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The dynamics of repeated temporary jobs

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Abstract

The path to a permanent job often implies a sequence of temporary contracts, sometimes including periods of unemployment. This has usually been disregarded in previous studies on the transition from temporary to permanent employment. To account for these transitions, I apply multiple-spell duration techniques to an Italian dataset. I find that the probability of moving from a temporary to a permanent job increases with the duration of the contract, but decreases with repeated temporary jobs and especially with interruptions. This suggests that it is not temporary employment per se but the intermittence associated with it that is detrimental to employment prospects.

JEL classification: J24; J64
Keywords: Temporary employment; Duration dependence; Multiple-spells; Nonparametric

1. Introduction

The path to a permanent job often implies a sequence of temporary contracts, sometimes including periods of unemployment. By looking solely at a single contract, one might not capture all the dynamics that could arise when temporary contracts accumulate over time. For instance, young workers may need more than one temporary job in order to acquire the right expertise to be promoted to a permanent job. In this case, focusing on a series of temporary jobs rather than a single temporary job, is more appropriate.

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The main purpose of this study is to analyze the effect of repeated temporary contracts on the probability of finding a permanent job. This is not the first attempt to apply time-event analysis to temporary employment. Among others, Guell and Petrongolo (2004), using a duration model with competing risks of terminating into permanent employment versus alternative states, find that conversion rates from temporary to permanent jobs increase with tenure. Van Ours (2004) investigates locking-in effects of temporary subsidized jobs using a natural experiment that occurred in the Slovak labour market in the early 1990s. He finds that if the subsidized job lasts too long, workers start reducing their job search intensity. In addition, the idea of looking at repeated temporary contracts is not a new phenomenon. Booth et al. (2002) study the effect of the number of temporary contracts held in the past on current wages. Zijl et al. (2004) also take into consideration the presence of multiple spells for identification purposes, finding that temporary jobs serve as stepping-stones towards regular employment.

In this paper I merge the two prospects (survival analysis and repeated temporary jobs) to account for the effect of the time spent in one, but possibly more, fixed-term contracts on the probability of obtaining a permanent job.

To pursue this objective I select a sample of individuals who enter the labour market via temporary employment and follow them until they obtain a permanent contract. To account for the employment discontinuity a multiple-spell hazard model with competing-risks is implemented. This empirical specification allows me to control for both state and duration dependence, as in the standard single-spell framework, and in addition for lagged duration dependence (i.e. the impact of time spent in any previous temporary work or unemployment spell). To avoid parametric assumptions about the unobservable heterogeneity, I leave its distribution unspecified and correlated across states, as suggested in Heckman and Singer (1984). By doing so, job transitions are endogenously characterised and any possible selection bias avoided.

I estimate the model using the ILFI survey (*Indagine Longitudinale sulle Famiglie Italiane*, 1997 interview). This retrospective panel is particularly attractive in allowing for a simpler treatment of the *initial conditions* since it covers a long period of time and I can observe workers from the beginning of their career. Moreover, it refers to Italy, where the recent growth of temporary employment (see Fig. 1) has raised many concerns regarding their capacity to act as a springboard towards permanent employment. In this context, understanding the dynamics underlying this kind of contracts becomes particularly important.

The main results of the paper can be summarized as follows: first, on average, the probability of moving to a permanent job increases with the length of the temporary contract, but decreases during interruptions. However, as in other studies, I find that duration dependence in temporary jobs is not linear: good matches are converted into permanent contracts immediately after the initial screening, while for longer contracts the probability of being converted first increases, and then decreases over time. Finally, and more importantly, people experiencing repeated fixed-term contracts, and especially interruptions, have a lower probability of finding a stable job.

This evidence seems to suggest that it is not temporary employment per se, but the intermittence associated with it that is detrimental to employment prospects. Therefore,

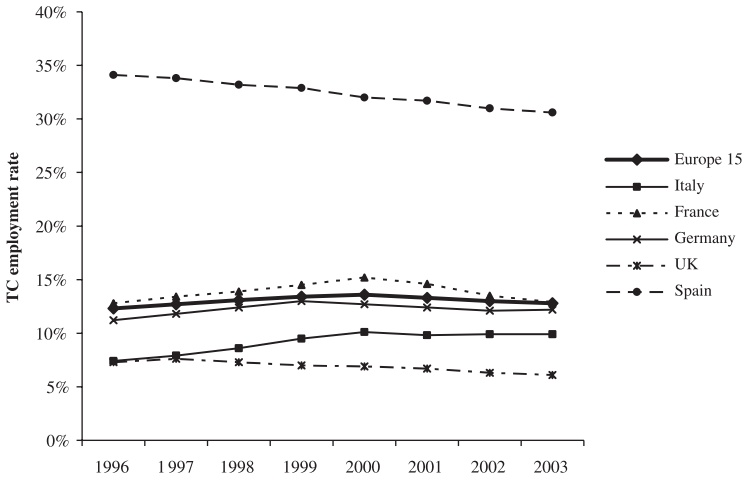


Fig. 1. Trends in TC employment rates.

any concern with temporary employment should be addressed not to the nature of the contract in itself (the limited duration), but to the employment continuity this kind of contracts effectively provide.

The rest of the paper is structured as follows: Section 2 presents the theoretical and empirical framework; Section 3 describes the data and the sampling procedure; Section 4 discusses the main results. Conclusions are summarised in the last section.

2. The framework of analysis

To what extent and how does accumulating temporary job experiences affect the probability of finding a permanent job? Existing theory fails to provide a unequivocal answer, given the number of alternative scenarios.

From a supply side point of view, as explained in the literature on career interruptions starting with Mincer and Ofek (1982), frequent job changes might imply human capital depreciation and consequently a decrease in productivity. This is mostly due to the loss of a work-specific productivity and to short spells of unemployment that usually follow the expiration of a temporary contract. Given this conjuncture, the theory predicts that the less similar two contracts are in terms of skill requirements, as well as the longer the interruption in between, the lower the probability of finding a stable job. There may be, however, a positive effect: a roughly continuous sequence of jobs increases the worker's human capital through the accumulation of work-non-specific productivity, and it also connects the worker to a network of acquaintances who can possibly help him to find a permanent job.

In addition to the human capital considerations, it may also be important to account for the signalling component. It may be that frequent temporary work experiences are an indication of individual dynamism. On the other hand, it may

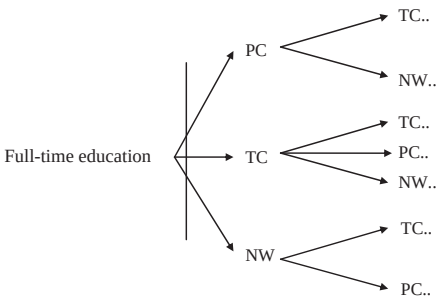


Fig. 2. The general scheme of transitions.

imply scarce ability, since otherwise a firm would have employed the worker on a permanent basis.

From a demand side point of view, there is a concern that some employers may be using temporary employment as a short-run buffer. As a consequence, firms are reluctant to moving temporary employees into permanent positions, irrespective of the workers' human capital. This behaviour could be exacerbated when there is excess supply in the labour market or if the labour market is regulated by stringent permanent job security provisions.[1]

In order to capture these dynamic effects and to detect the net effect of repeated temporary work experiences, I use an econometric specification which discriminates between three possible labour market circumstances: non-working (NW), temporary employment (TC) and permanent employment (PC).[2] It is important to note that contiguous non-working spells, like people being first unemployed and then moving out of the labour force, is considered as a unique state as PC. Temporary contracts, on the other hand, are kept separate, allowing for workers to move from one temporary job to another. As mentioned in the introduction, a relevant component of temporary employment is when a person moves from one temporary contract to another, either within or across firms.[3]

Fig. 2 presents seven possible transitions: PC-TC, PC-NW, TC-PC, TC-TC, TC-NW, NW-PC and NW-TC. For each transition, the left-hand states are referred to as the *origin states*, represented by the first subscript (k), while the right-hand states are referred to as the *destination states*, represented by the second subscript (j).

For each individual we observe a sequence $t_i = \{t_i^c\}$ of contiguous periods of time (*spells*) spent in different states, where t denotes the elapsed duration in a specific state, the subscript i denotes the individual and the superscript c denotes the c^{th} spell for the individual I in that state. Following Bonnal et al. (1997) I assume that individual labour market transitions are governed by intensity functions of the mixed

[1] See Blanchard and Landier (2002) and Cahuc and Postel-Vinay (2002).

[2] In order to depict more complex behaviors (like discouraged people leaving the labor market after some attempts to find a permanent job) NW includes, in addition to unemployed, also people out of the labor force.

[3] Formally the renewal of a temporary contract into another one within the same firm is not allowed in Italy. However, it is not so infrequent that, in order to escape this obligation, workers are moved to a different but still temporary contractual position, or to another controlled business.

proportional hazard (MPH) type. More specifically, I assume that the intensity of the transition (*hazard rate*) to state j after a sojourn in state k for the individual i at his c^{th} spell, θ_{kj}, is defined by:

$$\theta_{kj}\left(t_i^c|X_{ikj}, v_{ikj}; \beta\right) = h_{kj}\left(t_i^c\right)\exp\left(\beta'_{kj}X_{ikj}\right)v_{ikj'}, \tag{1}$$

where:

- $h_{kj}(t_i^c)$ is a baseline hazard which measures the effect of the elapsed duration (*duration dependence*). The form of the baseline hazard may depend on the origin and destination but not on the rank order *cth* of the current spell.
- X_{ikj} is a vector of time-varying individual covariates which capture both macroeconomic conditions and demographic characteristics. These covariates also include the time spent before in any of the origin states (*lagged duration dependence*), such that they account for the effect of repeated temporary jobs, as well as of interruptions.[4]
  These variables are assumed to affect the move from state k to state j through a vector of unknown parameters, β_{kj}, which can vary depending on the origin and destination states (*state dependence*).
- v_{ikj} is a random individual effect (*unobservable heterogeneity*), which is intended to capture the effect of individual heterogeneity such as preferences for leisure, risk attitude or ability.

The model is in continuous time and the unit of time is one month. All the individual covariates X_{ikj} are fixed to their values at the beginning of each spell. The contribution to the likelihood function of an incomplete (right-censored) spell, that is, the probability of surviving in state k until time t, can be expressed as follows:

$$\bar{F}_k\left(t_i^c|Z_i; \Omega\right) = \exp\left\{ - \Theta_k\left(t_i^c|Z_i; \Omega\right)\right\}, \tag{2}$$

where

$$\Theta_k = \int_0^{t_i} \sum_{j\neq k} \theta_{kj}(s|Z_i; \Omega)\,\partial s \tag{3}$$

is the corresponding integrated hazard function with $j=k$ only if $j=$TC.[5] Z_i is the vector of all observed and unobserved variables and Ω is the vector of all unknown parameters.

[4] The number of TC and NW spells would have been informative too. However, econometric theory does not provide conditions for the identification of both parameters (the number and the length of past experiences) simultaneously.

[5] This means that transitions to the same state are allowed only between different TCs but not between different NWs or PCs.

The individual contribution to the likelihood function of a completed spell of duration t_i^c in state k that ends in state j is therefore:

$$P_{kj}\left(t_i^c|Z_i;\Omega\right) = \bar{F}_k\left(t_i^c|Z_i;\Omega\right)*\theta_{kj}\left(t_i^c|Z_i;\beta\right). \tag{4}$$

Two terms remain to be specified: the baseline rate and the unobserved heterogeneity component.

I allow the baseline rate of transition to be piecewise constant. More precisely, $h_{kj}(t_i^c)$ can be a linear function of the elapsed duration in state k before transiting to state j with spikes at 6, 12 and 24 months:

$$\begin{aligned} h_{kj}\left(t_i^c\right) = \exp\big(&a_{1kj}\ln(t) + a_{2kj}I(t{>}6)\left(\ln(t) - \ln(6)\right) + a_{3kj}I(t{>}12)\left(\ln(t) - \ln(12)\right) \\ &+ a_{4kj}I(t{>}24)\left(\ln(t)\right)\ \ln(24)\big)\big), \end{aligned} \tag{5}$$

where $I(.)$ is an indicator function. This specification allows for possible nonmonotone evolutions of the exit rates.[6] However, in the special case where $a_{2kj}=0$, $a_{3kj}=0$ and $a_{4kj}=0$ for all k and j, specification (5) may also test the overall effect of time spent in a specific state, giving useful policy indications.

I assume that the individual effects are identically and independently distributed for all individuals with a joint distribution function $G(v_{iTC\text{-}TC}, v_{iTC\text{-}NW}, \ldots v_{iNW\text{-}TC}, v_{iNW\text{-}PC})$. This specification allows the unobservable heterogeneity terms to be correlated across different transitions.[7] To avoid the computational burden of a completely flexible specification, I reduce the dimensionality of $G(.)$ to two by assuming a two-factor loading specification, $v_{ikj}=\exp(\delta_{kj}w_{1i}+\lambda_{kj}w_{2i})$, where w_{1i} and w_{2i} are the common factors, which are independently and identically distributed across individuals with a distribution function of $H(w_{1i},w_{2i})$. The parameters δ_{kj} and λ_{kj} are the corresponding loading parameters for different types of transitions that are estimated jointly with the rest.[8]

The joint distribution for the unobserved heterogeneity factors, $H(w_{1i},w_{2i})$, can then be estimated using a parametric function but, given that H is usually unknown, the results of this procedure, as noted by Heckman and Singer (1984), may be biased when the chosen distribution for the unobservable term is incorrect. They show that this problem can be avoided by using the Non-Parametric Maximum Likelihood Estimator (NPMLE). This procedure approximates the distribution function of unobservables with a finite mixture

[6] The selection of the spikes is motivated by evidence coming from KM estimates presented in Section 4. In particular, the first one is meant to capture short-run effects, while the third one is introduced to capture longer renewal dynamics around the expiration date (as you can see in Table 1, about 70% of TCs have a duration of less than two years).

[7] See Van Den Berg (2001). In this way working transitions are completely internalized: this allows, if some regularity conditions are fulfilled (among which, recovering *initial conditions*), to identify the duration dependence parameters. For details, see also Flinn and Heckman (1982) and Honorè (1993).

[8] In a preliminary stage I also tried with different specifications (like 1 or 3 unobserved factors), but the bivariant turned out to be the likelihood function maximizer. Alternatively, the number of support points may have been determined internally, but in that case the asymptotic distribution of the estimator would not be standard and the inverse of (minus) the covariance matrix does not provide consistent estimates for the standard errors. See Meghir and Whitehouse (1997).

distribution, in my case, bivariant. In particular, assuming that $v_i = (w_{1i}, w_{2i})$ is the vector containing the two unobserved factors, each of which can take only two values, w_m^a and w_m^b $(m = 1,2)$, for a total of four points of support. The points of support of the finite mixture distribution are the unknown vectors (v^1, v^2, v^3, v^4) to which the four unknown probabilities (p_1, p_2, p_3, p_4) are attached, respectively.

The contribution to the likelihood of an individual then becomes:

$$L_i\left(\Omega, v, p | t_i^1, t_i^2 .., t_i^{C_i}; X_i\right) \sum_{m=1}^{4} \left\{ \left(\prod_{c=1}^{c_i} \prod_{k=1}^{2} \prod_{j \neq 1} P_{kj}\left(t_c | X_{ikj}, v_{ikj}; \Omega\right)^{d_{kj}^c} \right) \times \left(\prod_{c=1}^{c_i} \prod_{k=1}^{2} \bar{F}_k\left(t | X_{ikj}, v_{ikj}; \Omega\right)^{s_k^c} \right) \right\} p_m, \tag{6}$$

where m denotes the number of support points and where d_{kj}^c is one if the individual moves from state k to state j in the c^{th} spell and zero otherwise. In addition s_c^k is one if the c^{th} spell is incomplete (*right censored*) and zero otherwise.

The points of support, as well as the probabilities assigned to each of them, are estimated jointly with the remaining Ω's. The estimation is implemented, as proposed by Heckman and Singer (1984), by an EM-algorithm.[9]

3. The data

The sample used in this paper is drawn from the ILFI dataset (*Indagine Longitudinale sulle Famiglie Italiane*), which is a retrospective panel survey for the Italian population in 1997. This is a random sample of 4,713 private households with 10,423 individuals at least 18 years old (i.e., born before 1st January 1979). From this initial dataset I extract a set of personal working histories starting after the end of full-time education, which leaves me with 7,914 individuals.[10]

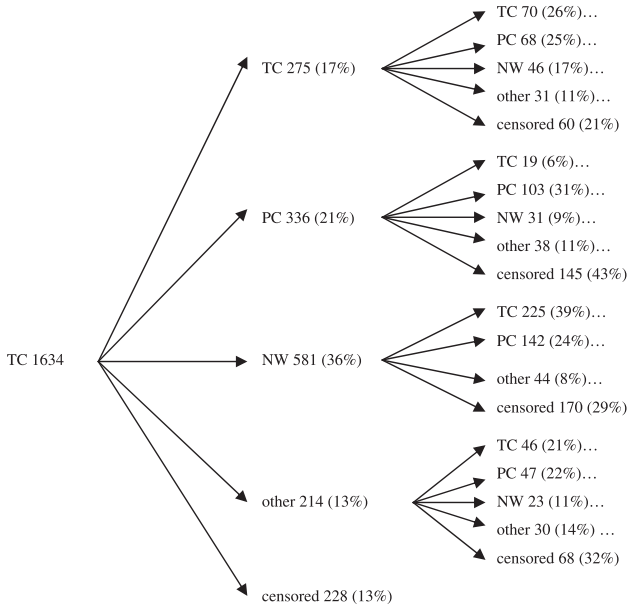
The ILFI dataset gathers retrospective information on all the significant events occurring to the members of the sample in the period between their birth and the interview, such that *initial conditions* can be recovered. It also has the advantage of covering a long horizon, which allows for a more complete analysis than most of the available datasets. For the same reason it does not suffer from left truncation nor from missing episodes.

However, like all the datasets using retrospective information, it may suffer from recall bias, implying that shorter or more distant spells could be underreported. To reduce this possibility, I select individuals between 18 and 55 years at the time of the interview, for whom I expect this bias to be lower, leaving me with 5,346 individuals.[11]

[9] See Heckman and Singer (1984) for a description of the EM algorithm.

[10] End of full-time education means the first interruption after the end of compulsory education. It follows that occasional working experiences during full-time education are not accounted for.

[11] See next section for a more detailed discussion of this issue.



Notes. Individuals between 18-55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type. *other* includes SE and retirement.

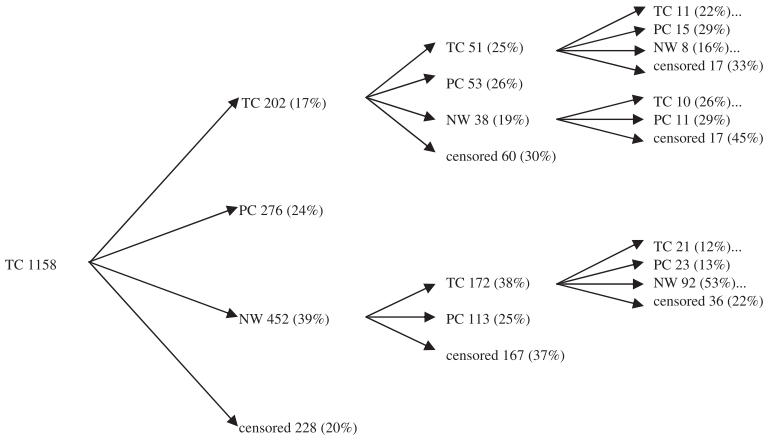
Fig. 3. Individual labour market histories – initial sample.

Since my primary interest is in workers who enter the labour market via temporary employment, I select only those individuals whose first job was temporary, for a total of 1,634 individuals (see Fig. 3). Thus, there is only one initial state (namely, TC) and then the entry into subsequent spells is completely internalized.

Following the classification presented in the previous section, I group working spells into three main categories (TC, NW, PC) plus, for the moment, another category, labelled "other". The TC state includes workers employed under a fixed-term contract, workers with a "contratto formazione lavoro" (a contract introduced in 1985 to provide people between 16 and 32 years with training opportunities) and all the workers declaring to be employed on a temporary basis but without any formal arrangement.[12] The PC state only includes people employed under a permanent contract. The NW state includes unemployed, people doing housework and people who have gone back to education.[13] Finally, "other" includes self-employed and retired people. This grouping allows me to

[12] Doing so, TC is intended to capture any sort of "precarious" employment except for interim workers, since TWAs have been introduced in Italy only in 1997. This category does not include "Co.Co.Co." These contracts are legally framed as self-employed (and so presumably registered as autonomous workers in the ILFI dataset), but very often they have the attribute of temporary dependent workers.

[13] As for TC, a unique category of NW, instead of separating unemployment and out-of-labor-force states, represents a more extensive proxy for employment interruptions in temporary careers. In order to account for any remaining heterogeneity in temporary employment and inactivity, I will use a control dummy for each specific type of TC and NW.



Notes. Individuals between 18-55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type.

Fig. 4. Individual labour market histories _ final sample.

limit the amount of parameters to be estimated that, with a higher number of states and transitions, would be otherwise intractable.

For the same reason of tractability, given that the fraction of workers moving to self-employment or retirement is quite low, I eliminate sequences going through "other" since it is not directly relevant in the context of temporary careers. In doing so I assume they are randomly distributed across individuals and then the final sample is still representative.

In order to minimize the initial sample heterogeneity, I make another restriction: I only select on workers who at the time of their first TC were aged between 14 and 35.[14] In this way I am left with a final sample of individuals who can be considered very similar a priori and whose following achievements in the labour market can then be attributed, after controlling for observable and unobservable heterogeneity, only to their career.

Finally, I consider PC to be an absorption state, meaning that every spell after the transition to PC is removed from the sample.[15] These selection conditions are fulfilled by 1,158 individuals, providing 2,423 spells for five possible transitions: from TC to TC, from TC to NW, from TC to PC, from NW to TC and from NW to PC (see the final sample in Fig. 4), plus a TC and a NW censored spell.

The set of explanatory variables X_{ikj}, all referring to the beginning of the spell, includes the following controls: dummies for the presence of children (under 18 years old), sex and marital status; two dummies for education, two for the past experience in TC and NW respectively (measured in months); the regional (NUTS2) unemployment rate; a continuous variable for age and finally two cohort dummies. In addition, to account for heterogeneity in TCs and NWs, for each transition starting from TC, I control for the type of occupation and for the type of temporary job held ("contratto formazione lavoro", fixed-

[14] I thank an anonymous referee for this suggestion.

[15] You can see in Fig. 3 that persistence in PC is quite strong, with very few individuals moving to a TC after PC.

Table 1
TC and NW spells composition

	n. of spells	%	median length	% in 1st spell
TC				
"formazione lavoro"	298	17.1	21 (15)	17.8
Fixed-term	753	42.9	16 (11)	38.0
No contract	700	40.0	27 (22)	44.2
NW				
Unemployed	437	67.0	10 (7)	–
Housework	179	26.6	88 (78)	–
Education	56	6.4	21 (21)	–
Total	2423			

Notes. Sample size: 1,158 individuals between 18–55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type. "formazione lavoro" only available since 1985. "median length" measured in months, in parenthesis for complete spells only.

term and no contract) and for each transition starting from NW, I also control for the type of non working condition (out of labour force and unemployment).[16]

Descriptive statistics by type of transition are provided in Tables 1–4. Table 1 shows the composition of the two main categories: most of TC spells are of fixed-term type (42.9%), but a not irrelevant component is represented by people without a written contract (40.0%). People without a formal arrangement have also longer tenures and, when I look at the first spell, their weight increases (44.2%): this means that the early stages of temporary careers are typically more precarious. Unemployed people represent most of non-working spells (67.0%), while the percentage of people moving to education after a temporary job is quite low (6.4%). Moreover, the average duration of house-working spells is longer than both education and unemployment.

Most of the people in the sample (see Table 2) do not have any NW experience (56.7%), although it is not rare to observe workers with more than one temporary job (32.3%). In particular, among those observed two times in TC, 55% had at least one interruption in between; among those observed three times in TC, 62% had at least one interruption and 34% had at least two; among those observed four times in TC, 67% had at least two interruptions and 50% had at least three. This supports the idea that repeated temporary contracts frequently imply non working spells.

Table 3 shows that the length of transitions from TC to PC is longer than from TC to TC and, especially, from TC to NW. This may imply that employers generally use temporary contracts as a probation period and that "good" matches (in terms of renewal into PC or TC) last longer. At the same time, it is more frequent to observe transitions from NW to PC lasting for more than two years than from NW to TC.

[16] Given the available number of observations, any additional control like age^2, part-time/full-time job, public/private sector, industry sector, is omitted, otherwise the number of parameters to be estimated would be too high and then the program would not converge to a final solution. I am aware that there might be strong seasonal effects in sectors like tourism and agriculture. However, they only represent 3.2% and 2.9% of the observed spells, respectively.

Table 2
Number of individuals by TC and NW experiences

n. of TC spells	n. of NW spells									total
	0	1	2	3	4	5	6	7	8	
0	–	–	–	–	–	–	–	–	–	0
1	504	280	–	–	–	–	–	–	–	784
2	113	82	54	–	–	–	–	–	–	249
3	28	20	16	9	–	–	–	–	–	73
4	4	6	5	13	2	–	–	–	–	30
5	6	4	3	0	1	–	–	–	–	14
6	–	1	1	1	–	2	–	–	–	5
7	1	1	–	–	–	–	–	–	–	2
8	–	–	–	–	–	–	1	–	–	1
total	656	394	79	23	3	2	1	0	0	1,158

Notes. Individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type.

Finally, Table 4 presents descriptive statistics at the entry time into the panel. Females represent 58% of the sample. On average workers have a "medium" or "low" education and, although cohorts are equally represented, the percentage of people born between 1946 and 1956 is lower (19%). At the time of their first job, few workers are married or have children.

4. Results

In Fig. 5 (Kaplan-Meier monthly estimates) I provide preliminary evidence on the effect of past TC and NW experiences on the transition from temporary to permanent employment.

In general no monotonic duration dependence, either positive or negative, can be detected. In particular, it appears that the time spent in temporary employment, at least at the beginning, helps the worker to find a better job but in the long-run this positive effect disappears. More interestingly, when a worker reaches his/her second temporary experience, the probability of obtaining a permanent job deteriorates, even more so when there is an interruption in between.

Table 3
Length of spell by type of transition

Months	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
	n.	%	n.	%	n.	%	n.	%	n.	%
0–6	63	19.3	236	36.0	60	15.5	103	37.7	63	38.4
7–12	56	17.1	113	17.2	45	11.6	59	21.6	27	16.5
13–24	68	20.8	88	13.5	75	19.3	36	13.2	18	11.0
25–60	99	30.3	135	20.6	121	31.2	39	14.3	28	17.1
>61	41	12.5	83	12.7	87	22.4	36	13.2	28	17.1
	327	100	655	100	388	100	273	100	164	100
	Censored: 381						Censored: 235			

Notes. Sample size: 1,158 individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st spell, for a total of 2,423 spells. 1st spell after the end of full-time education is of TC type.

Table 4
Summary statistics — 1st TC spell

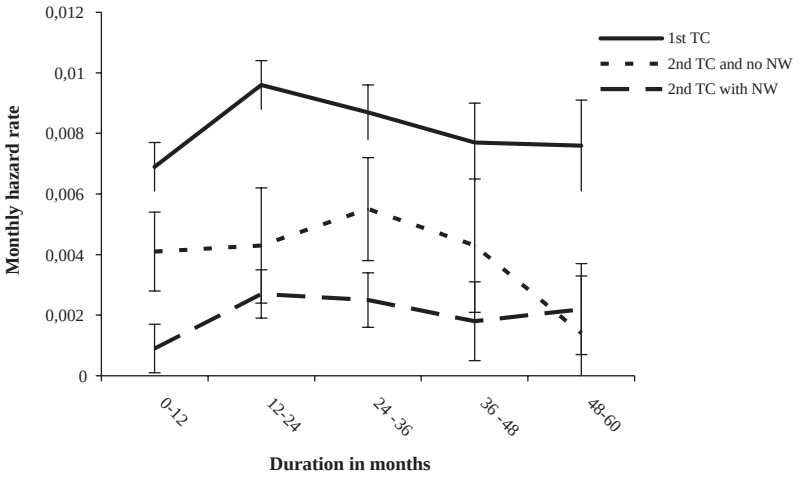
	n. of spells	mean	min	max
Age	1158	20	14	35
Children	1158	.05	0	1
Male	1158	.42	0	1
Married	1158	.08	0	1
Low Education	1158	.45	0	1
Medium Education	1158	.40	0	1
High Education	1158	.15	0	1
Low Occupation	1158	.64	0	1
Medium Occupation	1158	.32	0	1
High Occupation	1158	.04	0	1
Public sector	1158	.25	0	1
Private sector	1158	.75	0	1
Tourism	1158	.03	0	1
Services other than tourism	1158	.41	0	1
Industry	1158	.54	0	1
Agriculture	1158	.05	0	1
NW exp.	1158	2.23	0	23
"Formazione Lavoro"	1158	.18	0	1
Fixed-term contract	1158	.38	0	1
No contract	1158	.44	0	1
Cohort 1946–1956	1158	.19	0	1
Cohort 1957–1967	1158	.39	0	1
Cohort 1968–1979	1158	.32	0	1

Notes. Individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type. All characteristics referred at the beginning of the spell. *Children:* dummy for at least one child with less than 18 years. *TC exp.* and *NW exp.* expressed in months. *Low Education*: primary school. *Medium Education*: secondary school. *High Education*: university degree or more. *Low Occupation*: blue-collar type. *Medium Occupation*: clerical type. *High Occupation*: managerial type. "*Formazione Lavoro*": training contract. *No contract*: no contract. *Olf*: out of labour force.

In Table 5 I present the results from the non-parametric maximum likelihood estimation (NPMLE) with a log-linear baseline hazard specification.[17]

On the one hand, the duration parameters (variable *Ln(time)*) indicate that in the duration of the temporary contract, the probability of receiving another TC decreases (−0.147), as does the probability of it ending without any working arrangement (−0.282). The probability of finding a stable position, however, slightly increases (+0.035) during this period. On the other hand, when experiencing an interruption, the probability of finding a job declines. In particular the longer the non-working period, the less likely the worker is to find a job (either temporary (−0.011) or permanent (−0.048)).

[17] Standard errors are computed using the inverse of the final information matrix although this procedure may lead to an underestimation. Robust standard errors are too demanding in terms of observations to be computed here. Moreover, to prevent the possibility of identifying a local instead of a global maximum, a variety of starting points was used in the implementation of the EM algorithm. They actually turned out to converge to the same result. Estimates without the unobserved heterogeneity term are available from the author upon request (in this case duration dependance parameters would be upward biased).



Notes. KM estimates computed as an "averaged" estimate centred on the midpoint of the interval. Confidence interval (5% level) around the bars.

Fig. 5. TC-PC hazard rate by n. of TC and NW experiences. Kaplan-Meier estimates.

This result is confirmed when looking at the lagged duration dependence parameters (variables *TC exp.* and *NW exp.*). When starting in state TC, the time spent previously with a temporary contract helps the worker to find another temporary contract (+0.023). There is, however, the problem that repeated TC experiences have a detrimental effect on the search for a PC, independently of the point of departure (−0.081 from TC and −0.140 from NW, respectively). It appears as though a worker has a chance of moving from TC to PC and this chance increases with the time spent in a temporary job. However, for those who fail, the probability of being promoted decreases with the next TC contracts, and not just because of repeated TC experiences, but also because of interruptions in-between. In fact, non-working experiences always have a negative effect on the probability of finding a job, varying from −0.015 for the NW-TC transition to −0.068 for the NW-PC transition.

It is important to note that, following the model specification in Section 2, the lagged duration dependence is measured in terms of cumulative length. Additional measures, like the number of TC and NW spells, are also informative too, since we might expect the length and the number of TC held in the past to have a different effect on transition probabilities.[18] As we can see in Table 6, these two measures are highly correlated. Therefore, as long as the time spent in TC (NW) increases with the number of TC (NW) held, the lagged duration dependence terms (*TC exp.* and *NW exp.* respectively) can be considered a good proxy for intermittence in temporary careers.[19]

From Table 5 it can be seen that for a male temporary worker, the probability of finding either another temporary (+0.083) or a permanent (+0.441) job increases. This gender

[18] As pointed out in Section 2, this could also arise identification issues.

[19] Where intermittence means stopping and starting at intervals. See also the discussion of Table 2 in the previous section.

Table 5
NPMLE (linear baseline) hazard rate estimates

	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Age	−.008**	(.003)	.069***	(.003)	.009*	(.004)	−.019***	(.004)	.014***	(.004)
Married	−.595***	(.025)	−.164*	(.066)	−.519***	(.021)	−.002	(.015)	−.219***	(.061)
Male	.083	(.044)	−.736***	(.021)	.441***	(.036)	.848***	(.034)	1.147***	(.030)
Children	.016	(.029)	−.067	(.062)	.639***	(.028)	.405***	(.051)	.166	(.070)
Low education	−.223***	(.031)	−.113***	(.026)	−.657***	(.050)	−.245***	(.039)	−.207***	(.022)
High education	.336***	(.028)	−.559***	(.023)	.068	(.049)	.905***	(.022)	.243***	(.029)
Local U. rate	−.018***	(.002)	−.003**	(.001)	−.060***	(.001)	−.072***	(.001)	−.143***	(.005)
Cohort '57–'67	.437***	(.042)	.159***	(.031)	.283***	(.020)	.495***	(.035)	.309***	(.027)
Cohort '68–'79	.525***	(.037)	.272***	(.027)	−.138***	(.025)	.332***	(.036)	−.419***	(.032)
Low occupation	.273***	(.036)	.625***	(.032)	.069	(.041)	–		–	
High occupation	.029	(.038)	−.240***	(.060)	−.746***	(.017)	–		–	
"Form. Lavoro"	.117*	(.053)	−.518***	(.033)	.163***	(.039)	–		–	
No contract	.192***	(.048)	−.329***	(.029)	−.014	(.010)	–		–	
Olf	–		–		–		−1.241***	(.053)	−1.181***	(.040)
NW exp.	−.015*	(.007)	−.035***	(.008)	−.067***	(.013)	−.030**	(.010)	−.068***	(.019)
TC exp.	.023*	(.009)	−.142***	(.014)	−.081***	(.019)	−.088***	(.016)	−.140***	(.023)
Ln(time)	−.147***	(.025)	−.282***	(.017)	.035***	(.006)	−.011*	(.005)	−.048*	(.021)
Constant	−2.732***	(.038)	−3.120***	(.023)	−1.907***	(.065)	−1.715***	(.022)	−1.997***	(.022)
δ	1.000	–	.835***	(.051)	1.098***	(.040)	.250***	(.045)	−.185***	(.034)
λ	1.000	–	2.077***	(.045)	1.080***	(.047)	10.483***	(.146)	9.811***	(.138)
					$v_1^a=0$, $v_1^b=-1.138$*** (.041)					
					$v_2^a=0$, $v_2^b=.211$*** (.008)					
					$P_1=.236$, $P_2=.126$, $P_3=.355$, $P_4=.283$					
mean log-lik:					−2.3106					
n. spells:					2423					

Notes. (*), (**), (***): significant at 10%, 5% and 1% level respectively. Individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st TC spell. N. of individuals: 1,158. All characteristics referred at the beginning of the spell. *Children:* dummy for at least one child with less than 18 years. *TC exp.* and *NW exp.* and *Age* expressed in years. *Low Education*: primary school. *High education*: university degree or more. *Ln(time)*: log of duration in years. *Local U. rate*: regional unemployment rate. *Low Occupation*: blue-collar type. *High Occupation*: managerial type. "*Form. Lavoro*": training contract. *No contract*: no contract. *Olf*: out of labour force. δ and λ set to 1 in one transition and v_1^a and v_2^a set to 0 for identification issues.

effect is even stronger for spells starting from NW (+0.848 and +1.147).[20] The same results apply to people with a higher educational level. It appears to be that being married always has a negative effect on the change of state, while for older workers there is a better chance of getting a PC starting from NW (+0.014) as from TC (+0.009), but less to get a TC if starting from another TC (−0.008) or from NW (−0.019). The results also show that when the unemployment rate is high, firms can keep on searching for better employees and so the probabilities that a worker is renewed or converted into a permanent job are lower (respectively −0.018 and −0.060).

The type of occupation seems to play an important role here, since being employed with a "high" occupational function (managerial type), as opposed to a "medium" one

[20] This is probably due to the high percentage of women going back to housework after some TC experience.

Table 6
Length of previous TC and NW experiences by the n. of TC and NW experiences

length of TC exp. (in months)	n. of TC exp.					
	1	2	3	4	5+	
0–11	73%	19%	5%	2%	1%	100%
12–23	43%	34%	12%	5%	6%	100%
24–35	50%	32%	9%	2%	7%	100%
36–47	38%	35%	14%	9%	4%	100%
48+	36%	35%	17%	8%	4%	100%
length of NW exp. (in months)	n. of NW exp.					
	1	2	3	4	5+	
0–11	76%	17%	5%	0%	2%	100%
12–23	73%	20%	7%	0%	0%	100%
24–35	75%	14%	9%	2%	0%	100%
36–47	65%	23%	10%	1%	1%	100%
48+	60%	25%	11%	1%	3%	100%

Notes. Individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st spell. 1st spell after the end of full-time education is of TC type.

(clerical type), increases the chances of persistence in temporary employment (+0.029) and reduces the probability of moving to a permanent position (−0.746). This result, even if apparently contradictory, reflects the idea that the higher the occupational level of a worker (usually associated to an higher wage), the more willing he is to accept some job instability in exchange for an higher position.

The last set of controls concern the type of TC and NW. On the one hand, having a training contract ("Formazione lavoro"), as opposed to a standard fixedterm contract, increases the probability of obtaining another job, both temporary (+0.117) or permanent (+0.163), and reduces the probability of becoming inactive (−0.518). In addition, having no formal arrangement increases employment precariousness by reducing the probability of finding a stable employment relationship (−0.014). On the other hand, being out of labour force as opposed to unemployed strongly reduces the probability of getting a job offer (−1.241 and −1.181 for TC and PC types, respectively).

In Section 2 I address the issue that the data could potentially suffer from recall bias. Although there may be no straightforward way of preventing this problem, it is possible to check whether the results for a restricted sub-sample of individuals who should, in principle, be less affected by this bias (namely, those whose age at the time of the interview was between 18 and 35), coincide with those referring to the main sample. I test this hypothesis on 887 individuals for a total of 1,629 spells and find that the results with regards to the parameters of interest (the baseline hazard, the lagged duration terms, the time dummies and the local unemployment rate) remain essentially unchanged in absolute terms.[21] It can be argued, therefore, that recall bias is not a relevant problem in the ILFI dataset.

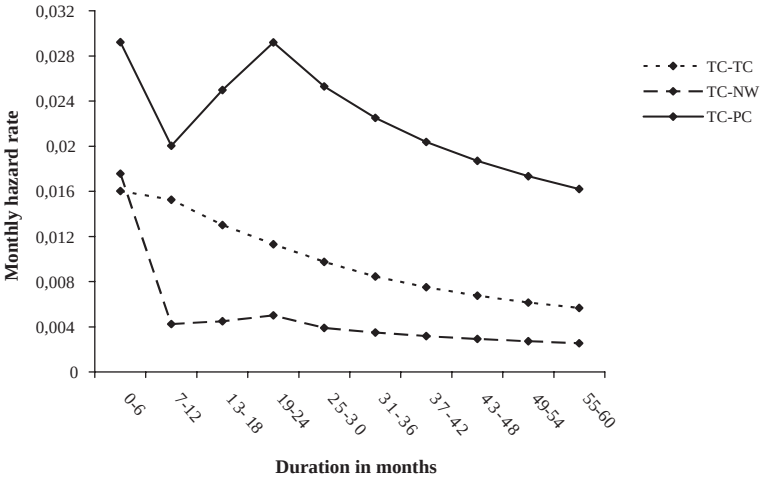
[21] Results of this test are available upon request from the author.

Finally, to account for the non-linearity highlighted in the KM estimates, Table 7 shows results from a flexible specification of the baseline hazard. There I control for the effects of three specific durations: 6, 12 and 24 months. While the parameters

Table 7
NPMLE (flexible baseline) hazard rate estimates

	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Age	−.015*	(.006)	.067	(.082)	.002	(.005)	−.011	(.008)	.022*	(.009)
Married	−.545***	(.092)	−.169*	(.080)	−.485***	(.126)	.107	(.065)	−.130	(.074)
Male	.111*	(.051)	−.716***	(.073)	.459***	(.077)	.668***	(.113)	.906***	(.126)
Children	.014	(.015)	−.046	(.062)	.626***	(.146)	.252*	(.111)	.076	(.083)
Low education	−.189**	(.059)	−.170**	(.056)	−.614***	(.072)	−.151*	(.068)	−.066	(.061)
High education	.336***	(.089)	−.555***	(.092)	.077	(.053)	.829***	(.119)	.278*	(.114)
Local U. rate	−.022***	(.001)	−.005	(.003)	−.064***	(.002)	−.066***	(.008)	−.135***	(.014)
Cohort '47–'57	.368***	(.071)	.123**	(.044)	.216**	(.073)	.388***	(.105)	.190*	(.079)
Cohort '69–'79	.419***	(.083)	.210***	(.059)	−.197**	(.073)	.378**	(.118)	−.366***	(.105)
Low occupation	.224**	(.070)	.584***	(.073)	.009	(.007)	–		–	
High occupation	.039	(.036)	−.233*	(.111)	−.722***	(.082)	–		–	
"Form. Lavoro"	.104	(.081)	−.515***	(.096)	.161*	(.067)	–		–	
No contract	.194**	(.065)	−.323***	(.063)	−.011	(.009)	–		–	
Olf	–		–		–		−1.685***	(.122)	−1.624***	(.142)
NW exp.	−.012*	(.005)	−.034***	(.009)	−.058***	(.014)	−.032**	(.012)	−.076***	(.018)
TC exp.	.031**	(.011)	−.138***	(.017)	−.067***	(.017)	−.073***	(.015)	−.126***	(.024)
Ln(time)	.499***	(.049)	.532***	(.053)	.562***	(.087)	.440***	(.077)	.575***	(.087)
Spike 6	−.570***	(.108)	−2.582***	(.093)	−1.106***	(.136)	−1.454***	(.162)	−1.943***	(.167)
Spike 12	−.321*	(.163)	2.127***	(.138)	1.086***	(.165)	.480**	(.181)	1.306***	(.169)
Spike 24	−.393***	(.119)	−.691***	(.101)	−1.184***	(.134)	.304	(.191)	−.208	(.186)
Constant	−1.845***	(.180)	−1.808***	(.199)	−1.107***	(.145)	−.770**	(.253)	−.912***	(.265)
δ	1.000	–	.730***	(.081)	.976***	(.135)	.664***	(.155)	−.257**	(.089)
λ	1.000	–	13.821***	(.144)	.469***	(.046)	19.299***	(1.703)	16.424***	(1.919)
	$v_1^a=0$, $v_1^b=-.627***$ (.073)									
	$v_2^a=0$, $v_2^b=.032***$ (.002)									
	$P_1=.206$, $P_2=.065$, $P_3=.510$, $P_4=.219$									
Mean log-lik:	−2.3243									
n. spells:	2423									

Notes. (*), (**), (***): significant at 10%, 5% and 1% level respectively. Individuals between 18 and 55 in 1997 and between 14 and 35 at the beginning of the 1st TC spell. N. of individuals: 1,158. All characteristics referred at the beginning of the spell. *Children:* dummy for at least one child with less than 18 years. *TC exp., NW exp.* and *Age* expressed in years. *Low Education*: primary school. *High education*: university degree or more. *Ln(time)*: log of duration in years. *Spike 6*, *12* and *24*: time dummies. *Local U. rate*: regional unemployment rate. *Low Occupation*: blue-collar type. *High Occupation*: managerial type. "*Form. Lavoro*": training contract. *No contract*: no contract. *Olf*: out of labour force. λ and δ set to 1 in one transition and v_1^a and v_2^a set to 0 for identification issues.



Notes. Monthly predicted hazard (as from table 7). Reference category: male, not married, 25 years old, medium education, fixed-term contract, no children, cohort '56-'67, unemployment rate 5.5%, clerical type occupation. Unobservable heterogeneity integrated out.

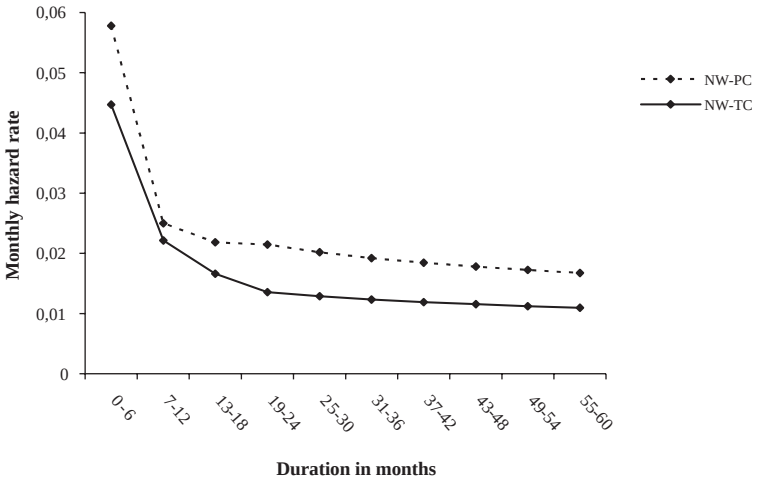
Fig. 6. Predicted Hazard rate from TC.

referring to the individual characteristics remain essentially unaffected, the results from the new baseline specification are interesting since they now presents some elements of non-monotonicity (see predicted hazards in Figs. 6 and 7). When looking at the two transitions from NW, I find that the more time that passes, the higher the "locking-in" effect of inactivity. This is the case even if it is easier to find a PC than a TC. For workers moving from TC to PC, the hazard rate first declines, then increases and after two years starts declining again. Similarly, for workers moving from TC to NW, the hazard rate decreases rapidly during the first six months, recovers around two years and then sharply declines over time. Finally, the probability that a temporary worker will get another fixed-term contract consistently declines after the initial jump.

In particular, with regard to the transition from TC to PC this result implies that the positive effect of the time spent in a temporary job, observed in Table 3, was mainly driven by a short and mid-term rush: workers who successfully pass the initial screening obtain a permanent renewal during the first months, while others are transferred into permanent jobs only when there is no other way to hold them (that is in the proximity of the second year). Thereafter, the probability of leaving a temporary job for stable employment starts decreasing.[22]

Furthermore, the conclusions concerning the adverse effect on future mobility given previous spells of inactivity or temporary employment still holds. In the event that the worker experiences previous interruptions, he is particularly penalised in terms of the probability of finding a stable job (-0.058 from TC and -0.076 from

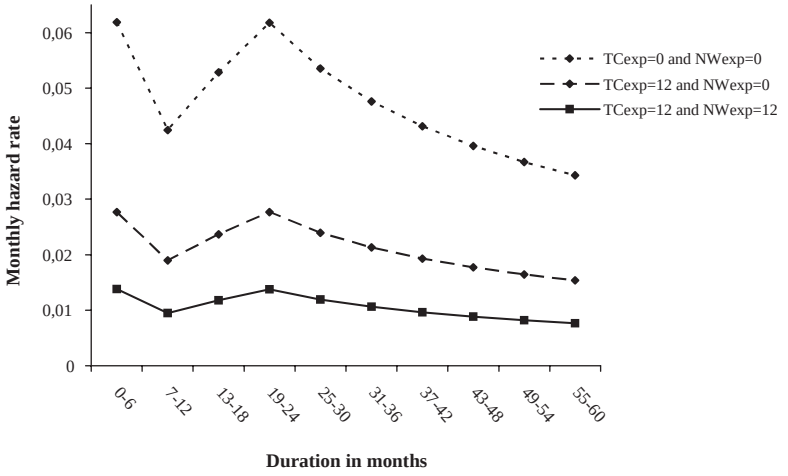
[22] This result partly replicates findings in Guell and Petrongolo (2004), as well as in Van Ours (2004).



Notes. Monthly predicted hazard (as from table 7). Reference category: male, not married, 25 years old, medium education, unemployed, no children, cohort '56-'67, unemployment rate 5.5%. Unobservable heterogeneity integrated out.

Fig. 7. Predicted Hazard rate from NW.

NW). The same is true for workers going through more than one temporary contract (-0.067 from TC and -0.126 from NW). This is summarised in Fig. 8. There I have plotted the predicted hazards from TC to PC by the length of time spent before in TC and NW. As long as *TC exp.* and *NW exp*. increase, the predicted hazard, i.e. the probability of obtaining a PC after surviving up to that point, decreases.



Notes. Monthly predicted hazard (as from table 7). Reference category: male, not married, 25 years old, medium education, fixed-term contract, no children, cohort '56-'67, unemployment rate 5.5%, clerical type occupation. Unobservable heterogeneity integrated out.

Fig. 8. Predicted hazard rate TC-PC by n. of TC and NW experiences.

5. Conclusions

The main purpose of this study was to analyze the effect of repeated temporary work experiences on the probability of finding a stable job. To conduct the empirical analysis I selected a sample of individuals who entered the labour market via temporary employment (from a retrospective Italian panel), and followed them until they obtained a permanent contract. I found three main results:

- first, the probability of moving to a permanent job while employed on a temporary basis increases with the duration of the contract, but decreases if there are interruptions.
- second, duration dependence in a temporary job is not linear: "good" matches are converted into permanent contracts as soon as their value is revealed, while for prolonged contracts the probability of conversion increases at first and then falls in the long run.
- third, and more importantly, people experiencing more than one fixed-term contract have a lower probability of finding a stable job, usually because of interruptions in between.

All these findings suggest that it is not temporary employment per se, but the intermittence associated with it that deteriorates employment prospects. It follows that any concern with temporary employment should be addressed not to the nature of the contract in itself (the limited duration), but to the level of employment continuity this kind of contracts provide. There may be countries, in fact, where it is easy to move from one TC to another without interruptions. Where as in other countries, where temporary employment does not mimic the same continuity as permanent employment, these concerns may become more relevant.

If the latter is the case, then there is space for policy intervention. In particular, policy should be aimed at promoting longer contractual durations, as well as at minimising the interruptions between different temporary jobs. In Italy job discontinuity is particularly more painful given the lack of both active and passive labour market policies. Here the introduction of public training programs to facilitate workers re-employability, more generally, by providing effective support to individuals while searching for a new job, could alleviate the problem of short disruptions.

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