Stepping-stone effect of atypical jobs: Could the least employable reap the most benefits?*

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Abstract

The causal impact of starting atypical work on the return to regular employment is measured using the timing-of-events approach. The employment and unemployment history of $1/25^{th}$ of French workers was reconstructed using three linked administrative data sources. During unemployment, starting atypical work is found to raise the likelihood of finding regular work by 75% in the following months, a robust stepping-stone effect. We find no evidence atypical work on wage growth and no lock-in effects. Long term unemployed workers, older job seekers, and those who did not work in the months before starting to look for a job have a lower chance of entering atypical work, but they benefit more from doing so.

1 Introduction

With the parallel rise in part-time jobs, temporary contracts, and agency work, there is considerable interest in understanding how atypical work arrangements affect the ability of workers to find regular

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work later in their career. But even after ample research, the question remains unsettled, because of varying methodology, context and data quality. This paper estimates the causal impact of atypical work – either part-time work or temporary work – on the transition to regular, full-time work, using a novel French administrative dataset. Contrary to previous studies, our data allows us to restrict our analysis to those workers who look specifically for permanent work and, using the exact timing and duration of labor contracts, to define precisely our outcomes of interest. We are also able to focus our analysis on specific sub-groups and disentangle between lock-in effects stepping-stone effects and wage growth effects.

For workers with weak ties to the labor market or those lacking the right skill set or experience, temporary atypical work may help improve skill levels, meet potential new employers, and eventually succeed in having a temporary position converted into a permanent contract. Agency work can also play a similar role (see Neugart and Storrie (2002) and Houseman et al. (2003)), as well as subsidized jobs (see Gerfin et al. (2005)). This is often referred to as the "stepping stone" effect of atypical work. However, atypical work may also reduce the time available or the incentive to search for the desired job. In many countries, the possibility of collecting partial unemployment benefits also raises the same moral hazard concerns as regular unemployment benefits do (see Ek and Holmlund (2011), for instance). These effects could potentially trap workers in a string of atypical jobs and repeated unemployment spells, the so-called "lock-in" effect.

Although all of these channels can exist simultaneously, it seems likely that not all workers will be affected uniformly. Workers with the lowest chances of finding work are probably the ones for whom atypical work may become a stepping stone towards a better job. For more skilled or experienced workers however, atypical work could provide little benefits, or even prove detrimental. Little attention has been paid in the literature to this potential heterogeneity, a neglect which could lead to poorly targeted labor policies. Another possible reason why the impact of atypical work on exit from unemployment may prove ambiguous is that workers with better skills may actually find it benefitial to search longer for a higher quality job.

We estimate the impact of atypical work on the probability of finding long-term stable employment using the well known timing-of-events model (Abbring and Van den Berg, 2003) on three linked French administrative datasets. We were able to obtain privileged access to a data set of $1/25^{\text{th}}$ of the French population covering a 7-year period. This data contains detailed information on the duration and motives for which workers registered at the French employment agency, data used to compute their unemployment benefits, and detailed information on all their employers, including their working hours, annual earnings, and firm-specific identifiers. It was therefore possible to define unemployment spells with great precision and identify at which point workers returned to stable full-time work without suffering from the censoring bias often encountered in the empirical literature.

Contrary to earlier contributions, we find no evidence of lock-in effect of atypical work, but a significant stepping stone effect. Having previously occupied an atypical job during an unemployment spell raises the monthly probability of finding regular work by 75% on average. We find larger stepping stone effects for long-term unemployed workers, younger and older workers, and those who did not work in the year prior to the start of the spell benefitted more. We also find no effect of atypical work on subsequent wages, suggesting that the benefits to workers may accrue entirely from reduced unemployed time.

The rest of the paper is organized as follows. Section 2 examines from a theoretical perspective the trade-off between an increased the probability of finding regular work and a higher expected wage. Section 3 presents the empirical model and its assumptions and Section 4 discusses several studies that have used similar approaches. Section 5, presents the data and details the construction of our variables of interest. Section 6 presents the results and Section 7 concludes.

2 The trade-off between wage and unemployment duration

This section formalizes the problem of a worker who, after atypical work, faces a trade-off between finding regular work more quickly or waiting for better job offers. The worker accepts a job offer when the value of accepting it at the proposed wage is higher than the value of remaining unemployed and receiving benefits b. To keep the model completely general, new job offers are heterogenous along two dimensions: i) the skill set required to occupy them and ii) the wage offer, which also includes any non-pecuniary aspects of the job offer from the worker's perspective. Jobs requiring skill set $s = 1..S$ arrive at rate p_s, and their value W is drawn from a distribution F_s with support $\left[0, \overline{W}\right]$. The variation in s captures the fact that while more job offers should be available for most job types, we do not want to exclude the possibility that gaining extra work experience in one area could deteriorate the chance of obtaining a job in some other sector.

At the beginning of an unemployment spell, a worker has not yet performed atypical work, which he can do only if he finds a suitable firm. There is a probability q of starting atypical work. For simplicity, we treat atypical work as an instantaneous, skill-enhancing event. The worker is risk neutral and the interest rate is r.

The value of being unemployed before atypical work is

$$\left(\sum_{s=1}^{S} p_s + r + q\right) U = b + \sum_{s=1}^{S} p_s \int_0^{\overline{W}} \max\left(W, U\right) dF_s\left(W\right) + qU^A. \tag{1}$$

Note that since atypical work is beneficial, $U^A > U$. For simplicity, we consider atypical work like any other skill-enhancing, instantaneous intervention. Modelling time spent in atypical work would slightly complicate the model without qualitatively changing its conclusions. Furthermore, this modelling assumption is in line with the empirical section where we argue that accounting for time spent in atypical work is non trivial.

Define R as the threshold value of a job offer that leaves the worker indifferent between accepting or rejecting it (before atypical work). Using $R = U$, we can rewrite equation 1 and obtain a solution for R:

$$rR = b + \sum_{s=1}^{S} p_s \int_R^{\overline{W}} (W - R)\, dF_s(W) + q\left(R^A - R\right) = b + \sum_{s=1}^{S} \theta_s E(S_s) + q\Delta R,$$

where $\theta_s = p_s (1 - F_s(R))$ is the job finding rate for skill set s and $E(S_s) = \frac{\int_R^{\overline{W}} (W-R) dF_s(W)}{1-F_s(R)}$ is the average surplus obtained from an accepted job of skill set s.

After performing atypical work, the worker faces a new set of probabilities of job offers, p_s^A, as a result of the new acquired skill, and adjusts its reservation value to R^A. Since $U^A > U$, $R^A > R$. The reservation value of a job offer after atypical work is

$$rR^A = b + \sum_{s=1}^{S} \theta_s^A E\left(S_s^A\right),$$

reflecting changes in both job finding rates θ_s^A and the expected value of accepted jobs $E\left(S_s^A\right)$ of skill set s. The difference in reservation value $\Delta R = R^A - R$ can be decomposed as

$$(r + q)\, \Delta R = \sum_{s=1}^{S} \left(\theta_s^A \Delta E(S_s) + \Delta\theta_s E(S_s)\right)$$

where $\Delta E(S_s) = E\left(S_s^A\right) - E(S_s)$ and $\Delta\theta_s = \theta_s^A - \theta_s$ are the differences in mean surplus and mean job finding rates of skill set s, respectively, before and after performing atypical work. This difference reflects the change in the expected surplus of an accepted job and the change in probability of exiting unemployment.

The change in job finding rates for skill s can be decomposed as

$$\Delta\theta_s = \Delta p_s \left(1 - F_s(R)\right) - p_s^A \left(F_s\left(R^A\right) - F_s(R)\right),$$

a combination of the change in job offers and change in reservation value. There is no guarantee that $\Delta\theta_s$ is positive. As discussed previously, Δp_s should be positive or zero for most skill sets s. But even if Δp_s was positive for all s, this effect could be counteracted by the change in reservation value and the density of job offers between R and R^A. If the worker no longer accepts many low-wage jobs, the net impact could be to actually reduce the job finding rate.

With $R^A > R$, atypical work is guaranteed to weakly increase the expected wage of any skill set s:

$$\frac{d\left(E\left(W_s\right)\right)}{dR} = \frac{\partial}{\partial R}\left(\frac{\int_R^{\overline{W}} W dF_s(W)}{1 - F_s(R)}\right) = \frac{f_s(R)\, E\left(S_s\right)}{1 - F_s(R)} \geq 0.$$

The impact of atypical work on the overall expected wage is also ambiguous, since it depends on its impact on the job finding rate of each skill set. If it increases the arrival of a disproportionate number of low-paying jobs that the worker still finds acceptable, the net effect on average wage gain could be negative. This is another version of the lock-in effect, whereby atypical work would only open doors to a career in less qualified, lower paid professions with fewer advancement opportunities.

Even though both impacts are ambiguous, we are able to establish a link between them. After algebraic manipulation, ΔU can be expressed as

$$\Delta U = \Delta R = \frac{\theta^A \Delta E(W) + E(S)\,\Delta\theta}{\theta^A + r + q}, \tag{2}$$

where $\theta^A = \sum_{s=1}^{S} \theta_s^A$ is the total job finding rate after atypical work, $E(S) = \frac{\sum_{s=1}^{S} \theta_s E(S_s)}{\theta_s}$ is the average surplus before atypical work, $\Delta\theta = \theta^A - \theta$ is the change in job finding rate brought about by atypical work and $\Delta E(W) = E\left(W^A\right) - E(W)$ is the increase in mean value of accepted regular jobs following atypical work. Equation 2 confirms that the impact of atypical work goes through expected wage and the expected length of unemployment. Since $\Delta U > 0$ by assumption, it follows that $\Delta\theta$ and $\Delta E(W)$ cannot both be negative at the same time. This provides a concrete prediction. If either term is negative, the other has to be positive.

The main focus of this paper is to estimate precisely $\Delta\theta$, and provide evidence concerning $\Delta E(W)$, to understand which dimension is more important for ΔU. Note, however, that since $q > 0$, the measured value of ΔU is affected by anticipations of entering in atypical work. It is a lower bound on the real impact of atypical work on the value of unemployment. To minimize the effect of anticipations (if q were close to zero), a 1^{st} order Taylor expansion can be employed. Denoting $\Delta R(q)$ as ΔR when q has its true value,

$$\Delta R(0) \approx \Delta R(q) - q\frac{d(\Delta R(q))}{dq},$$

where $\Delta R(0)$ would be the value of ΔR if q were equal to 0. Substituting $\frac{d(\Delta R(q))}{dq} = -\frac{\Delta R(q)}{r+\theta+q}$, we obtain

$$\Delta R(0) \approx \Delta R(q)\left(1 + \frac{q}{r+\theta+q}\right),$$

a non-negligible adjustment if the probability of entering atypical work, q, is large compared $r+\theta$.

Similarly, adjusted change in the job finding rate would be

$$\begin{aligned}
\Delta\theta(0) &\approx \Delta\theta(q) - q\frac{d(\Delta\theta(q))}{dq} \\
&\approx \Delta\theta(q) - q\sum_{s=1}^{S} p_s f_s(R)\frac{dR}{dq} \\
&\approx \Delta\theta(q) - \frac{q}{r+q+\theta}\sum_{s=1}^{S} p_s\left(F_s\left(R^A\right) - F_s(R)\right),
\end{aligned}$$

where $f_s(R)$ has been estimated by $\frac{F_s\left(R^A\right)-F_s(R)}{R^A-R}$ to obtain line 3. Hence, contrary to the measured net utility gain from atypical work, the measured gain in terms of job finding probability will be overestimated because of the change in the reservation wage value. The magnitude of this bias depends on $f_s(R)$, the density of job offers at the reservation wage R. Unfortunately, there is no direct way to estimate $f_s(R)$, or $F_s\left(R^A\right)$. Hence, we can only know that $\Delta\theta$ will be an upper bound for $\Delta\theta\,(0)$.

3 The empirical approach

The main difficulty in estimating the causal impact of atypical work on the rate at which workers find regular jobs is determining the appropriate counterfactual. A correlation between search effort for atypical work and search effort for full-time unexplained by observable factors could be spuriously interpreted as the effect of atypical work itself. More motivated job seekers might find both types of jobs more easily, leading to a positive correlation. However, workers with ample savings or with highly sought-after skills may focus on searching only for permanent positions, whereas those who have lost hope may also choose to accept atypical work, giving rise to a negative correlation. For these reasons, workers entering atypical jobs may not be comparable to workers who do not. The measured effect could also be biased due to dynamic sorting. Since workers enter atypical jobs only after a certain time spent in unemployment, those who have a higher probability of finding regular work will tend to do so before starting atypical work. Lastly, if probability of entering atypical work varies, so will anticipation, as shown in the last section, which will affect the measured causal impact of atypical work.

Two main strategies have been proposed to address the risk of spurious correlation. One strategy involves creating a synthetic comparison group by matching on observable criteria. The second strategy, used here, is often referred to as the "timing-of-events" (TOE) approach. Pioneered by Abbring and Van Den Berg (2003), it exploits the randomness of the timing of the entry into a treatment to calculate its causal impact while controlling for stable unobservable individual characteristics. It is especially useful for applications involving administrative datasets which often lack important demographic information. For instance, household savings are key to explaining an individual's job search behavior (see Bloemen (2002)), but this variable is seldom available. This approach also dispenses with the need for exclusionary restrictions in the form of covariates affecting the relevant outcome only through treatment assignment such as in IV approaches. Because entering into atypical work and into regular work are similar events, it would be difficult to find a variable that directly influences one, but not the other.

3.1 Timing of events

The fundamental assumption of the TOE approach is that events can be modelled as dynamic processes in which subjects don't know in advance the exact moment at which a treatment will begin, or when the outcome of interest will occur. This makes it well suited for the study of labor markets. From a worker's point of view, entry into treatment signifies starting a new atypical job. As in standard DMP search and matching models, workers are presumed to search continuously and not to know in advance when their search efforts will result in a new match. There may be heterogeneity in terms of search effort or employability across workers and over time, which varies the underlying risk of finding work. But, workers may not know in advance the exact moment at which an employer will hire them.

Finding regular work can be represented by a mixed proportional hazard model

$$\theta_R\left(t \mid x_t, a\left(t\right), V_R\right) = \lambda_R\left(t\right) \exp\left(x_t \beta_R + a\left(t\right)\gamma + V_R\right)$$

where θ_R is the risk of finding regular work and t is the time elapsed since the start of the unemployment spell.[1] We discretize the time intervals by month, an obvious choice given that many data sets already record information on part-time work on a monthly basis.

The baseline risk of finding work as function of time $\lambda_R(t)$ is independent of other covariates and will be modelled as piecewise constants for 10 time intervals (choosing different time intervals did not affect the results significantly).

Control variables in the vector x_t can vary with time. The treatment variable is $a(t)$, which equals 0 if a worker has never done atypical work during the spell (either worked part-time or accepting a temporary contract), and equals 1 as soon as he has done atypical work for at least once during the spell. As will be discussed in the next section, we will not separate the impact of doing atypical work currently and having done it previously in the spell. The impact of atypical work is captured by γ and assumed to be effective only after atypical work has occurred. This assumption, what Abbring and Van Den Berg (2003) call the "non-anticipation" assumption, is crucial for identification since it is the source of randomness in the treatment assignment.[2] The treatment effect, captured by γ, is not allowed to vary during and after atypical work; it is not heterogeneous in the benchmark specification.

V_R is an unobserved heterogeneity term that captures stable workers characteristics influencing the risk of finding regular work that are not included in x_t. As discussed earlier, V_R could be correlated

[1]Note that the notation of the empirical section is separate from the notation used in the previous section.

[2]One could challenge this assumption since some workers might be informed a few months ahead of time of the start of an atypical job. In all likelihood, workers could reduce their search activity in the months preceding the start of their atypical jobs, leading to a slightly over-estimated positive impact. However, since atypical jobs tend to start relatively quickly and since γ measures the difference in job finding rates for the whole period preceding and following the start of atypical work, such bias is probably small.

Alternatively, we may consider that the treatment starts at the moment at which the worker is informed that he will start a new job. This would be considered an information shock, as discussed by Abbring and Van Den Berg (2003). This information was not available in our data.

Also note that the non-anticipation assumption could be tested indirectly with information on search efforts, or on other behavior related to job market outcomes, such as consumption.

Finally, note that if some workers are indeed informed in advance of the start of an atypical job, they could potentially reduce their search effort in the meantime. However, the bias to the coefficient of interest should be mild since it compares the whole period before starting atypical work with the whole period following it.

with $a(t)$. If V_R is not included, the model is not identified since the treatment effect might spuriously capture the correlation between the probability of treatment and the probability of the outcome.

To deal with this selection effect, Abbring and Van Den Berg (2003) propose to compute the correlation between treatment assignment and outcome using information contained in the data itself. The TOE approach models jointly the outcome and the treatment assignment, allowing for unobserved heterogeneity in both processes. The instantaneous hazard rates are denoted θ_R for exiting unemployment and θ_A for entering treatment:

$$\theta_R(t \mid x_t, a(t), V_R) = \lambda_R(t)\exp(x_t\beta_R + a(t)\gamma + V_R)$$

$$\theta_A(t \mid x_t, V_A) = \lambda_A(t)\exp(x_t\beta_A + V_A).$$

V_R and V_A are unobserved heterogeneity terms that capture other worker characteristics influencing the risk of finding regular work and the risk of entering atypical work. They are allowed to be correlated, which captures the potential endogeneity of the outcome with the probability of starting atypical work.[3][4]

The model is estimated by maximum likelihood. Let $\tau_R \in (0, \infty)$ denote the time at which a spell is completed, and let $\tau_A \in (0, \infty)$ be the time at which an individual enters atypical work. All spells are censored after 36 months. The likelihood contribution of a single spell for an individual can be expressed as

[3] As discussed in Cockx et al. (2013), echoing Chamberlain (1980) and Wooldridge (2002) (p. 488), one consequence of this heterogeneity is its potential correlation with the explanatory variables. In that case, these variables would not carry a structural interpretation. Nevertheless, identification of the treatment effect remains unaffected.

[4] A common and equivalent formulation replaces V_R and V_A with $\ln(V_R)$ and $\ln(V_A)$.

$$
L\left(V_R, V_A\right) = \begin{array}{c} \left(\theta_R\left(\tau_R \mid x_{\tau_R}, a\left(\tau_R\right), V_R\right)\right)^{I\left(\tau_R \leq 36\right)} \exp\left[-\int_0^{\min\left(\tau_R, 36\right)} \theta_R\left(t \mid x_t, a\left(t\right), V_R\right) dt\right] \\ \times \theta_A\left(\tau_A \mid x_{\tau_A}, V_A\right)^{I\left(\tau_A \leq \tau_R \cap \tau_A \leq 36\right)} \exp\left[-\int_0^{\min\left(\tau_A, \tau_R, 36\right)} \theta_A\left(t \mid x_A, V_A\right) dt\right]. \end{array}
$$

Many individuals in our data experience multiple spells. We assume that an individual worker's V_R and V_A do not vary between spells. Owing to this assumption, several assumptions concerning the MPH model are no longer necessary. Abbring and Van Den Berg (2003) show that if V_R and V_A are stable for the same individual over different spells and if spells are independent of other spells given x, V_R and V_A, the proportionality assumption becomes less critical. The lack of independence between x, V_R, and V_A is also less problematic (van den Berg, 2001). We assume stability for the main specification, but let V_R, and V_A be spell-specific as robustness check.

The unconditional likelihood contribution of an individual with m unemployment spells is obtained by integrating $L\left(V_R, V_A\right)$ over V_R and V_A:

$$
L = \int\int\left(\prod_{i=1}^{m} L_i\left(V_R, V_A\right)\right) dG\left(V_R, V_A\right).
$$

It is possible to be flexible in the specification of the unobserved heterogeneity. We specify the distribution as bivariate discrete (see Lindsay (1983), Heckman and Singer (1984), Aitkin and Rubin (1985)). Because G is a finite mixture model with discrete support points, we can rewrite L as

$$
L = \sum_{j=1}^{J}\sum_{k=1}^{K}\left(\pi_{j,k}\prod_{i=1}^{m} L_i\left(v_{Rj}, v_{Ak}\right)\right)
$$

where $\pi_{j,k}$ is the probability of the individual having the vector of heterogeneity values (v_{Rj}, v_{Ak}) ((v_{Rj}, v_{Ak}) is an occurrence of the random vector (V_R, V_A)), J is the number of classes for the hazard heterogeneity of exiting unemployment, and K is the number of classes for the hazard heterogeneity of starting atypical work. Note that v_{R1} and v_{A1} are the constant terms of the reference group, and v_{Rj} and v_{Ak}, for $j, k \neq 1$, capture the heterogeneous risk of classes j and k in comparison with the reference group.

Because the weights $\pi_{j,k}$ are estimated as part of the likelihood, they are specified as logit to ensure that each probability is bounded between zero and one and that $\sum_{j=1}^{J}\sum_{k=1}^{K}\pi_{j,k} = 1$. Hence,

$$\pi_{j,k} = \frac{\exp(p_{j,k})}{\sum_{j=1}^{J}\sum_{k=1}^{K}\exp(p_{j,k})}.$$

One of the probabilities $\pi_{j,k}$ is residual with $p_{j,k} = 0$.

Montecarlo studies by Gaure et al. (2007) have shown that the TOE approach is very robust in computing causal effects and Lalive et al. (2008) have found that accounting for unobserved heterogeneity produces different results than the matching estimator. However, an important concern is identifying the proper number of support points of the distribution of V_R and V_A. Considering the nonparametric nature of both heterogeneity and baseline time dependence, Baker and Melino (2000) have indicated a risk of bias for the duration dependence and the coefficients of unobserved heterogeneity. To identify the number of support points, we adopt an approach commonly used in the literature, adding support points based on the improvement of model fit (based on the Akaike information criterion, as recommended by Gaure et al. (2007), or on the Bayesian information criterion).[5] The presence of time-varying covariates is also helpful in identifying heterogeneity in the data (see Brinch, 2011). Multiple spells play a similar role (see Gaure, 2007). As is discussed in the results section, even with a large sample, there is ultimately little heterogeneity in the data, and many models clearly favored the specification with only two support points.

This procedure is designed to control for selection bias arising from stable individual characteristics. However, in addition to V_R and V_A, there could also be unobserved, time-varying factors

[5] For specifications with spell-specific heterogeneity specifications, we follow Li and Smith (2015).

co–influencing the risk of finding atypical work and regular work. As a concrete example, imagine that after attending a job fair, a worker accepts an offer for a part-time job. Soon after, the worker also obtains an offer for regular work. If the econometrician cannot observe the job fair, its effect on the probability of finding regular work will be spuriously attributed to the temporary part-time job. Unfortunately, this eventuality is impossible to detect in an administrative data set containing little information about search efforts. Therefore, a necessary exclusionary restriction is the absence of time varying unobserved heterogeneity at the individual level.

A similar mechanism may be at play if, for instance, macroeconomic conditions influence the probability of finding both types of jobs. To account for this effect, we controlled for time- and region-specific unemployment rates. We also considered including a set of time dummies. However, it made the model prohibitively longer to estimate without affecting the results markedly.

4 Timing-of-events and time-varying treatment effects in the literature

The impacts of atypical work and of programs allowing to collect partial unemployment or similar employment-conditional benefit programs have been studied in a growing number of countries. We review the main contributions to this literature.[6]

Using Finnish data, Kyyrä (2010) find that workers benefitting from partial unemployment benefits have a greater likelihood of entering full-time work after the program, and that the likelihood of finding work during the program is not reduced. Using Danish data, Kyyrä et al. (2013) find

[6]Numerous other empirical methods have been used, and many took advantage of the access to administrative data. Most found that such programs have a positive impact on the return to regular work. See Givord and Wilner (2015) for the impact of short-term contracts and temporary agency work in France, see Ichino et al. (2008) for the impact of temporary help jobs and Berton et al. (2007) and Picchio (2008) for the impact of temporary jobs in Italy, Hartman et al. (2010) for the impact of temporary jobs for young British women, Hartman et al. (2010) for replacement contracts in Sweden, and Cockx and Picchio (2012) for short-term jobs in Belgium.

that exit rates from unemployment are reduced for workers receiving partial benefits, but slightly increased post treatment. A similar pattern is found by Fremigacci and Terracol (2013) in France, who measure also measure a reduced probability of finding regular work for workers currently receiving partial unemployment benefits, but markedly increased afterwards.

Differentiating between an in-treatment effect and a post-treatment effect is not trivial from a methodological point of view. As Cockx et al. (2013) point out, if the entry into treatment can lead to selection biases, so can exit from treatment. For instance, if there is heterogeneity in the chance of finding regular employment, workers still unemployed after exiting a temporary job will not have the same composition as those at the start of the job. The post-treatment effect will be affected by dynamic sorting. Fremigacci and Terracol (2013) address this issue by modelling both time-to-treatment and time-in-treatment. However, to be identified properly, the time-in-treatment model must also rely on the same assumptions required for the validity of the TOE approach. Crucially, a worker must not anticipate the end of a temporary contract, a strong assumption given that some workers may choose to quit voluntarily at a certain date in the future and that a substantial number of part-time jobs may have a predefined duration. This is especially true for France, which has stringent rules governing the maximum duration of temporary contracts.

To circumvent the possible endogeneity of exiting treatment, Cockx et al. (2013) do not differentiate between in- and post-treatment effects, but seek to identify a potential lock-in effect indirectly by allowing the treatment effect to vary over time. Using Belgian data, they find a positive impact of the program with no evidence of a lock-in effect. Richardson and van den Berg (2013) point out that, just like the baseline risk, an apparent variation in the treatment effect over time could be the result of compositional effects. If a program has a lock-in effect on some workers and a stepping stone effect on other workers, the composition of the workers participating in the program will change over time and the perceived treatment effect will inevitably decline as the group exhibiting the stepping stone effect exits to employment more quickly (Cockx et al. (2013) measure a negative but insignificant time dependence of the treatment effect). To distinguish between a time-varying and a heterogeneous treatment effect, Richardson and van den Berg (2013) prove identification of a time-dependent treatment effect and an unobserved heterogeneity in the treatment effect. In addition to Richardson and van den Berg (2013)'s methodology for identifying varying treatment effects over time, we estimate a specification in which the treatment effect depends on the time at which an individual entered treatment. This is potentially very helpful from a policy perspective in order to know whether active labor market policy should or should not target recipients that may have been unemployed for a long time.

If atypical work does raise a worker's career prospects, the worker could also choose to wait for a higher-wage job. Hence, the impact on the length of unemployment spells could in principle be ambiguous. To investigate this possibility, a secondary analysis examines the correlation between atypical work and wage growth. The following Section models clearly the link between the speed of exiting unemployment, the expected wage and their impact on unemployed worker's current utility.

5 The data

5.1 The FH-DADS dataset

An important contribution of our work is in terms of data quality. The FH-DADS is a combination of three matched French administrative data sources: The FH, the D3, and the DADS. The FH (historical file) contains information on an individual's history of interaction with the government employment agency (*Pôle emploi*). Unemployed or employed individuals can register with the agency to obtain job-finding assistance. The large majority of unemployed workers, defined according to the International Labour Organization, choose to do so. The FH contains information on the type of work sought, previous work experience, and socio-demographic background variables such as age, sex, marital status, and children. Crucially, the date of registration with the agency is used to determine the start of an unemployment spell. The agency also records a job seeker's hours worked per month for the duration of their registration.

The D3 is an extract from the national beneficiary file on workers receiving unemployment benefits. It contains detailed data on past wages used to calculate benefits. It is also a second source of information on atypical work, given that benefit collectors must declare current wage income to compute the net monthly UI benefits that they are allowed to receive.

Finally, the DADS (annual declaration of social data) is a matched worker-firm data set derived from the administrative declaration all French companies are required to file for fiscal purposes. It details the wages and hours worked for all their employees. In the version of the DADS matched with the FH and the D3, it provides for each worker the starting date of the first contract of the year and the ending date of the last contract of the year (January 1^{st} and December 31^{st} if the contract is ongoing) for all employers during the year. Data on the firms include three different sector classifications and an identification number that allows each firm to be tracked and could be used to match a firm with outside information. The main use of the DADS is to identify when a worker has returned to stable, full-time employment.

The information in the FH-DADS allows tracking the employment and unemployment history of individual workers from 1996 to 2004. It therefore permits a very precise definition of the start of unemployment spells, the end of unemployment spells, and several definitions of atypical work and partial unemployment benefits. The size of the data set permits an examination of various subgroups according to sector, employment history, age, etc.

A great advantage of the DADS data is that we can avoid the issue of non-random right censoring, an almost ubiquitous concern when using administrative data. Unemployment spells are often defined by participation in a government program, and spells are considered censored when a job seeker exits the program without further information.[7] Without data on future employment trajectories, there is no way of knowing when a new full-time open-ended job has been found. Workers who transit from a state of unemployment to another situation such as education, training, job placement programs, or nonparticipation in the labor force are typically recorded as censored. This censoring is, of course, non-random and will bias the estimates if it is not taken into account. Workers who perceive that they have a poor chance of finding full-time work are the ones most likely to exit the labor force for non-activity or education. Fremigacci and Terracol (2013) are the only authors who explicitly model this type of censoring by treating it as another random process.[8] With information on jobs contained in the DADS, it is possible to identify the exact moment at which a worker finds full-time work. Since we restrict our sample to workers who explicitly want regular work, decisions to eventually leave the labor force are not treated as censoring, but as part of the spell. Delaying the search process is simply considered an endogenous decision by the worker and enters the underlying risk dynamically. This is captured by the piecewise-constant baseline risk.

Unfortunately, observing only the first and last day of employment and the total hours worked during the year does not allow us to determine the exact number of hours worked each month, especially for part-time jobs. If monthly hours vary throughout the year or if there are periods of unemployment in-between two periods of employment, then these variations in work hours are necessarily averaged out. Also, if there is a change in the terms of a contract or in the wage level, it is impossible to determine during which month the change has occurred. Consequently, monthly hours worked derived from DADS data represent the average hours worked during the entire employment period over the course of a year.

[7] Kyyrä (2010) and Kyyrä et al. (2013) use periods of unemployment-related transfers as basis for spells. Fremigacci and Terracol (2013) use registration with employment centers as proxy for spells.

[8] For this treatment to be valid, censoring has to occur through a random process and be non-anticipated by the worker prior to its occurrence over and above the underlying risk.

In terms of scope, certain individuals are excluded from the DADS, notably government workers, public servants, those working for an individual private employer (15%, as estimated by Le Barbanchon and Vicard (2009)), and the self-employed. By restricting our sample to individuals already present in the DADS, these groups are excluded from the start. However, an individual previously in the DADS who finds work in a sector not covered by the DADS is considered still unemployed. Our estimates of interest would most likely be affected if the probability of moving to a sector not covered by the DADS differed between individuals who did atypical work and those who did not. Although this is possible, we believe that the resulting number of misclassifications should be relatively low.

Aside from these limitations, the FH-DADS offers numerous advantages, including its large data volume and long panel. It provides a 1/25th sample of the entire French population. Selecting for individuals present in both the FH and the DADS, the FH-DADS covers more than 250 000 individuals, each of whom experienced at least one unemployment spell. For the benchmark specification, a representative sample of 50 000 individuals was selected from the total sample.

Administrative data often have the drawback of offering fewer and less useful variables for researchers. This is not the case with the FH-DADS. Thanks to the combination of the three data sources, we were able to reconstruct the complete career history of a worker over many years. This makes it possible to precisely create each labor market variable. Notably, the DADS contains the complete employment history of workers after their return to work, allowing us to specify precisely what constitutes a true return to full-time stable employment. The following section provides exact definitions of unemployment spells and of atypical work.

5.2 Unemployment spells

A spell starts when an individual who has not been in a spell during the previous month begins a new job-seeking process with the employment agency.[9]

Here, we are interested in regular and stable employment. A worker is considered to have returned to work when the following three conditions are met:

1. From the DADS, we observe a month during which the worker has worked at least 140 hours.[10]

2. For the following six consecutive months, the worker works at least an average of 100 hours per month.[11]

3. The worker is no longer registered at the employment agency at the end of the six-month period.[12]

We tested different definitions for ending of unemployment spells, some of which are shown as robustness checks, but the results were not affected in notable ways. This definition of unemployment spells results in longer spell length than is typically reported in the literature. In part, this is due to our emphasis on stable jobs with sufficient average work hours, contrary to other authors who often

[9]Working with the FH data set, we have noticed that some spells start the day after a previous spell ends. These 'new' registrations seem to serve purely administrative purposes since only one parameter usually changes from one spell to the next. Thus, a spell that started immediately after a previous spell was considered the continuation of the previous one. Consequently, when many spells were merged together, the values of the variables at the start of a spell refer to the first of these 'sub-spells'.

[10]Because the DADS includes the beginning date and the end date of each job accepted over the course of the year and the total hours worked, we estimate the work hours in every month employed based on the total hours divided by the number of months worked. Total hours worked for all jobs during a month are simply the sum of the hours of every job.

[11]The worker is allowed to have several jobs or change employers during the period.

This ex-post way of observing a return to regular employment is similar to Cockx and Picchio (2012). It is an imperfect metric because even a seemingly stable job could nonetheless end abruptly, or a precarious job could last for a long time. This could be interpreted as a mismeasurement of the true duration, which would lead to conservative biases of hazard ratios (Meier et al., 2003). Nevertheless, we argue that the labor market information available for our investigation makes it possible to measure spells with greater precision than previously done in the literature.

[12]We only require deregistration at the end of the period because it may take some time for a worker to gain confidence in the stability of the new job and end his interaction with the agency, or for the agency to recognize that a worker is no longer using its services.

cannot observe work hours in the new jobs, or know how long the new job lasts. It is also partly due to the comparatively less dynamic French labor market with longer unemployment spells.

All censoring is non-informative. Censored spells are those ending after December 2004 or lasting longer than 36 months, the maximum length considered. There is thus no correlation between the length of a spell and the moment of censoring.

5.3 Atypical work

As explained in the previous section, our benchmark specification identifies a job seeker as treated for a given month if he or she is currently doing atypical work (and possibly receiving partial unemployment benefits) or has already entered into atypical work at least once during the spell. An intuitive definition of atypical work would be any work that does not satisfy the definition of regular employment. However, the structure of the DADS data set is ill suited for this purpose.[13] Therefore, our main treatment variables will be atypical work as defined in the FH data set on job seekers. Job seekers who are registered with the state employment agency are required to declare all professional activity on a monthly basis, regardless of whether they are eligible for unemployment benefits. Even after finding part-time work, they typically remain registered with the agency because it offers several advantages such as counselling, training, and internships, and could accelerate the process of qualifying for UI benefits in the future.[14]

An alternative definition of atypical work will also be used as a robustness test. The D3 data set of UI benefits recipients also provides information on monthly work activity. A worker is considered

[13] We did attempt to create a treatment variable using the DADS when we observed a new job that was part-time and not part of a new regular job. However, since we cannot observe changes of contracts within a single firm during a year, it prevents us from observing any short term contract that would have been followed by a regular contract in the same firm during the same year, rendering it virtually useless.

[14] A potential drawback of this variable is that once workers are deregistered from the agency (often following a missed appointment with a counsellor), their activity is no longer recorded. However, their unemployment spell might have continued because they are considered unemployed until we observe their return to regular employment in the DADS data set. Hence, it could be miscoded as zero if a worker exits the agency's lists without finding work. That said, workers are considered treated as soon as they show at least one month of atypical work within a spell. Thus, this type of miscoding would likely have occurred late in the spell and be negligible.

treated if he has received a positive amount of UI benefits while working a positive number of hours. We excluded individuals reported as having worked with zero hours, and those having worked long enough or earned enough income to have their UI benefits suspended completely.[15] Contrary to our preferred treatment variable, non-UI recipients or workers whose UI benefits have expired cannot be observed, which makes this variable less attractive. The results with this variable were nevertheless similar to those obtained with our preferred treatment variable.[16]

Figure 1 shows the empirical hazard rates into atypical work, the hazard rate out of unemployment if treated, and the hazard rate out of employment if no atypical work has been done according to the number of months since the start of the spell. For clarity, only the 95% confidence interval is shown. The figure is created from the entire sample.

All risks were fairly high in the first months of the spell and decreased substantially over time. Of course, we cannot know at this stage whether this is due to a decrease in search intensity or to a composition effect because highly active job seekers left the sample sooner. Workers who have already done atypical work show a higher probability of exiting unemployment, suggesting a positive impact of accepting atypical work on the probability of finding permanent work. This difference may be driven by selection effects and cannot be interpreted as causal.

Figure 2 shows the resulting stocks for workers who start atypical work (are treated) and those who do not during the spell. The complete data set contained 320206 spells. After 36 months, $12.9\% + 6.5\% + 24.2\% = 43.6\%$ of all spells had included at least one month of atypical jobs, and 55.6% of the workers had exited to full-time employment without being censored. In total, only $24.2\% + 29.2\% = 53.5\%$ of all entrants had found a job without being censored after three years. At

[15] To be eligible for PUI during the studied period, a job seeker must not have worked more than 136 hours per month or have earned more than 70% of his or her reference income.

[16] The FH, D3 and DADS data sets are complementary, each of them providing a different type of information about atypical jobs and PUI. We experimented with the three sources, attempting to merge their information into a single concept of atypical employment. Albeit a useful exercise, it would require intimate administrative knowledge of the three sources to do properly, which exceeds the scope of the present paper.

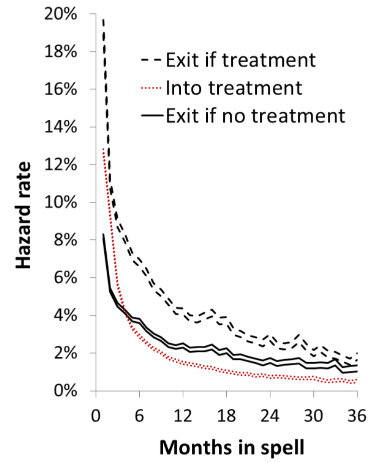

Figure 1: Probabilities of starting atypical work and finding regular work

Note: Only 95% confidence intervals are shown.

that time, the total fraction of censored spells was 12.9% + 21.6% = 34.5%. Note that those who eventually returned to unemployment after exiting were not recounted as unemployed.

Control variables

Control variables include an interaction of sex and marital status, considering that the impact of marital status on the labor market probably differs by sex. We also include 8 age dummy variables, 10 qualification dummy variables, the number of children, a dummy variable for non-French European citizens, and a dummy variable for citizens of non-European countries. As in Kyyrä et al. (2013), we also include information on work history during the year prior to the start of an unemployment spell because it might influence a worker's eligibility for receiving benefits and his motivation to start atypical work. Specifically, we include the total hours worked, the number of months during which benefits were collected, and the number of months registered at the employment agency. We also include the quarterly unemployment rate at the local level (over 300 employment zones), a variable that changes during the course of a spell.

A notable advantage of the FH-DADS is its wealth of detailed information on job seekers, which

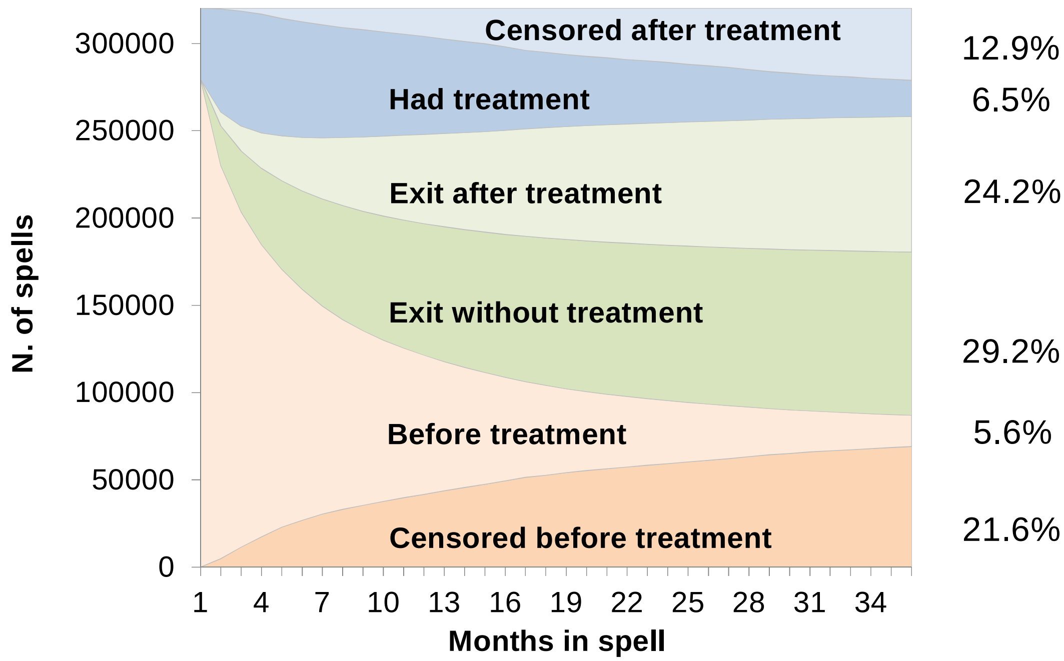

Figure 2: Number of unemployed workers according to time in spell.

allow us to exclusively retain those workers who are immediately available and looking for a full-time job, criteria that are rarely available in other data sets. We also excluded special worker categories such as show business workers with intermittent career paths. We retain spells with complete records only.

Table 4 shows descriptive statistics for the entire final sample. It shows that 44% of unemployed workers will eventually take atypical work at some point in their spell before going back to regular work. Men and unmarried workers are over-represented. Half of our sample is between 20 and 30 years old. In the year preceding the start of the spell, job seekers had worked on average 1083 hours, had been collecting UI benefits for 0.38 months, and had been registered at the employment agency for 1.44 months.

5.4 Alternative specifications

As a robustness check, the model is estimated using the second variable for atypical work, joint with UI, extracted from the D3 dataset. We also experiment with two alternative specifications for the definition of a new stable job. Our second – less stringent – specification requires a worker to work at least 100 hours per months in the three following months instead of six. The third – more stringent – requires 140 hours per months for the six following months to be considered as permanently employed with a stable job.

The FH-DADS has the advantage of providing a large volume of data that makes it possible to focus our attention on various subgroups and various subtreatments while enjoying appreciable sample sizes. This could facilitate fine-tuning active labor market programs and target job seekers who are most likely to benefit from atypical jobs. An important dimension to consider is labor market experience, especially in the year prior to the job loss. We split the sample in terms of the number of hours worked, the number of months registered at the employment agency, and the number of months unemployment benefits were collected, since this may affect eligibility to UI benefits and may predict the ability of a worker to find work quickly. We also consider specific age groups and occupation categories (according to French administrative classification), which may have varying difficulty in finding new work and, thus, benefit more from a stepping stone effect of atypical work.

We also consider a specification in which we let the effect of atypical work vary as a function of the time elapsed since the start of the spell. Presumably, atypical work could be especially beneficial for workers who have spent a long time unemployed and may be viewed as less employable by potential employers. If so, the long-term unemployed could represent a good target for active labor market policy.

As discussed in Section 4, identifying effects during and after atypical work runs into potential problems of dynamic sorting. However, to present potential lock-in effects of atypical work, we present estimates where the time elapsed since the entry into atypical work is decomposed into a series of lags, regardless of whether a worker is still doing atypical work or not. Finally, we implemented the methodology suggested by Richardson and van den Berg (2013) to identify the dynamic treatment effect.

5.5 The impact of atypical work on wages

As formalized in Section 2, the labor market benefits to workers from atypical work is not merely reflected in terms of speed of finding a regular job, but also in its expected wage. If an atypical job increases human capital and work opportunities, a worker could find the same jobs as before at faster rates, but may choose to wait for a better job offers. We find that this trade-off between speed and wage will depend on the distribution of job offers near the reservation wage. We also show that for the worker, the utility gain from doing atypical work can be expressed as a combination of its impact on the probability of finding regular work and on the average wage, adjusted by the probability of starting atypical work.

Obviously, many unobservable factors, current and expected, enter in the subjective valuation of a new job. The best that can be done is to use wage as proxy for subjective job quality. To verify if workers who do atypical work did in fact benefit from better wage increases, we estimate at the spell level the following linear model:

$$\Delta w_i = a_i \gamma + x_i \beta + \varepsilon_i$$

where Δw_i is the percentage increase in wage income six months after the end of the unemployment spell i compared to six months prior to the start of the spell and a_i has value 1 if the spell contained at least one month of atypical work. The vector of controls x_i includes a set of spell length dummies, the unemployment rate at the beginning of the spell, a set of age dummies, interaction terms between sex and marital status, the total hours worked, the number of months benefits were collected, and the number of months registered at the employment agency in the year before the beginning of the spell, the number of children, non-French European and non-European dummies, a dummy recording whether UI benefits received in the first month of the spell and professional category dummies. The disturbance term ε_i is assumed i.i.d..

In conformity with Section 2, this formulation assumes that job losers are uniform in terms of job prospects and that the impact is identical. Hence, the average wage gain of job finders is on average the same as the potential wage gains of those who do not find a job directly. If there was heterogeneity in terms of reservation wage or in terms of arrival of job offers, it could bias the estimate of γ upward or downward. Addressing these issues would require a model for labor market participation as well, a refinement that goes beyond the scope of this exercise.

6 Results

Table 1 shows results for the benchmark specification, with coefficients displayed as hazard ratios. Columns 1 and 2 correspond to the model without heterogeneity, and columns 3 and 4 correspond to the model with our benchmark two support points for (V_R, V_A). Despite the large data set, a specification with a larger number of support points could not be estimated. This suggests that most of the stable unobserved heterogeneity is already captured by the control variables.

The equations for finding regular work are presented in columns 1 and 3, and the equations for entry into atypical work are found in columns 2 and 4. Coefficients in bold are significant at the 5% level. Both specifications are displayed because the Akaike information criterion and the Bayesian information criterion do not agree on the best model. The coefficients of interest are not statistically different between both models. With 2 mass points, the correlation between V_R and V_A has to be ± 1. It is 1 here, implying that workers more likely to find regular work are also more likely to find atypical work.

In the 2 mass points specification, atypical work increases job finding rates by 75%, a relatively large impact in light of the literature and one that clearly supports a stepping stone effect rather than a lock-in effect, at least in terms of the probability of finding regular work. As discussed in Section 2, this impact may be partly amplified by anticipation since, as seen in Figure 1, the probability of starting atypical work is in fact higher than that of finding regular work in the first months of spells, probably raising workers' early reservation wage and slowing job finding rates.

The estimates for the control variables have intuitive interpretations. Younger workers, especially those between 20 and 29 years old, have a higher probability of exiting unemployment as well as a higher likelihood of finding atypical work, probably reflecting both higher levels of education, general skills and less experience, which makes them more mobile and opens more opportunities. Fewer savings could also motivate them to find a job more quickly.

Men, especially married, find both regular and atypical work more quickly. As for atypical work, single and married women find it with higher probability than men. This may reflect their reduced need for a stable, long-term job.

Workers who have worked more hours in the year preceding the spell find a new job more easily, especially regular ones. They may be more engaged with the labor market and are potentially recalled more often to their old job.

The coefficients associated with unemployment agency and UI reception in the past year are not easily interpretable since these two variables are probably highly collinear. The fact that workers who were registered at the employment agency for longer have a higher likelihood of finding any type of job may capture individual differences in the motivation of finding work, especially for individuals

Table 1: Benchmark results for a_{Aty}

Process	No heterogeneity				2 points of support			
	Exit		Treatment		Exit		Treatment	
	1		2		3		4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Did atypical work	**1.77**	0.02			**1.75**	0.024		
Spell dur. 1-2 mos	**5.62**	0.213	**9.14**	0.559	**5.46**	0.223	**8.99**	0.557
Spell dur. 3-4 mos	**3.67**	0.143	**5.08**	0.315	**3.59**	0.146	**5.01**	0.314
Spell dur. 5-6 mos	**3.09**	0.122	**3.63**	0.231	**3.03**	0.124	**3.6**	0.229
Spell dur. 7-8 mos	**2.67**	0.109	**2.99**	0.195	**2.63**	0.109	**2.97**	0.194
Spell dur. 9-11 mos	**2.15**	0.087	**2.44**	0.159	**2.12**	0.087	**2.43**	0.159
Spell dur. 12-14 mos	**1.96**	0.082	**2.08**	0.14	**1.94**	0.082	**2.07**	0.14
Spell dur. 15-17 mos	**1.89**	0.081	**1.9**	0.133	**1.87**	0.081	**1.9**	0.133
Spell dur. 18-21 mos	**1.59**	0.069	**1.48**	0.107	**1.58**	0.069	**1.47**	0.106
Spell dur. 22-25 mos	**1.33**	0.062	**1.28**	0.099	**1.33**	0.062	**1.27**	0.098
Spell dur. 26-30 mos	**1.24**	0.059	1.08	0.087	**1.24**	0.059	1.08	0.087
Unempl. rate (reg.×yr.)	**0.98**	0.003	**0.99**	0.003	**0.98**	0.003	**0.99**	0.003
Under 20	**3.68**	0.71	**3.14**	0.568	**3.72**	0.717	**3.15**	0.57
Aged 20 to 29	**5.02**	0.954	**3.81**	0.678	**5.07**	0.963	**3.82**	0.68
Aged 30 to 39	**4.12**	0.782	**3.24**	0.578	**4.14**	0.787	**3.25**	0.579
Aged 40 to 49	**3.5**	0.666	**3.09**	0.55	**3.52**	0.669	**3.1**	0.551
Aged 50 to 59	**2.05**	0.391	**1.93**	0.346	**2.04**	0.39	**1.93**	0.346
Single man	**0.87**	0.016	**0.87**	0.019	**0.87**	0.017	**0.87**	0.019
Single woman	**0.77**	0.016	**1.11**	0.026	**0.77**	0.016	**1.11**	0.026
Divorced man	**0.87**	0.029	**0.79**	0.03	**0.86**	0.029	**0.79**	0.03
Divorced woman	**0.74**	0.025	1.07	0.037	**0.74**	0.026	1.06	0.037
Married woman	**0.67**	0.013	**1.07**	0.023	**0.67**	0.014	**1.07**	0.023
Hours wrk p.y./1000	**1.27**	0.01	**1.12**	0.01	**1.27**	0.01	**1.12**	0.01
Months UI p.y.	**1.01**	0.005	**0.98**	0.005	**1.01**	0.005	**0.97**	0.005
Months Agcy p.y.	**1.03**	0.002	**1.05**	0.002	**1.03**	0.002	**1.05**	0.002

Number of children	0.99	0.007	**0.97**	0.008	0.99	0.007	**0.97**	0.008
European (non-Fr)	**0.89**	0.037	**0.87**	0.039	**0.89**	0.037	**0.87**	0.039
Non-European	**0.77**	0.021	**0.77**	0.022	**0.77**	0.021	**0.77**	0.022
Qual. N.S.	**1.39**	0.038	**0.73**	0.029	**1.4**	0.039	**0.73**	0.029
Qual. Routine tasks	**0.7**	0.033	**1.33**	0.068	**0.69**	0.034	**1.33**	0.068
Qual. Spec. wrk	**0.85**	0.024	**1.61**	0.052	**0.85**	0.025	**1.61**	0.053
Qual. Wrk w resp.	1.02	0.026	**1.73**	0.051	1.03	0.026	**1.73**	0.052
Highly qual. wrk	**1.11**	0.034	**1.68**	0.061	**1.12**	0.034	**1.68**	0.061
Non-qual. empl.	**0.7**	0.018	**1.31**	0.038	**0.7**	0.018	**1.31**	0.038
Qual. empl.	**0.94**	0.02	**1.49**	0.037	**0.94**	0.02	**1.49**	0.038
Technicians	**1.14**	0.03	**1.63**	0.051	**1.14**	0.03	**1.63**	0.051
Administrators	1.05	0.037	**1.34**	0.056	1.06	0.037	**1.34**	0.056
v_{R1} / v_{A1}	**0**	0.001	**0**	0	**0.01**	0.002	**0**	0.001
v_{R2}-v_{R1} / v_{A2}-v_{A1}					**-0.49**	0.137	0.7	0.13
$\pi_{1,1}$		1	-			0.066	0.085	
$\pi_{2,2}$						**0.934**	0.085	
Observations	812439				812439			
Nb Individuals	50000				50000			
Nb Spells	62830				62830			
Log Likelihood	-236566				-236563			
A. I. C.	473207				473204			
B.I.C.	474152.6				474187.4			
Corr(V_R, V_A)					1			

Note: Estimates showing hazard ratios (except weights $\pi_{i,j}$). Standard errors next to coefficients. Coefficients sig. at the 5% level in bold.

with fewer work hours. The impact of UI reception in the previous year, although significant, is close to zero.

Non-French and especially non-European job seekers find work with lower probability.

6.1 Time-varying impact of atypical work

Table 2 shows results for specifications allowing the effect of atypical work to vary. Column 1 allows the impact to vary since the start of atypical work, while column 2 also interacts atypical work with other explanatory variables as specified by Richardson and van den Berg (2013). In both specifications, we see that the effect diminishes over time in similar fashion. This result does not support the hypothesis of an initial lock-in effect due to reduced time available to search for regular work.

Column 3 shows the impact of atypical work as function of the time since job loss. The impact is high from the start, as was already suggested by Figure 1, but the multiplicative impact clearly increases as the spell gets longer, up to 333% for spells of 31-36 months. Clearly, the longer an individual has been unemployed, the more he will benefit from starting any job even if it is an atypical one. Considering that long-term unemployed workers have a very low job finding rate, it is not surprising to see them benefit from a stronger stepping stone effect. As shown in Table 1, long-term unemployed workers also have a low probability of entering into atypical work, implying that atypical work comes as a surprise for them and that this measured effect is barely affected by anticipation. From the point of view of a long-term unemployed worker, accepting a job considered less desirable in the short term can increase career prospects meaningfully in the medium term. From an active employment policy perspective, all else being constant, long-term unemployed worker assistance programs could be an attractive strategy.

Table 2: Impact of atypical work, alternative specifications / subgroups

	1		2*		3	
	Coef.	SE	Coef.	SE	Coef.	SE
Started aty. w. 1 mth ago	**2.042**	0.03	0.938	0.126		
Started aty. w. 2 mths ago	**1.504**	0.033	**0.687**	0.093		
Started aty. w. 3 mths ago	**1.586**	0.035	**0.727**	0.099		
Started aty. w. 4 mths ago	**1.495**	0.036	**0.697**	0.096		
Started aty. w. × age			**1.218**	0.046		
Started aty. w. × man			**0.931**	0.021		
Started aty. w. × time since spell st.			**1.006**	0.002		
Started aty. w. × Unemp. rate			**1.016**	0.005		
Started aty. w. × European (non Fr.)			1.107	0.091		
Started aty. w. × Non-European			1.054	0.058		
Started aty. w. at mth 1-2					**1.728**	0.023
Started aty. w. at mth 3-4					**1.813**	0.038
Started aty. w. at mth 5-6					**1.828**	0.052
Started aty. w. at mth 7-8					**1.759**	0.065
Started aty. w. at mth 9-11					**1.765**	0.07
Started aty. w. at mth 12-14					**1.91**	0.095
Started aty. w. at mth 15-17					**2.219**	0.132
Started aty. w. at mth 18-21					**2.125**	0.155
Started aty. w. at mth 22-25					**2.282**	0.224
Started aty. w. at mth 26-30					**2.234**	0.293
Started aty. w. at mth 31-36					**3.333**	0.623

Notes: Estimates showing hazard ratios. Standard errors next to coefficients. Coefficients sig. at the 5% level in bold. *Note unobserved heterogeneity rejected not supported by the data in this specification.

6.2 Alternative specifications and subgroups

Table 3 presents the results for various robustness checks and specific subgroups. Our alternative atypical work variable, which by construction only includes work while receiving partial unemployment insurance, causes an increase of 23.5% of the probability of finding regular work. This is because it may compare UI claimants to all unemployed workers, some of whom may lack assets and need to find a job more quickly and hence may reduce their reservation wage. Alternative definitions of regular employment has no effect on the measured effect of atypical work, neither does allowing the heterogeneity to vary between spells.

It is remarkable to see how uniform the impact of atypical work is on all the subgroups considered, all between 44.9% and 126.4%. The age groups that benefit the least from atypical work are the 20-29 year-old workers and those who benefit the most are workers over 60 years old. For workers younger than 20 years old, atypical work probably provides valuable entry experience in the labor market whereas for the old, it may provides a new means to enter the labor market after being displaced from a tenured job.

In terms of tasks, those who benefit the most are specialized workers, while those who benefit the least are executives and workers with non-specified qualifications. It is possible that these position is by nature more likely to start out as a regular open-ended job. Part-time or temporary positions might represent interim assignments with fewer possibilities of extending a contract.

Note that these results may also carry different implications for individual workers and for policymakers. Individual workers may be happier when their baseline job finding rate is multiplied by the highest amount. However, this does not necessarily mean that a policy maker should focus on groups who have the highest multiplicative effect of atypical work, since their baseline job finding rate may be already very low. For example, the model predicts that for workers aged 20-29 years old, at regressors mean for this sub group, the probability of finding regular employment goes from a

Table 3: Impact of atypical work, alternative specifications / subgroups

	Coef.	SE
Atypical work and UI	**1.235**	0.027
2^{nd} def. of reg. employment	**1.761**	0.024
3^{rd} def. of reg. employment	**1.721**	0.023
Spell specific heterogeneity	**1.768**	0.02
Worked >= 1000 hours year before spell	**1.694**	0.024
Worked < 1000 hours year before spell	**1.702**	0.022
Did not work year before spell	**1.768**	0.03
Was registered at emp. agency year before spell	**1.608**	0.017
Not registered at emp. agency year before spell	**1.793**	0.023
Received benefits year before spell	**1.467**	0.023
Did not receive benefits year before spell	**1.793**	0.022
Under 20	**1.752**	0.058
20 to 29	**1.611**	0.017
30 to 39	**1.759**	0.024
40 to 49	**1.822**	0.042
50 to 59	-	-
over 60	**2.264**	0.564
Qualification Not Specified	**1.449**	0.033
Qualified, Routine task	**1.655**	0.101
Qualified, Specialized worker	**1.925**	0.049
Highly qualified. worker	**1.815**	0.049
Non-qualified employee	**1.837**	0.039
Qualified employee	**1.772**	0.027
Technicians	**1.64**	0.029
Administrators	**1.829**	0.053
Executive	**1.496**	0.028

Notes: Estimates showing hazard ratios. Standard errors next to coefficients. Coefficients sig. at the 5% level in bold.

point estimate of 5.5% to 8.8%, a 60% increase, but also a 3.3 percentage points gain. For a worker over 60, the rate would go from 0.26% to 0.6%, an impressive 130% increase, but a modest 0.34 percentage-point gain. If the goal is to maximize the flow of unemployed workers into regular employment, maximizing the percentage-point increase by focussing on the 20-29 age group would seem the most beneficial. However, if the goal is to help the least employable, focussing on the workers over 60 years old would be preferable since they proportionally have the most to gain. This trade-off is present for most subgroups considered. The least employable seem to have the most to gain from atypical work and the stepping stone effect is the strongest for them.

6.3 Wage regression

Finally, Table 5 in appendix shows the results of the regressions for the impact of atypical work on the increase in wage between spells. Neither our main variable nor our alternative one have a measurable impact. Note that workers heterogeneity cannot be accounted for by this simple linear model. Nevertheless, these results suggest that the benefits of atypical work are mainly in terms of probability of finding work rather than wage increase, at least in the short term. Similar results were found by Fontaine and Rochut (2014) using dynamic matching on the same data set, whereas Booth et al. (2002) and Caliendo et al. (2016) did find a negative impact for the starting wage of certain subgroups of workers. Of course, other non-pecuniary aspects of jobs could be affected apart from the wage.

7 Conclusion

We have shown that atypical work and partial unemployment insurance significantly increase the probability that a French job seeker will find regular employment later on in his unemployment spell.

Our benchmark specification estimates that entering into atypical work results in a 75% increase in the monthly probability of exiting unemployment completely in the following months. Unobserved heterogeneity is present, but weak. We measured a positive correlation between the likelihood of finding regular work and that of finding atypical work.

Overall, the stepping stone effect is homogeneous for most subgroups of workers considered and for various time-varying versions of the impact of atypical work. There is an obvious inverse relationship between the likelihood of finding work and the impact of atypical work on job-finding rates. Job seekers who are younger, older, who have not worked in the year prior to their spell, and those who have been unemployed for a long time all start with a lower hazard rate into regular. Yet for them, the stepping stone effect is stronger in proportion. However, we find that a policy targeting groups who already have a higher chance of finding regular work would be better at increasing the total flow of workers out of unemployment. Hence, there is a tension between the objective of providing a stepping stone to the least employable and increasing equilibrium employment levels.

Our results support the idea that partial unemployment programs, specifically the French *Activité réduite* program, could help workers find regular work. At the individual level, entry into atypical work increases future career stability. However, partial unemployment programs do not encourage all types of contracts equally. It is an indirect subsidy for part-time or temporary jobs and its net impact on the composition of contracts in the labor market is unclear because firms might tend to decrease their use of permanent contracts in response. Because of the obvious risk of spillover effects on other job seekers, a meaningful cost–benefit analysis would require studying a real reform to the program or at least, modelling the entire labor market.

In addition, it is difficult to determine the specific impact of the *Activité réduite* program in its current form. Its monetary incentives vary from person to person according to the individual situation, but the program is available universally to all workers. Since the level of benefits received is the direct result of the number of hours worked during a month, the impact of PUI programs cannot be disentangled from the impact of atypical work without an identification strategy based on variation in legislation, or a structural approach in a general equilibrium setting. Finally, a more theoretical analysis of the program could address the context of optimal progressive income taxation.

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8 Appendix

Table 4: Descriptive statistics (spell level)

Variable	Mean	SE	Variable	Mean	SE
Will do atypical work	0.436	0.496	UI benefits/1000	4.02	27.89
Single male	0.336	0.472	Hours wrk p.y.	1083.3	735.99
Single female	0.24	0.427	Months UI p.y.	0.384	1.382
Div./sep./wid. male	0.037	0.188	Months Agcy p.y.	1.437	2.864
Div./sep./wid. female	0.038	0.19	Spell length 1-2 months	0.154	0.361
Married male	0.195	0.396	Spell length 3-4 months	0.085	0.279
Married female	0.155	0.362	Spell length 5-6 months	0.062	0.241
Qual. N.S.	0.082	0.274	Spell length 7-8 months	0.046	0.209
Qual. Routine tasks	0.019	0.136	Spell length 9-11 months	0.048	0.214
Qual. Spec. wrk	0.063	0.242	Spell length 12-14 months	0.036	0.186
Qual. Wrk w resp.	0.097	0.296	Spell length 15-17 months	0.03	0.17
Highly qual. wrk	0.046	0.209	Spell length 18-21 months	0.027	0.162
Non-qual. empl.	0.131	0.338	Spell length 22-25 months	0.019	0.135
Qual. empl.	0.359	0.48	Spell length 26-30 months	0.017	0.13
Technicians	0.076	0.265	Spell length 30-36 months	0.013	0.113
Administrator	0.033	0.179	Spell was censored	0.463	0.499
Executive	0.095	0.294	Under 20 y.o.	0.045	0.208
French origin	0.929	0.257	20 to 29 y.o.	0.492	0.5
European (non-French)	0.02	0.14	30 to 39 y.o.	0.239	0.427
Non-European origin	0.051	0.22	40 to 49 y.o.	0.139	0.346
Number of children	0.549	1.009	50 to 59 y.o.	0.081	0.272
			Over 60 y.o.	0.004	0.064

Table 5: Wage regressions on atypical work

	Type of atypical work	Coef.	SE
1	Atypical work	0.015	0.011
2	Atypical work (alt.)	-0.0043	0.0032

Note: Dependent variable: percentage change in wage before and after unemployment spells. Ordinary least squares estimation. Standard errors next to coefficients. Coefficients sig. at the 5% level in bold. Controls include a set of spell length dummies, the unemployment rate at the beginning of the spell, a set of age dummies, interaction terms between sex and marital status, the total hours worked, the number of months benefits were collected, and the number of months registered at the employment agency in the year before the beginning of the spell, the number of children, non-French European and non-European dummies, the amount of UI benefits received in the first month of the spell and professional category dummies.