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Unemployment duration, job search and labour market segmentation Evidence from urban Ethiopia

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Abstract[2]

Although it is a common theoretical assumption that the chances to find a job fall with time in unemployment, this is not systematically confirmed by empirical evidence, and there is no evidence for developing countries. We develop a framework that allows us to test the four major explanations why we may observe non-negative duration dependence while genuine duration dependence is negative: financial support for the unemployed, active labour market policies, a change in the economy over time, and segmentation of the labour market into 'good' and 'bad' jobs. Using data for urban Ethiopia we observe a constant hazard while controlling for unobserved heterogeneity, and find that labour market segmentation is the only convincing explanation.

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Estragon: *Wait.*
Vladimir: *Let's wait until we know exactly how we stand.*
[Becket S., 1955, Waiting for Godot]

1. Introduction

The notion that the probability to leave unemployment falls as one remains longer in unemployment has considerable intuitive appeal, and is a central assumption in many of the standard theoretical models (see for example Blanchard and Diamond, 1994; Ljungqvist and Sargent 1998). However, empirical work does not systematically observe a falling conditional probability to leave unemployment - or negative duration dependence, as illustrated in Table 1. Indeed, many studies observe non-negative duration dependence.[3] Why this apparent contradiction? There seems to be four potential explanations. In this paper we develop a framework to understand why observed duration dependence may be non-negative, while genuine duration dependence is negative, and test each of the four explanations. While existing work focuses on OECD countries, we carry out an analysis for a developing country, and apply the tests to data from urban Ethiopia.

The premise of this paper is that genuine duration dependence is negative in the long run. The reason is that unemployment implies a loss of skills, because of unlearning-by-not-doing, or because long periods of unemployment lead to a loss of self-confidence which lowers one's chances to get a job. In the short run, however, duration dependence may be non-negative. Four potential reasons are alluded to in the literature. A first reason is that the unemployed receive financial support that is limited in time. In richer countries this may take the form of state benefits, in poor countries the

[3] Although the increased observation of non-negative duration dependence may to some extent be the consequence of better observing the characteristics that lead to long term unemployment, or to advanced techniques to model unoabserved heterogeneity, this cannot fully explain non-negative duration dependence as argued by van den Bergh (2001).

unemployed receive support from their family. In both cases this support is limited in time, and as the expiry date approaches, the unemployed become more eager to find a job and lower their reservation wage. This pushes the hazard rate up and may lead to a non-negative hazard. Financial support of the unemployed has been found to explain why observed duration dependence is non-negative in the US (Katz 1986) and Norway (Hernaes and Strom 1996). A second potential explanation lies in the presence of active labour market policies, loosely defined as policies that help the long term unemployed finding a job quicker. This lifts up the hazard and may lead to a non-negative hazard rate. Employment programmes targeted to the long term unemployed have this effect, but the public sector, an important employer in urban areas in developing countries, may have similar effects, as we will see. Increasing the probability to leave unemployment for the long term unemployed, they lift the hazard rate. This explains why there is non-negative duration dependence in Sweden (Edin 1989) and in The Netherlands (van den Berg and van Ours, 1994). A third potential reason is that the economy changes over time. Since the long term unemployed are more likely to find a job in an upswing of the economy this lifts the hazard and creates the impression of non-negative duration dependence. Van den Bergh and van der Klaauw (2000), Abbring, van den Berg and van Ours (2002) and Cockx and Dejemeppe (2005) find that the hazard changes over time due to business cycle effects in The Netherlands, France and Belgium respectively, while Arulampalam and Stewart (1995) and Imbens and Lynch (2006) find that exit probabilities are different for distinct cohorts in the UK and US. A fourth potential explanation lies in the segmentation of the labour market into 'good' and 'bad' jobs. If the difference in earnings between the two types of jobs is large enough, it induces queuing in unemployment for a good job. Assuming that the hazard for getting a 'good' job falls with time in unemployment while the hazard for a 'bad' job remains constant over time, and since the probability of getting a good job is stochastic, people will lower their reservation wages – and thus be more likely to accept a bad job, as they stay longer in unemployment. This leads to a non-decreasing hazard rate. Korpi (1995) argues that this offers a good explanation for non-negative duration dependence in Sweden.

In the next section we set out a framework that allows us to test each of these explanations. In Section 3 we then describe the context and data for urban Ethiopia. In Section 4 we analyse the course of the hazard rate and in Section 5 we test each of the potential explanations, while Section 6 concludes.

2. A Framework for testing

Consider a classic job search model where a career is a dynamic game, where individuals start in unemployment and decide at each stage of the game whether they should leave unemployment or not. They do this by comparing their own preference with what is on offer in the labour market. Assuming (for now) that individuals are homogenous, the probability to leave unemployment at each point in time can then be seen as a product of the job arrival rate and the probability of accepting the job (π), which is conditional on not having accepted a job yet. The job arrival rate can further be written as the product of two factors: the probability that there is a vacancy (ν) and the probably of getting selected for the job (σ). Thus, we can write[4]:

$$\lambda_t = \nu_t \sigma_t \pi_t \tag{1}$$

[4] This can be seen as part of an extension of the classic job search model in two directions. The traditional job search model, as set out in Mortensen (1986), focuses on the reservation wage (π). Extensions of the basic model, for example a model that allows for liquidity constraints (Mortensen, 1986) or one that assumes finite lives, as described by Gronau (1971), relax one parameter and allow π to change over time, but it still assumes a constant job arrival rate. In order to explain the course of the hazard we are interested in changes over time and we also want to make the job matching process more explicit, dividing it into a vacancy and selection factor.

Let the first factor depend on the economy: $\nu_t = \nu(e_t)$, while the third factor is, like in the classic job search model, the probability that the job offer has a wage that exceeds the individual's reservation wage, at time t:

$$\pi_t = \pi\left(w > w_t^r\right) = \pi\left(w_t^r < w\right) = 1 - F_t^w\left(w^r\right) \tag{2}$$

Where F_t^w is the cumulative distribution of wages at time t.[5] Further assume that ν_t, σ_t and π_t are continuous and that their first derivative exists; we can write the change of the hazard over time, or observed duration dependence, as[6]:

$$\frac{d\lambda}{dt} = \underset{(A)}{\sigma\pi\frac{d\nu}{dt}} + \underset{(B)}{\nu\pi\frac{d\sigma}{dt}} + \underset{(C)}{\nu\sigma\frac{d\pi}{dt}} \tag{3}$$

The second term on the right hand side reflects the (unobserved) probability of being hired or genuine duration dependence, which we assume to be negative, as argued before $\left(\frac{d\sigma}{dt} < 0\right)$. This provides us with a framework to test each of the above explanations. Observed duration dependence is non-negative when

$$\sigma\pi\frac{d\nu}{dt} + \nu\sigma\frac{d\pi}{dt} \geq -\nu\pi\frac{d\sigma}{dt} > 0 \tag{4}$$

2.1. Financial support for the unemployed

The presence of financial support affects the hazard through term (C) in equation (3). Considering no changes in the economy we set term (A) equal to zero and observe a non-negative hazard when

[5] Like in the classic job search model we also maintain the assumption that the unemployed accept or refuse a job only on the basis of the wage and abstract from other job characteristics. Accepting a job thus depends on the reservation wage only and that π_t is a continuous monotonous function of reservation w^r.

[6] We further assume that the hazard is separable in the three factors.

$$\frac{d\lambda}{dt} = \nu\pi\underbrace{\frac{d\sigma}{dt}}_{(B)} + \nu\sigma\underbrace{\frac{d\pi}{dt}}_{(C)} \geq 0 \tag{5}$$

Since term (B) is strictly negative, ν, π, σ are positive, equation (6) holds iff:

$$\frac{d\pi}{dt} > 0 \tag{6}$$

Now let the reservation wage depend on household welfare:

$$w_t^r = S_t\left(HHW\right) \tag{7}$$

and let *S* and *π* be monotonic functions in *t* and *HHW*, and assume that their first derivatives exist. It is straightforward to show that (6) holds as long as

(i) $$\frac{d\pi}{dS\left(HHW\right)} < 0 \tag{8}$$

(ii) $$\frac{dS\left(HHW\right)}{dt} < 0 \tag{9}$$

since $$\frac{d\pi}{dt} = \frac{d\pi}{dS\left(HHW\right)} \frac{dS\left(HHW\right)}{dt} > 0 \tag{10}$$

Equation (8) states that reservation wages are higher for those coming from richer households, because wealthier households provide more support; while equation (9) states that financial support decreases with time in unemployment in all households - because it represents a serious draw on the household's resources or because free riding behaviour is punished after some time. To test this we combine (1), (2) and (7). Since λ is positive in *π* and assuming (9), we can write:

$$\frac{d\lambda}{dS} = \frac{d\lambda}{d\pi} \frac{d\pi}{dS} < 0 \tag{11}$$

We test whether $\frac{d\lambda}{dS} < 0$

2.2. Active labour market policies

Public sector employment affects the hazard through term (B) in equation (3). Let the selection rate be the sum of the market or genuine selection rate (σ_m) and the selection rate from the government programme or public sector (σ_p): $\sigma = \sigma_m + \sigma_p$, and let both σ_m and σ_p be continuous monotonic functions in *t*, and their first derivative exist. While the genuine selection rate decreases with time spent in unemployment $\left(\frac{d\sigma_m}{dt} < 0 \right)$, the public sector selection rate may increase or decrease over time. When the vacancy rate in the public and private sector are constant, we will observe non-negative duration dependence when

$$\frac{d\sigma_p}{dt} \geq -\frac{d\sigma_m}{dt} > 0 \tag{12}$$

or, when the probability to get a public sector job is at least as large as, but opposite in sign to genuine duration dependence. The public sector may for example prefer to hire candidates who have been in unemployment for longer out of fairness consideration when labour demand is censored and the unemployed are queuing for a(ny type of) job. We test whether $\frac{d\sigma_p}{dt} > 0$

2.3. Changes in the economy over time

Changes in the economy over time work through term (A) in equation (3) as they affect the probability that there is a vacancy $\nu_t = \nu(e_t)$. To get a non-decreasing hazard, the vacancy rate has to increase enough to compensate for genuine duration dependence:

$$\sigma\pi \frac{d\nu(e)}{dt} \geq -\nu(e)\pi \frac{d\sigma}{dt} > 0 \tag{13}$$

Solving this for $\nu(e)$, and substituting in equation (1) we obtain

$$\lambda \geq \sigma^2 \pi \left(\frac{-1}{d\sigma / dt} \right) \frac{d\nu(e)}{dt} \tag{14}$$

Since σ and π are positive while $\frac{d\sigma}{dt}$ is negative this only holds if the hazard is positively related to a change in the economy, which we can test.

2.4. Segmented labour market

In a segmented labour market, where good and bad jobs coexist, and the wage of the good job always exceeds that of the bad job $(w_G > w_B)$, the hazard will be the sum of the respective hazards in the two sectors, so equation (3) can be rewritten as:

$$\lambda = \nu_G \sigma_G \pi_G + \nu_B \sigma_B \pi_B \tag{15}$$

Further assuming that:

$$\pi_G = 1 \tag{16}$$

and:

$$\nu_B = \sigma_B = 1 \tag{17}$$

or, that a good job is never refused, that anyone can always get a job in the bad sector and that bad jobs require no skills so there is no duration dependence in the bad sector. Also assume that $\lambda, \nu_G, \sigma_G, \pi_G, \pi_B$ are continuous and that their first derivative exists.

We can the write duration dependence as:

$$\frac{d\lambda}{dt} = \frac{d\nu_G}{dt}\sigma_G + \nu_G \frac{d\sigma_G}{dt} + \frac{d\pi_B}{dt} \tag{18}$$

Where the second term on the right hand side now captures genuine duration dependence and falls over time as before $\left(\frac{d\sigma_G}{dt} < 0 \right)$. Observed duration dependence is non-negative when:

$$\frac{dv_G}{dt}\sigma_G + \frac{d\pi_B}{dt} \geq -v_G \frac{\partial \sigma_G}{\partial t} > 0 \qquad (19)$$

Under the assumption of a constant vacancy rate for bad jobs, a change in the vacancy rate of good jobs is identical to the case treated in the previous section, and is therefore further neglected here. For equation (25) to hold, the second term has to be strictly positive, and since $\frac{d\pi}{dw_r} < 0$ holds per definition, this requires:

$$\frac{dw^r}{dt} < 0 \qquad (20)$$

which we can test.

3. Ethiopian context and data

There are few studies of unemployment duration in developing countries. Existing work suggests that unemployment in low income countries is often concentrated among the urban middle classes, confirming Myrdall's (1968) early conclusion that it is a 'bourgeois phenomenon'.[7] Recent evidence also indicates that unemployment duration may be very long in this context, expressed in years rather than months.[8] We use the first round (1994) of the Ethiopian Urban Social-Economic Survey (EUSES) household data collected by the Economics Department of Addis Ababa University in co-operation with the University of Oxford and Goteborg University. The survey collected

[7] Similar points are made by Udall and Sinclair (1982) who talk about 'luxury unemployment' and Hirschman (1982) who argues it is a middle class phenomenon. Recent evidence suggests that it is indeed often a middle class phenomenon, but not a luxury, as it is not concentrated among the most well-off (see a.o. Serneels 2007).

[8] Dickens and Lang (1996) find that unemployment duration in Sri Lanka is four years; Kingdon and Knight (2004) find that thirty seven percent of the unemployed in South Africa are unemployed for three years or more, while Appleton et al. (2001) study unemployment duration among retrenched workers in China and find a mean duration of forty seven months.

cross section data and single spell unemployment duration data from a random sample of one thousand five hundred households in the seven largest cities.

Table 2 presents the characteristics of the urban labour market in Ethiopia. The public sector employs almost one third (27%) of the male labour force, while self-employment, casual and informal sector work employ another third (33%). The formal private sector is small (7%), a direct consequence of the plan economy under the Dergue.[9] The public sector pays the highest wages, followed by the formal private sector; while the self-employed have the lowest income from labour, earning less than half the salary of public sector employees. At the time of data collection unemployment was one of the highest unemployment rates worldwide, with about one in three of all active men unemployed. The private sector was expected to grow strongly as a new government had just come to power and it signed agreements to restructure and liberalise the economy.[10]

As in other economies, unemployment is concentrated among the young. It peaks at age nineteen and falls thereafter, to reach a sustained level only beyond age thirty. Our analysis therefore focuses on young men between age fifteen and thirty, who represent 81% of the unemployed.[11] Part 2 of Table 2 reports the descriptive statistics of the young. Over fifty percent of the young men are unemployed, with a mean duration of close to four years. Eighty seven percent of the unemployed have completed at least primary education while almost two thirds have finished junior secondary school or

[9] The Dergue ruled from 1974 till 1991 and implemented Soviet style policies. Most medium and large-scale enterprises were under government control while private firms were explicitly restricted in size and were not allowed in all sectors (e.g. construction, wholesale trade and transport).

[10] Given the closed nature of the previous regime, there is no reliable economic data on the years under the previous regime, not even on basic indicators like economic growth.

[11] The lower bound is driven by the legal context: employment below age fifteen is illegal and the data has no observations. The upper bound is chosen because beyond age thirty, unemployment is at a sustained and significant lower level. A t-test test indicates that the level of unemployment up to age thirty is significantly higher than beyond age thirty; while the level of unemployment up to age thirty one is no longer significantly different from that beyond age thirty one

more. On average one household member out of six is unemployed. Average consumption per household member is 25 USD and 70% of the household budget is spent on food. The mean value of household assets, excluding dwellings, is 289 USD.

Part three of Table 2 gives more details on the nature of unemployment. It is concentrated among the relatively well-educated first time job seekers, with about fifty percent of the urban young men being unemployed. About half of the unemployed are looking for a public sector job and unemployment duration is higher for those aspiring to a public sector job.[12] With these characteristics, the nature of unemployment in urban Ethiopia is similar to that observed in other developing countries like Sri Lanka (Dickens and Lang, 1996, Rama 1999), Tunisia (Rama, 1998), and China (Appleton et al 2001).

How did we measure unemployment and its duration? Unemployment is self-reported, but the level of detail of the questions and the presence of control questions make it impossible to pretend to be unemployed.[13] The duration of unemployment is measured as follows. Working men were asked how long their last spell of unemployment had lasted, giving a direct measure for unemployment duration. Because the unemployed themselves were not asked how long they had been unemployed, we calculate their

[12] For a detailed analysis of the nature of unemployment in urban Ethiopia, see Serneels (2007)

[13] Respondents were asked to describe their main activity, after which the enumerator selected one of the twenty five categories that best described the stated activity; if needed, a new category was added. Then, the respondent was asked a list of questions for that specific activity. We have information on two types of unemployment: those 'looking for work but unable to find any', and those 'not in paid work and not looking for work'. While some authors doubt whether the latter should be considered unemployed (see for example Flinn and Heckman 1983), others argue that in an environment with high unemployment, job search may be passive and people may be waiting for, rather than actively looking, for a job (See Kingdon and Knight 2004). This may even more valid when job search takes place through social networks, for which we find indications in Ethiopia. However, the second category only represents 6% of the unemployed in urban Ethiopia, implying a difference between the narrow and broad unemployment rate of less than 2%. Throughout the paper we use the use the broad unemployment rate, but all our results are robust using the more narrow definition. We also find that the unemployed in the two categories do not differ in their main characteristics.

duration as age minus time worked, minus the age at which schooling was completed.[14] The resulting mean duration is forty five months, which is close to the *observed* average duration of forty two months obtained from a more recent round of the survey where the currently unemployed were asked directly how long they had been unemployed. A unique feature of the data is also that we have information on the reservation wages of the unemployed.[15]

4. The course of the hazard rate

We first look at the course of the hazard rate and establish that we have non-negative duration dependence. Because duration model estimates are very sensitive to the underlying distributional assumptions - much more than ordinary regression analysis (see van den Bergh 2001) - we start from a non-parametric approach, to then compare with the results obtained from a parametric specification.

4.1. Non-parametric estimation

The Kaplan Meier survival function reflects the proportion of people who stay in unemployment as time proceeds and is plotted in Figure 1; it also allows us to calculate the product-limit estimate of the hazard function, which reflects the number of people leaving unemployment relative to the total number of people unemployed at each point

[14] Including the unemployed in the duration analysis is crucial because otherwise the analysis would suffer from a selection bias excluding those who remain unemployed. Completed spells also reflect past rather than present unemployment. Our approach is similar to the one used in early analysis of unemployment duration in OECD countries, but because many students in developing countries finish school late, we predict the age at which schooling was completed using a model that includes individual and household characteristics, including a term correcting for self-selection.

[15] This is obtained by asking ‘What is the lowest amount that you would be willing to accept as gross monthly income?’. Other work shows that the reservation wages are realistic, i.e. that it is plausible to find jobs that pay above the reservation wages (see Serneels 2007).

in time. [16] Figure 2 plots this non-parametric estimate of the hazard and indicates that it follows an upward trend – although not monotonic; it also remains below ten percent - which is in line with estimates for OECD countries.[17] The upward slope is somewhat surprising given the length of the duration spells; nevertheless this is a robust finding; when we drop outliers or restrict ourselves to shorter spells, the hazard drops to a lower level but is still increasing. [18]

4.2. Parametric estimation

To formally test whether the hazard increases, we carry out a parametric estimation. To do this we need to impose distributional assumption on the data, which in the case of duration data easily lead to biases in the results; we therefore compare estimations from different models using distinct distributional assumptions. The most general fully parametric model assumes a generalised gamma distribution and encompasses the Lognormal, Weibull and Exponential models.[19] However, the Gompertz and the log-logistic model can not be written as a restriction of any of these models and we therefore compute the Akaike Information Criterion (AIC) to compare the relative

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[16] The Kaplan Meier survival function can formally be defined as $\hat{S}(t) = \prod_{j|t_j<t} \left(\frac{r_j - n_j}{r_j} \right)$ where n is the number of indivdiuals, t_i is the observed duration for the i-th individual, n_j is the number of exits at j and r_j is the number of potential exist at j. the hazard can be written as $\hat{\lambda}_j = \frac{n_j}{r_j}$

[17] We also observe that the hazard has peaks at integer values of years. This is because respondents tend to report their unemployment duration in years - fifty two percent of reported duration is expressed in years; while for the cases where duration was not directly observed, it reflects that the variable is constructed based on age and age at leaving school, which are both reported in integer years.

[18] As a robustness check we did the same analysis for the completed spells of duration only, which are reported rather than being the result of construction. Although this will give an upward biased estimate of the hazard, it is interesting to see whether its course over time is similar. We find that the course is very similar.

[19] The form and properties of the generalized gamma are described in detail in Lee and Wang (2003) and Stata (2005). Its survival function is $S(t) = 1 - I(\gamma, u)\ if\ \kappa > 0; 1 - \Phi(z)\ if\ \kappa = 0;\ and\ I(\gamma, u)\ if\ \kappa < 0$ where $\gamma = |\kappa|^2$, $u = \gamma \exp(|\kappa| z)$ and $z = sign(\kappa)\{\ln(t) - \mu\}/\sigma$. The gamma collapses to the lognormal when $\kappa = 0$; to the Weibull when $\kappa = 1$ and to the Exponential when $\kappa = 1$ and $\sigma = 1$.

performance of the models.[20] An issue of special concern is how to control for unobserved heterogeneity. As has been well documented, duration dependence may appear to be negative just because unobserved heterogeneity is not taken into account (see van den Berg, 2001). We control for unobserved heterogeneity in all the models, and do so in a parametric way for three reasons.[21] First, evidence shows that the main cause of bias in estimation results is misspecification of the baseline hazard rather than the distribution of heterogeneity (see Ridder and Verbakel, 1983). Second, because the estimation of mixture models (which control for unobserved heterogeneity in a non-parametric way) is complex and its calculations are long and error prone it has not been applied frequently, and little is known about the properties of the estimator (see (Lancaster 1990). Finally, and more pragmatically, we find that our estimates are robust for alternative distributions for unobserved heterogeneity.

Starting from a Generalised Gamma model with Inverse Gaussian heterogeneity we test the appropriate restrictions and find that we can reject the Lognormal against the Gamma at the p=0.00 level, while we can reject the Weibull only at p=0.84 level. [22] When we compare the Log Likelihood scores, we find that the Gamma model, which uses one parameter more than the other models, scores best, followed by the Weibull and the Lognormal model. Using the AIC to compare with the non-nested models we find that the Log-logistic model scores best, followed by the Weibull model, and the

[20] Although the AIC is a pragmatic, relative and arbitray measure it offers a way of comparing non-nested models. The Survival function for the Gompertz model can be written as $S(t)=\exp\left\{-\lambda\gamma^{-1}\left(e^{\gamma t}-1\right)\right\}$ while the hazard can be written as $h(t)=\lambda\exp(\gamma t)$; whereas the survival and hazard functions of the log-logistic can be written as $S(t)=\left\{1+(\lambda t)^{1/\gamma}\right\}^{-1}$ while the density can be written as $f(t)=\lambda^{1/\gamma}t^{1/\gamma-1}\Big/\gamma\left\{1+(\lambda t)^{1/\gamma}\right\}^{2}$

[21] For the proportional hazard models the hazard can then be defined as $h(t|\alpha)=\alpha h(t)$ where α is assumed to be Inversze Gaussian distributed.

[22] The results remain unchanged when we assume a gamma distribution for unobserved heterogeneity.

Exponential model, as reported in Table 4. The Log-logistic model allowing for Inverse Gaussian heterogeneity is thus the preferred model.

What does this imply for the course of the hazard rate? The predicted hazard for the two best performing models is plotted in Figure 3 and looks very similar. [23] It first rises and then falls with a maximum occurring around 6 years, when more than four fifths of the unemployed have already left unemployment, suggesting that the majority of unemployed face an increasing hazard.

Since the Weibull model, which came second according to the AIC, is widely used to analyse unemployment duration it is useful to investigate this model further. Using a conditional moment test (Stewart 1998) as well as diagnostic tests (Lancaster 1990, Cox and Snell 1968), which are discussed in detail in the appendix, we find that the Weibull model fits the data quite well. It does however fail a test for monotonicity (Lancaster 1990), as we expected from the non-parametric estimate in Figure 2, and suggests that the hazard follows a more complex course.

A key advantage of the Weibull model is also that it encompasses the exponential model, which predicts a constant hazard and which came third in our case according to the AIC score. Testing the Weibull against the Exponential model using a Wald test we can only reject the former model at p=0.70. Combined, these findings indicate that a piece-wise constant hazard model which uses a constant hazard but allows it to shift up or down for each period, may be more appropriate.[24] Table 4 shows that using step dummies for the annual period, the hazard shifts up during the first year but falls in

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[23]The other models predict a similar course, except for the Gompertz model, which does (by construction) not allow the hazard to fall in the long term. Note that the Weibull hazard rate in a basic model is only allowed to increase or decrease monotonically, but introducing (control for unobserved) heterogeneity, makes a decrease at the end possible, as can be seen in Figure 3b.

[24] The pice wise constant model is an exponential model with a dummy variable for each period: $h(t) = \lambda d_i$ where d_i is an indicator variable for each period.

years three to five to again shift up in the sixth year and then fall. However, none of the changes in the first years is significant and only after twelve years does the step dummy variable become significant. At the same time the constant is highly significant, as is the parameter indicating unobserved heterogeneity (p-value 0.00). We conclude that the hazard rate follows a rather flat inverse-U shaped course, which is difficult to distinguish from a constant.

5. Testing the Different Explanations

Having established that we observe a non-negative hazard, we revisit the potential explanations why this so as set out above.

5.1. Financial support during unemployment

Eighty four percent of the young male unemployed in our sample are supported by their parents, which illustrates that family support is important. To test (11) we test

$$\lambda_i = \alpha_1 + \beta_1 S_i + \Gamma_1 X_i \quad \text{with } H_0 : \beta_1 < 0 \tag{21}$$

Where X_i is a vector of control variables. Estimating (A) using an exponential model we can reject the null, as the results, reported in Table 5, show that household support has a significant positive effect $(\beta_1 > 0)$ on the hazard, whether we use consumption per household member or value of household assets per household member. The finding is robust when using other parametric specifications, and is in sharp contrasts with findings for OECD countries where financial support for the unemployed – which take the form of unemployment benefits – typically have a negative effect, often small and short term (see for example Layard et al (1990), Atkinson and Micklewright (1985, 1991)), while household support is also found to have a negative effect, but again limited (Atkinson, 1999).[25] More recent evidence fro Norway, however, suggests that time-limited benefits contribute to a rise in the employment hazard as the moment of exhaustion approaches (Roed and Zhang, 2005).

We conclude that in the case of urban Ethiopia, household support cannot be the explanation for observing a non-negative hazard because the unemployed that come from better off households are more likely to leave unemployment early.

5.2. Active labour market policies

Unemployment duration can be a signal that is used for screening participants in labour market programs. Similarly, public sector employers may target the long term unemployed as part of the government's employment policy.[26] Although there is no hard empirical evidence for this, it is useful to test whether the public sector, which is the largest employer in urban Ethiopia, targets the long term unemployed, as (12) would require. To do this we test whether the probability of getting a government job is positively related with unemployment duration[27]:

$$\sigma_p = \alpha_2 + \beta_2 t_i + \Gamma_2 X_i \quad \text{with} \qquad H_0 : \beta_3 > 0 \tag{22}$$

We find no relationship $(\beta_2 = 0)$, as reported in Table 5, indicating that those who have been longer in unemployment are not more likely to get a public sector job, or that public sector employment does not target the long term unemployed and is therefore

[25] Note also that in most of the cases where a non-decreasing hazard has been found, the considered sample existed of unemployment insurance recipients only (see for example Moffitt (1985), Katz (1986), Meyer (1986), Vodopovic (1995), Hernæs and Strøm (1996))
[26] Alternatively, they may also see unemployment duration as a signal of ability, believing that the more able will wait longer in unemployment because they are more certain about themselves; or as a signal of household wealth, as those coming from wealthy households can stay longer in unemployment.
[27] Note that we only observe the probability of getting a government job, which is σv, but assume v to be constant over time, to distinguish from section 2.4, where we test this as an alternative explanantion.

not a good explanation for observing non-negative duration dependence in urban Ethiopia. [28]

5.3. Changes in the economy

The single major change in the Ethiopian economy during the period before data collection was the change in political regime in 1991, and the resulting liberalization of the economy.[29] Let r reflect the shift in economic regime such that:

$$\begin{cases} v_t = v_0 & r = 0 \\ v_t = v_1 & r = 1 \end{cases} \tag{23}$$

We then test whether the change in the vacancy rate is positively related with the hazard rate, as implied by (14) as follows:

$$\lambda = \alpha_3 + \beta_3 r_i + \Gamma_3 X_i \quad \text{with } H_0 : \beta_3 > 0 \tag{24}$$

where X is a vector of control variables. We find that the change in political regime does not show up significant $(\beta_3 = 0)$, as shown in Table 6, even if we allow the effect to be delayed and take place one year later, indicating that any shift in the economic activity had no effect on the probability to leave unemployment.

5.4. Segmented labour market

The large differences in wages between different types of jobs suggests that the labour market in urban Ethiopia is segmented, with jobs in an international organization, civil service, public sector and formal private enterprises to be considered good jobs because they pay higher wages, offer fringe benefits and offer a higher job security, while self-

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[28] Note that we also control for household welfare here and that the estimates are robust for different proxies of household welfare.

[29] The Tigrayan People Liberation Front (TPLF) overthrew the Dergue regime, which had followed Soviet style policies, in 1991. Short after coming to power the new government signed a structural adjustment programme with the World Bank, which contained measures to liberalize the economy and privatize the public sector. This was expectated to boost the private sector and attract foreign investors.

employment and informal private employment are considered to be 'bad' jobs.[30] If segmentation plays a role, we expect the reservation wages to fall over time, as expressed in (20). We test this as follows:

$$w^r = \alpha_4 + \beta_4 t + \Gamma_4 X \quad \text{with } H_0 : \beta_4 < 0 \qquad (25)$$

Using OLS we find that reservations wages fall with time spent in unemployment, as reported in Table 7. This suggests that a segmented labour market, where unemployed are queuing for a good job, offers a good explanation for the constant hazard rate.[31]

6. Summary and conclusion

The presumption that the chances to find a job fall with time in unemployment is a very appealing one and a common theoretical assumption. It is also often seen as a stylized fact. Empirical analysis, however, often reports non-negative duration dependence. How can these two be reconciled? Assuming that genuine duration dependence is negative in the long run we develop a framework that allows us to test four reasons why observed duration dependence may be non-negative. Using a more general formulation of the traditional job search models, the key identity is that, at each point in time, the hazard is the product of the vacancy rate, the probability of being selected for a job, and the probability of accepting the job. We first examine the course of the hazard rate and establish that it follows an inverse U-shaped course that is not significantly different from a horizontal line, except in the long run. This means that duration dependence is non-negative for most of the time spent in unemployment.

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[30] This is a stylized (average) picture and in reality some of the self-employed are good jobs as well.
[31] We apply (25) to the unemployed aspiring to a good job. The results are similar if we include all the unemployed, but less significant because reservation wages do not fall substantially for those aspiring to a 'bad' job. This is because v_B may be smaller than unity, for example due to credit constraints. We also assess assumption (16) by testing $H_0 : \overline{w^r} < \overline{w_G}$ and find that the mean reservation wage (41 USD) is well below the mean wage for a good job (72 USD), as reported in Table 2.

We then test the four explanations. The first explanation lies in the financial support that the unemployed receive from the household. As this support is limited in time, the unemployed are more eager to get a job and lower their reservation wages as they approach the expiry date. Observed duration dependence may be non-negative if, ceteris paribus, the unemployed from wealthier households stay longer in unemployment as this pushes up the hazard and may be big enough to compensate for genuine negative duration dependence, leading to observe a non-negative hazard. We find, however, that household welfare has a positive effect on the hazard, and thus financial support does not provide a good explanation for non-negative duration dependence. A second explanation would be that the public sector plays the role of a an employment program and targets the long term unemployed; this would increase the probability of leaving unemployment, or hazard rate, for the long term unemployed. We test whether the chances to get a public sector job increase as time in unemployment proceeds, but find that this does not. Active labour market policies do therefore not explain why duration dependence is negative. A third potential explanation is that the economy changes over time, affecting especially the vacancy rate. The most important shift in the economy in the years before the survey was the overthrow of the Dergue and the coming to power of a new government that introduced more liberal economic policies, and we test whether this has affected the hazard. We find that it does not and therefore economic change does not offer a good explanation for observed non-negative duration dependence. A fourth and final explanation assumes that the labour market is segmented into good and bad jobs. The hazard for a good job falls with time spent in unemployment because the skills needed for a good job are lost when not used. The hazard for a bad job, however, remains constant because the skills required are basic, and people can always get a bad job. Because the unemployed who aspire to a good job cannot all get a good job, they drop their reservation wages and this increases their chances to get a job and lifts up the hazard rate. We find strong evidence that reservation wages fall with time in unemployment, especially for those aspiring to a good job, indicating that this explains why we observe a constant hazard. Our findings underline the importance of labour market segmentation.

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8. Figures and Tables

Figure 1: Kaplan Meier survival function

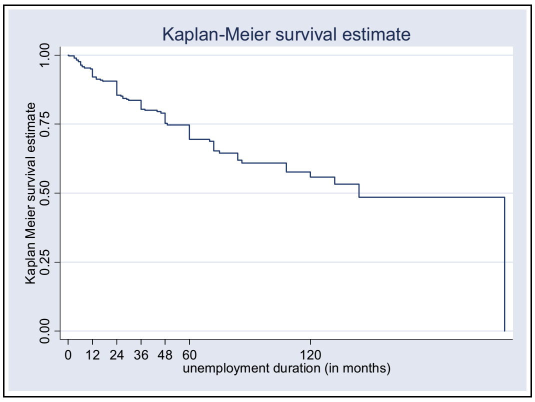


Figure 2: Hazard rate estimated from a Kaplan-Meier survival function

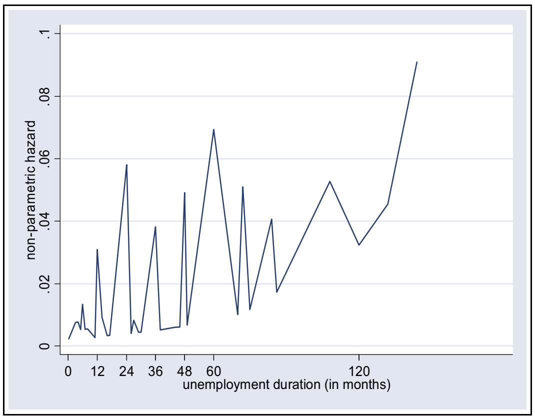
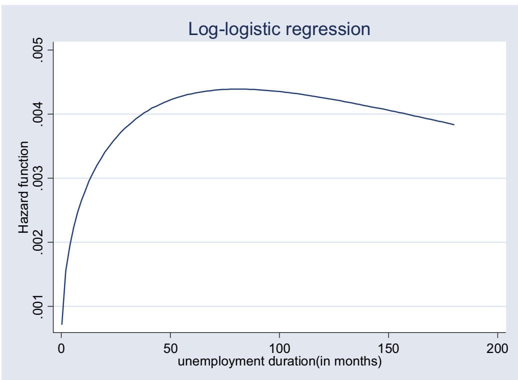


Figure 3: Predicted hazard rates allowing for inverse Gaussian heterogeneity

(a) Log-logistic model



(b) Weibull model

Table 1:Overview of the empirical literature on duration dependence

Data	Duration dependence	Source
Spain 1999-2002, reemployed except with ex-employer	Positive	Alba-Ramirez et al (2007)
Norway,1989-1992, entitled to unemployment benefits	positive	Hernas and Strom (1996)
Denmark, 1981-1990	weak positive	Rosholm (2000)
Sweden, 1976-1977	positive	Edin (1989)
US, 1983, male benefit recipients	weak positive	Meyer (1986)
Australia, early 80's, young	positive	Hui (1986)
US, 1980-82, household heads	weak positive	Dynarski and Sheffrin (1987)
US, 1980 – 1981, unemp insurance recipients	positive	Katz (1986)
France, 1990-1993, male	U-shaped	van den Berg and van der Klaauw (2000)
US, 1983, male benefit recipiemts	U-shaped	Moffitt (1985)
Canada, 1979-1980, male	U-shaped	Ham and Rea (1987)
Norway, 1989-1998, experience in a 'recall sector'[32]	inverse U-shaped	Roed and Nordberg (2003)
Spain, 1999-2002, reemployed with ex-employer	constant	Alba-Ramirez et al (2007)
Spain, 1987-1996, young women	constant	Alba-Ramirez (1998)
Germany, 1983-1995	Constant	Steiner (2001)
Belgium 1989-1994	Constant	Cockx and Dejemeppe (2005)
France, 1982-1992	constant	van den Berg and van Ours (1994)
Greece, 1981, male	constant	Meghir, Ionnides et al (1989)
Slovak Republic, 1994-1996	inverse U-shaped	Lubyova and van Ours (1998)
Russia, 1992-1994	inverse U-shaped	Foley (1997)
Hungary, 1992-1993, unemp. Benefit recipients	Inverse U-shaped	Micklewright and Nagy (1996)
Slovenia, 1990-1992, unemp. Benefit recipients	inverse U-shaped	Vodopovic (1995)
The Netherlands, 1978-1991	inverse U-shaped positive net effect	van den Berg and van Ours (1994)
US, 1978-1989, younsters who were 14-21 in 1978	Inverse U-shaped	Imbens and Lynch (2006)
France, 1986-1989, long term unemployed	inverse U-shaped	Bienvenue, Carter et al (1997)
US, 1984-1988	inverse U-shaped	Addison and Portugal (1998)
The Netherlands, 1987	inverse U-shaped followed by constant	Kerckhoffs, de Neubourg et al (1994)
UK, 1978-1979, male	inverse U-shaped	Arulampalam and Stewrat (1995)
Ukraine, 1998-2002	negative	Kupets (2006)
Norway,1992-1997, Insured unemployed	Negative	Roed and Zhang (2005)
Spain, 1987-1996, young men	negative	Alba-Ramirez (1998)
Germany, 1989-1995	negative	Frijters and van der Klauuw (2006)
UK, W-Belfast, 1995, long term unemployed	negative	Sheehan and Tomlinson (1998)
France, 1982-1994	Negative	Abbring, van den Berg and van Ours (2002)
France, 1990-1993	negative	van den Berg and van der Klaauw (2000)
Norway,1989-1992, first time job seekers	negative	Hernase and Strom (1996)
UK, 1979-1992	negative	van den Berg and van Ours (1994)
US, 1968-1992	negative	Abbring, van de Berg et al (2001)
US, 1967-1991, white males	negative	van den Berg and van Ours (1996)
UK, 1987-1988	negative	Arululampalam et al (1995)
UK, 1967-1987	negative	Jackman and Layard (1991)
Italy, Lombardy, 1986, young	negative	Torelli and Trivellato (1989)
US, 1978-1985, young	negative	Lynch (1989)
Australia, 1984	negative	Trivedi and Hui (1985)
UK, 70's, young workers	negative	Lynch (1984)
UK, 1972	negative	Nickel (1979)

Note: Only the studies that have controlled for unobserved heterogeneity are listed. If no further details are mentioned, the results are for the entire labour force, male and female, young and adults.

[32] Sector that tends to re-employ unemployed that have worked for them before like manufacturing, construction, transport, tourism, seafood industries.

Table 2: Descriptive statistics

FOR ALL ACTIVE MEN	All active men
Employment distribution	
Public sector	27%
Formal private sector	7%
Self employment, casual workers and informal private sector	33%
Unemployed	34%
Median real earnings per month (1994 PPP USD)	
Public sector employee:	80
Private sector wage employee	44
Self-employed	29
FOR ACTIVE YOUNG MEN	Active young men
Employment distribution	
Public sector	15%
Private sector wage employment	7%
Self employment, casual workers and informal private sector	27%
Unemployed	51%
Duration of unemployment	
Mean duration of unemployment	45 months
Sample Size	
Number of household	1,500
Number of men between 15 and 30	680
FOR UNEMPLOYED YOUNG MEN	Unemployed young men
Highest Level of Education	
None	13%
Primary education	14%
Junior secondary education	36%
Senior secondary education	31%
Tertiary education	6%
Household characteristics	
Average monthly total household expenditures per capita (in 1994 PPP USD)	25
Average value of household assets per household member (in 1994 PPP USD)	289
Ever worked before?	
No	0.85
Yes	0.15
Ever refused a job?	
Have never refused a job	0.98
Have ever refused job	0.02
Job looking for	
Public sector	0.50
Private sector wage employment	0.13
Self-employment, casual work and informal private sector work	0.14
Any work	0.23
Reservation wage (1994 PPP USD)	
Mean	41
Standard deviation	28
How support yourself while unemployed	
Through parents' help	0.84
Through help from friends, spouse, own savings or loan from relative	0.04
Other	0.12

Table 3: Overview of the Akaike Information Criterion scores

	loglikelihood	Number of covariates	Number of parameters	AIC	rank
inverse Gaussian heterogeneity					
Exponential	-254.244	16	0	540.4884	3
Piecewise exponential with 15 1 year pieces	-253.287	30	0	566.5732	7
Weibull	-253.071	16	1	540.1429	2
Gompertz	-254.011	16	1	542.0214	4
Lognormal	-254.291	16	1	542.5818	6
Log-logistic	-253.066	16	1	540.1325	1
Generalised gamma	-253.067	16	2	542.133	5
Cox partial likelihood	-432.901	16	0	897.8013	8

Table 4: Estimates for proportional hazard models assuming Inverse Gaussian heterogeneity

d2	0.13583
	(0.29402)
d3	-0.26181
	(0.37805)
d4	-0.02808
	(0.39256)
d5	-0.02340
	(0.43137)
d6	0.12948
	(0.47318)
d7	-0.24914
	(0.62702)
d8	-0.93149
	(1.06089)
d9	-0.55166
	(1.03304)
d10	-0.24466
	(1.04644)
d11	-0.08302
	(1.04830)
d12	0.31444
	(0.92275)
d13	-27.88370
	(0.48946)***
d14	-27.91665
	(0.54207)***
d15	-27.80898
	(0.61466)***
Constant	10.85783
	(4.58286)**
Parameter for (unobserved heterogeneity	-13.41132
	(0.97456)***
Observations	378

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in parentheses. The model controls for age, age squared, levels of education, body mass index, ethnicity, father's activity, mother's education, place of living and local unemployment rate. Unobserved heterogeneity is assumed to be inverse Gaussian distributed.

Table 5: The effect of household welfare on the hazard

	(1)	(2)	(3)
Consumption per household member	0.00193	0.00208	
	(0.00036)***	(0.00034)***	
Value of household assets per household member	0.00006		0.00009
	(0.00005)		(0.00004)**
Parameter for unobserved heterogeneity	-14.99707	-13.40895	-14.35325
	(0.63983)***	(0.65511)***	(0.82200)***
Observations	342	342	342

Table 6: The effect of unemployment duration on getting a public sector job for men

	(1)	(2)	(3)
Time spent in unemployment	0.0000113	-0.0000108	0.000012
	(0.0006403)	(0.0006404)	0.0006406)
Consumption per household member		-0.0000770	
		(0.0001276)	
Value of household assets per hh member			0.0000003
			(0.0000056)
Observations	342	342	342

Table 7: Effect of a change in political regime on the hazard

	(1)	(1)
Unemployment spell started in or after 1991	-0.02322	
	(0.41274)	
Unemployment spell started in or after 1992		0.3640
		(0.4266)
Observations	342	342

Table 8: The change of reservation wages over time for those aspiring to a good job

	All	130 months or less	84 months or less
	-1.149	-1.441	-1.359
Time spent in unemployment	(0.576)**	(0.606)***	(0.649)**
Observations	131	125	110
R-squared	0.33	0.31	0.29

* significant at 10%; ** significant at 5%; *** significant at 1%; All models report robust standard errors in parentheses and control for age, age squared, levels of education, ethnicity, father's activity, mother's activity, local unemployment rate, household welfare and a constant.
Unobserved heterogeneity is assumed to be inverse Gaussian distributed.

Appendix

A. 1. Description of the sample

A sample of one thousand five hundred households was drawn from the seven largest cities, which all have a population above one hundred thousand citizens. The number of households per city corresponds to its relative size. The sample is distributed as shown in Table A.1.

The sample is stratified by wereda, and a number of kebele is selected in each wereda. [33] Within each kebele, households are selected from a list of house numbers, using a fixed interval from a random start. The number of households selected within each kebele was in proportion to the population size of the kebele, taking average household size into account. The number of households per wereda was determined by its population size, using projections based on figures from the 1984 census (CSA 1987). The data has rich information on labour issues as household members aged fifteen or above were asked their employment and unemployment history. Only those working were asked how long their last spell of unemployment had lasted, expressed in months. The unemployed were not asked how long they had been in unemployment, but we *construct* a measure of duration for them. The methodology to do this is described in Section 3.

Table A.1: Sample design

	Location	Description	Number of households
Addis Ababa	Centre	Capital, national economic centre	900
Awassa	South	Administrative centre of the South, regional economic centre for Enset region	75
Bahir Dar	North West	Regional economic centre, main cereal producing area	100
Dire Dawa	East	National trading centre	125
Dessie	North	Regional economic centre	100
Jimma	South West	Coffee region	100
Mekele	North	regional economic centre	100
Total			1500

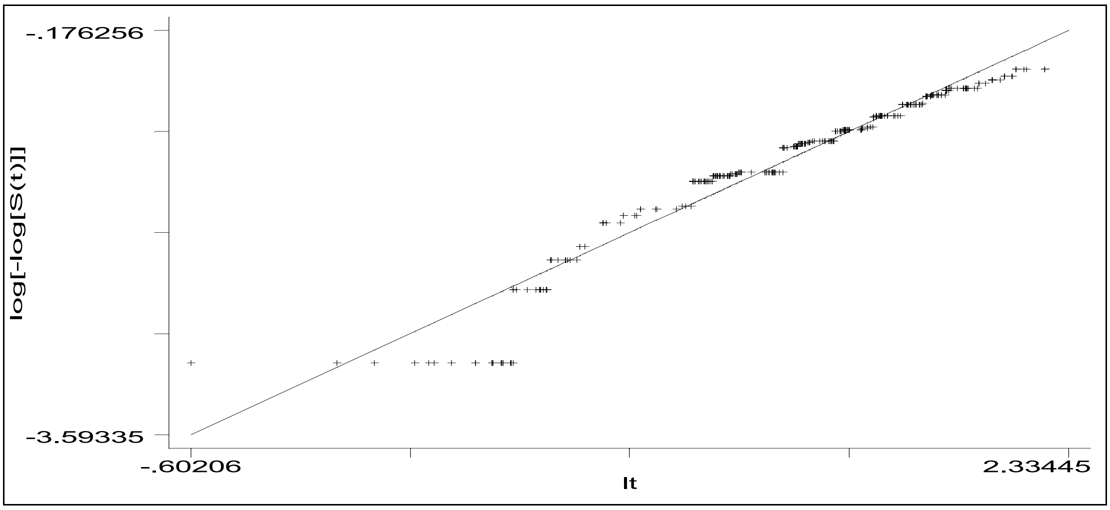
[33] A Wereda is an administrative unit which is geographically well defined. The Wereda coincides with the town for all towns except for Addis Ababa, which counts several Weredas. A Kebele is the smallest administrative unit; it is the urban dwellers' association.

A.2. Diagnosing the Weibull model

1. We first test the appropriateness of the Weibull using a conditional moment test. The test diagnoses whether the sum of squared generalised residuals equals two, taking censoring into account, using the test statistic $\hat{e} = \frac{1}{n}\left[\sum_{j=1}^{n}(\hat{\eta}_j - 1)^2 - \sum_{j=1}^{n}(1-\delta_j)\right]$ where $\eta_j = CS_j + \delta_j$ (Stewart 1998). We find that a fitted Weibull does not fail a score test for the second moment (p-value 0.93).

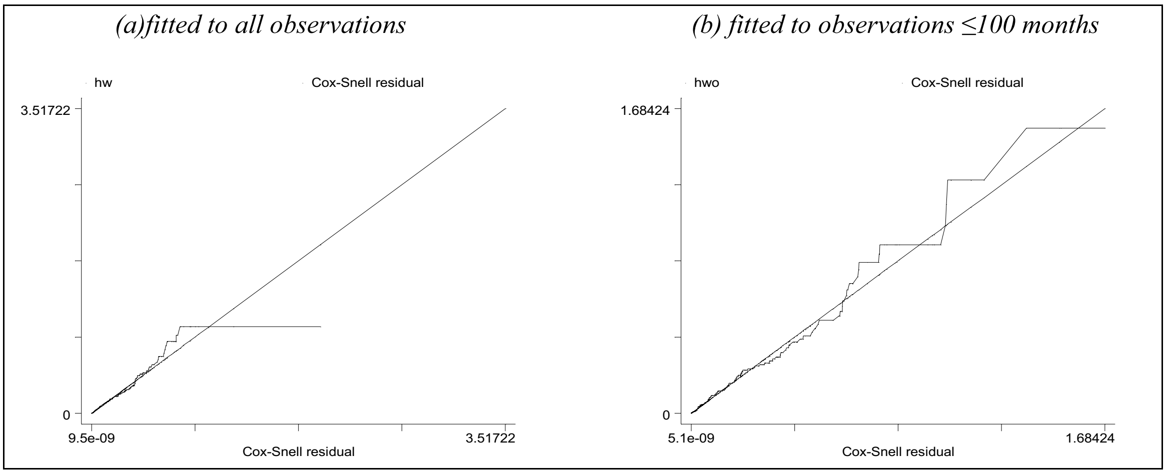
2. A second test we apply is a simple visual test described by Lancaster (1990). Figure A.1 plots the logarithm of integrated hazard against the logarithm of duration. If the Weibull is the appropriate distribution, the result should be a linear curve. Indeed, under the assumption of Weibull distributed duration spells, $\Lambda(t) = (\lambda t)^{\alpha}$, or, $\log[\Lambda(t)] = \alpha \log \lambda + \alpha \log t$, meaning that the left hand side is linear in $\log(t)$. Proxying the integrated hazard by the negative of the logarithm of the (non-parametric) Kaplan-Meier survival function we observe that although the relationship is not perfectly linear, most observations are close to the forty-five degree line. These results remain the same when we drop outliers.

Figure A.1: Visual test for the appropriateness of the Weibull model



3. A third test is again a diagnostic visual test and plots the Cox-Snell residuals against their cumulative hazard rate. Cox-Snell residuals are defined as the estimated cumulative hazard function obtained from the fitted model (Cox and Snell 1968). Cox and Snell (1994) argue that if the correct model has been fitted to the data, these residuals are n observations from an exponential distribution with unit mean. Hence a plot of the cumulative hazard rate against the residuals themselves should result in straight line with slope unity. Figure A.1 (a) indicates that the Weibull does not fit perfectly for all values. However, when we leave out very long durations (those above 100 months, which represent only 9% of the non-zero durations), the Weibull seems appropriate, as can be seen in Figure A.1 (b). A comparison with similar plots for other distributions suggests that the Weibull fits the data better than other distributions.

Figure A.2 : Log of Kaplan Meier cumulative hazard versus Cox-Snell residuals for the Weibull

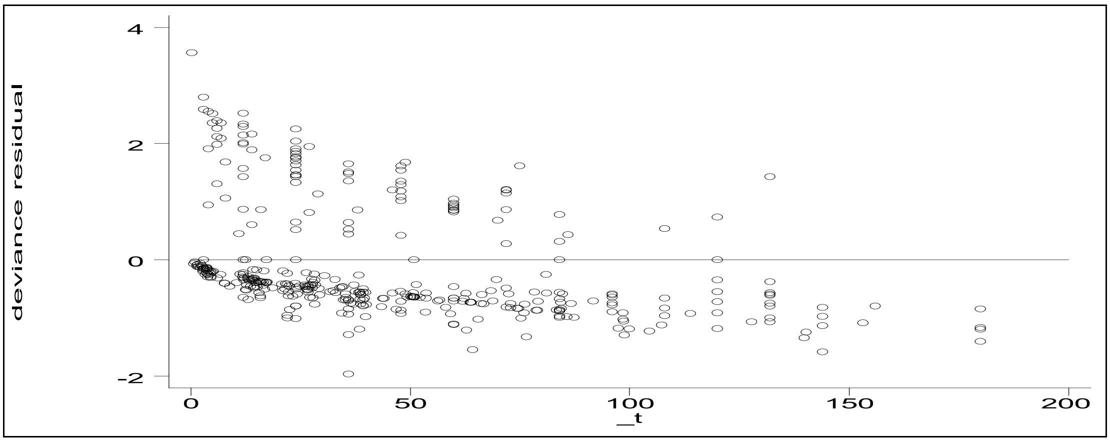


4. Another diagnostic test is to plot the <u>deviance residuals</u>. We first define Martingale-like residuals as the difference over time between the actual number of those leaving unemployment and the expected number based on the model. They are derived from Cox-Snell residuals and are defined as:

$$M_j(t) = \delta_j - CS_j(t_j), \text{ where } \begin{cases} \delta_j = 1 & \textit{if} \quad \textit{employed} \quad \textit{at} \quad t_j \\ \delta_j = 0 & \textit{if} \quad \textit{unemployed} \quad \textit{at} \quad t_j \end{cases}$$

However, because these residuals take values between $-\infty$ and 1, they are difficult to interpret and we therefore focus on deviance residuals, which are a rescaling of Martingale-like residuals to make them symmetric about zero, which makes detection of outliers easier. The transformation used is $D_j(t) = sign\left[\left(M_j(t)\right)\left(-2\left(M_j(t) + \delta_j - M_j(t)\right)\right)\right]$. The graphical analysis plots those residuals against duration. The diagnostic graph for the Weibull model is shown in Figure A.3 and indicates that the hazard may be overestimated for very long durations ($\geq$ 100 months).

Figure A.3: Deviance residuals for the Weibull model for all observations



5. A final test is that for monotonicity of the hazard rate. Comparison of the AIC scores for different models (see Table 2) suggests that a model that allows for the hazard rate to fall after its initial rise may still fit better than the Weibull model. Lancaster (1990, p322) provides a formal test to check whether the hazard rate is monotonically increasing. We find that we can strongly reject monotonicity (p-value 0.00). This suggests that the hazard rate falls at least once over the considered duration. In the simplest case, the hazard rate initially increases and falls after a certain point, suggesting that there is only one maximum. The high fit of the log-logistic model for the completed-spells-only, which allows for a final decrease, supports this. A more complicated case occurs when several intermediate downward movements interrupt the upward trend of the hazard. This corresponds to our findings when we use the piece wise constant hazard, although there the changes inbetween are insignificant.

A.3. Testing for the Exponential model

Since the Weibull model encompasses the exponential model, we can formally test the latter as a restriction of the former. Using a Wald test to test that ln(p)=0 is rejected at p=0.70 suggesting that the Weibull does not fit signficantly better than the exponential.

A very similar test to the one we applied above can be used to investigate the appropriateness of the exponential model. *Figure 4* plots the integrated hazard against duration. Since $\hat{\Lambda}(t) = -\log \hat{S}(t)$ and $\Lambda = \lambda t$, plotting Λ against t should be a straight line through the origin if λ is indeed constant. The more the plotted line deviates from the 45% degree line through the origin, the less appropriate is the exponential distribution. We observe that the Weibull fits well overall, although less so for higher values of duration.

Figure 4: Visual test for the appropriateness of the exponential model