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Explaining Non-Negative Duration Dependence Among the Unemployed[1]

Pieter Serneels
Center for the Study of African Economies, Oxford University
pieter.serneels@economics.ox.ac.uk

Abstract

We investigate why we observe non-negative duration dependence among young unemployed men in urban Ethiopia. Assuming that genuine duration dependence is negative, there are five explanations for a non-decreasing hazard: the presence of unemployment benefits, the existence of Active Labour Market Policies, the change in labour demand, segmentation of the labour market, and unemployment as a queuing phenomenon. We test each of these explanations and find that labour market segmentation is the only convincing one. We also establish that genuine duration dependence is indeed negative in the long run.

JEL classification: J64, C41, R23
Keywords: unemployment, duration, segmented labour markets, urban labour market

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Estragon: Wait.

Vladimir: Let's wait until we know exactly how we stand[2]

1. Introduction

Negative duration dependence of unemployment has often been thought of as an established fact and has been a basic assumption in influential models [see for example Blanchard and Diamond (1994)]. The (conditional) probability of leaving unemployment would thus fall as one remains longer in unemployment; or spending time in unemployment would negatively affect someone's chances to get a job. However, an overview of the literature on duration dependence in OECD countries (it is nonexistent for developing countries) shows that this is not what is found empirically, as is clear from Table 1. In particular recent research often observes non-negative duration dependence. This has to do with the improved modelling techniques as well as with the richer information on the unemployed, both of which improve the ability to control for unobserved heterogeneity. [3] Negative duration dependence can indeed just be the consequence of not *observing* the characteristics that lead to long term unemployment in the first place.

[2] Becket (1955) Waiting for Godot

[3] A telling illustration is that when I started writing this paper, one could only control for unobserved heterogeneity in duration models by writing one's own likelihood function. Halfway through working on the paper, new software became available which had built in the option to choose between different distributions for unobserved heterogeneity.

Table 1:Overview of the empirical literature on duration dependence

Data	Duration dependence	Source
UK, 1972	negative	Nickel (1979)
UK, 70's, young workers	negative	Lynch (1984)
UK, 1967-1987	negative	Jackman and Layard (1991)
UK, 1979-1992	negative	van den Berg and van Ours (1994)
UK, 1987-1988	negative	Arulampalam and Stewart (1995)
UK, West Belfast, 1995, long term unemployed	negative	Sheehan and Tomlinson (1998)
US, 1978-1985, young	negative	Lynch (1989)
US, 1967-1991, white males	negative	van den Berg and van Ours (1996)
US, 1968-1992	negative	Abbring, et al. (1997)
Australia, 1984	negative	Trivedi and Hui (1985)
Italy, Lombardy, 1986, young	negative	Torelli and Trivellato (1989)
Norway,1989-1992, first time job seekers	negative	Hernaes and Strom (1996)
Spain, 1987-1996, young men	negative	Alba-Ramirez (1998)
France, 1990-1993	negative	van den Berg & van der Klaauw (2000)
Greece, 1981, male	no	Meghir, et al. (1989)
France, 1982-1992	no	van den Berg and van Ours (1994)
Spain, 1987-1996, young women	no	Alba-Ramirez (1998)
US, 1980 – 1981, unemp insurance recipients	positive	Katz (1986)
US, 1980-82, household heads	weak positive	Dynarski and Sheffrin (1987)
US, 1983, male benefit recipients	weak positive	Meyer (1986)
Australia, early 80's, young	positive	Hui (1986)
Sweden, 1976-1977	positive	Edin (1989)
Norway,1989-1992, entitled to unemp. benefits	positive	Hernaes and Strom (1996)
The Netherlands, 1987	inverse U-shaped followed by constant	Kerckhoffs, et al. (1994)
The Netherlands, 1978-1991	inverse U-shaped positive net effect	van den Berg and van Ours (1994)
UK, 1978-1979, male	inverse U-shaped	Arulampalam and Stewart (1995)
Slovenia, 1990-1992, unemp. benefit recipients	inverse U-shaped	Vodopovic (1995)
France, 1986-1989, long term unemployed	inverse U-shaped	Bienvenue, et al. (1997)
Russia, 1992-1994	inverse U-shaped	Foley (1997)
US, 1984-1988	inverse U-shaped	Addison and Portugal (1998)
Slovak Republic, 1994-1996	inverse U-shaped	Lubyova and van Ours (1998)
Hungary, 1992-1993, unemp. benefit recipients	Inverse U-shaped	Micklewright and Nagy (1996)
US, 1983, male benefit recipiemts	U-shaped	Moffitt (1985)
Canada, 1979-1980, male	U-shaped	Ham and Rea (1987)
France, 1990-1993, male	U-shaped	van den Berg & van der Klaauw (2000)

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.

We analyse duration dependence for male young adults in urban Ethiopia. As described elsewhere, unemployment among young men in Ethiopia has special characteristics, but is not dissimilar from unemployment in other developing countries [see Serneels (2002)]. It is concentrated among relatively well-educated first time job seekers. Half of them are looking for a public sector job.[4] Time spent in

[4] With around fifty percent of the urban young men unemployed, Ethiopia has one of the highest unemployment rates worldwide. Serneels (2002) investigates the nature of unemployment in urban Ethiopia in more detail and finds that it is concentrated among young, relatively well educated, first time job seekers, who come from the middle classes. Almost two thirds of them are looking for a well paid formal sector job, mostly a public sector job. Mean duration of unemployment is close to four years and is higher for those aspiring to a public sector job.

unemployment is negatively correlated with household welfare, but we cannot say anything about the direction of causation. Those coming from households with lower levels of welfare have the same job preferences as those coming from households with high levels of welfare, but they are less likely to get a public sector job. This raises the question if it is unemployment duration itself that has a negative effect on getting a job, i.e. whether duration dependence is negative. The question seems more pertinent for developing countries, where unemployment duration is expressed in years rather than months [see Dickens and Lang (1996), and Rama (1999) for Sri Lanka, Rama (1998) for Tunisia; Appleton, Knight, Song and Xia (2001) for China], in contrast to OECD countries where mean duration is typically below one year (see references in Table 1). For urban Ethiopia, we find a mean duration of forty five months. An additional reason why it is interesting to know whether there is duration dependence, is that it may reveal the importance of path dependency for young person's career. When we consider a career as a dynamic process, the early stages will have an effect on the later opportunities. Narendranathan and Elias (1993), Arulampalam, Booth and Taylor (2000) and Gregg (2001) show for the UK that it is men who have been unemployed once, who are more likely to become unemployed again. But the effect may go beyond employability and unemployment may affect future wages, as Ackum (1991) shows for Sweden and Arulampalam (2001) and Gregory and Jukes (2001) show for the United Kingdom.[5]

Our theoretical framework starts from the assumption that genuine duration dependence is negative in the long run. The reason for this is that unemployment implies a loss of skills, so there is an unlearning-by-not-doing effect. Another potential justification, often quoted for OECD countries, would be that long periods of unemployment lead to a loss of self-confidence. But it is not clear whether this would be because other

[5] Another interesting result for us is that van Dijk and Fomer (1999) find that unemployment duration has little effect on wages in areas with high unemployment in the UK.

people's unemployment spells are much *shorter*; loss of self-confidence may have a *relative* dimension. Empirical findings confirm that duration dependence is negative in the (very) long run. But while genuine duration dependence is negative, observed duration dependence may be non-negative. The literature suggests four potential reasons why observed duration dependence may be non-negative for part of, or the entire period of unemployment, while genuine duration dependence is negative.

One reason is the presence of unemployment benefits and their limited duration over time. The mechanism works as follows. The unemployed know that the support they receive is time limited. The closer they come to the expiry date, the more eager they become to get a job. They increase their chances to get a job by reducing their reservation wage. Unemployment benefits explain non-negative duration dependence in, for example, the US (Katz 1986) and Norway (Hernaes and Strom 1996).

A second explanation is the presence of active labour market policies. When a government targets the long term unemployed with a special employment programme, the probability to leave unemployment, or hazard rate, will increase for the long term unemployed. This explains why there is non-negative duration dependence in The Netherlands (van den Berg and van Ours 1994) and Sweden (Edin 1989).

A third factor is that the economy changes over time. In an upswing of the economy, the long term unemployed are more likely to find a job. This creates the impression of non-negative duration dependence. Arulampalam and Stewart (1995) find evidence that distinct cohorts have different exit probabilities, while van den Berg and van der Klaauw (2000) find that the hazard changes due to business cycle effects.

A fourth explanation assumes that labour markets are segmented into good and bad jobs. The hazard for getting 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 remains constant because the skills required are very basic. People can always get a bad job. In this setting people will queue in unemployment for a good job. But as they spend more time in unemployment, they will lower their reservation wages and be more likely to accept a bad job. This creates the illusion of a non-decreasing hazard. Korpi (1995) argues that this is the case for Sweden.

A fifth explanation is a more general version of the previous one and argues that queuing in unemployment in general – whether labour markets are segmented or not – creates the illusion of non-negative duration dependence. When the number of jobs is constrained and employment is purely 'waiting your turn', then the hazard will not fall with time spent in unemployment.

We will test each of these five explanations for unemployed male young adults in urban Ethiopia. In the next section we set out the conceptual framework. We then investigate the course of the hazard rate in Section 3. Once we have established that duration dependence is non-negative over a large part of durations, we test each of the five explanations. In the final section we summarize our findings and draw conclusions.

2. A Framework for Testing

We develop a framework to test the different explanations. The larger picture is one where a career is a dynamic game. Individuals start in unemployment and at each stage of the game, leave unemployment or not. We consider individuals to be homogenous.

At each moment, the probability to leave unemployment is a function of three factors: the probability that there is a vacancy (ν), the probably that one gets selected (σ) and the probability that the job is accepted (π). The latter is conditional on not having accepted a job yet.

$$\lambda_t = f\left(\nu_t, \sigma_t, \pi_t\right) \tag{1.1}$$

At each point in time, the hazard equals the product of these three factors, so we can write the reduced form equation as:

$$\lambda_t = \nu_t \sigma_t \pi_t \tag{1.2}$$

The product of the two first factors on the right hand side can be interpreted as the job arrival rate, as in a traditional job search model. Note that the (simple) traditional search model, as set out in Mortensen (1986) is a special case of this general framework, holding all three factors constant over time. Extensions of the basic model, for example a model that allows for liquidity constraints [see Mortensen (1986)], or one that assumes finite lives, as described by Gronau (1971), relax one parameter by allowing π to change over time, but still assume a constant job arrival rate. Because we are particularly interested in the changes over time, we need a more general framework than the traditional model. Equation (1.2) offers this framework and is our key equation. The disadvantage of the more general form is that the job arrival rate can no longer be given its usual interpretation, where a job results from a draw of a sample of job offers (with attached wages) which are Poisson distributed.

We let the first factor depend on labour demand (*d*).

$$\nu = \nu\left(d\right) \tag{1.3}$$

The probability π is the probability that the vacancy has a wage that exceeds the individual's reservation wage.

$$\pi = \pi\left(w > w^r\right) = \pi\left(w^r < w\right) = 1 - F_w\left(w^r\right) \tag{1.4}$$

Assuming that ν, σ and π are continuous and that their first derivative exists, we can write the change of the hazard over time, using equation (1.2), as follows:

$$\frac{\partial \lambda}{\partial t} = \sigma\pi\frac{\partial \nu}{\partial t} + \nu\pi\frac{\partial \sigma}{\partial t} + \nu\sigma\frac{\partial \pi}{\partial t} \tag{1.5}$$

The second term on the right hand side captures genuine duration dependence. It reflects the change over time in the probability of being hired. We assume that this probability is negative. Employers will be less likely to hire long term unemployed because there is unlearning-by-not-doing. We can now write genuine negative duration dependence as:

$$\frac{\partial \sigma}{\partial t} < 0 \tag{1.6}$$

When do we observe non-negative duration dependence? This occurs when (1.5) is non-negative:

$$\frac{\partial \lambda}{\partial t} = \sigma\pi\frac{\partial \nu}{\partial t} + \nu\pi\frac{\partial \sigma}{\partial t} + \nu\sigma\frac{\partial \pi}{\partial t} \geq 0 \tag{1.7}$$

or

$$\sigma\pi\frac{\partial \nu}{\partial t} + \nu\sigma\frac{\partial \pi}{\partial t} \geq -\nu\pi\frac{\partial \sigma}{\partial t} > 0 \tag{1.8}$$

Let us now revisit the five explanations set out above.

2.1. Unemployment benefits

This explanation argues that people are more likely to stay in unemployment when they receive benefits. But, the closer they come to the point where their benefits run out, the more likely it is that they want to leave unemployment. They increase their chances to leave unemployment by lowering their reservation wage. Non-negative duration dependence is observed when reservation wages fall enough to compensate for genuine negative duration dependence.

In the context of a developing country, benefits only make sense if we include household support since the state does not provide unemployment benefits. We assume that richer households support their unemployed members more than poor households; therefore household wealth is a good proxy for unemployment benefits. Then, if unemployment benefits explain the observation of a non-negative hazard rate, we expect household welfare to be negatively associated with the hazard: those coming from better off households stay longer in unemployment.

More formally, we assume that the probability of accepting a job is a monotonically decreasing function of the level of benefits or support (*S*) received; so its first differential exists and is negative.

$$\frac{\partial \pi}{\partial S} < 0 \tag{1.9}$$

We also assume that household support or benefits fall over time.

$$\frac{\partial S}{\partial t} < 0 \tag{1.10}$$

Assumptions (1.9) and (1.10) imply that the probability to accept a job rises over time, or reservation wages fall over time:

$$\frac{\partial \pi}{\partial t} = \frac{\partial \pi}{\partial S}\frac{\partial S}{\partial t} > 0 \tag{1.11}$$

This result is analogous to the traditional job search model with finite lives (Gronau 1971) or the model allowing for liquidity constraints (Mortensen 1986).

Why does this lead to observing a non-negative hazard? Let us revisit equation (1.8) . We assume that demand does not change over time, so $\frac{\partial \nu}{\partial t} = 0$, and write:

$$\sigma \frac{\partial \pi}{\partial t} \geq -\pi \frac{\partial \sigma}{\partial t} > 0 \tag{1.12}$$

Since $\sigma > 0$, we can write condition (1.12) as:

$$\frac{\partial \pi}{\partial t} > 0 \tag{1.13}$$

This is equivalent to equation (1.11). Hence falling reservation wages may lead to observing non-negative duration dependence.

How do we test this? Our null hypothesis is that the decrease of household support over time leads to a fall in reservation wages, and that this explains non-negative duration dependence. We write:

$$H_0 : \frac{\partial \lambda}{\partial t} \geq 0 \tag{1.14}$$

Because we assume (1) that π to be a monotonic continuous function of S, and (2) that receiving support does not affect the probability of being selected or getting a vacancy $\left(\frac{\partial v}{\partial S} = \frac{\partial \sigma}{\partial S} = 0 \right)$, we can write:

$$H_0 : \frac{\partial \lambda}{\partial t} = \frac{\partial \lambda}{\partial S} \frac{\partial S}{\partial t} \geq 0 \tag{1.15}$$

From (1.10) we know that the second term on the right hand side is negative. This means that we can rephrase (1.15) as:

$$H_0 : \frac{\partial \lambda}{\partial S} \leq 0 \tag{1.16}$$

To test (1.16), we model:

$$\lambda = \alpha + \beta S + \gamma X \tag{1.17}$$

where X is a vector of control variables and S is proxied by household welfare. We test whether its coefficient is smaller than or equal to zero.

$$H_0 : \beta \leq 0 \tag{1.18}$$

2.2. Active Labour Market Policies oriented towards the long term unemployed

Active labour market policies affect the probability of leaving unemployment when they target those with the lowest probability of getting a job, in particular the long term unemployed. More formally, this policy affects hiring rates, or the probability of being selected. Assume that the selection rate exists of two components: the market or genuine selection rate (σ_m) and the selection rate from the public sector or government programme (σ_p).

$$\sigma = \sigma_m + \sigma_p \tag{1.19}$$

We assume that both are continuous monotonic functions in t, and that their first derivative exists. We further assume that the genuine (market) selection rate decreases with time spent in unemployment, while the public sector selection rate can increase or decrease over time.

$$\frac{\partial \sigma_m}{\partial t} < 0 \tag{1.20}$$

We will observe non-negative duration dependence when:

$$\frac{\partial \sigma}{\partial t} = \frac{\partial \sigma_m}{\partial t} + \frac{\partial \sigma_p}{\partial t} \geq 0 \tag{1.21}$$

or

$$\frac{\partial \sigma_p}{\partial t} \geq -\frac{\partial \sigma_m}{\partial t} > 0 \tag{1.22}$$

This means that the effect of the programme is at least as large as the genuine duration dependence, but has the opposite sign. This is possible when the programmes are implemented on a large scale, so that their aggregate effect compensates genuine negative duration dependence and result in a neutral or positive net-effect. Is this case relevant for Ethiopia? Ethiopia does not have large scale programmes that target the long term unemployed. However, it may be argued that large scale government employment may have exactly the same effect. But this can only be true if government programmes consistently target *long* term unemployed. Although the public sector may be less strict in using unemployment duration as a screening device, there is no reason why the public sector systematically prefers long term unemployed.[6]

We can test this formally. Equation (1.22) states that the probability of being selected to work for the government should increase with time spent in unemployment. This implies that unemployment duration has a positive effect on the probability of getting a public sector job. Or more formally:

$$\sigma_p = \alpha + \beta t + \gamma X \tag{1.23}$$

Where t stands for time spent in unemployment, and X is a vector of control variables. We test whether its coefficient is strictly positive.

$$H_0 : \beta > 0 \tag{1.24}$$

[6] Some would argue that unemployment is a signal of ability, for example because those who are more certain about themselves wait longer in unemployment for the right job. There is, to my knowledge, no empirical evidence for this. Furthermore, the argument may be convincing in an OECD context where duration is mostly below one year, but is not convincing when unemployment duration is very long, as it is in the Ethiopian context.

2.3. Changes in labour demand

When demand for labour has risen over the observed time period, this will have a positive effect on the hazard rate. Neglecting changes in reservation wages $\left(\frac{\partial \pi}{\partial t} = 0\right)$, we write (1.8) as:

$$\sigma\pi \frac{\partial \nu}{\partial t} \geq -\nu\pi \frac{\partial \sigma}{\partial t} > 0 \tag{1.25}$$

Since σ is positive, this condition is equivalent to:

$$\frac{\partial \nu}{\partial t} > 0 \tag{1.26}$$

How can we test this formally? Can we find a proxy for labour demand? An increase in demand for labour occurs when the economy grows. We do not have regional or even national growth rates for the period for which we consider the hazard, namely the years before 1994, the time of data collection. The most important change in Ethiopia before 1994 occurred in 1991 when a new government came into power and started a process of restructuring the economy. There are indications that the economy has shrunk in the last years of the previous regime, when civil war got more intense [see MEDAC (1999)]. The most likely candidate for an increase in demand is therefore the change of government. More formally we consider that there is a shift in labour demand due to change in political regime (r):

$$\begin{cases} \nu_t = \nu_0 & r = 0 \\ \nu_t = \nu_1 & r = 1 \end{cases} \tag{1.27}$$

The change in labour demand can then be represented by the switch in regime.

$$\frac{\Delta \nu}{\Delta t} = \frac{\Delta r}{\Delta t} \tag{1.28}$$

We then examine how this change in political regime affects the hazard rate by modelling:

$$\lambda = \alpha + \beta r + \gamma X \tag{1.29}$$

where X is a vector of control variables. We test whether the coefficient on the regime switch is strictly positive.

$$H_0 : \beta > 0 \tag{1.30}$$

2.4. Segmented labour market

In a segmented labour market, where good and bad jobs coexist, the observed hazard may be non-decreasing because a substantial number of the unemployed are queuing for a good job. If they do not get the good job at a certain point, they accept a bad job. The framework is still one where a career is seen as a dynamic game. But now the labour market is segmented into good and bad jobs. People start in unemployment and have two choices: take up a bad job or queue in unemployment for a good job. They accept or refuse a job only on the basis of the wage - we make an abstraction from other job characteristics. The wage of the good job exceeds that of the bad job. The probability of accepting a job depends on the reservation wage. We assume that people can always get a bad job, and that there is no duration dependence in the bad sector. We also make the assumption that people never refuse a good job. Summarized we assume:

$$w_G > w_B \tag{1.31}$$

$$\pi_i = \Pr\left(w_i > w^r\right) \qquad \text{for i= G, B} \tag{1.32}$$

$$\sigma_B = 1 \tag{1.33}$$

$$\pi_G = 1 \tag{1.34}$$

In a segmented labour market the hazard will be the sum over the two sectors. We write the segmented labour market version of equation (1.2) as:

$$\lambda = v_G \sigma_G \pi_G + v_B \sigma_B \pi_B \tag{1.35}$$

Using (1.33) and (1.34) we write:

$$\lambda = v_G \sigma_G + v_B \pi_B \tag{1.36}$$

Assuming as before that the hazard, as well as the vacancy, selection and acceptance functions are continuous and that their first derivative exists, we now write the change of the hazard over time spent in unemployment as:

$$\frac{\partial \lambda}{\partial t} = \frac{\partial v_G}{\partial t} \sigma_G + v_G \frac{\partial \sigma_G}{\partial t} + \frac{\partial v_B}{\partial t} \pi_B + v_B \frac{\partial \pi_B}{\partial t} \tag{1.37}$$

The second term on the right hand side captures genuine duration dependence, where the probability to get a good job falls with time spent in unemployment because of unlearning-by-not doing, which means:

$$\frac{\partial \sigma_G}{\partial t} < 0 \tag{1.38}$$

Observed duration dependence can only be non-negative when:

$$\frac{\partial v_G}{\partial t} \sigma_G + \frac{\partial v_B}{\partial t} \pi_B + v_B \frac{\partial \pi_B}{\partial t} \geq -v_G \frac{\partial \sigma_G}{\partial t} > 0 \tag{1.39}$$

This occurs either when demand for (good or bad) labour rises over time; or when the probability of accepting a bad job rises with time spent in unemployment. The first effect implies that there are business cycle effects or other changes in the macro-environment that cause a rise in labour demand. We have seen in Section 2.3 that this does not hold. The second effect implies that the probability of accepting a job offer rises with time spent in unemployment.

$$\frac{\partial \pi_B}{\partial t} > 0 \tag{1.40}$$

When will this hold? Assuming that π_B , as described in (1.32), is a continuous monotonous function of reservations wages, we can write (1.40) as:

$$\frac{\partial \pi_B}{\partial t} = \frac{\partial \pi_B}{\partial w^r} \frac{\partial w^r}{\partial t} > 0 \qquad (1.41)$$

The first term on the right hand side is per definition negative $\left(\frac{\partial \pi}{\partial w_r} > 0 \right)$ since given a particular wage, the probability of accepting a job is lower for a higher reservation wage. Therefore equation (1.41) is equivalent to:

$$\frac{\partial w_r}{\partial t} < 0 \qquad (1.42)$$

This means reservation wages are lower for longer durations, i.e. they fall with time spent in unemployment.

How to test this? Our null hypothesis is that segmented labour markets offer an explanation for observing non-negative duration dependence because reservation wages fall with time spent in unemployment. A unique feature about the data is that we have information on the reservation wages of the unemployed. [7] We examine whether reservations wages fall with time spent in unemployment by running the following regression:

$$w^r = \alpha + \beta t + \gamma X \qquad (1.43)$$

and test whether the coefficient on unemployment duration is strictly negative.

$$H_0 : \beta < 0 \qquad (1.44)$$

2.5. Queuing in a non-segmented labour market

Do we need a segmented labour market to explain queuing in unemployment? Not necessarily. Assume a homogenous job market; when demand is censored, people will

[7] This is obtained by asking 'What is the lowest amount that you would be willing to accept as gross monthly income?'. As argued in Serneels (2002), the reservation wages turn out to be highly realistic.

queue in unemployment for any job. However, when genuine duration dependence is negative, employers will prefer the job candidates with the shortest duration. Someone who has *not* been unemployed has therefore a higher probability of being hired than someone who has been queuing in unemployment. Only if genuine duration dependence is non-negative, can we have general queuing in unemployment.

In the segmented labour market model, duration dependence is non-negative for bad jobs only. If queuing in general is an explanation, duration dependence has to be non-negative for all jobs. Time spent in unemployment should thus not affect the probability of leaving unemployment. And this must hold for all types of jobs. To test this against the segmented labour market model, we examine whether unemployment duration affects the probability of getting a good job.

$$\sigma_G = \alpha + \beta t + \gamma X \tag{1.45}$$

The null hypothesis is that time spent in unemployment has a non-negative effect:

$$H_0 : \beta \geq 0 \tag{1.46}$$

The test is similar to the one we formulated in 2.2, but now we consider all good jobs, not just the public sector. If (1.46) is rejected, general queuing is rejected as an explanation for non-negative duration dependence in favour of the segmented labour market model.

2.6. Can we have non-negative genuine duration dependence?

We argued that, from a conceptual point of view, genuine duration dependence has to be negative in the long run because skills are lost while in unemployment. If technological progress is slow, the genuine hazard falls only slowly because the loss of skills is limited. Nevertheless, in the long run the genuine hazard will still be negative because skills are lost by spending a long time in unemployment. This means that, although there may be mechanisms at play that make us observe non-negative duration dependence for considerable periods, in the long run the hazard must be negative, even when technological progress is slow. We test whether observed duration dependence in the long run is negative by examining whether a step dummy for long durations affects the hazard rate.

$$\begin{cases} lt = 0 \text{ if } \; duration \leq 12 \; years \\ lt = 1 \text{ if } \; duration > 12 \; years \end{cases} \tag{1.47}$$

$$\lambda = \alpha + \beta lt + \gamma X \tag{1.48}$$

The null hypothesis is that the hazard is lower for longer durations.

$$H_0 : \beta < 0 \tag{1.49}$$

We will test this in Section 4. However, before carrying out the constructed tests, we examine the course of the hazard rate.

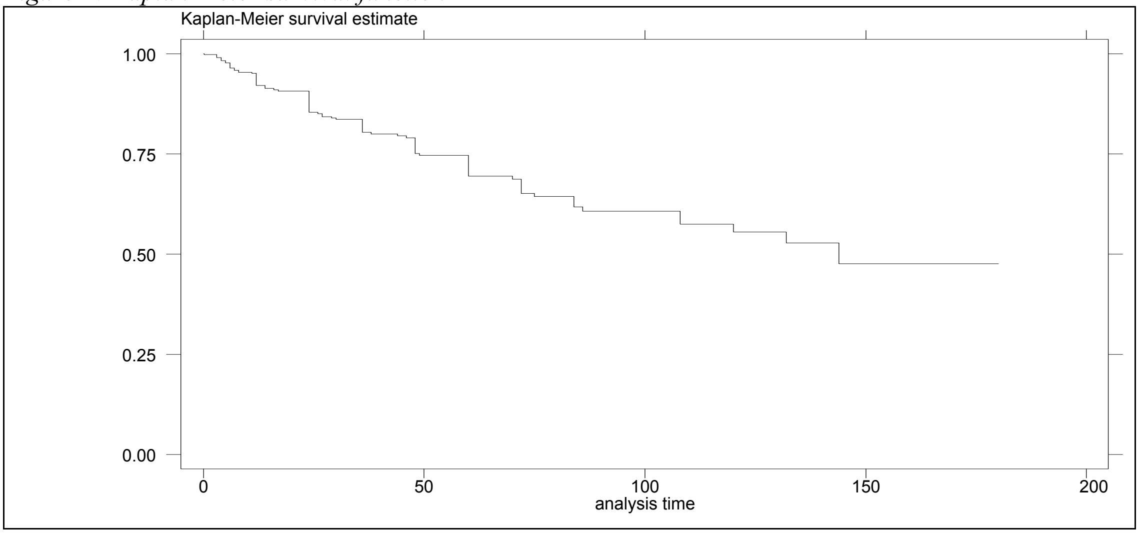
3. The course of the hazard rate

In this section we analyse the course of the hazard rate of unemployment for young men in urban Ethiopia, and show that it is non-decreasing over a large period. For a detailed description of the data see Serneels (2002). That paper also discusses the nature of unemployment including the determinants of the hazard rate, but restricst itself to proportional hazard (PH) models, because these models allow a straightforward interpretation of the coefficients. In this paper we consider a wider range of models, including Accelerated Failure Time (AFT) models. A characteristic of all duration models is that the estimation results are sensitive to the underlying distributional assumptions, much more so than in the case of ordinary regression analysis [see van den Berg (2000)]. Wrongly imposing a distribution may result in heavily biased estimates. We therefore start from a non-parametric approach and then compare with parametric specifications.

3.1. Non-parametric estimation

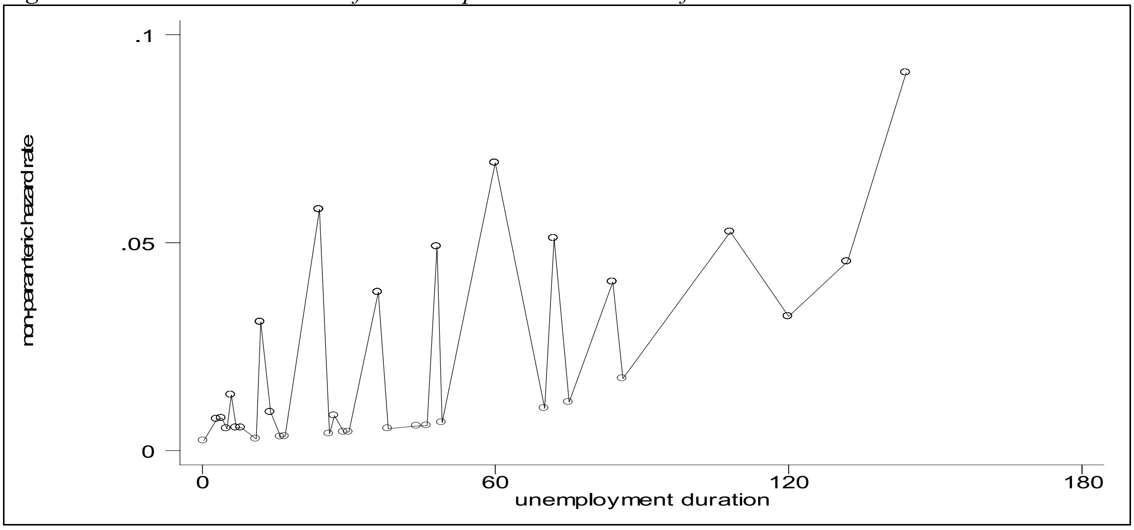
Figure 1 plots the Kaplan Meier survival function. This reflects how many people stay in unemployment as time proceeds.

Figure 1: Kaplan Meier survival function



From this we can calculate the product-limit estimate of the hazard function. It reflects the number of people leaving unemployment relative to the total number of people unemployed, at each point in time. This non-parametric estimate of the hazard rate is plotted in Figure 2. We observe that the hazard follows an upward trend. It does not exceed ten percent, which is similar to the estimated hazard rates for OECD countries. We also observe that it peaks at integer numbers. The reason for this is twofold. For those cases where duration is directly observed, this reflects the tendency of respondents to round their duration to integer years; fifty two percent of reported duration is expressed in integer years. For the other cases, the clustering around integer values is a consequence of the way the variable is constructed.[8]

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



The observation that the hazard rate is upward sloping is the most striking one. It means that the probability of getting a job does not fall with time spent in unemployment. This is even more surprising given the length of the duration spells. Mean duration is forty five months. To investigate whether this upward sloping course is driven by outliers, we restrict the analysis to shorter spells. We find the hazard to be at a lower level but still increasing. [9]

3.2. Parametric estimation

A parametric estimation allows us to test formally whether the hazard increases or decreases, and also allows us to draw a smooth plot of the hazard rate. The disadvantage of parametric models is that they impose stringent distributional

[8] For the currently unemployed, duration is calculated as current age minus experience minus age at leaving school. Both the first and last variable is expressed in integer years. Because of this truncation, duration is clustered around integer values. For a detailed description of the construction of unemployment duration for the currently unemployed, see the appendix of the previous Serneels (2002).

[9] 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.

conditions on the data. Different duration models assume different distributions for the unemployment spells, and the results are sensitive to the assumptions made. It is therefore important to test as carefully as possible which distribution fits the data best. Ideally one would follow a general-to-specific approach, starting from a model that encompasses all the others and formally test for restrictions. But there is no such model at hand. The most general fully parametric model is the one assuming a generalised gamma distribution. This model encompasses the lognormal and Weibull models. The exponential model is a restricted version of the Weibull. Alternative models like the Gompertz or the log-logistic are not nested and can therefore not be written as a restricted form of any of the other models. We will compare those models using the Akaike Information Criterion (AIC).[10]

An issue of special concern is unobserved heterogeneity. A model may lead to the conclusion that duration dependence is negative, just because it does not take unobserved heterogeneity into account. People who stay longest in unemployment may do so because of unobservable characteristics, and not because of the time spent in unemployment. Controlling for unobserved heterogeneity is therefore crucial in duration analysis [see van den Berg (2000)]. We control for it in a parametric way in all the models. We do not control for it in a non-parametric way, using a mixture model, because we find that our estimates are robust for alternative distributions for unobserved heterogeneity. There is also evidence that the main cause of bias in the results of mixture models is misspecification of the baseline hazard rather than the distribution of heterogeneity [see Ridder and Verbakel (1983)]. A final reason is that

[10] The AIC compares the likelihood scores while taking into account the degrees of freedom used in each model. AIC= -2* loglikelihood + 2 * (number of covariates + ancillary parameters), where the number of covariates = number of variables + constant – 1. We are well aware that the AIC is an unorthodox, relative and arbitrary measure. Unorthodox because it has no firm base in theory. Relative because it only shows which one of the evaluated models performs best relative to the others, not whether that model is appropriate in itself. The AIC is also arbitrary in the way it penalises: one could use a factor three instead of two to penalise for the number of covariates and ancillary parameters. The obvious advantage of the AIC is that it offers a way of comparing non-nested models.

the method to estimate mixture models is complex and its calculations are long and error prone [see Lancaster (1990)] Because it has not been applied frequently, little is known about the properties of the estimator.

We start from a generalised gamma model with Inverse Gaussian heterogeneity. [11] Testing the appropriate restrictions we 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. 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 models. To enable comparison with non-nested models, we calculate the Akaike Information Criterion (AIC). Table 2 shows that according to this criterion, the log-logistic model scores best, followed by the Weibull model. The exponential model comes third. According to the AIC, the log-logistic allowing for inverse Gaussian heterogeneity is thus the preferred model, followed by the Weibull and the exponential model.

Table 2: Overview of the Akaike Information Criterion scores

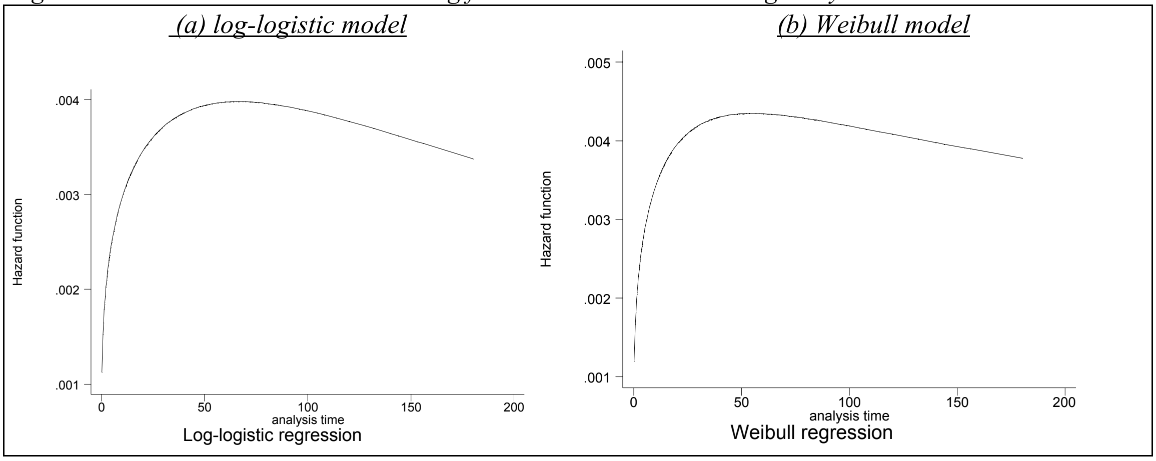
	loglikelihood	Number of covariates	Number of parameters	AIC	rank
inverse Gaussian heterogeneity					
Exponential	-254.244	16	0	540.4884	3
Piecewise exponential with 15 1 year pieces	-253.287	30	0	566.5732	7
Weibull	-253.071	16	1	540.1429	2
Gompertz	-254.011	16	1	542.0214	4
Lognormal	-254.291	16	1	542.5818	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

What are the implications for the course of the hazard rate? The predicted hazard for the two best performing models is plotted in Figure 3. We can see that both models

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

predict a hazard rate that first rises and then falls.[12] The maximum occurs around 6 years of duration, when more than four fifths of the young unemployed have already left unemployment. This suggests that the majority of unemployed face an increasing hazard. [13]

Figure 3: Predicted hazard rates allowing for inverse Gaussian heterogeneity



It is interesting to investigate the Weibull model still further for two reasons. First, it is widely applied to unemployment duration analysis in OECD countries and thus allows comparison; second, it encompasses the exponential model, which came third according to the AIC score. Using a variety of tests, discussed in detail in the appendix, we find evidence that the Weibull model is appropriate, although it fails monotonicity indicating that the hazard is not increasing monotonically, but follows a more complex course, as indicated by the non-parametric estimate plotted in the above Figure 2. When we test Weibull against the exponential model we can only reject the Weibull model at p=0.71. This suggests that a more flexible form, the piece-wise constant hazard model, may be more appropriate. This is an exponential model that implies a constant hazard rate, but by including step dummies we allow the hazard to shift each period. When we allow the level of the hazard to vary per year, we find a pattern close

[12] 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.

[13] 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.

to what we expect. The hazard shifts up during the early years but falls after the sixth year. However, none of these changes is significant, apart from the decrease beyond twelve years. Table 3 shows that the step dummy variables only become significant after twelve years. Note that the constant is highly significant, as is the parameter indicating unobserved heterogeneity (p-value 0.00).

Table 3: Estimates for proportional hazard models assuming Inverse Gaussian heterogeneity

	Piece wise constant
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

Robust standard errors in parentheses + significant at 10%; * significant at 5%; ** significant at 1%
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.

We conclude that the hazard rate follows a very flat inverse-U shaped course, which is difficult to distinguish from a constant course. The maximum occurs between five and six years, after which the hazard falls. By then more than four fifths of the unemployed have left unemployment.

4. Testing the Different Explanations

In the sections which follows, we carry out the tests designed in Section 2.

4.1. Unemployment benefits

As we argued before it only makes sense to talk about benefits in the Ethiopian context if we include household support, since state benefits are entirely absent. We also know that eighty four percent of the male young unemployed are supported by their parents [see Serneels (2002)]. Using household welfare as a proxy for household support, we test condition (1.17) using an exponential model. We find that household support has a significant positive effect on the hazard, whether we use consumption per household member or value of household assets per household member, as shown in Table 4. The result is also robust for other parametric specifications. Although we cannot exclude that household welfare is endogenous, it is clearly negatively associated with duration.

Our finding contrasts with OECD countries where unemployment benefits have a negative effect, be it not very large and mostly in the short run [see Layard, Nickell and Jackman (1990), Atkinson and Micklewright (1985, 1991)] while household support also has a negative effect, be it limited (Atkinson, 1999). 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)]. We conclude that in the case of Ethiopia, household support cannot be the explanation for observing a non-negative hazard – while assuming that genuine duration dependence is negative - because the unemployed who are coming from better off households are *more* likely to leave unemployment *sooner*.

Table 4: 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

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

4.2. Active Labour Market Policies

We argue in Section 2.2 that labour market programmes oriented towards the long term unemployed can make the hazard rate appear non-negative. Although there are no such policies in Ethiopia, we examine whether public sector employment, which is still the largest employer, has a similar effect by testing condition (1.24) in equation (1.23). However, we find that the probability of getting a public sector job is *negatively* related to time spent in unemployment, as shown in Table 5. This means that those who have been *longer* in unemployment are *less* likely to get a public sector job. Public sector employment has thus not the same effect as labour market programmes oriented towards the long term unemployed. Therefore this is not a good explanation for observing non-negative duration dependence.

Table 5: The effect of unemployment duration on getting a public sector job for men

	(1)	(2)
Time spent in unemployment	-0.01169	-0.00936
	(0.00256)**	(0.00216)**
Consumption per household member	-0.00346	
	(0.00089)**	
Value of household assets per household member		-0.00006
		(0.00002)**
Observations	908	908

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

The estimates are obtained from an instrumented variable probit, with working in the public sector as the dependent variable. Because we find evidence that unemployment duration is endogenous, we use an instrumental variable model.[14] We also control for household welfare, which we allow again to be endogenous. The results are robust for different proxies of household welfare.[15]

4.3. Changes in the demand for labour

The only way we can control for changes in labour demand is to look at structural changes. As argued in 2.3, since our data is from 1994, the major change in the Ethiopian economy that is relevant to us is the change in political regime in 1991, when the new government took power and signed an adjustment programme with the World Bank. As set out in (1.27) we include a step dummy representing the regime switch and test whether it has a significant effect on the hazard. We find that it does not, as shown in Table 6.

[14] Using a Hausman test we find that the coefficients from an instumented variable probit are significantly different from those of an ordinary probit. We also allow household welfare to be endogenous. Instruments are location, local unemployment rate, and sex, age, education level, marital status, ethnicity, religion, activity and labour income from the household head.
[15] Note that the estimates are obtained from applying the model to all men to get a perspective over the longer term.

Table 6: Effect of a change in political regime on the hazard

Unemployment spell started in or after 1991	-0.02322
	(0.41274)
Observations	378

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

When we try a step dummy for the neighbouring years, we find they also have a small and insignificant effect. This confirms that if there were changes in labour demand due to a change in political regime, they had no immediate effect on the hazard.

4.4. Segmentation in the labour market

A final explanation for observing non-negative duration dependence is that the labour market is segmented into good and bad jobs. As set out above, people can take up a bad job whenever they want and there is no negative duration dependence in the bad sector. This is because the skills needed for a bad sector job are basic. We argued that people will queue in unemployment for a good job, and this leads to non-negative duration dependence because, as time proceeds, more people accept a bad job by lowering their reservation wage. We estimate equation (1.43) for those unemployed who aspire to a good job[16] and test whether reservation wages fall with time spent in unemployment, following the test in (1.44). The results in Table 7 show that we find a negative relationship between reservations wages and duration, indicating that reservation wages fall with time spent in unemployment.

[16] Jobs in an international organization, civil service, public sector enterprises and formal private enterprises are considered to be good jobs because they pay higher, offer fringe benefits and offer a higher job security.

Table 7: The change of reservation wages over time for those aspiring to a good job

	reservation wage
Time spent in unemployment	-0.88832
	(0.52542)+
Observations	148
R-squared	0.33

Robust standard errors in parentheses + significant at 10%; * significant at 5%; ** significant at 1%
The model controls 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.

This confirms earlier results, like those from Kasper (1967) who was the first to empirically establish the fall of reservation wages with time spent in unemployment.

4.5. Queuing in a non-segmented labour market

We showed above that explaining unemployment by queuing in general, without having to assume a segmented labour market, is equivalent to accepting that time spent in unemployment has no effect on the probability of getting a job. We test whether unemployment duration affects the probability of getting a good job by estimating equation (1.45) and using the test formulated in (1.46).

Table 8: The influence of unemployment duration on the probability of getting a good job for young and adult men

Time spent in unemployment (I)	-0.01120
	(0.00226)**
Observations	908

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

We allow unemployment duration to be endogenous by instrumenting for it, using household and local characteristics as instruments.[17] We find that time spent in unemployment does affect the probability of getting a good job. Therefore general queuing in the labour market is not a good explanation for observing non-negative duration dependence.

4.6. Is duration dependence negative in the long run?

We argued above that, however slow technological progress, unemployment will eventually have an unlearning-by-not-doing effect. This means that, although observed duration dependence may be non-negative for a considerable time, in the (very) long run, we expect duration dependence to be negative. When we examined the course of the hazard rate in Section 3. , we found that the hazard has an inverse U-shaped shape, which is indistinguishable from a flat line for most of the time spent in unemployment. However, we found the hazard to fall significantly in the last years. To follow the procedure set out in Section 2.6 we define a step dummy for the long term following (1.47). We then estimate equation (1.48) and test whether the hazard falls in the long term, following (1.49).

Conforming with earlier results we find that the observed hazard falls in the long run.

Table 9: Observed duration dependence in the long term for young men

Long term (>12 years)	-27.54564
	(0.45231)**
Constant	10.80867
	(4.56454)*
Observations	378

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

[17] Using a Hausman test we find that the coefficients from an instumented variable probit are significantly different from those of an ordinary probit. We also allow household welfare to be endogenous. Instruments are location, local unemployment rate, and sex, age, education level, marital status, ethnicity, religion, activity and labour income from the household head.

5. Summary and conclusion

It is often accepted as a stylized fact that unemployment duration dependence is negative. Time spent in unemployment would thus have a negative effect on someone's probability of leaving unemployment. The recent literature, however, often observes non-negative duration dependence. This research is only applied to OECD countries. We investigate whether we observe negative unemployment duration dependence among male young adults in a developing country, namely urban Ethiopia. This is intriguing because unemployment duration is often much longer in developing countries - in urban Ethiopia mean duration is forty-five months - raising the possibility that unemployment leads to a higher depletion of skills. Another reason is that the existence of negative duration dependence would reveal the importance of path dependency in a men's career.

Our theoretical framework starts from the assumption that genuine duration dependence is negative in the long run. This is because, however slow technological progress, there is unlearning-by-not-doing when spending time in unemployment. But while genuine duration dependence is negative, observed duration dependence may be non-negative. The literature suggests four potential reasons why this may be the case.

The first reason is the presence of unemployment benefits, and their limited duration over time. Because the unemployed know that the support they receive is limited in time, they are more eager to get a job the closer they come to the expiry date. They increase their chances of getting a job by lowering their reservation wages. In the Ethiopian context we include household support as benefits.

A second explanation is the presence of active labour market policies that target the long term unemployed. Therefore the probability of leaving unemployment, or hazard rate, will increase for the long term unemployed. Ethiopia has no labour market programmes targeted towards the unemployed, but one might argue that public sector employment works in the same way.

A third factor is that the economy changes over time. In an upswing of the economy, the long term unemployed are more likely to find a job.

A fourth 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 left unused. The hazard for a bad job, however, remains constant because the skills required are very basic. People can always get a bad job. This can create the illusion of a non-decreasing hazard.

A fifth explanation is a more general version of the previous one and argues that queuing in unemployment in general – whether labour markets are segmented or not – creates the illusion of non-negative duration dependence. When the number of jobs is constrained and employment is purely ‘waiting your turn’, then the hazard will not fall with time spent in unemployment.

We develop a theoretical framework to test each of these explanations. The key equation to our framework is that at each point in time, the hazard is the product of three factors: the probability that there is a vacancy, the probability of being selected for a job, and the probability of accepting the job. This is a more general formulation than the one found in traditional job search models. Within this framework we can translate each of the above explanations into an empirical test.

Before that, we examine the course of the hazard rate and establish that it follows an inverse U-shaped course, which is not significantly different from a flat line. This means that the hazard does not fall for most of the time spent in unemployment, or that duration dependence is non-negative for most of the time spent in unemployment.
We then test each of the potential explanations using the tests developed within the theoretical framework.

In the theoretical framework, we show that under certain assumptions, unemployment benefits can only explain the observation of non-negative duration dependence if household support has a negative effect on the hazard rate. We test this and find that a significant positive relationship. Therefore this does not offer an explanation.

We also show that public sector employment can only offer an explanation if time spent in unemployment has a positive effect on the probability of getting a public sector job. When we test this we find a significant negative relationship.
To test the third explanation, whether an increase in labour demand can explain observed non-negative duration dependence, we consider the most important shift in macro-economic policy proceeding the date of data collection. In 1991 a new regime was installed and a process of economic liberalization was begun. This may have brought about a shift in labour demand. We show that if this is to be an explanation, the regime switch should have a positive effect on the hazard. We find that it has no significant effect.

To test whether segmentation of the labour market can explain non-negative duration dependence, we show in the theoretical framework that we have to prove that reservation wages fall for those unemployed who are queuing for a good job. Because

our data contains information on reservation wages, we can test this. We find that those who have spent a longer time in unemployment have indeed lower reservation wages. This indicates that segmented labour markets are a valid explanation for observing non-negative duration dependence.
But do we need a *segmented* labour market, or would queuing in general offer as good an explanation? We show that queuing in a homogenous labour market can only explain a non-negative hazard when genuine duration dependence is non-negative. We also test the general queuing model against the segmented labour market model and reject the former in favour of the latter.

Finally, we show that however slow technological progress, observed duration dependence should be negative in the very long run. We show that this indeed is what we find in our data.

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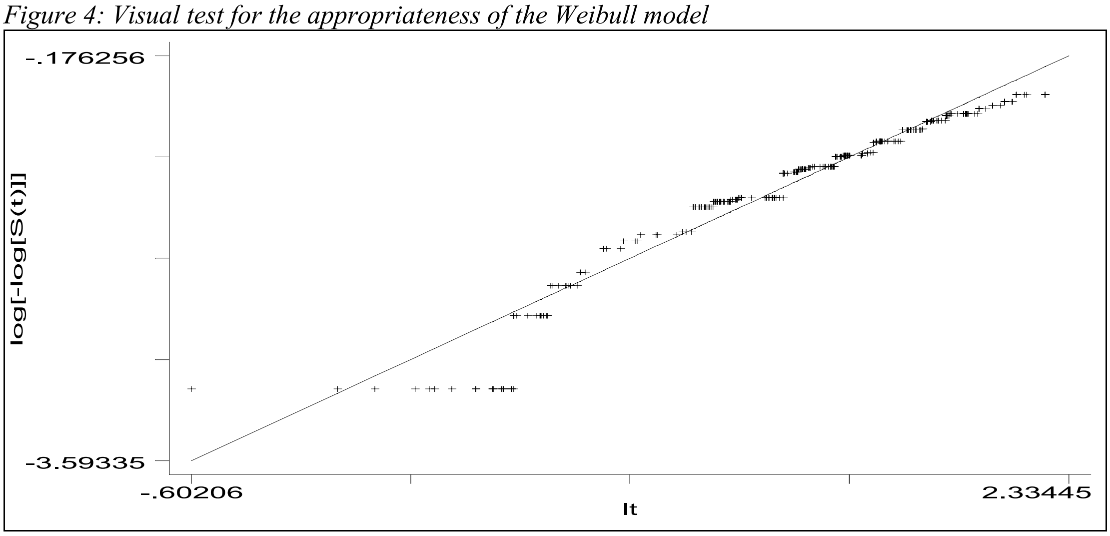
7. <u>Appendix</u>

7.1. Diagnosing the Weibull model

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

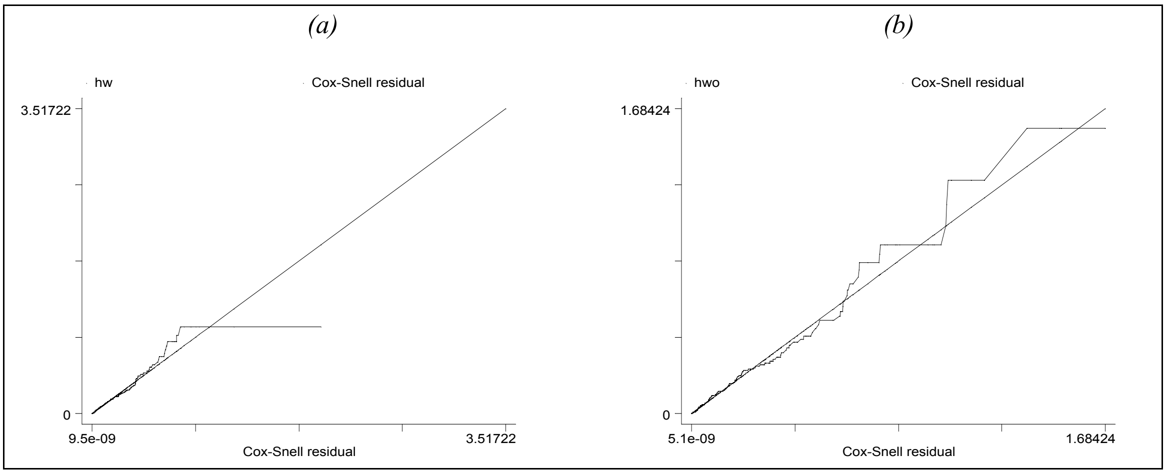
A second test we apply is a simple visual test to evaluate whether the Weibull is the appropriate model, as set out by Lancaster (1990). Figure 4 plots the logarithm of integrated hazard against the logarithm of duration. If the Weibull is the appropriate distribution, the result should be a linear curve. Indeed, under the assumption of Weibull distributed duration spells, $\Lambda(t) = (\lambda t)^{\alpha}$, or, written in logs this gives $\log[\Lambda(t)] = \alpha \log \lambda + \alpha \log t$. This means that the logarithm of the cumulative hazard {log[Λ(t)]} is linear in the logarithm of duration [log(t)]. The integrated hazard can be proxied by the negative of the logarithm of the (non-parametric) Kaplan-Meier survival function. Although the relationship is not perfectly linear, most observations are close to the forty-five degree line. The result remains the same when we leave out the outliers.

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



A third test is again a diagnostic visual test. We plot 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 5(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 5(b). A comparison with similar plots for other distributions shows us that the Weibull does not seem to fit the data worse than any of the other distributions.

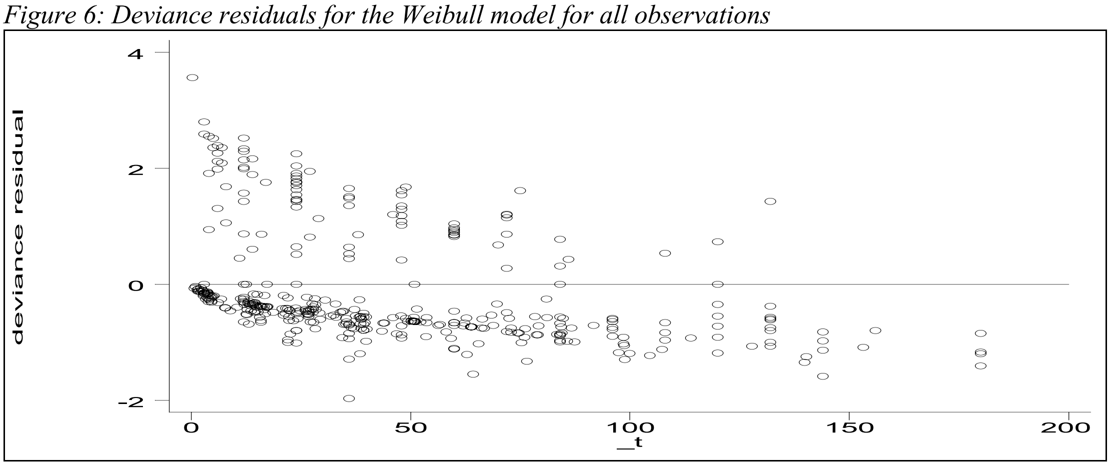
Figure 5: Log of Kaplan Meier cumulative hazard versus Cox-Snell residuals for the Weibull for all observations



Another diagnostic test is to plot the <u>deviance residuals</u>, following Stata (1999). We first define Martingale-like residuals. They can be interpreted as reflecting the difference over time between the actual number of those leaving unemployment and the expected number based on the model. They are easily derived from Cox-Snell residuals: and are defined as: $M_j(t) = \delta_j - CS_j(t_j)$, where $\begin{cases} \delta_j = 1 & if \quad employed \quad at \quad t_j \\ \delta_j = 0 & if \quad unemployed \quad at \quad t_j \end{cases}$

However, because these residuals take values between $-\infty$ and 1, they are difficult to interpret. Therefore we 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 6 and indicates that the hazard may be overestimated for very long durations (>= 100 months).

Figure 6: Deviance residuals for the Weibull model for all observations



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 what we find using the piece wise constant hazard, although the changes in between are insignificant.

7.2. Testing the Weibull against the exponential model

Since the Weibull model encompasses the exponential model, we can formally test the latter as a restriction of the former. We carry out a Wald test for the ancillary parameter p being equal to unity, which is the condition to restrict the Weibull to the exponential. The hypothesis that ln(p)=0 is rejected at p=0.70. This suggests that the Weibull does not fit much 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 7 plots the integrated hazard against duration. Since $\lambda = -\frac{d \log S(t)}{dt}$ and Λ is the integration of λ over t, we get that $\hat{\Lambda}(t) = -\log \hat{S}(t)$. Now, since $\Lambda = \lambda t$, plotting Λ against t should be a straight line through the origin if λ is indeed assumed to be constant. The more the plotted line deviates from a straight line through the origin, the less appropriate is the exponential distribution (Stewart, 1998). We observe deviation from the line especially for higher values of duration, but overall the fit does not seem much poorer than the Weibull model.

Figure 7: Visual test for the appropriateness of the exponential model