What is really bad in temporary employment?

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Abstract

So far, most of the studies analyzing the transition from temporary to permanent employment have been restricted to a single fixed-term contract prospect. However, the way to get a permanent job may be much more complex than that: it often implies a sequence of temporary jobs, sometimes staggered with periods of inactivity. In order to take this intermittence into account, I apply duration techniques to an Italian prospective panel, the ILFI survey (1997 interview). In particular, I use a multiple-spell specification that allows controlling, apart from state and duration dependence, also for lagged duration dependence. Unobservable heterogeneity is left unspecified and correlated across states as suggested by Heckman and Singer (1984). As in other studies (Guell et al. 2003), I find that the probability of moving from a temporary job to a permanent one increases with the duration of the contract, but not linearly; however, and more interestingly, repeated temporary jobs and in particular unemployment interruptions reduce it. This suggests that it is not exactly temporary employment *per se* but the job interruptions in between that detriment employment prospects.

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Data used here come from the ILFI (*Indagine Longitudinale sulle Famiglie Italiane*, 1997 interview) survey, a prospective panel collected and provided by the University of Milano-Bicocca, Dep. of Sociology. For more detailed information see http://www.sociologia.unimib.it/ilfi/.

1. Introduction

So far, any kind of analysis about the transition from temporary to permanent employment has been restricted to a single fixed-term contract prospect only. However, the way to get a permanent job may be much more complex than that: in many cases it implies a sequence of temporary jobs, sometimes staggered with periods of inactivity. Then, looking at a single contract only, we might not capture more composite dynamics arising when repeated experiences collect over time. For example, young workers may need a longer time than just one temporary job to acquire the right expertise and be promoted to a permanent job. In this case, talking about "temporary careers" instead of "temporary jobs" is more appropriate.

In particular, I am interested in investigating duration patterns in temporary careers. All the recent studies applying survival analysis to temporary employment do not in fact go further than a single-spell prospect. This is the case of Guell and Petrongolo (2003) who estimate a duration model on single fixed-term contracts, with competing risks of terminating into permanent employment versus alternative states, and flexible duration dependence. But this is also the case of Booth et al. (2002). Even when we look at the rest of the literature, any attempt at moving to a longer horizon in the analysis of temporary employment is missing.

To take intermittence in temporary careers more properly into account, a multiple-spell hazard model with competing risks is then implemented. This empirical specification allows controlling not only for *state* and *duration dependence*, as in the single-spell case, but also for *lagged duration dependence*, i.e. the time spent before in temporary employment or unemployment. I will leave the distribution of the unobservable heterogeneity correlated across states and to be determined internally, as suggested in Heckman and Singer (1984). In this way working transitions are endogenously specified and any possible selection bias is avoided.

I estimate the model using the ILFI survey (*Indagine Longitudinale sulle Famiglie Italiane*, 1997 interview), which is particularly appealing because, being a prospective panel, it covers an extremely long period of time. In addition, we can observe workers from the beginning of their career, such that any *initial conditions'* problem is ruled out.

The main results can be summarized as follows: firstly, the probability of moving to a permanent job from a temporary one increases with the length of the contract, but decreases during interruptions. Secondly, duration dependence in temporary jobs is not linear: good matches are converted into permanent contracts immediately after the initial screening (in the first six months), while for those prolonged the probability of being converted first increases (up to around the second year), and then decreases over time. Thirdly, people experiencing more than one fixed-term contract, and in particular spells of inactivity, have a lower probability of finding a stable job.

All these findings suggest that it is not temporary employment *per se*, but the job interruptions in between that really detriment employment prospects. This leaves space for policy intervention. That should not be aimed at limiting temporary employment *to court*, but at promoting a more efficient use of it by preventing excessive prolongations, and especially by reducing interruptions in between. In this way we might preserve what is good and trash what is really bad in temporary employment.

The paper is organized 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. Lastly, section 5 suggests final considerations.

2. The framework of analysis

To what extent and in which way do repeated temporary job experiences affect the probability of finding a permanent job? Existing theory provides contradictory answers to this question.

On one hand, as well explained in all the literature on career interruptions starting with Mincer and Ofek (1982), frequent job changes might imply human capital depreciation and consequently productivity to fall: this is mostly due to the partial loss of a work-specific productivity accumulated on the job and to the fact that the end of a temporary contract is often accompanied by short spells of unemployment or inactivity, until the next job is found.[1] We should consequently expect a reduction in the probability of finding a stable job the less similar are two contiguous temporary jobs in terms of skill requirements, as well as the longer the period of inactivity in between. Moreover, temporary jobs usually do not provide as much or as good on-the-job training as permanent ones.[2] On the other hand, there might be a positive effect represented by subsequent job experiences: a roughly continuous sequence of jobs increases the human capital of the worker through the accumulation of work-non-specific productivity, but it also connects the worker to a network of acquaintances who could help him to find a permanent

[1] Here human capital is intended as the combination of general skills, specific skills and technical and scientific knowledge.

job.

At the same time, we may also have a signaling argument. Short and frequent temporary experiences can be evaluated by the next employer as a signal of a prompt willingness to work, but when they are too long and too many, they can be interpreted as a signal of low skillfulness.

Lastly, there is a concern that some employers may be using temporary employment just as a short-run buffer. As a consequence, they would in any case be reluctant to move them to a permanent position, no matter workers' human capital, thus leaving the worker rolling into sequence of temporary contracts. This behavior could be exacerbated when occurring in a labor market with an excess of supply, or already regulated by stringent permanent job security provisions.[3]

To capture this dynamics I then use an econometric specification which discriminates between three possible labor market circumstances: non-working (NW), temporary employment (TC) and permanent employment (PC).[4] Let us also consider contiguous NW spells as a unique one, the same for PC, though I keep adjacent temporary contracts separated allowing for workers to move from a temporary job to another one. As mentioned in the introduction, a relevant component of temporary employment refers in fact to people moving from one temporary contract to another one, either within the same firm or to a different one.[5]

As shown in box 1, we are left with 7 possible transitions. For each transition, left-hand states are called the *origin states*, which are represented by the first

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[2] See OECD (2002) for evidence on this.
[3] See Blanchard and Landier (2002) and Cahuc and Postel-Vinay (2002).
[4] Note that, in order to capture more complex behaviors (like discouraged people leaving the labor market after some attempts to find a permanent job), in addition to unemployed NW also includes people moving out of the labor force. Moreover, transitions from and to self-employment are excluded and considered as exogenous with respect to the others.

subscript, while right-hand states are the *destination states*, which are represented by the second subscript. Since *initial conditions* are recovered and education controlled for, I assume that the entry into the first state right after the end of full-time education can be considered as exogenous.[6]

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. Following Bonnal et al. (1997) I assume that individual labor market transitions are governed by intensity functions of the mixed 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:

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

where:

- $h_{kj}(t_i^c)$ is a positive baseline hazard which measures the effect of the elapsed duration (*duration dependence*). Its form may depend on the origin (k) and destination (j), but not on the rank order c^{th} of the current spell.
- X_{ikj} is a vector of time-varying individual covariates capturing both macroeconomic conditions and demographic characteristics. They also include the time spent previously in any of the origin states (*lagged duration dependence*), such that the effect of career interruptions and repeated

[5] Formally in Italy the renewal of a temporary contract into another one within the same firm is not allowed. 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 firm.
[6] See Heckman and Flinn (1982).

temporary jobs can be accounted for. These variables are assumed to affect a 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.

Note that the model is in continuous time and all the individual covariates X_{ikj} will be 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:

$$\bar{F}_k\left(t_i^c \mid Z_i;\Omega\right) = \exp\left\{ \quad \Theta_k\left(t_i^c \mid Z_i;\Omega\right)\right\} \ , \qquad (2)$$

where

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

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

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

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

Now two issues remain that have to be specified before we can estimate the model: the baseline rates and the unobserved heterogeneity terms.

I allow the baseline rates 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:

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

where $I(.)$ is an indicator function. This specification allows for possible non-monotone evolutions of the exit rates. 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 be used to test the overall effect of time spent in a specific state.

Let us assume that the individual effects are identically and independently distributed for all individuals with a joint distribution function $G(v_{iTC\text{-}TC}, v_{iTC\text{-}NW}, \dots v_{iNW\text{-}TC}, v_{iNW\text{-}PC})$. 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 $H(w_{1i},w_{2i})$, and δ_{kj} and λ_{kj} are the

[7] See Van den Berg (2000). Note that the unobservable terms are correlated across states. In this way working

corresponding loading parameters for different types of transitions that are estimated jointly with the rest.[8] From an economic point of view, one of the factors underlying the unobserved heterogeneity could represent heterogeneous tastes for leisure while the other could relate to risk preferences (or ability).

The joint distribution for the unobserved heterogeneity factors, $H(w_{1i},w_{2i})$, could then be estimated using maximum likelihood. However, given that H is usually unknown, the results of this procedure might, as Heckman and Singer (1984) pointed out, be biased when the chosen distribution for the unobservable term is not the true one. They show that this problem can be avoided by using the Non-Parametric Maximum Likelihood Estimator (NPMLE), which does not make any distributional assumption. This procedure approximates the distribution function of unobservables with a finite mixture distribution, in our case bivariant. In particular, assume that $v_i=(w_{1i},w_{2i})$ is the vector containing the two unobserved factors, each of which can take two different values, $w^a{}_m$ and $w^b{}_m$ ($m=1,2$), 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.[9]

The contribution to the likelihood of an individual then becomes:

$$L_i\left(\Omega, v, p \mid t_i^1, t_{i\ldots}^2, t_i^{C_i}; X_i\right) = \sum_{m=1}^{4} \left\{ \begin{array}{l} \left(\prod_{c=1}^{C_i} \prod_{k=1}^{4} \prod_{j \neq k} P_{kj}\left(t_c \mid X_{ikj}, v_{ikj}; \Omega\right)^{d_{kj}^c} \right) \times \\ \left(\prod_{c=1}^{C_i} \prod_{k=1}^{4} P_{kj}\left(\overline{F}_k \mid X_{ikj}, v_{ikj}; \Omega\right)^{s_k^c} \right) \end{array} \right\} p_m \quad , \tag{6}$$

transitions are completely internalized: this allows, if some regularity conditions are fulfilled, to exactly identify the duration dependence parameters. For details, see Heckman and Flinn (1982) and Honorè (1993).

[8] As suggested in Bonnal, Fougere and Serandon (1997).

[9] Note that 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).

where m denotes the number of support points and where d^c_{kj} is one if the individual moved from state k to state j in the c^{th} spell and zero otherwise, s^k_c is a one if the c^{th} spell is incomplete and zero otherwise and $j=k$ only if j=TC.

The points of support, as well as the probabilities assigned to each of them, are estimated jointly with the rest of the Ω's. The estimation is implemented, as proposed by Heckman and Singer (1984), by an EM-algorithm.[10]

3. The data

The sample used in this paper is drawn from the ILFI (*Indagine Longitudinale sulle Famiglie Italiane*) dataset, which is a prospective panel survey carried out in 1997 and referring to the Italian population. This is a nationally representative random sample of 4713 private households with 10423 individuals at least 18 years old (i.e., born before 1st January 1979). From this initial dataset I extract a set of individuals with personal working histories starting after the end of full-time education and after WW2 (i.e., from 1947 on): thus I am left with 7914 individuals.[11]

Note that the ILFI dataset gathers retrospective information on all the significant events occurring to the members of the sample in the period between their births and the date of the interview, such that *initial conditions* are recovered. It also has the advantage of covering a very long horizon, which allows for a more complete analysis than most of the available datasets, and it does not

[10] See Heckman and Singer (1982) for a description of the EM algorithm.

suffer from left truncation, or 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 only individuals between 18 and 55 years at the time of the interview, leaving us with 5346 individuals.

Following the classification presented in the previous section, I have grouped working spells in three main categories: TC, NW and PC. The TC state includes workers employed under a proper fixed-term contract, workers with a training contract ("contratto formazione lavoro", only available since 1984) and all the workers without any formal arrangement.[12] The PC state only includes people employed on a permanent basis. Finally, the NW state includes unemployed, people doing housework and people who have gone back to school.[13] This way of grouping allows to limit the number of parameters to be estimated that, with an higher number of statuses and transitions, would be otherwise intractable.[14]

I then select only those careers starting with a temporary job. In addition, PC now becomes an absorption state, meaning that every spell after the transition to PC is removed from the sample. These selection conditions are fulfilled by 1242 individuals, providing 2612 spells (see table 5). We have remained therefore with 5 possible transitions: from TC to TC, from TC to NW, from TC to PC, from NW to TC and from NW to PC (see box 2). Note that this selection, although it could be somewhat restrictive, leaves us exactly with workers who use temporary

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

[12] In this way, TC is intended to capture any sort of "precarious" employment except for interim workers, since TWAs have been introduced in Italy only in 1997. It does not also include the "Co.Co.Co.": these workers are legally framed as a 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] A unique category of NW, instead of separating unemployment and out-of-labor-force states, avoids any discretional differentiation between people declaring to seek for a job and people who do not. Moreover, it represent a more comprehensive proxy for employment interruptions in temporary careers.

employment to enter the labor market, and may have experienced interruptions, as well as other temporary contracts, while seeking for a permanent job. Moreover, given that there is only one initial state (namely, TC), the entry into subsequent TC and NW after the first temporary job is completely internalized, thus avoiding any assumption of exogeneity needed instead with multiple initial states.

The set of regressors X_{ikj} includes the following controls for each transition: a dummy for the presence of children, for sex and marital status; two dummies for the educational level, a continuous variable for age, two for the past experience in TC and NW respectively, the standardized national unemployment rate, and finally three cohort dummies.[15] In addition to that, in all the transitions starting from TC I also control for the type of occupation, and for the type of temporary job held ("Contratto formazione lavoro", proper TC and "no contract"), while in all the transitions starting from NW I also control for the type of non-working condition (out-of-labor-force or unemployed).[16] As in all the continuous hazard models, these regressors refer to the beginning of the spell.

Descriptive statistics by type of transition are provided in tables 2 to 6. Table 2 shows the composition of the two main categories in detail: the majority of TC spells are proper fixed-term contracts (42%), even if a strong component is represented by people working on temporary basis but without a formal contract (36.5%). People without a formal arrangement have usually longer spells and, when we look at the first spell, their percentage also increases (47%): this means

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[14] However, in order to account for any possible heterogeneity in temporary employment and inactivity, I will use a control dummy for each specific type of TC or NW state.
[15] The regional unemployment rate instead of the national one would be better. Unfortunately, regional unemployment rates are not available for the entire horizon covered by the ILFI dataset.
[16] In 1984 "Contratto Formazione Lavoro" was introduced in order to provide young people (16-32 years of age) with training opportunities. Any additional control like age^2, part-time/full-time job, public/private sector, is omitted since, given the available number of observations, the program would not converge to a final solution.

that the early stages of temporary careers are typically more precarious. Unemployed people represent most of NW spells (64.3%), but the percentage of people moving to education after the first temporary spell is also relevant (7.5%). Moreover, the average duration of housework spells is larger than education spells, and even more than unemployment.

When we look at tables 3 and 4, we find that most of the people in the sample do not have any experience of inactivity (56.3%), although it is not rare to observe workers with more than one temporary job (32.8%). Table 5 also shows that the length of transitions from TC to PC is much longer than from TC to TC, and especially from TC to NW. This is preliminary evidence of the fact that employers usually use the temporary contracts as a probation period and that good (in terms of renewal into PC or TC) matches last longer. Last two columns (transitions from NW) seem instead to support the idea that to get a better job while inactive requires a longer search, as it is more frequent to observe transitions from NW to PC lasting for more than two years.

Finally, table 6 presents descriptive statistics at the entry in the panel: we can see that females represent 63.4% of the sample, 43.8% of the people entered the sample after the reform, while cohorts are equally represented, even if the percentage of people born between 1957 and 1968 is higher (38%). As expected, at the time of their first job few workers were married or had children.

4. Results

The Kaplan-Meier (KM) product limit estimator provides preliminary survival analysis by giving an unadjusted estimate of the single-spell hazard function. In this sense it can be considered as a “spurious” measure of the effect of time on the probability of exit, averaged across the entire sample.

Looking at the KM monthly estimates for each of the five transitions (graphs 1 to 5) we can try to understand the ongoing trend in exit rates. Almost all the types of transition show, in the long run, a negative duration dependence: this is the case for both the transitions out of inactivity NW (graphs 4 and 5), where the more a worker persists in NW the less likely is to find a job, even if the probability of receiving a temporary job offer is higher than a permanent one over all the horizon. The same trend is observed for the transitions from TC to NW (graph 2): as previously suggested in table 3, the more a worker stays on a temporary job the more he will keep on being employed. Quite different results come from the other two KM estimates: while for the transition from TC to TC (graph 1) there is a clear decreasing trend, even if staggered by periodical fluctuations, no clear duration dependence, either positive or negative, can be detected for workers moving from TC to PC (graph 3).

It should be noted, however, that the nature of these estimates is still descriptive. KM estimates do not allow competing alternatives to be controlled for, or many personal and aggregate characteristics that may influence each single transition. I then move to the estimation of the econometric model outlined in section 2.

In table 7 I present results from the non-parametric maximum likelihood estimation (NPMLE) with a log-linear baseline hazard specification, as described in section 2.[17] Looking at the duration parameters (variable *LnTime*), I find that as

[17] Standard errors are computed using the inverse of the final information matrix from the optimization. Robust standard errors are too demanding in terms of observations to be computed here. To prevent the possibility of locating a local instead of a global maximum, a variety of starting points is used in the implementation of the EM

long as the temporary contract lasts, the probability of receiving another TC decreases (-0.255), as well as the probability of ending without any working arrangement (-0.187), while the probability of finding a stable position increases (+0.112).[18] On the other hand, during NW interruptions the probability of finding a job is declining: in particular I find that the longer the spell of inactivity the less likely the worker will be to find a job, both of a temporary (-0.372) or a permanent type (-0.365).

This finding is partly confirmed by looking at the lagged duration dependence parameters (variables *TC exp.* and *NW exp.*). It seems in fact that, while one single temporary experience is helpful, repeated TC experiences may instead have a null or detrimental effect on the search for a stable job (while not statistically significant for the TC-PC transition, this parameter is -0.107 for the NW-PC transition). In some sense it is as if people have a first chance of moving from TC to PC: this chance increases with time spent on a temporary job, but for those who fail the probability of being promoted decreases with the next opportunities. Note however this is not only because of repeated TC experiences *per se*, but also because of implicit interruptions in between (from -0.093 for the TC-PC transition to –0.102 for the NW-PC transition).

As expected, I find that being a male temporary worker helps in finding either another temporary (+0.116) or a permanent (+0.357) job, but this gender effect is even stronger for spells starting from NW (+ 0.892 and +0.721). The same results apply to people with a higher educational level. Being married always has a negative effect on the change of state; at the same time older workers have more

algorithm. They actually turned out to converge to the same result for every specification of the model. Estimates without the unobserved heterogeneity term are available on request.

[18] The fact that the parameter attached to the transition TC-NW is positive is evidently due to the limit imposed by law to the TC renewal within the same firm.

chance of getting a PC starting from NW (+0.049), but less to get a TC if starting from another TC (-0.026). 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 (-0.014 and –0.008).

At the same time, being employed at a high occupational level (managerial type), as opposed to a medium one (clerical type) increases the chances of persisting in temporary employment (+0.093) and reduces the probability of moving to a permanent position (-0.789). This result, even if apparently contradicting, reflects the idea that the highest the occupational level of a worker (usually associated to an higher wage), the more he is willing to accept some job instability in exchange of an higher mobility.

Last controls concern the type of TC and NW. As expected, having a training contract ("contratto formazione lavoro"), as opposed to a proper fixed-term contract, increases the chances of obtaining another job, both temporary (+0.140) or permanent (+0.102), while having no formal arrangement increases employment precariousness by reducing the probability of finding a stable employment relationship (-0.074). On the other hand, being out-of-labor-force as opposed to unemployed, reduces the probability of getting a permanent offer (-0.098) but increases the probability of finding a temporary job (+0.127).[19]

Finally, table 8 presents results from a flexible specification of the baseline hazard where I control for the effect of three specific points in time: 6, 12 and 24

[19] In Section 2 I mentioned that the data could suffer from recall bias. Even if there is 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. In a separate estimation (available on request) I tested this hypothesis finding that the results concerning the parameters of interest (the baseline hazard, the lagged duration terms, the time dummies and the unemployment rate) have remained unchanged. It can therefore be argued that recall bias is not a relevant problem in the ILFI dataset.

months. In particular, the first spike is meant to capture short-run effects, while the third one was introduced to capture longer renewal dynamics for temporary workers.

While, as before, the parameters referring to the individual characteristics remain more or less unchanged, interesting results come from the new baseline specification, which now presents strong elements of non-linearity. For all the five transitions I find that during first months the probability of exiting is higher, but after that the duration dependence paths start differentiating (see graphs 6 and 7). For workers moving from TC to NW, from TC to PC and from NW to PC, the hazard rate first declines, then increases and after two years starts declining again; for workers moving instead from NW to TC, the hazard rate first declines, but then it starts increasing for the rest of the time, which means that TC is a preferred exit for NW spells than PC; finally, the probability that a temporary worker will get another fixed-term contract constantly declines after the initial jump.

In particular, concerning the transition from TC to PC, this result means that the positive effect of time spent on a temporary job observed in table 7 was mainly driven by a short and mid-term rush: workers who successfully pass the initial screening obtain a permanent renewal in the first months of the contract, while others are converted into permanent ones only when there is no other way to hold them, that is in the proximity of the second year. Then human capital, and with it the probability of leaving temporariness for stable employment, start decreasing.[20]

[20] This result partly replicates findings in Guell and Petrongolo (2003) for the Spanish labor market. Notice also that the decline over the two years may be due to the presence of temporary workers without any formal arrangement, which on average last more than two years and are less binding for the employer in terms of renewal.

Furthermore, every consideration on the effect of previous experiences of inactivity and temporary employment still holds.

A Wald test for the joint significance of the unobservable terms, provided in table 9, rejects the hypothesis that there are no unobservable characteristics driving the transition process. The same table also provides a test for the monotonicity (joint and individual) of the baseline hazard: this hypothesis is rejected in all the specifications, thus meaning that time has a non-linear effect on transition probabilities. However, the monotonic specification in Table 7 still remains meaningful as long as it helps in defining an overall trend and to get more general conclusions in terms of policy advising.

5. Conclusions

The main purpose of this paper was to analyze the effect of repeated temporary job experiences on the probability of finding a stable job. To this aim I selected a sample of individuals who entered the labor market *via* temporary employment and then I followed them until they got 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 length of the contract, but decreases with the length of job 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 workers who are prolonged the probability of being converted first increases and

then falls in the long run.

- third, in all the specifications people experiencing more than one fixed-term contract have a lower probability of finding a stable job, particularly because of unemployment spells in between.

All these findings suggest that it is not temporary employment *per se*, but especially job interruptions that detriment employment prospects, thus leaving space for policy action. In particular, it follows that any intervention should not be aimed just at limiting temporary employment *to court* but at promoting an efficient conversion of temporary contracts into permanent, and especially at reducing interruptions in between. This could be done by supporting on-the-job training for temporary employment too, by improving the matching between labor demand and supply such as to reduce the periods of inactivity, or by creating a system of incentives that could make employers less reluctant to move temporary employees to a stable employment relationship. In this way we might preserve what is good and trash what is really bad in temporary employment.

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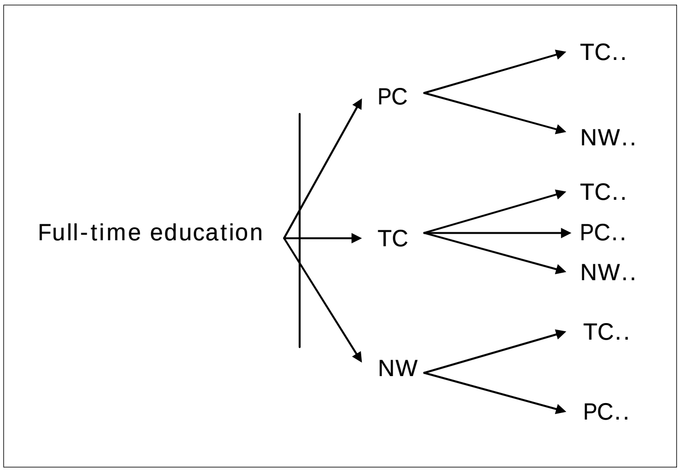
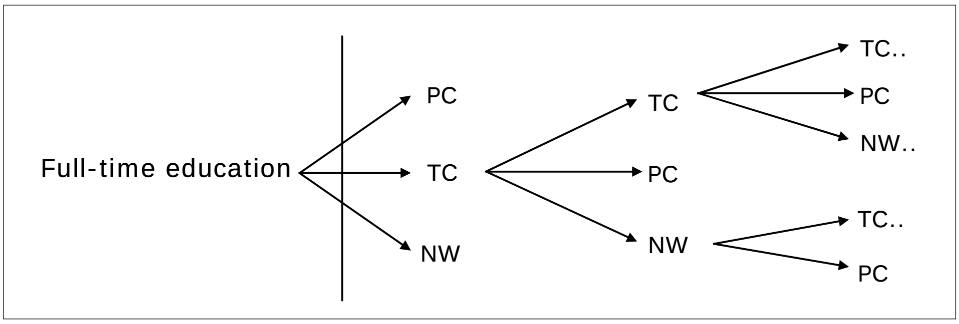
Boxes

Box.1 The general scheme of transitions



Box.2 The selected sample of transitions in “temporary careers”



Tables

Table.1 Number of spells by origin and destination

	PC	TC	NW	censored	Total
TC	420	378	710	399	1907
NW	168	287	-	250	705
Total	588	665	710	649	2612

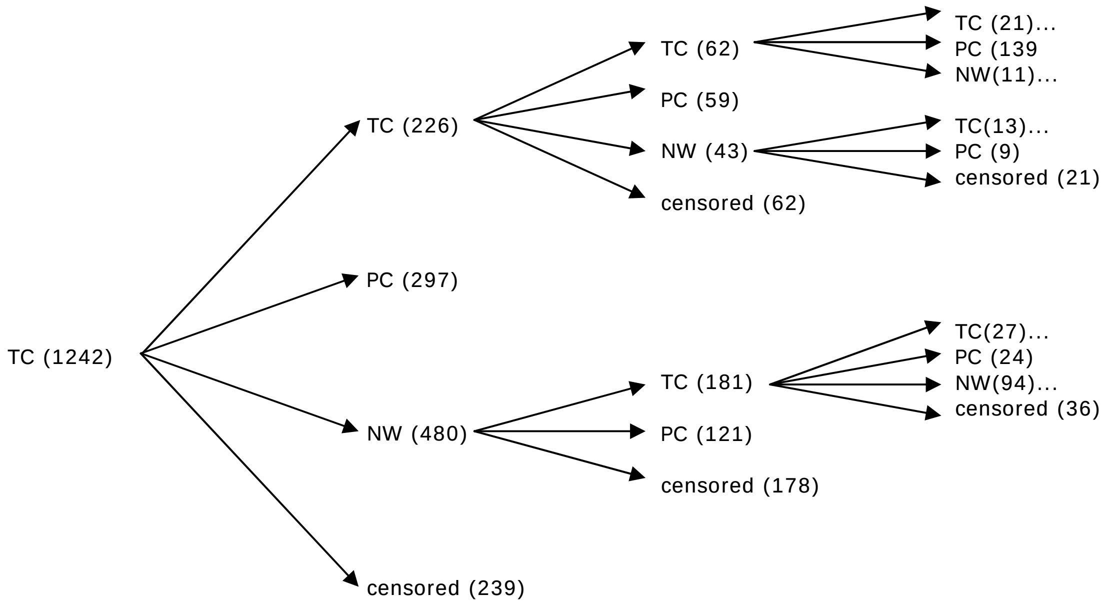
Notes. Sample size: 1242 individuals between 18 and 55 in 1997. 1st spell after the end of full-time education is of TC type.

Table.2 Number of individuals by TC and NW experiences

		NW spells									
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**total**
	0	-	-	-	-	-	-	-	-	-	0
	1	536	299	-	-	-	-	-	-	-	835
	2	121	90	54	-	-	-	-	-	-	265
	3	30	23	15	9	-	-	-	-	-	77
	4	5	8	6	14	1	-	-	-	-	34
TC spells	**5**	6	6	4	2	1	1	-	-	-	20
	6	-	2	1	2	-	1	1	-	-	7
	7	2	1	-	-	-	-	-	-	-	3
	8	-	-	-	-	-	-	1	-	-	1
	total	700	429	80	27	2	2	2	0	0	1242

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

Table.3 Individual labor market histories



Notes. Individuals between 18 and 55 in 1997.

Table.4 TC and NW spells composition

		n. spells	%	average length	% in the 1st spell
TC					
	"Formazione lavoro"	407	21.3%	42 (30)	17.1%
	Fixed-term	810	42.2%	43 (28)	36.1%
	No contract	690	36.5%	55 (41)	46.8%
NW					
	Unemployed	453	64.3%	33 (19)	61.1%
	Housework	199	28.2%	88 (84)	30.2%
	Education	53	7.5%	35 (31)	8.7%
	Total	2612			

Notes. Sample size: 1242 individuals between 18 and 55 in 1997. 1st spell after the end of full-time education is of TC type. "Formazione lavoro" only available since 1984. "Average length" measured in months, in parenthesis for complete spells only. For NW "first spell" means the one just after the first TC.

Table.5 Length of spell by type of transition

	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
months	n.	%	n.	%	n.	%	n.	%	n.	%
0-6	68	18,0%	244	33,9%	61	14,5%	103	37,2%	63	36,5%
7-12	61	16,1%	119	16,6%	47	11,2%	61	27,0%	27	22,1%
13-24	85	22,5%	105	14,6%	79	18,8%	41	15,8%	18	16,7%
25-60	116	30,7%	138	20,6%	137	32,6%	41	11,8%	28	13,7%
>61	48	12,7%	103	14,3%	96	22,9%	31	8,2%	32	11,0%
	378	100%	710	100%	420	100%	287	100%	168	100%

Notes. Sample size: 1242 individuals between 18 and 55 in 1997 for a total of 2612 spells. 1st spell after the end of full-time education is of TC type.

Table.6 Summary statistics – 1st TC spell

	n. spells	mean	st. dev.	Min	max
Age	1242	18	(5,71)	10	44
Children	1242	0.08	(0.27)	0	1
Male	1242	0.36	(0.48)	0	1
Married	1242	0.06	(0.23)	0	1
NW exp.	1242	17	(0.34)	0	202
Low Education	1242	0.48	(0.49)	0	1
Medium Education	1242	0.38	(0.48)	0	1
High Education	1242	0.14	(0.34)	0	1
Low Occupation	1242	0.66	(0.47)	0	1
Medium Occupation	1242	0.30	(0.32)	0	1
High Occupation	1242	0.04	(0.18)	0	1
"Formazione Lavoro"	1242	0.17	(0.37)	0	1
Proper TC	1242	0.36	(0.38)	0	1
No contract	1242	0.47	(0.49)	0	1
Cohort 1947-1957	1242	0.31	(0.46)	0	1
Cohort 1958-1968	1242	0.38	(0.48)	0	1
Cohort 1969-1979	1242	0.31	(0.46)	0	1

Notes. Individuals between 18 and 55 in 1997. 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. *Proper TC*: proper fixed-term contract. *No contract*: no contract.

Table.7 NPMLE, linear baseline hazard

	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio
Age	-0.026	(-6.636)	0.056	(14.668)	0.024	(1.155)	0.033	(0.903)	0.049	(8.270)
Married	-0.429	(-10.707)	-0.1498	(-3.810)	-0.550	(-14.096)	-0.269	(-3.801)	-0.182	(-2.293)
Male	0.116	(4.258)	-0.821	(-15.526)	0.357	(6.807)	0.892	(34.698)	0.721	(17.228)
Children	-0.117	(-2.873)	0.067	(2.525)	0.650	(14.146)	0.421	(5.468)	-0.252	(-2.540)
Low education	-0.193	(-4.692)	-0.256	(-6.346)	-0.627	(-9.405)	-0.438	(-9.761)	-0.115	(-3.853)
High education	0.389	(15.546)	-0.521	(-9.399)	0.057	(2.564)	0.656	(12.078)	-0.016	(-0.894)
U. rate	-0.014	(-3.695)	-0.013	(-3.245)	-0.008	(-2.870)	-0.004	(-1.031)	0.059	(4.433)
Cohort '47-'57	-0.259	(-4.929)	-0.395	(-8.023)	-0.197	(-4.155)	-0.303	(-5.249)	0.151	(2.908)
Cohort '69-'79	0.189	(4.105)	0.016	(2.397)	-0.574	(-9.106)	0.122	(2.703)	-0.731	(-12.295)
Low occupation	0.172	(4.960)	0.592	(11.760)	0.027	(3.229)	-		-	
High occupation	0.093	(4.134)	-0.270	(-11.725)	-0.789	(-6.718)	-		-	
"Form. Lav."	0.140	(3.104)	-0.531	(-14.666)	0.102	(2.093)	-		-	
No contract	0.264	(6.411)	-0.379	(-7.608)	-0.074	(-2.969)	-		-	
Olf	-		-		-		0.127	(1.876)	-0.098	(-3.789)
NW exp.	-0.019	(-3.810)	-0.040	(-6.770)	-0.093	(-6.974)	-0.027	(-3.007)	-0.102	(-6.182)
TC exp.	0.051	(4.985)	-0.019	(-3.271)	0.005	(1.309)	-0.097	(-7.368)	-0.107	(-5.907)
LnTime	-0.255	(-11.556)	-0.187	(-11.375)	0.112	(4.991)	-0.372	(-15.411)	-0.365	(-11.822)
Constant	-2.434	(-30.423)	-1.696	(-45.334)	-1.458	(-18.933)	-2.030	(-19.139)	-3.248	(-26.176)
δ	1.000	-	-28.835	(-53.870)	36.077	(89.719)	20.406	(87.034)	-9.993	(-47.611)
λ	1.000	-	-11.674	(-16.730)	-5.456	(-4.130)	-7.634	(-52.847)	-4.520	(-16.837)
	$v_1^a=0$, $v_1^b=0.713$ (32.967)									
	$v_2^a=0$, $v_2^b=0.027$ (9.553)									
	$P_1=0.331$, $P_2=0.103$, $P_3=0.287$, $P_4=0.299$									
mean log-lik:	-2.4167									
n. spells:	2612									

Notes. Individuals between 18 and 55 in 1997. N. of individuals: 1,242. 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. *LnTime*: log of duration in years. *U. rate*: standardized national unemployment rate. *Low Occupation*: blue-collar type. *High Occupation*: managerial type. *"Formazione Lavoro"*: training contract. *No contract*: no contract. *Olf*: out-of-labor-force. δ and λ set to 1 in one transition and v_1^a and v_2^a set to 0 for identification issues.

Table.8 NPMLE, flexible baseline hazard

	TC-TC		TC-NW		TC-PC		NW-TC		NW-PC	
	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio	coeff.	t-ratio
Age	-0.091	(-4.756)	0.056	(8.125)	0.003	(1.540)	0.013	(2.312)	0.032	(4.015)
Married	-0.405	(-11.678)	-0.213	(-3.974)	-0.526	(-6.342)	-0.188	(-2.887)	-0.151	(-2.877)
Male	0.128	(3.015)	-0.691	(-9.354)	0.487	(6.349)	0.666	(12.772)	0.716	(13.876)
Children	-0.106	(-1.247)	0.066	(2.756)	0.594	(4.003)	0.320	(5.763)	-0.181	(-3.233)
Low education	-0.209	(-5.618)	-0.242	(-6.387)	-0.657	(-10.654)	-0.267	(-2.978)	-0.076	(-2.124)
High education	0.362	(7.849)	-0.512	(-12.870)	-0.017	(-1.876)	0.520	(2.343)	-0.102	(-1.804)
Urate	-0.023	(-3.253)	-0.005	(-1.978)	-0.017	(-4.863)	-0.019	(-2.835)	0.051	(4.875)
Cohort '47-'57	-0.193	(-3.668)	-0.296	(-5.985)	-0.034	(-2.115)	-0.295	(-3.617)	0.225	(3.698)
Cohort '69-'79	0.135	(4.845)	0.091	(2.002)	-0.478	(-8.312)	-0.010	(-1.376)	-0.707	(-13.842)
Low occupation	0.187	(3.765)	0.548	(8.478)	0.012	(2.321)	-		-	
High occupation	0.054	(2.978)	-0.174	(-8.234)	-0.683	(-6.487)	-		-	
"Form. Lav."	0.110	(1.987)	-0.463	(-9.774)	0.172	(3.345)	-		-	
No contract	0.204	(4.654)	-0.355	(-5.567)	-0.071	(-2.865)	-		-	
Olf	-		-		-		0.098	(1.567)	-0.103	(-3.775)
NW exp.	-0.017	(-1.268)	-0.034	(-5.801)	-0.085	(-5.869)	-0.046	(-3.224)	-0.088	(-5.943)
TC exp.	0.050	(2.943)	-0.053	(-3.264)	-0.037	(-2.829)	-0.062	(-4.011)	-0.141	(-6.237)
LnTime	0.547	(9.384)	0.525	(8.644)	0.575	(10.679)	0.519	(7.487)	0.702	(8.983)
Spline 6	-0.723	(-11.451)	-2.476	(-19.876)	-1.070	(-14.007)	-2.075	(-22.501)	-2.844	(-18.996)
Spline 12	-0.034	(-2.006)	2.082	(18.761)	1.145	(10.713)	0.607	(5.213)	1.798	(7.394)
Spline 24	-0.702	(-12.543)	-0.518	(-4.478)	-1.143	(-15.421)	0.401	(3.998)	-0.170	(-4.102)
Constant	-1.327	(-11.910)	-0.763	(-5.876)	-1.442	(-16.231)	-0.189	(-7.959)	-1.209	(-4.657)
δ	1.000	-	0.998	(19.006)	0.536	(10.943)	1.255	(14.990)	0.251	(4.719)
λ	1.000	-	-1.751	(-13.583)	-0.609	(-8.010)	-0.407	(-7.187)	-0.361	(-7.866)
	$v_1^a=0$, $v_1^b=0.429$ (9.654)									
	$v_2^a=0$, $v_2^b=0.054$ (3.965)									
	$P_1=0.343$, $P_2=0.097$, $P_3=0.265$, $P_4=0.295$									
mean log-lik:	-2.3956									
n. spells:	2612									

Notes. Individuals between 18 and 55 in 1997. N. of individuals: 1,242. 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. *Age* expressed in years. *Low Education*: primary school. *High education*: University degree or more. *LNDuration*: log of duration in years. *Spline 6*, *12* and *24*: time dummies. *U. rate*: standardized national unemployment rate. *Low Occupation*: blue-collar type. *High Occupation*: managerial type. *"Formazione Lavoro"*: training contract. *No contract*: no contract. *Olf*: out-of-labor-force. δ and λ set to 1 in one transition and v_1^a and v_2^a set to 0 for identification issues.

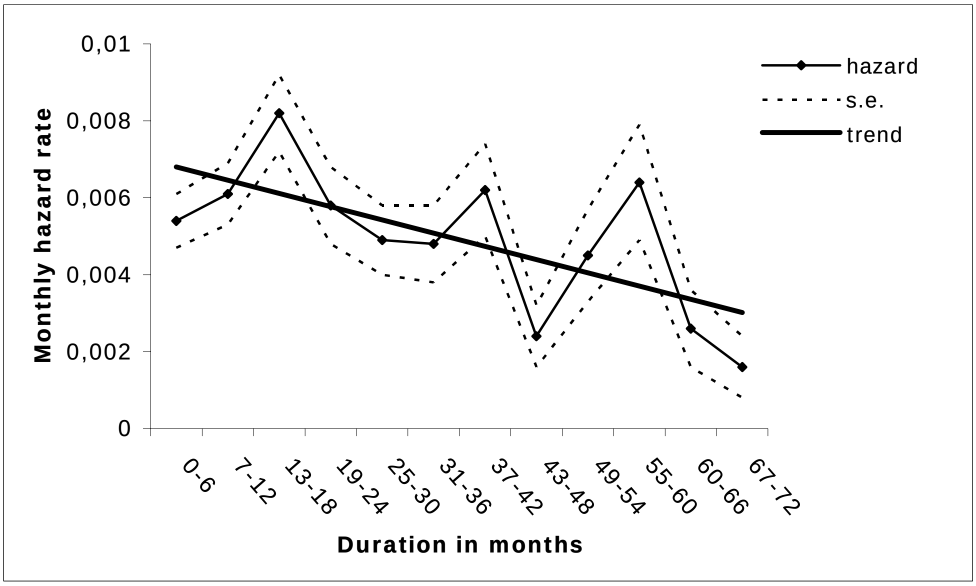
Table.9 Specification tests

	wald test	dg. of freedom	p-value
overall duration dependence	237.14	20	4,4226E-39
duration dependence TC-TC	41.95	4	1,70845E-08
duration dependence TC-NW	128.97	4	6,46639E-27
duration dependence TC-PC	78.65	4	3,36468E-16
duration dependence NW-TC	87.23	4	5,10184E-18
duration dependence NW-PC	103.45	4	1,8119E-21
flexible dependence TC-TC	28.47	3	2,89383E-06
flexible dependence TC-NW	67.94	3	1,17835E-14
flexible dependence TC-PC	78.98	3	5,07934E-17
flexible dependence NW-TC	132.48	3	1,57976E-28
flexible dependence NW-PC	154.97	3	2,23117E-33
unobserved heterogeneity	104.36	10	7,28182E-18

Notes. All tests performed on estimates presented in table 8. P-values computed on a Chi-squared distribution. The null hypothesis is the opposite of what specified in the first column.

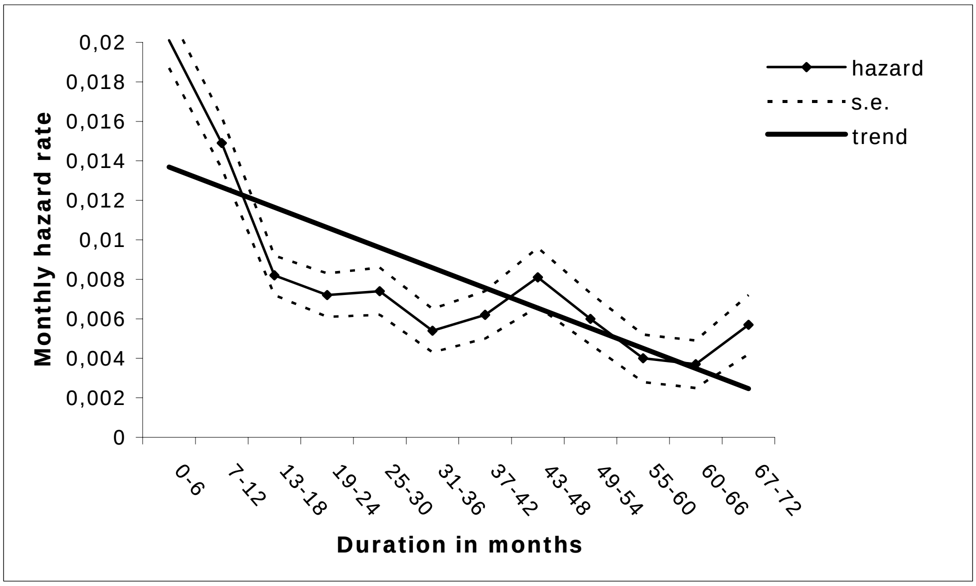
Graphs

Graph.1 Hazard rate TC-TC, Kaplan-Meier estimates



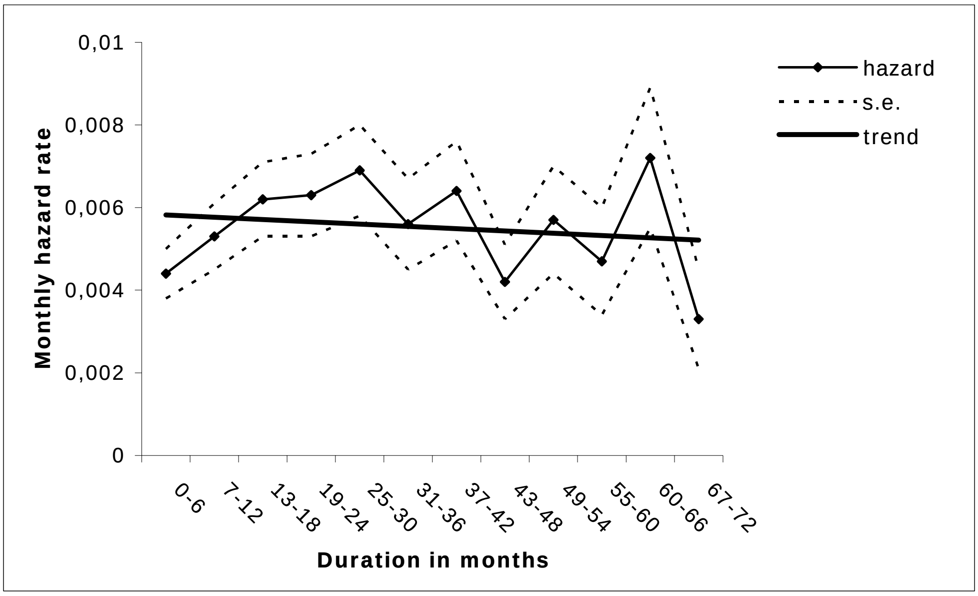
Notes. KM estimates computed as an “averaged” estimate centered on the midpoint of the interval. *s.e.* are standard errors. *trend* is a linear interpolation.

Graph.2 Hazard rate TC-NW, Kaplan-Meier estimates



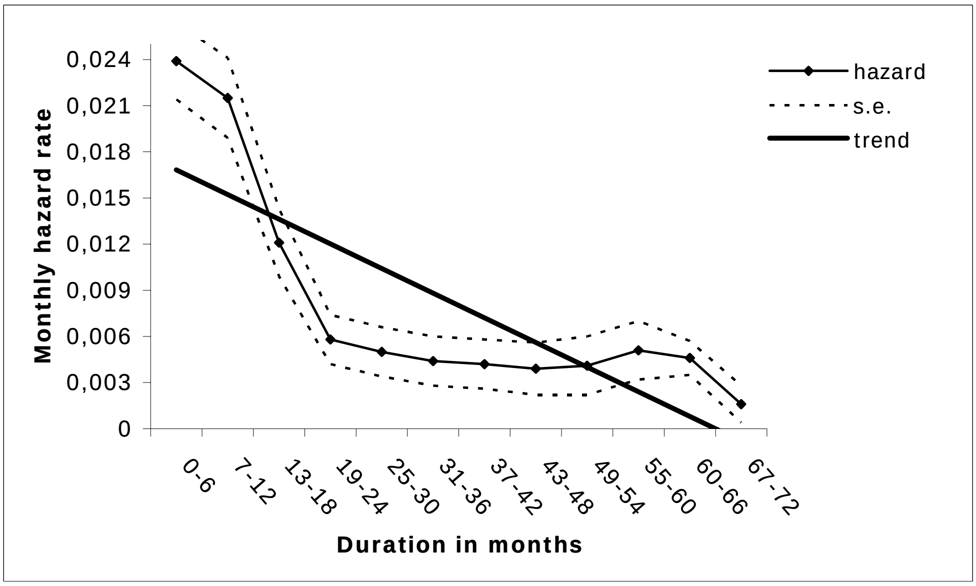
Notes. KM estimates computed as an “averaged” estimate centered on the midpoint of the interval. *s.e.* are standard errors. *trend* is a linear interpolation.

Graph.3 Hazard rate TC-PC, Kaplan-Meier estimates



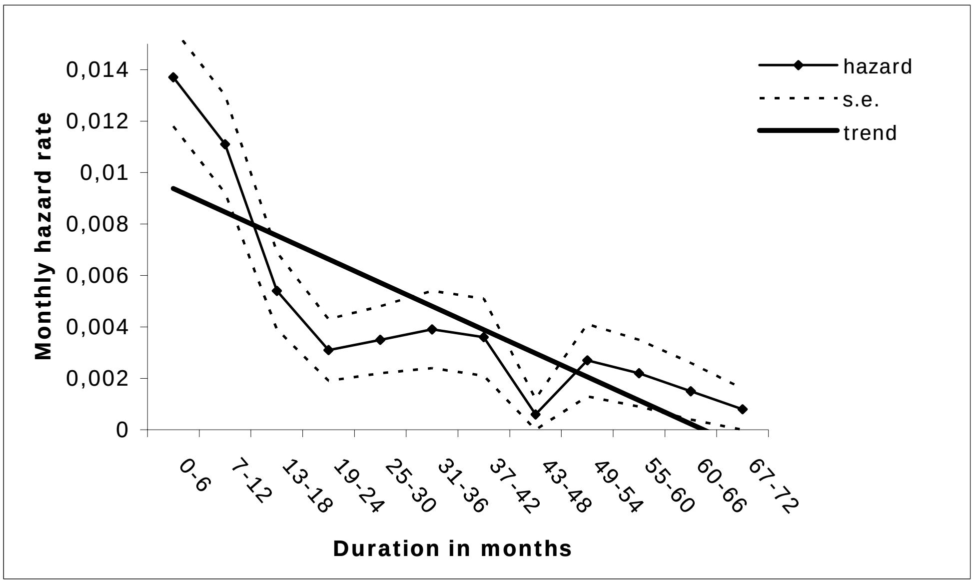
Notes. KM estimates computed as an "averaged" estimate centered on the midpoint of the interval. *s.e.* are standard errors. *trend* is a linear interpolation.

Graph.4 Hazard rate NW-TC, Kaplan-Meier estimates



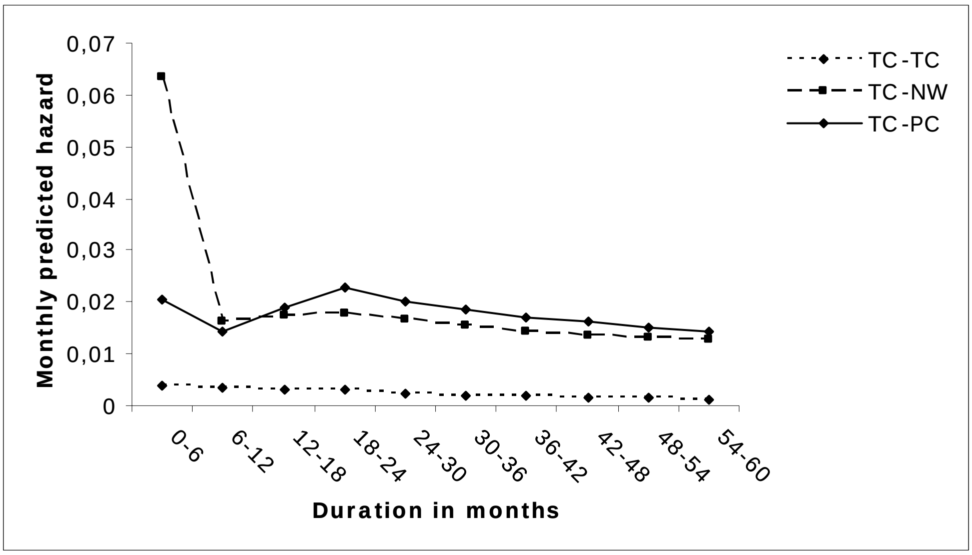
Notes. KM estimates computed as an "averaged" estimate centered on the midpoint of the interval. *s.e.* are standard errors. *trend* is a linear interpolation.

Graph.5 Hazard rate NW-PC, Kaplan-Meier estimates



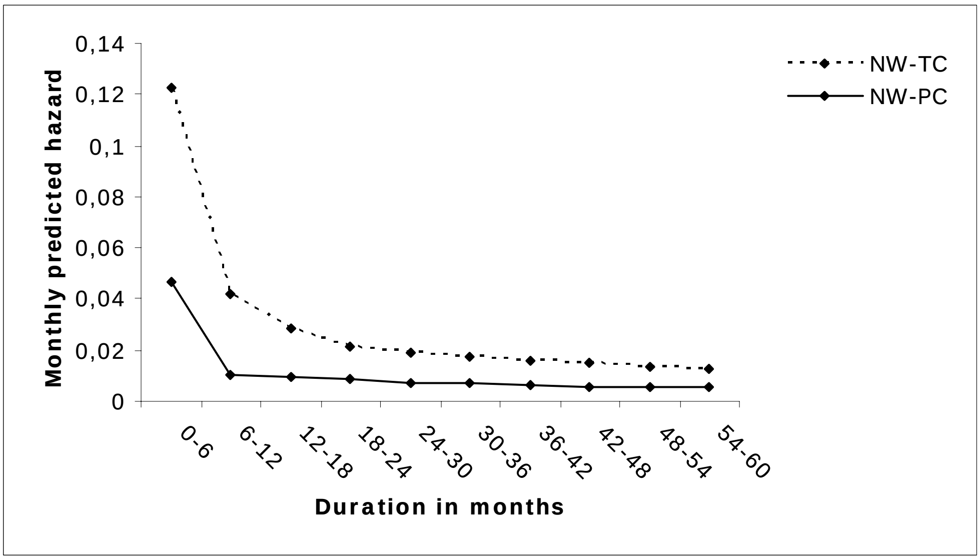
Notes. KM estimates computed as an "averaged" estimate centered on the midpoint of the interval. *s.e.* are standard errors. *trend* is a linear interpolation.

Graph.6 Predicted Hazard rate from TC, NPMLE estimates



Notes. Monthly predicted hazard (see table 8). Reference Category: male, not married, 25 years hold, medium education, no children, cohort '58-'68, unemployment rate 5,5%, medium occupation, proper fixed-term contract. Unobservable heterogeneity integrated out.

Graph.7 Predicted Hazard rate from NW, NPMLE estimates



Notes. Monthly predicted hazard (see table 8). Reference Category: male, not married, 25 years hold, medium education, no children, cohort '58-'68, unemployment rate 5,5%, unemployed. Unobservable heterogeneity integrated out.