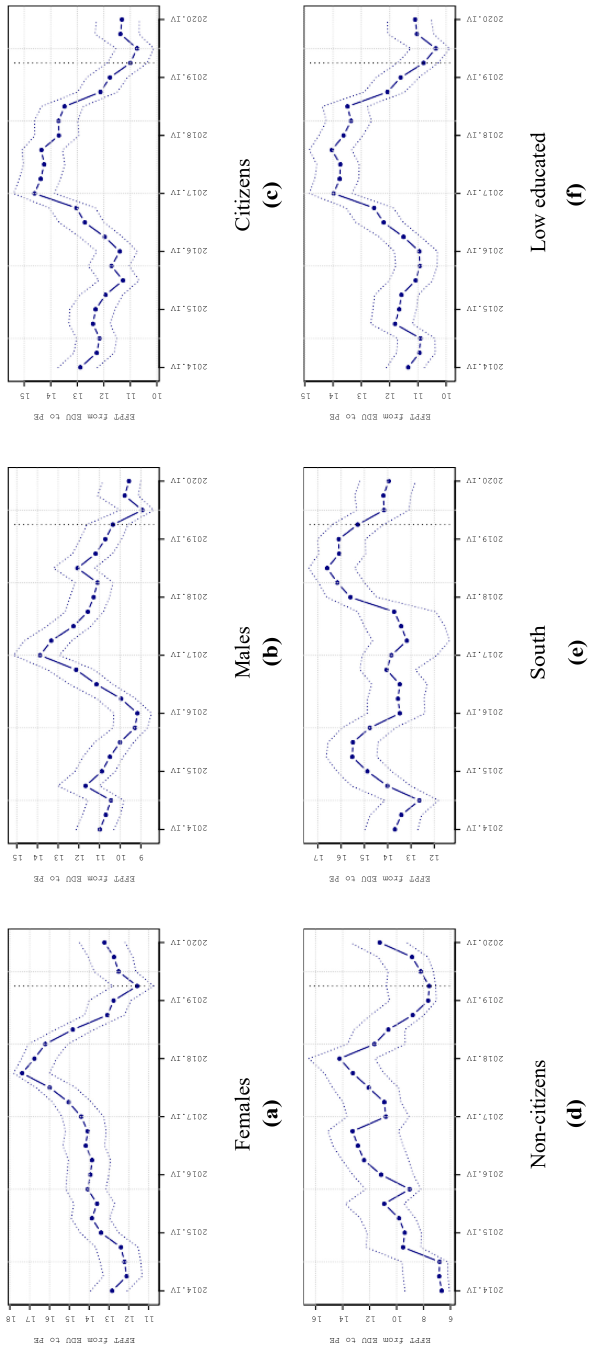
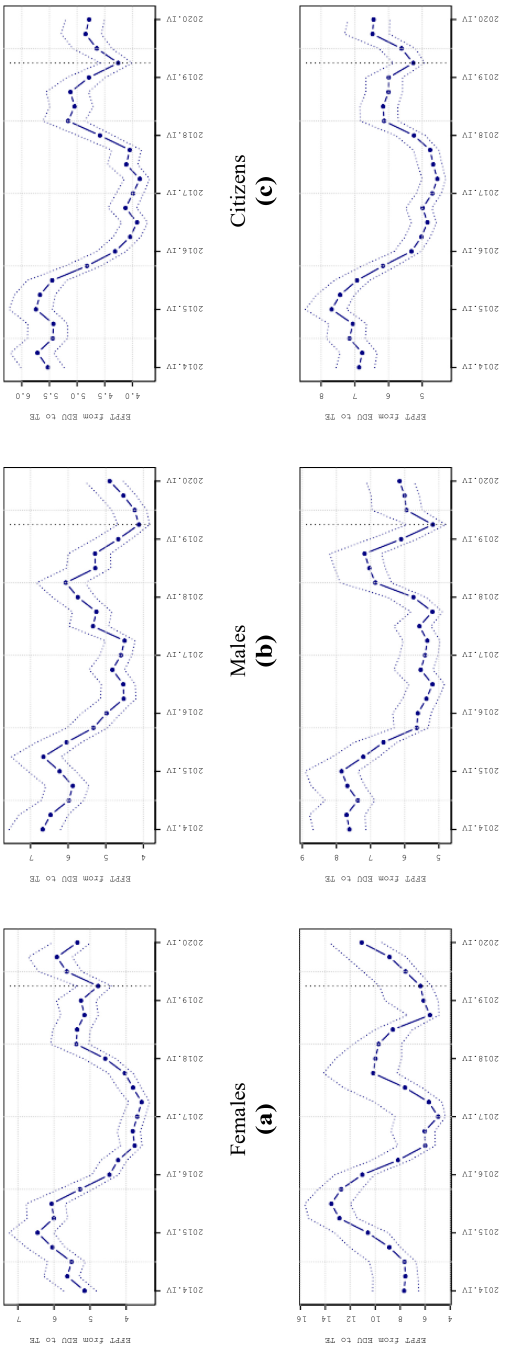


Figure 7.
Expected first passage time (FPT) to permanent employment (PE) from education (EDU) for individuals aged 20–24

Note(s): Confidence intervals at 90% are computed using 1000 bootstraps. The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The low educated category includes individuals with a primary or secondary level of education
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)



Note(s): Confidence intervals at 90% are computed using 1000 bootstraps. The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia. The high educated category includes individuals with a tertiary level of education

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure 8.
Expected first passage time (FPT) to temporary employment (TE) from education (EDU) for individuals aged 25–29

Labour Force nor in Education or Training) state and reduced probabilities to find a (permanent or temporary) job. The shares of individuals across states provide an equally gloomy picture: persistently higher shares in the NLFET state and lower shares in (permanent and temporary) employment. These changes, which are shown to be remarkably large among females and non-Italian citizens, are indicative of longer times needed to achieve both permanent and temporary employment. These findings signal potentially long-lasting negative effects of the pandemic among the weakest categories of individuals.

Notes

1. The analysis for individuals aged 15–19 and 30–34 is available upon request.
2. Evidence shows that young people with a history of unemployment face worse career developments, lower wages, poorer job opportunities, and ultimately lower pensions (OECD, 2016).
3. See https://ilostat.ilo.org/transition-from-school-to-work-remains-a-difficult-process-for-youth.
4. Some studies have focused on university graduates (Biggeri *et al.*, 2001; Salas-Velasco, 2007), while others on specific aspects of the transitions (Brunetti and Corsini, 2019; Berloffa *et al.*, 2019), on the role of on-the-job training (Pastore, 2019; Cappellini *et al.*, 2019), and active labour market policies Speckesser *et al.* (2019).
5. Fields of studies are for instance economics, administration, technology, tourism, agronomy; technical institutes often require a three/six months internship in a company, association or university, from the third to the fifth and last year of study.
6. Sectors identified as essential, which could continue operating, included mainly agriculture, some manufacturing, energy and water supply, transports and logistics, ICT, banking and insurance, professional and scientific activities, public administration, education, healthcare and some service activities. Non-essential sectors which were completely shut include most manufacturing, wholesale and retail trade, hotels, restaurants and bars, entertainment and sport activities Casarico and Lattanzio (2020).
7. Before the pandemic only firms with more than 15 employees were eligible to use the furlough scheme.
8. Original data for the period 2013 (quarter I) to 2020 (quarter IV) are available upon request at: https://www.istat.it/it/archivio/185540. Dataset and codes used in our analysis are available at https://people.unipi.it/davide_fiaschi/ricerca/
9. Panel attrition may occur at subsequent waves due to household non-contact, refusal, etc.; however, the weights account for the panel attrition (usually not at random) and ensure consistency with the other LFS quarterly estimates (Discenza *et al.*, 2014).
10. Details about the four methods are reported in Appendix 1.
11. In the 15–19 group, approximately 86% of individuals are in the education state and 93% of them persist in the state, even during the pandemic. Among individuals in the 30–34 age group only approximately 2.5% are in education; hence, for both groups the transition from education to work does not seem a relevant phenomenon (Table A1 in Appendix 2).
12. The same figures are reported for the 25–29 age category in Appendix 4.
13. The same figures are reported for the 25–29 age category in Appendix 4. We observe a large positive sudden response of the transitions from education to permanent employment and unemployment and a large drop of the persistence in education in quarter I of 2020. Similarly, we observe a large decrease in the transition probability from unemployment to education (Figure A1 in Appendix 3).
14. Tables with the changes in the shares of *males* and *citizens* in different labour market states are reported in Appendix 5. The intersection of females and non-citizens includes too few observations and therefore is not reported.

15. The FPT calculations are based on the assumption that the process represented by the transition matrices is *ergodic*. The share of 20–24 years old in self-employment is rather small, i.e. approximately 3.5%, hence we do not focus on the transition from school to self-employment for this age category. Moreover, in Italy self-employment among young people often represents a form of "franchise working" by means of which many firms seek to bypass the costs and rigidities of the permanent contract (Barbieri, 2001; Barbieri and Scherer, 2008).
16. We focus on quarter III, which is the quarter in which the probability to transition from the education state to employment is higher among quarters (Figure 2).
17. FPT to permanent employment for individuals aged 25–29 are reported in Appendix 7.
18. The EFPT estimates to permanent employment for the 25–19 age group are reported in Appendix 7.

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Appendix 1

Forecasting methodology

We use a simple combination of four forecasting models to forecast transition probabilities: *Time Series Linear Model* (TSLM), *Auto Regressive Integrated Moving Average* (ARIMA), *Exponential Smoothing* (ETS) and *Theta Forecasting Method* (THETAF). The model selection in all estimates is based on modified AIC (AICc) (Hyndman and Khandakar, 2008).

In particular, TSLM is used to fit a linear model with seasonal and trend components, which naturally emerge from the observed time series. An ARIMA model forecasts a value which is a linear combination of its own related past values, past errors and current and past values of other time series. The idea behind ETS is that forecasts are the weighted average of past observations, where the weights decay exponentially with time, i.e. current observations have larger weights compared to older ones. While ETS models are based on a sophisticated description of trend and seasonality in the data, ARIMA models describe auto-correlations in the data. Finally, THETAF is a model which modifies the local curvature of the time series through the coefficient θ, which is directly applied to the second difference of the times series of interest in the estimate. ETS and ARIMA models are by far the two most widely used approaches to time series forecasting (Hyndman and Athanasopoulos, 2021). Hyndman and Billah (2003) show that forecast obtained via THETAF is equivalent to the simpler ETS with drift.

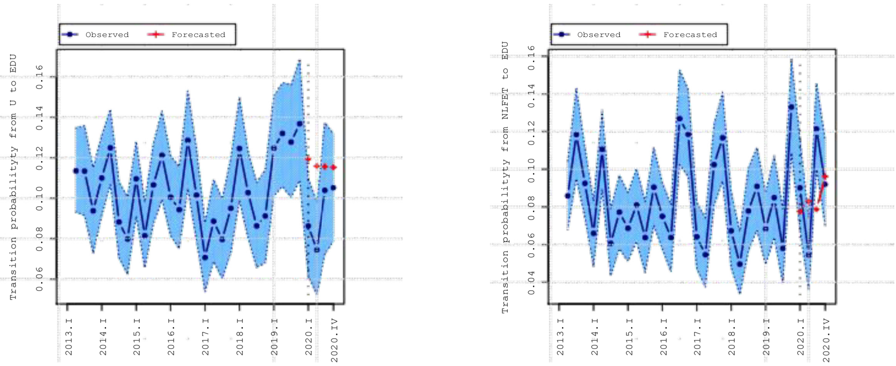
Appendix 2
Share of young individuals in different labour market states

	Self employment		Temporary employment		Permanent employment		Unemployment		NLFET		Education		Furlough scheme	
	Quarter III													
	2019.III	2020.III	2019.III	2020.III	2019.III	2020.III	2019.III	2020.III	2019.III	2020.III	2019.III	2020.III	2019.III	2020.III
All	0.126 (0.124–0.127)	0.123 (0.122–0.125)	0.079 (0.078–0.08)	0.072 (0.071–0.073)	0.379 (0.377–0.381)	0.368 (0.366–0.37)	0.063 (0.062–0.064)	0.057 (0.056–0.058)	0.237 (0.235–0.239)	0.245 (0.244–0.247)	0.116 (0.114–0.117)	0.118 (0.116–0.119)	0.001 (0–0.001)	0.016 (0.016–0.017)
15.19	0.003 (0.002–0.004)	0.004 (0.003–0.005)	0.031 (0.028–0.033)	0.03 (0.027–0.032)	0.009 (0.007–0.01)	0.007 (0.005–0.008)	0.035 (0.033–0.038)	0.032 (0.029–0.035)	0.056 (0.052–0.059)	0.059 (0.056–0.062)	0.867 (0.862–0.872)	0.869 (0.864–0.874)	0 (0–0)	0.001 (0–0.001)
20.24	0.035 (0.032–0.037)	0.033 (0.03–0.035)	0.182 (0.177–0.188)	0.162 (0.157–0.168)	0.111 (0.106–0.115)	0.11 (0.106–0.115)	0.107 (0.103–0.112)	0.1 (0.096–0.105)	0.132 (0.128–0.137)	0.14 (0.135–0.145)	0.433 (0.426–0.439)	0.444 (0.436–0.451)	0 (0–0)	0.01 (0.009–0.012)
25.29	0.088 (0.084–0.092)	0.09 (0.086–0.094)	0.178 (0.173–0.183)	0.169 (0.163–0.174)	0.288 (0.282–0.294)	0.271 (0.264–0.277)	0.118 (0.114–0.123)	0.107 (0.102–0.111)	0.184 (0.178–0.189)	0.2 (0.194–0.206)	0.145 (0.14–0.149)	0.146 (0.14–0.151)	0 (0–0.001)	0.019 (0.016–0.02)
30.34	0.134 (0.13–0.138)	0.13 (0.125–0.134)	0.114 (0.11–0.119)	0.108 (0.103–0.112)	0.436 (0.429–0.442)	0.415 (0.408–0.422)	0.094 (0.09–0.097)	0.078 (0.074–0.082)	0.197 (0.192–0.203)	0.218 (0.212–0.224)	0.024 (0.022–0.026)	0.029 (0.027–0.032)	0 (0–0.001)	0.023 (0.02–0.025)
	Quarter IV													
	2019.IV	2020.IV	2019.IV	2020.IV	2019.IV	2020.IV	2019.IV	2020.IV	2019.IV	2020.IV	2019.IV	2020.IV	2019.IV	2020.IV
All	0.125 (0.124–0.127)	0.122 (0.121–0.123)	0.079 (0.078–0.08)	0.071 (0.07–0.072)	0.38 (0.379–0.383)	0.366 (0.364–0.368)	0.062 (0.062–0.063)	0.056 (0.055–0.057)	0.236 (0.234–0.238)	0.249 (0.247–0.251)	0.116 (0.115–0.117)	0.118 (0.116–0.119)	0.001 (0–0.001)	0.019 (0.018–0.019)
15.19	0.003 (0.002–0.004)	0.005 (0.004–0.006)	0.032 (0.03–0.035)	0.029 (0.027–0.032)	0.008 (0.006–0.009)	0.007 (0.005–0.008)	0.036 (0.034–0.039)	0.03 (0.027–0.032)	0.055 (0.052–0.058)	0.058 (0.055–0.062)	0.865 (0.86–0.87)	0.871 (0.866–0.876)	0 (0–0)	0.001 (0–0.001)
20.24	0.035 (0.032–0.038)	0.031 (0.029–0.033)	0.184 (0.178–0.189)	0.16 (0.155–0.166)	0.114 (0.11–0.119)	0.106 (0.101–0.11)	0.1 (0.095–0.104)	0.098 (0.094–0.103)	0.13 (0.125–0.135)	0.151 (0.145–0.156)	0.438 (0.43–0.444)	0.441 (0.434–0.448)	0 (0–0)	0.012 (0.011–0.014)
25.29	0.089 (0.085–0.093)	0.087 (0.083–0.091)	0.184 (0.179–0.189)	0.165 (0.159–0.17)	0.292 (0.285–0.298)	0.271 (0.264–0.277)	0.114 (0.109–0.118)	0.106 (0.102–0.11)	0.18 (0.175–0.185)	0.205 (0.199–0.211)	0.141 (0.136–0.145)	0.146 (0.141–0.151)	0 (0–0.001)	0.022 (0.02–0.024)
30.34	0.136 (0.132–0.141)	0.132 (0.127–0.137)	0.114 (0.109–0.118)	0.105 (0.101–0.109)	0.434 (0.427–0.441)	0.41 (0.403–0.417)	0.093 (0.089–0.098)	0.078 (0.074–0.082)	0.198 (0.192–0.203)	0.221 (0.215–0.227)	0.025 (0.023–0.027)	0.028 (0.025–0.031)	0 (0–0.001)	0.026 (0.024–0.028)

Note(s): Confidence intervals at 90% are computed using 1,000 bootstraps and reported in parenthesis

Table A1.
Share of young individuals in different labour market states

Appendix 3
Additional transition probabilities for the 20–24 age group



From U to EDU
(a)

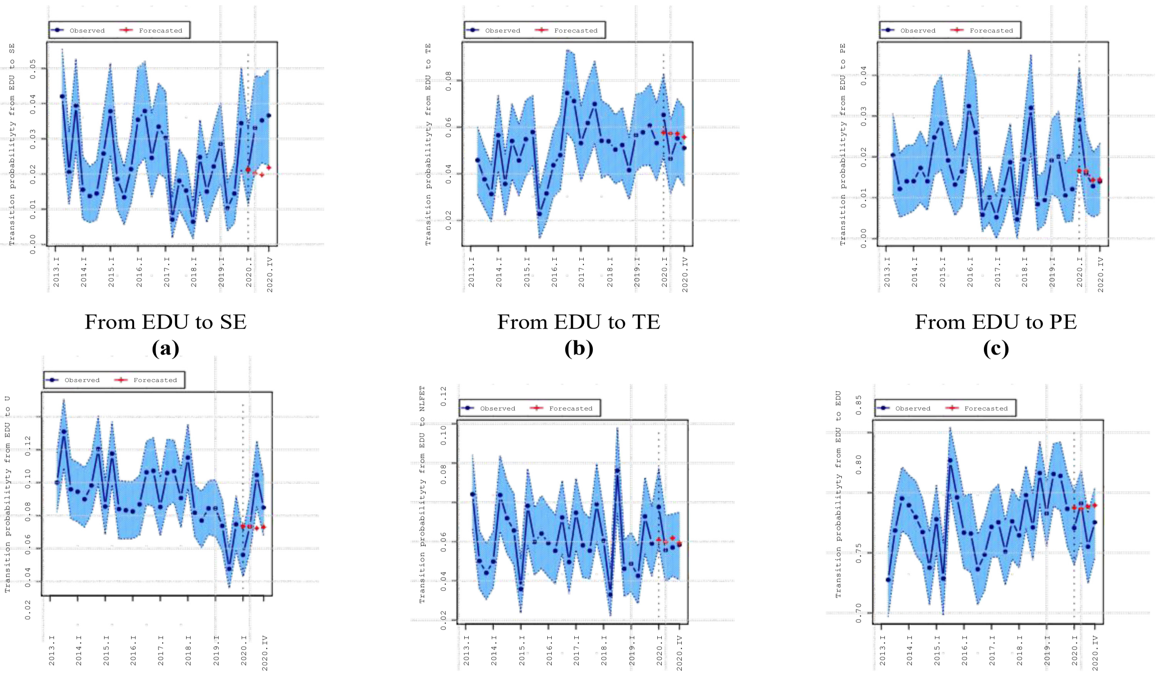
From NLFET to EDU
(b)

Note(s): The forecasted transition probabilities are computed using a combination of four forecasting models (ETS, TSLM, THETAF, and ARIMA) (Hyndman and Athanasopoulos, 2021) in the period 2013 (quarter I)-2019 (quarter IV). Confidence intervals at 90% are computed using 1000 bootstraps and reported in parenthesis.EDU refers toeducation, TE to temporary employment, PE to permanent employment, U to unemployment
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure A1.
Transition probabilities to education for individuals aged 20–24 and forecasted transition probabilities for quarters I-IV of 2020

Appendix 4

Transition probabilities for the 25–29 age group



From EDU to SE
(a)

From EDU to TE
(b)

From EDU to PE
(c)

From EDU to U
(d)

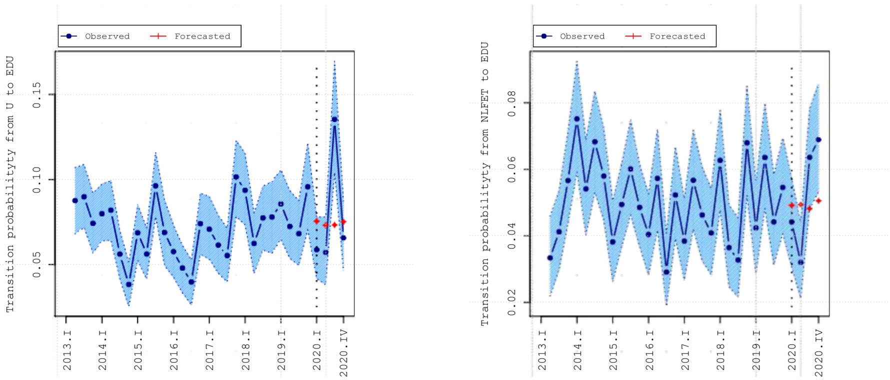
From EDU to NLFET
(e)

From EDU to EDU
(f)

Note(s): The forecasted transition probabilities are computed using a combination off our forecasting models (ETS, TSLM, THETAF,and ARIMA) (Hyndman and Athanasopoulos, 2021) in the period 2013 (quarter I)-2019 (quarter IV). Confidence intervals at 90% are computed using 1000 bootstraps and reported in parenthesis.EDU refers toeducation, TE to temporary employment, PE to permanent employment, U to unemployment

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure A2.
Transition probabilities from education for individuals aged 25–29 and forecasted transition probabilities for quarters I-IV of 2020



From U to EDU
(a)

From NLFET to EDU
(b)

Note(s): The forecasted transition probabilities are computed using a combination off our forecasting models (ETS, TSLM, THETAF, and ARIMA) (Hyndman and Athanasopoulos, 2021) in the period 2013 (quarter I) - 2019 (quarter IV). Confidence intervals at 90% are computed using 1000 bootstraps and reported in parenthesis. EDU refers to education, TE to temporary employment,PE to permanent employment, U to unemployment
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure A3. Transition probabilities to education for individuals aged 25–29 and forecasted transition probabilities for quarters I-IV of 2020

Appendix 5
Changes in the shares for groups of individuals

Table A2.
Changes in the shares of *females* in different labour market states

	SE	TE	PE	U	NLFET	EDU	FS
2019.III vs 2020.III							
All (15–64)	−0.002*** (0.000)	−0.009** (0.089)	−0.010*** (0.000)	−0.005** (0.020)	0.010*** (0.000)	0.002 (0.359)	0.014*** (0.000)
20–24	−0.004** (0.030)	−0.024 (0.175)	−0.003*** (0.000)	−0.004 (0.415)	0.011 (0.441)	0.017*** (0.000)	0.009*** (0.000)
25–29	−0.005*** (0.000)	−0.021** (0.028)	−0.008*** (0.000)	−0.011 (0.114)	0.030*** (0.000)	−0.004* (0.071)	0.020*** (0.000)
2019.IV vs 2020.IV							
All (15–64)	−0.004*** (0.000)	−0.009*** (0.000)	−0.015*** (0.000)	−0.006*** (0.000)	0.016*** (0.000)	0.002 (0.140)	0.017*** (0.000)
20–24	−0.006*** (0.004)	−0.034*** (0.000)	−0.014*** (0.000)	0.001 (0.431)	0.026*** (0.000)	0.018** (0.015)	0.010*** (0.000)
25–29	−0.002 (0.322)	−0.020*** (0.000)	−0.021*** (0.000)	−0.010** (0.028)	0.031*** (0.000)	−0.001 (0.419)	0.022*** (0.000)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal shares in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Table A3. Changes in the shares of *males* in different labour market states

	SE	TE	PE	U	NLFET	EDU	FS
2019.III vs 2020.III							
All (15–64)	−0.002 (0.114)	−0.005*** (0.000)	−0.012*** (0.000)	−0.008*** (0.000)	0.008*** (0.000)	0.002 (0.112)	0.017*** (0.000)
20–24	0.0004 (0.454)	−0.016*** (0.004)	0.002 (0.336)	−0.010** (0.030)	0.005 (0.186)	0.006 (0.231)	0.012*** (0.000)
25–29	0.009** (0.050)	0.003 (0.334)	−0.026*** (0.000)	−0.012*** (0.006)	0.004 (0.265)	0.006 (0.166)	0.017*** (0.000)
2019.IV vs 2020.IV							
All (15–64)	−0.003* (0.063)	−0.009*** (0.000)	−0.013*** (0.000)	−0.007*** (0.000)	0.011*** (0.000)	0.001 (0.202)	0.020*** (0.000)
20–24	−0.002 (0.268)	−0.014** (0.029)	−0.004 (0.242)	−0.003 (0.258)	0.017*** (0.000)	−0.008 (0.168)	0.014*** (0.000)
25–29	−0.003 (0.286)	−0.018*** (0.000)	−0.022*** (0.000)	−0.007* (0.087)	0.018*** (0.000)	0.011** (0.024)	0.021*** (0.000)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal shares in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Table A4.
Changes in the shares of *non-citizens* in different labour market states

	SE	TE	PE	U	NLFET	EDU	FS
2019.III vs 2020.III							
All (15–64)	−0.008*** (0.000)	−0.009*** (0.000)	−0.025*** (0.000)	−0.009*** (0.000)	0.037*** (0.000)	−0.002 (0.261)	0.015*** (0.000)
20–24	−0.002 (0.360)	0.009 (0.308)	−0.010 (0.262)	−0.038*** (0.000)	0.040*** (0.006)	−0.013 (0.242)	0.015*** (0.000)
25–29	0.002 (0.400)	−0.029*** (0.001)	−0.027** (0.038)	−0.001 (0.440)	0.053*** (0.000)	−0.016*** (0.004)	0.018*** (0.000)
2019.IV vs 2020.IV							
All (15–64)	−0.010*** (0.000)	−0.017*** (0.000)	−0.030*** (0.000)	−0.011*** (0.000)	0.050*** (0.000)	−0.001 (0.430)	0.019*** (0.000)
20–24	0.0005 (0.464)	−0.025* (0.058)	−0.039*** (0.001)	−0.018* (0.094)	0.072*** (0.000)	−0.005 (0.384)	0.015*** (0.000)
25–29	−0.011* (0.078)	−0.041*** (0.000)	−0.019 (0.107)	−0.013 (0.102)	0.076*** (0.000)	−0.013** (0.031)	0.022*** (0.000)

Note(s): The attained significance levels (ASL) for the null hypothesis of equal shares in the two quarters computed using 1000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL < 0.1; **ASL < 0.05; ***ASL < 0.01
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Table A5.
Changes in the shares of *citizens* in different labour market states

	SE	TE	PE	U	NLFET	EDU	FS
2019.IV vs 2020.IV							
All (15–64)	−0.002* (0.089)	−0.006*** (0.000)	−0.009*** (0.000)	−0.006*** (0.000)	0.005*** (0.000)	0.002** (0.030)	0.016*** (0.000)
20–24	−0.002 (0.213)	−0.022*** (0.000)	0.001 (0.400)	−0.004 (0.146)	0.005 (0.114)	0.013** (0.025)	0.010*** (0.000)
25–29	0.002 (0.330)	−0.006 (0.128)	−0.015*** (0.001)	−0.013*** (0.000)	0.011*** (0.006)	0.003 (0.235)	0.018*** (0.000)
2019.IV vs 2020.IV							
All (15–64)	−0.003*** (0.007)	−0.008*** (0.000)	−0.012*** (0.000)	−0.006*** (0.000)	0.009*** (0.000)	0.002* (0.081)	0.018*** (0.000)
20–24	−0.005** (0.019)	−0.024*** (0.000)	−0.006* (0.082)	0.0002 (0.467)	0.016*** (0.000)	0.006 (0.197)	0.012*** (0.000)
25–29	−0.001 (0.362)	−0.016*** (0.000)	−0.021*** (0.000)	−0.008** (0.035)	0.018*** (0.000)	0.007* (0.091)	0.022*** (0.000)

Note(s): The attained significance levels (ASLs) for the null hypothesis of equal shares in the two-quarters computed using 1,000 bootstraps are reported in parenthesis (Efron and Tibshirani, 1994, p. 220). *ASL<0.1; **ASL<0.05; ***ASL<0.01
Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Appendix 6
First passage time and expected first passage time

The distribution of times for which a random process arrives for the first time at state j starting from state i is called *the first passage time* from state i to state j. The expected time of going from state i to state j for the first time is called *expected first passage time* from state i to state j (Lieberman and Hillier, 2001, p. 818).

The first passage times are random variables, whose probability distributions depend upon the transition probabilities p_{ij}. In particular, let $f_{ij}^{(n)}$ denote the probability that the first passage time from state i to j is equal to n. For $n > 1$, this first passage time is n if (1) the first transition is from state i to some state k $(k \neq j)$; and (2) then the first passage time from state k to state j is $n - 1$. Therefore, these probabilities satisfy the following recursive relationships:

$$f_{ij}^{(1)} = p_{ij}; \tag{1}$$

$$f_{ij}^{(2)} = \sum_{k \neq j}^{K} p_{ik} f_{kj}^{(1)}; \tag{2}$$

$$\ldots \tag{3}$$

$$f_{ij}^{(n)} = \sum_{k \neq j}^{K} p_{ik} f_{kj}^{(n-1)}. \tag{4}$$

Thus, the probability of a first passage time from state i to state j in n steps can be computed recursively from the transition probabilities p_{ij}.

Finally, from Eq. (4) the expected first passage time from state i to state j, denoted by μ_{ij}, can be calculated as:

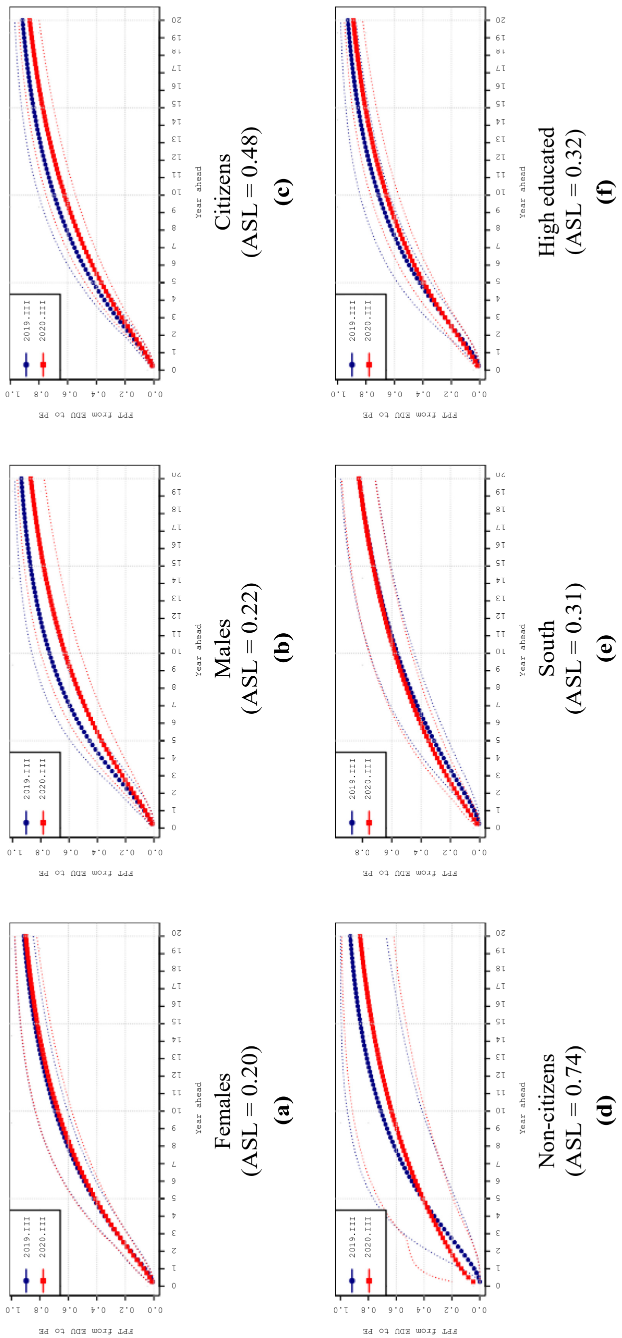
$$\mu_{ij} = \sum_{n=1}^{\infty} n f_{ij}^{(n)}, \tag{5}$$

which is well defined if (Lieberman and Hillier, 2001):

$$\sum_{n=1}^{\infty} f_{ij}^{(n)} = 1. \tag{6}$$

Appendix 7

First passage time and expected first passage time to permanent employment for the age group 25–29



Note(s): Joint confidence intervals at 90% are computed using 1000 bootstraps, taking as measure of distance between distributions the Kolmogorov–Smirnov statistic (see Appendix 8). The attained significant level (ASL) of the null hypothesis of equal FPT in the two quartersis the result of the one-side Kolmogorov–Smirnov test using a bootstrap procedure (see Appendix 8).The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia

Source(s): LFS3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Figure A4. First passage time (FPT) to permanent employment (PE) from education (EDU) for individuals aged 25–29

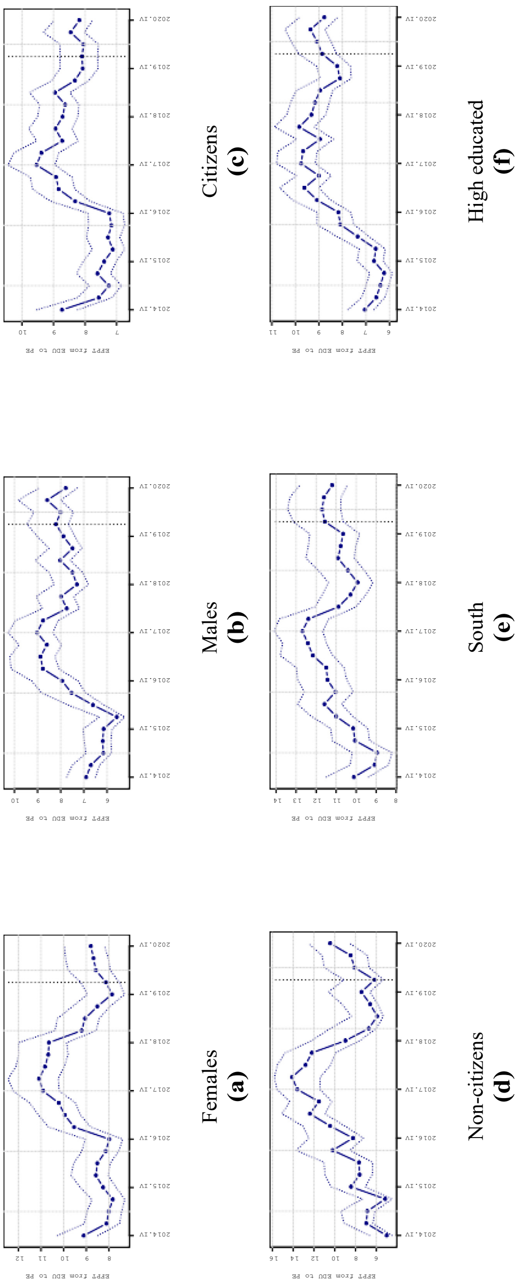


Figure A5.
Expected first passage time (FPT) to permanent employment (PE) from education (EDU) for individuals aged 25–29

Note(s): Confidence intervals at 90% are computed using 1000 bootstraps. The definition of South follows the Italian Institute of Statistics definition, which includes the regions of Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia

Source(s): LFS 3-month longitudinal data as provided by the Italian Institute of Statistics (ISTAT)

Appendix 8
Confidence intervals for the FPT curve and Kolmogorov–Smirnov test on the difference between two FPT curves

As the FPT curve is a cumulative probability distribution, the Kolmogorov–Smirnov statistics appears the most appropriate statistics for our inferential analysis. Let $FPT^{OBS}_{q_1}$ and $FPT^{OBS}_{q_2}$ be the observed quarter q_1 and q_2 FPT curves. Let $\mathcal{TM}^{S}_{q_1}$ and $\mathcal{TM}^{S}_{q_2}$ be the two sets of transition matrices of cardinality B resulting by sampling from the quarter q_1 and q_2 original datasets, using as drawing probabilities the sample weights. For each transition matrix we calculate the corresponding FPT curve and collect these curves in the two sets $\mathcal{FPT}^{S}_{q_1}$ and $\mathcal{FPT}^{S}_{q_2}$, each one with cardinality B.

The Kolmogorov–Smirnov statistics of $FPT^{OBS}_{q_1}$ and $FPT^{OBS}_{q_2}$ are calculated as:

$$KS\left(FPT^{OBS}_{q_1}, FPT^{OBS}_{q_2}\right) = \max\left(FPT^{OBS}_{q_1} - FPT^{OBS}_{q_2}\right),$$

i.e. the maximum difference between the observed quarters q_1 and q_2 FPT curves, calculated at the same number of quarters ahead.

H.1 Confidence intervals for the FPT curve

The calculation of the confidence intervals for the FPT curve is inspired by Staszewska-Bystrova (2011) and Wolf and Wunderli (2015). Let $\mathcal{KS}\left(FPT^{OBS}_{1}, \mathcal{FPT}^{S}_{q_1}\right)$ be the set of Kolmogorov–Smirnov statistics of $FPT^{OBS}_{q_1}$ and $\mathcal{FPT}^{S}_{q_1}$, where the element b ($b = 1, \ldots, B$) is calculated as:

$$KS\left(FPT^{OBS}_{1}, \mathcal{FPT}^{S}_{q_1}(b)\right) = \max\left(FPT^{OBS}_{1} - \mathcal{FPT}^{S}_{q_1}(b)\right).$$

The 90% confidence interval of the quarter q_1 FPT curve is then calculated by: (1) sorting the elements of $\mathcal{KS}\left(FPT^{OBS}_{1}, \mathcal{FPT}^{S}_{q_1}\right)$ on the basis of their Kolmogorov–Smirnov statistics; (2) discarding the top and the bottom 5% of the sorted elements; and, (3) using the remaining 90% elements to calculate the limits of the confidence bands, taking the minimum and the maximum value of quarter q_1 FPT curve for each quarter ahead.

H.2 Kolmogorov–Smirnov test on the difference between two FPT curves

Under the null hypothesis of equal quarter q_1 and q_2 FPT curves, $KS\left(FPT^{OBS}_{q_1}, FPT^{OBS}_{q_2}\right)$ should not be statistically different from:

$$KS\left(FPT^{b}_{1}, FPT^{b}_{2}\right) = \max\left(FPT^{b}_{1} - FPT^{b}_{2}\right),$$

where both FPT^{b}_{1} and FPT^{b}_{2} are drawn with replacement from the joint set $\mathcal{FPT}^{S}_{q_1,q_2} = \mathcal{FPT}^{S}_{q_1} \cup \mathcal{FPT}^{S}_{s}$. Hence, the achieved significance level (ASL) of the null hypothesis of equality of quarter q_1 and q_2 FPT curves is defined as (Efron and Tibshirani, 1994):

$$ASL\left(FPT^{OBS}_{q}, FPT^{OBS}_{s}\right) = \frac{\sum_{b=1}^{B} I\left(KS\left(FPT^{b}_{1}, FPT^{b}_{2}\right) > KS\left(FPT^{OBS}_{q}, FPT^{OBS}_{s}\right)\right)}{B},$$

where $I(\cdot)$ is the indicator function.

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