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Pieter Serneels

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Abstract[1]

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. Using a standard job search model we test the two main explanations why we may observe non-negative duration dependence while genuine duration dependence is negative, namely financial support for the unemployed and a change in the economy over time. We also identify a third explanation which may be relevant especially for developing countries, namely that the labour market is segmented, and extend the classic job search model. Using data for urban Ethiopia we first show that the observed hazard does not fall with time in unemployment for the majority of spells after controlling for unobserved heterogeneity. Using the tests developed from the model we can reject the classic explanations and find supportive evidence that labour market segmentation explains observed non-negative duration dependence, as searching for bad job lifts the hazard over time. Our findings underline the potential importance of labour market segmentation, especially in developing countries, and in particular in the presence of a large public sector.

JEL classification: J64, C41
Keywords: unemployment, duration dependence, labour market segmentation, urban labour market

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

Introduction

The notion that the probability to leave unemployment falls the longer one remains in unemployment has considerable intuitive appeal, and is a central assumption in many 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. Table 1 provides an overview of the studies in this field and illustrates that a substantial number observe non-negative average duration dependence.[2] Why this apparent contradiction? The literature, focusing exclusively on OECD countries, concentrates on three potential explanations: financial support for the unemployed, changes in the economy, and the presence of labour market programs targeting the long term unemployed. A fourth potential explanation, segmentation of the labour market, is seldom considered, but may be especially relevant for developing countries. Although labour market segmentation is hard to prove in a conclusive way in any context, existing work indicates that it may be important, especially in developing countries, but potentially also in OECD countries.[3] Starting from a standard job search model we develop tests for the first two explanations. We then extend the model to incorporate labour market segmentation and develop a test to see whether this may explain non-negative duration dependence. Because there are no labour market programs that target the long term unemployed in Ethiopia, we disregard the third explanation.[4]

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[2] While thirty one (64%) of the forty eight studies we identified observed negative or inverse u-shaped duration dependence, six (13%) observed no (constant) duration dependence and 11 (22%) found positive or u-shaped duration dependence. 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, and of more advanced techniques to model unobserved heterogeneity, this is unlikely to fully explain non-negative duration dependence, as argued by van den Bergh (2001).

[3] A convincing formal test for labour market segmentation is not available because sector allocation may always be driven by unobserved characteristics, as argued by Heckman & Hotz (1986), Heckman & Sedlacek (1985) and Magnac (1991). Nevertheless, most economists now agree that segmented labour markets have something to offer and that the evidence is too strong to neglect the model altogether, especially for developing countries (see for instance Stiglitz (1982), Magnac (1991), but also for OECD countries (See for example Katz & Summers (1989), Saint-Paul (1996),Lang & Dickens (1992), and Bulow & Summers (1986)).

[4] The presence of labour market programs explains why there is non-negative duration dependence for instance in Sweden (Edin 1989) and The Netherlands (van den Berg and van Ours 1994). We investigate whether the public sector implicitly functions as a labour market program in urban Ethiopia by targeting the long term unemployed, but we find that it does not. Public sector employees did not spend more time in unemployment than private sector employees, even after controlling for

In line with standard models, the premise of this paper is that genuine duration dependence is negative because unemployment implies a loss of skills. This may occur 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. Observed average duration dependence, however, may be non-negative for any of the reasons set out above. Here we discuss the three reasons that are relevant for our context in more detail. First, the unemployed receive financial support, and this is limited in time - in richer countries this may take the form of state benefits, in poor countries the unemployed receive support from their family. As the expiry date approaches, the unemployed become more eager to find a job and lower their reservation wage. This pushes up the hazard rate and may lead to a non-negative duration dependence. 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 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 & van der Klaauw (2000), Abbring, van den Berg & van Ours (2002) and Cockx & Dejemeppe (2005) find that the hazard changes over time due to business cycle effects in The Netherlands, France and Belgium respectively. Arulampalam & Stewart (1995) and Imbens & Lynch (2006) find that exit probabilities are different for distinct cohorts in the UK and US. A third 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 waiting in unemployment for a good job. Assuming that the probability to get selected for a 'good' job falls with time in unemployment while it remains constant over time for a bad job, and that the probability of getting a good job is stochastic, people will lower their reservation wage become 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 labour market segmentation offers a good explanation for observing non-negative duration dependence in Sweden.

In the next section we first present the job search model and derive tests for the first two explanations. We then extend the model to allow for a segmented labour market and develop a test to see whether this explains non-negative duration dependence. In Section 3 we describe the context and the data for urban Ethiopia. In Section 4 we analyse the course of the hazard rate while Section 5 tests each of the three explanations and Section 6 concludes.

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other characteristics. Running a probit model we estimate the following equation: $\sigma_p = \alpha_2 + \beta_2 t_i + \Gamma_2 X_i$ and test $H_0 : \beta_3 > 0$. We can reject the null.

Job search and duration dependence

Consider a classic job search model where individuals maximize the expected present value of their lifetime utility; for simplicity all utility is derived from wage income: $\underset{y,t}{Max}\int_{0}^{+\infty} d^t y_t$, where d is the discount rate, a function of the interest rate $d = 1/(1+r)$ and y_t denotes income during period *t*, which equals financial support *z* during unemployment and wage *w* when working.[5] All individuals start in unemployment.[6] Drawing a sample of job offers in each period, they compare the wage attached to the job offer with their reservation wage to decide whether they should leave unemployment or not. $H(w)$ Once they have left unemployment, they stay in the job for ever.[7]

Model without segmentation

Assuming there is only one type of job, we can write the life time value of a job offer with wage *w* as $V^E = \dfrac{wdt}{1+rdt}$ (1)

The optimal search strategy for individuals is to set their reservation wage *x* so that it maximizes life time earnings. This means they will stop searching when the job offer exceeds the reservation wage, which reflects the opportunity cost of remaining in unemployment for one more period $x = rV^U$ (2)

In other words, he will stop searching when the value of accepting the job equal the value of remaining unemployed $V^E(x) = V^U$ (3)

Let ϕ be the job arrival rate, which is exogenous to the individual, then the discounted expected value of employment is given by

$$V_\phi^E = \int_0^x V^U dH(w) + \int_x^{+\infty} V^E(w) dH(w) \quad (4)$$

Let *b* be the support received during unemployment, then we can write the value of unemployment in the stationary state as

$$V^U = \frac{1}{1+rdt}\left(bdt + \phi dt V_\phi^E + (1-\phi dt)V^U\right) \quad (5)$$

which can be written as $rV^U = b + \phi\int_x^{+\infty}\left(V_\phi^E(w) - V^U\right)dH(w)$ (6)

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[5] Individuals only know the cumulative distribution of the possible wages, which is the same in each period, and successive wage offers are independenty draws from this distribution.

[6] This appropriately reflects the situation in our most low income countries where unemployment is heavily concentrated among first time job seekers (see Glewwe (1989), Dickens & Lang (1996) and Rama (1999) for Sri Lanka; Rama (1998) for Tunisia; Manning & Junankar (1998) for Indonesia; and Tenjo (1990) for Colombia, Hirschman (1982) for Malaysia and Serneels (2007) for Ethiopia.

[7] They do not re-enter unemployment, which reflects the situation in most developing countries.

Combing (1), (3) and (6) we can write

$$x = b + \frac{\phi}{1+r}\int_{x}^{+\infty}(w-x)\,dH(w) \tag{7}$$

Where the partial derivatives take the following signs: $\frac{\partial x}{\partial b} > 0, \frac{\partial x}{\partial \phi} > 0, \frac{\partial x}{\partial r} < 0$, expressing that reservation wages will increase with financial support and when the job arrival rate increases.[8] The exit rate of unemployment, or hazard rate, is given by

$$\lambda = \phi\left(1 - H(x)\right) \tag{8}$$

Since the job arrival rate (ϕ) can be written as a product of the probability that there is a vacancy (ν) and the probably of getting selected for the job (σ), and letting $\pi = 1 - H(x) = \pi\left(x(\nu,\sigma,b)\right)$ be the probability to accept a job - which is a function of the reservation wage *x*, and conditional on not having accepted a job yet – and assuming (for now) that individuals are homogenous, the hazard can at each point in time be written as:

$$\lambda_t = \sigma_t \nu_t \pi_t \tag{9}$$

Assuming that σ_t, ν_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

$$\frac{d\lambda}{dt} = \underset{(A)}{\nu\pi\left(x(\nu,\sigma,b)\right)\frac{\partial\sigma}{\partial t}} + \underset{(B)}{\sigma\pi\left(x(\nu,\sigma,b)\right)\frac{\partial\nu}{\partial t}} + \underset{(C)}{\nu\sigma\frac{\partial\pi\left(x(\nu,\sigma,b)\right)}{\partial t}} \tag{10}$$

The first term on the right hand side (term A) reflects the change in the (unobserved) probability of being hired or genuine duration dependence, which we assume to be negative, as argued before $\left(\frac{\partial\sigma}{\partial t} < 0\right)$. Term (B) reflects the changes in reservation wages over time due to a change in financial support for the unemployed, and term (C) reflects changes in vacancy rate. Equation (10) thus provides a framework to test, and shows that observed duration dependence may be non negative $\left(\frac{d\lambda}{dt} \geq 0\right)$ either because of large enough changes in reservation wages (C>A keeping B constant), or because of a large enough change in the vacancy rate over time (B>A keeping C constant).[9] Now let $\frac{\partial\pi\left(x(\nu,\sigma,b)\right)}{\partial t} = \frac{\partial\pi}{\partial x}\frac{\partial x(\nu,\sigma,b)}{\partial t}$ and rearranging and collecting

[8] Rewriting (7) as $\mu(x,b,\phi,r) = x - b - \frac{\phi}{1+r}\int_{x}^{+\infty}(w-x)\,dH(w)$ we can find the first derivatives of this function with respect to each of the parameters $\partial\mu/\partial i$, and since $\partial x/\partial i = -\left(\partial\mu/\partial i\right)/\left(\partial\mu/\partial x\right)$ we obtain the signs of the partial derivatives of *x* with repect to each of the parameters.

[9] Note that the other reason for non-negtaive duration dependence, which is relevant for our case, namely the presence of labour market programs that target the long term unemployed can also be incorporated in this framework, for example by distinguishing a market selection rate and a progam selection rate with $\sigma = \sigma^m + \sigma^p$ and $\partial\sigma^p/\partial t > 0$ while $\partial\sigma^m/\partial t > 0$

terms we can rewrite (10) as follows in the case of non-negative duration dependence, providing a starting point for testing:

$$\frac{d\lambda}{dt}=\left(\pi(x)+\frac{\partial x}{\partial\sigma}\frac{\partial\pi}{\partial x}\sigma\right)\nu\frac{\partial\sigma}{\partial t}+\nu\sigma\frac{\partial\pi}{\partial x}\frac{\partial x}{\partial b}\frac{\partial b}{\partial t}+\left(\pi(x)+\frac{\partial x}{\partial\nu}\frac{\partial\pi}{\partial x}\nu\right)\sigma\frac{\partial\nu}{\partial t}\geq 0 \tag{11}$$

Financial support for the unemployed

Keeping the vacancy rate constant, so that the third term on the right hand side in (11) drops out, and since $\nu,\sigma,\frac{\partial x}{\partial b}>0$ and $\frac{\partial\pi}{\partial x}<0$ we can write

$$\nu\sigma\frac{\partial\pi}{\partial x}\frac{\partial x}{\partial b}\frac{\partial b}{\partial t}\geq-\left(\nu\pi(x)+\frac{\partial x}{\partial\sigma}\nu\sigma\right)\frac{\partial\sigma}{\partial t}\geq 0 \tag{12}$$

expressing that observing a non-decreasing hazard may be caused by a decrease in financial support that causes reservation to fall enough in order to compensate for genuine duration dependence. A necessary condition for this to happen is that the change in benefits has a negative effect on the hazard rate, reflecting that a drop in financial support would increase the hazard rate, which we can test as

$$\frac{d\lambda}{dt}=\alpha+\beta_1\frac{\partial b}{\partial t}\qquad\text{with}\quad H_0:\beta_1<0$$

or

$$\lambda=\alpha t+\beta_1\frac{\partial b}{\partial t}t\qquad\text{with}\quad H_0:\beta_1<0 \tag{13}$$

Changes in the vacancy rate over time

When we keep financial support constant, equation (11) can be written as:

$$\frac{d\lambda}{dt}=\left(\pi(x)+\frac{\partial x}{\partial\sigma}\frac{\partial\pi}{\partial x}\sigma\right)\nu\frac{\partial\sigma}{\partial t}+\left(\pi(x)+\frac{\partial x}{\partial\nu}\frac{\partial\pi}{\partial x}\nu\right)\sigma\frac{\partial\nu}{\partial t}\geq 0 \tag{14}$$

Define $D=\left(\pi(x)+\frac{\partial x}{\partial\sigma}\frac{\partial\pi}{\partial x}\sigma\right)\nu$ and $\beta_2=\left(\pi(x)+\frac{\partial x}{\partial\nu}\frac{\partial\pi}{\partial x}\nu\right)\sigma$ which we can proof to be both positive ($D\geq 0$ and $\beta_2\geq 0$).[10] Equation (14) thus expresses that observing a non-decreasing hazard may be caused by a vacancy rate rising enough over time to compensate for decreasing genuine duration dependence. A necessary condition for

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[10] For D to be positive requires that $\partial x/\partial\sigma<(-\pi/\sigma)(\partial\pi/\partial x)^{-1}$. Since $\phi=\sigma\nu$, and using (7), we can define $\mu(x,b,\sigma,\nu,r)=x-b-\sigma\nu(1+r)\int_x^{+\infty}(w-x)\,dH(w)$ and derive $\partial x/\partial\sigma=(\partial\phi/\partial x)(\partial x/\partial\sigma)$. We find that the condition for D to be positive can be written as $\partial\pi/\partial x<\pi(\sigma\nu+1+r)\left(\sigma\nu\int_x^{+\infty}(w-x)\,dH\right)^{-1}$ which always holds since the left hand side is always negative and the right hand side always positive. We find that for β_2 to be positive the same condition applies.

this to happen is that the change in the vacancy rate has a positive effect on the hazard rate, which we can test as

$$\frac{d\lambda}{dt} = \alpha_2 + \beta_2 \frac{\partial v}{\partial t} \qquad \text{with} \quad H_0 : \beta_2 \geq 0$$

or

$$\lambda = \alpha_2 t + \beta_2 \frac{\partial v}{\partial t} t \qquad \text{with} \quad H_0 : \beta_2 \geq 0 \tag{15}$$

where $\alpha_2 = D\frac{\partial \sigma}{\partial t}$

Model with segmentation

We assume that there are two types of jobs, good jobs and bad jobs, with two separate non-overlapping wage distributions. The wage of the good job always exceeds that of the bad job $(w_G > w_B)$ and individuals always accept a 'good job' offer. When searching for a bad job individuals compare the wage with their reservation wage, while accepting a good job only depends on the arrival rate of good jobs - we therefore abstract from the wage distribution for good jobs and represent it by a simple wage w_G. We also assume that bad jobs require skills that do not depreciate over time. In other words, while duration dependence is negative in the good sector, it is constant in the bad sector. We can write the life time value of a good and bad job respectively as

$$V^{EG} = \frac{w^G dt}{1+rdt}; V^{EB} = \frac{w^B dt}{1+rdt} \tag{16}$$

Individuals will wait for a good job as long as $V^U \geq V^{EG} > V^{EB}(x)$. They will consider a bad job when $V^U < V^{EG}$ and will accept a bad job when $V^U = V^{EB}$. In other words, individuals will compare the value of unemployment with each of the alternative employment states and choose the maximum, so $V^U = \max\left(V^{EG}, V^{EB}\right)$ (17)

If V^{EG} is the largest, $V^U = V^{EG}$, while if V^{EB} is the largest, reservation wages are set such that $x = rV^U$ as before. (18)

Let ϕ_G, ϕ_B be the job arrival rates of good and bad jobs respectively, both exogenous to the individual, then the discounted expected value of employment in good and bad jobs are given by

$$V_{\phi_G}^{EG} = V^{EG}$$

$$V_{\phi_B}^{EB} = \int_0^x V^U dH(w_B) + \int_x^{+\infty} V^{EB}(w_B)\, dH(w_B) \tag{19}$$

We can write the value of unemployment in the stationary state as

$$V^U = \frac{1}{1+rdt}\left[bdt + \phi_G dt V_{\phi_G}^{EG} + (1-\phi_G dt)\left(\phi_B dt V_{\phi_B} + (1-\phi_B dt)V^U\right)\right] \tag{20}$$

which can be written as

$$\max\left(V^{EG},V^{EB}(x)\right)=\frac{bdt+\phi_G dtV^{EG}+(1-\phi_G dt)\phi_B dtV^{EB}_{\phi_B}}{rdt+\phi_B dt+\phi_G dt-\phi_G\phi_B dt}$$

For those who get a good job, all variables are exogenous and using (16) we can find how large the good wage has to be as a function of the bad wage, the job arrival rates and the discount rate. Those who search for a bad job have to decide to set their reservation wage to maximize life time earnings. Using (19) we can write

$$rV^U=b+\phi_G V^{EG}+(1-\phi_G dt)\phi_B\int_x^{+\infty}\left(V^{EB}(x)-V^U\right)dH(w)-\phi_G V^U$$

Which, using (16) and (18) can be written as:

$$rV^U=b+\phi_G V^{EG}+(1-\phi_G dt)\phi_B\int_x^{+\infty}\frac{(w-x)}{1+rdt}dH(w)-\phi_G\frac{x}{1+rdt}$$

or: $$x=\frac{(1+rdt)b}{1+rdt-\phi_G}+\frac{\phi_G w_G(1-\phi_G dt)\phi_B}{(1+rdt-\phi_G)(1+rdt)}\int_x^{+\infty}(w_B-x)\,dH(w_B) \tag{21}$$

Where the partial derivatives take the following signs: $\frac{\partial x}{\partial b}>0,\frac{\partial x}{\partial\phi_G}>0,\frac{\partial x}{\partial\phi_B}>0\frac{\partial x}{\partial r}<0$, expressing that reservation wages will increase with financial support, and when the job arrival rate of either a good or bad job increases and will decrease with the interest rate.[11] In this labour market the hazard will be the sum of the hazards in the two sectors. Since $\lambda_G=\phi_G=\nu_G\sigma_G$ and $\lambda_B=\phi_B(1-H(x))=\nu_B\pi\left(x(\sigma_G,\nu_G,\nu_B,b,r)\right)$, we can write:

$$\lambda=\sigma_G\nu_G+\nu_B\pi_B\left(x(\sigma_G,\nu_G,\nu_B,b,r)\right) \tag{22}$$

Further assuming that $\lambda,\sigma_G,\nu_G,\nu_B,\pi_B,r$ are continuous and that their first derivative exists, we write observed duration dependence as:

$$\frac{d\lambda}{dt}=\underset{(E)}{\nu_G\frac{\partial\sigma_G}{\partial t}}+\underset{(F)}{\sigma_G\frac{\partial\nu_G}{\partial t}}+\underset{(G)}{\pi_B\frac{\partial\nu_B}{\partial t}}+\underset{(H)}{\nu_B\frac{\partial\pi_B\left(x(\sigma_G,\nu_G,\nu_B,b)\right)}{\partial t}} \tag{23}$$

Where the first term on the right hand side (E) now captures genuine duration dependence (in the good sector) and is negative. Equation (23) then points, like in the case of a non-segmented labour market, to two potential explanations for observing non-negative duration dependence $\left(\frac{d\lambda}{dt}\geq 0\right)$: a change in the vacancy rate (F+G), this time of either good or bad jobs, and a rise in the probability of accepting a bad job, brought about by a fall in reservation wages (H). The fall in reservation wages occurs - just as in the case of a non-segmented labour market – as a consequence of a fall in financial support (*b*), because of a change in vacancies (ν_G,ν_B), or as a

[11] As before we can define the function

$$\mu'(x,b,\phi_G,\phi_B,r)=x-\frac{(1+rdt)b}{1+rdt-\phi_G}-\frac{\phi_G w_G(1-\phi_G dt)\phi_B}{(1+rdt-\phi_G)(1+rdt)}\int_x^{+\infty}(w_B-x)\,dH(w_B)$$ and find the first derivatives of this function with respect to each of the parameters in order to find the sign of the partial derivatives of *x* with respect to each of the parameters.

response to a change in genuine duration dependence of the good job (σ_G). But the segmented model also points to another reason why reservation wages may fall, namely a change in the type of job searched for. Because switching from searching for a good job to searching for a bad job increases the unemployed's probability to find a job, this will pull up the hazard. Indeed, for those searching for a good job the change in hazard is defined by (E) and (F), while for those searching for a bad job it is determined by (G) and (H). Switching from searching for a good job to searching also for a bad job increases H and thus λ. Rewriting (25) as

$$\frac{d\lambda}{dt} = \left(\nu_G \frac{\partial \sigma_G}{\partial t} + \sigma_G \frac{\partial \nu_G}{\partial t} \right) G + \left(\pi_B \frac{\partial \nu_B}{\partial t} + \nu_B \frac{\partial \pi_B \left(x(\sigma_G, \nu_G, \nu_B, b) \right)}{\partial t} \right) B \tag{24}$$

where G stands for searching for a good job only and B stands for searching for a bad job as well. Defining $\beta_3^G = \nu_G \frac{\partial \sigma_G}{\partial t}$, $\beta_3^B = \nu_B \frac{\partial \pi_B \left(x(\sigma_G, \nu_G, \nu_B, b) \right)}{\partial t}$ and $\delta_3 \frac{\partial \nu_G}{\partial t} = \sigma_G \frac{\partial \nu_G}{\partial t} G + \pi_B \frac{\partial \nu_B}{\partial t} B$, and adding a constant for estimation we can write

$$\frac{d\lambda}{dt} = \alpha_4 + \beta_3^G G + \beta_3^B B + \delta_3 \frac{\partial \nu}{\partial t} \qquad \text{with} \quad H_0 : \beta_3^G < 0 \ \ or \ \ \beta_3^B > 0$$

or

$$\lambda = \alpha_4 t + \beta_3^G G t + \beta_3^B B t + \delta_3 \frac{\partial \nu}{\partial t} t \qquad \text{with} \quad H_0 : \beta_3^G < 0 \ \ or \ \ \beta_3^B > 0 \tag{25}$$

to test whether the hazard is lower for those searching for a good job than for those who are also searching for a bad job, after controlling for changes in vacancies.

When one is more likely to leave unemployment when searching for a bad job, we also expect that those searching for a good job are more likely to switch to searching for a bad job as time in unemployment proceeds. In other words, we expect reservation wages to fall more rapidly for the unemployed who are searching for a good job than for those who are searching for a bad job, after controlling for changes in vacancies. We write $\frac{\partial x}{\partial t} = \beta_4 G + \alpha_4 \frac{\partial \nu}{\partial t}$ with $H_0 : \beta_4 < 0$

or

$$x = \beta_4 G t + \alpha_4 \frac{\partial \nu}{\partial t} t \qquad \text{with} \quad H_0 : \beta_4 < 0 \tag{26}$$

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'.[12] Recent evidence also indicates that unemployment

[12] Similar points are made by Udall and Sinclair (1982) who talk about 'luxury unemployment' and Hirschman (1982) who also labels it as a middle class phenomenon. Recent evidence for Ethiopia

duration may be long in this context, expressed in years rather than months.[13] We use the first round (1994) of the Ethiopian Urban Social-Economic Survey (EUSES) household data collected by the Economics Departments of Addis Ababa University, the University of Oxford and Goteborg University. The survey collected cross section data from a random sample of one thousand five hundred households in the seven largest urban centres. The data contains rich information on both household and individual characteristics including household consumption and assets, and individual single spell unemployment duration data. A more detailed description of the sample and the survey can be found in Appendix A.1.

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 previous regime.[14] The wage structure shows that the public sector pays the highest wages, while the self-employed have the lowest income from labour, earning less than half the salary of public sector employees. Formal private sector employees earn somewhere in-between these two groups. In general the job market is thus rather polarized with the majority of jobs falling in the highest or lowest earnings category. As in many other developing countries, self-employment and especially casual work often relies on low skills or skills that tend to erode less over time. At the time of data collection urban Ethiopia had one of the highest unemployment rates worldwide, with about one in three men who participated in the labour market unemployed. The private sector was expected to grow as a new government had just come to power and had signed agreements to restructure and liberalise the economy.[15]

As in other economies, unemployment is concentrated among the young. It peaks at age nineteen and falls thereafter, to reach a sustained level and low only beyond age thirty. Our analysis therefore focuses on young men between age fifteen and thirty, who represent over eighty percent of the unemployed.[16] Part 2 of Table 2 reports the

indicates that it is indeed a middle class phenomenon, but not a luxury, as it is not concentrated among the better off (see a.o. Serneels 2007).

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

[14] 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).

[15] 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.

[16] 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

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 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 among young men and shows that it is concentrated among the relatively well-educated first time job seekers. About half of the young unemployed are looking for a public sector job and unemployment duration is higher for those searching for a public sector job.[17] This makes unemployment in urban Ethiopia very similar to that observed in other developing countries like Sri Lanka (Dickens and Lan, 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 virtually impossible to pretend to be unemployed.[18] For the duration of unemployment, working men were asked how long their last spell of unemployment had lasted, which yields a direct measure for unemployment duration. Because the unemployed themselves were not asked how long they had been unemployed, we calculate their duration as age minus time worked, minus the age at which schooling was completed.[19] The resulting mean duration is forty five months, which is very

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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.

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

[18] 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.

[19] 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

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 that we also have information on the reservation wages of the unemployed, and the welfare of the household where they reside.[20]

Serneels (2007) analysed the determinants of unemployment and its duration in urban Ethiopia in more detail, including the role of education, and finds that education has an inverse U-shaped effect on both incidence and duration, with a slightly later turning point for the incidence than for the duration. While tertiary educated are less likely to be unemployed compared to secondary educated, the latter are more likely to be unemployed than primary educated. At the same time senior secondary educated and above have shorter durations than junior secondary educated, who have longer durations than primary educated. We will control for education in all our models.

The course of the hazard rate

We first look at the course of the hazard rate and establish that observed duration dependence is non-negative. Because estimates from duration models 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, and then compare with the results obtained from a parametric specification.

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

finish school late, we predict the age at which schooling was completed using a model that includes several individual and household characteristics, including a term correcting for self-selection.

[20] 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).

at each point in time.[21] 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 consistent with estimates for OECD countries.[22] 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 still follows an upwards trend.[23]

Parametric estimation

To formally test whether the hazard increases with time in unemployment, we carry out a parametric estimation. To do this we need to impose a 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.[24] However, the Gompertz and the log-logistic model can not be written as a restriction of any of these models[25] and we therefore compute the Akaike Information Criterion (AIC) to compare the relative performance of all these

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[21] 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 $\hat{\lambda}_j = \frac{n_j}{r_j}$

[22] 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.

[23] 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 consider its copurse and we find that the course is very similar.

[24] The form and properties of the generalized gamma are described in detail in Lee and Wang (2003). 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 $\sigma = 1$. (see also and Stata, 2005).

[25] 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

$$f(t) = \lambda^{1/\gamma} t^{1/\gamma - 1} \Big/ \gamma \left\{1 + (\lambda t)^{1/\gamma}\right\}^2$$

parametric models.[26] 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.[27] 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 explaining why it is not applied frequently, and why 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.[28] 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 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.[29] 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 a non-decreasing 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

[26] Although the AIC is a pragmatic, relative and arbitray measure it offers a way of comparing non-nested models.

[27] 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.

[28] The results remain unchanged when we assume a Gamma distribution for unobserved heterogeneity.

[29]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 (or controling for) unobserved heterogeneity, makes a decrease at the end possible, as can be seen in Figure 3b.

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, suggesting 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 hazard rate that is constant over time and which came third 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.[30] Table 4 shows that using dummies for each annual period, the hazard shifts up during the first year but falls in years three to five to again shift up in the sixth year and fall subsequently. However, none of the changes in the first years is significant and only after twelve years does the 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, for most of the duration, and is negative in the long run.

Testing why observed duration dependence is non-negative

Having established that the observed hazard does not unambiguously fall with time in unemployment, we revisit the three potential explanations for how this can be reconciled with decreasing genuine duration dependence.

Financial support during unemployment

Over ninety percent of the unemployed in Ethiopia are supported by their household, underlining the importance of household support. Interestingly, those coming from poorer households have longer duration than those coming from richer households, as reported in Table 5. To test (14), and assuming that well to do households provide financial support to its unemployed members for a longer period than poor households[31], we estimate

$$\lambda_i = \alpha_1 t_i + \beta_1 \left(HHW_i * t_i \right) + \Gamma_1 X_i \qquad \text{with } H_0 : \beta_1 < 0 \tag{27}$$

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

[31] Or more formally that the change in financial support is an increasing function of the household's wealth: $HHW_i = h\left(\partial b_i / \partial t\right)$.

where HHW_i reflects household wealth and is proxied by per capita household consumption or the value of household assets per capita, while X_i is a vector of control variables including age, education, ethnicity, parents back ground and local unemployment rate to control for observed heterogeneity and also includes a constant. Using an exponential model that controls for (Inverse Gaussian) unobserved heterogeneity we first use per capita consumption as a proxy for household wealth. While the results in Column 1 in Table 6a shows that household support is significantly positively correlated with the hazard, this becomes insignificant when we control for unemployment duration itself (see Column 2). Column 3 in Table 6a reports the estimate of (27) and shows that household support over time has an insignificant negative effect on the hazard (p-value 0.86), implying that we can reject the null. This results remains the same if we add an additional control for household wealth, as reported in Column 4 of Table 6a. These results are confirmed when we use the value of household assets per capita as proxy for household wealth, as reported in Table 6b; and are robust for using other parametric specifications.

We conclude that in the case of urban Ethiopia, household support does not offer an explanation for observing non-negative duration dependence because the unemployed that come from better off households are not significantly more likely to stay in unemployment longer. This finding contrasts with the result for OECD countries where financial support for the unemployed – which take the form of unemployment benefits – typically have a significant 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 significant negative effect, but again limited (Atkinson 1999).[32] More recent evidence for 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).

Changes in the vacancy rate

Since there is no data on the number of vacancies or on employment in the economy, we proxy the change in vacancies by the growth in GDP.[33] Changes in the vacancy

[32] Note that studies that have found a non-decreasing hazard often considered a sample that existed of unemployment insurance recipients only (see for example Moffitt 1985; Katz 1986; Meyer 1986; Vodopovic 1995; Hernæs and Strøm 1996), not allowing to study the effect of financial support on the hazard.

[33] We use growth figures from the IMF as official government figures are unreliable for the period 1980-1992. Note that the most important change in the Ethiopian economy during the considered period was the change in political regime, which took place in 1991 when the Tigrayan People Liberation Front (TPLF) overthrew the Dergue, and which resulted in a liberalization of the economy as the new government signed a structural adjustment programme with the World Bank short after coming to power. This contained measures to liberalize the economy and privatize the public sector

rate are typically caused by changes in the economy, and this is particularly true for Ethiopia in the considered period over time. As expected, unemployment duration is longer for those who are unemployed in low growth period, as reported in Table 5. To test (15) we estimate

$$\lambda_i = \alpha_2 t_i + \beta_2 \left(GDPg_i * t_i \right) + \Gamma_2 X_i \quad \text{with } H_0 : \beta_2 \geq 0 \tag{28}$$

using an exponential model that controls for unobserved heterogeneity and where X_i is a vector of observed characteristics and also contains a constant. The results reported in Table 7 show that although GDP growth is significantly positively related to the hazard on its own (Column 1), it becomes insignificant once we include unemployment duration (Column 2), which itself has a highly significant negative effect. Column 3 of Table 7 reports the estimation results for (30) and shows that the change of GDP growth over the unemployment spell has no significant effect on the hazard. This result is again in sharp contrast with OECD countries where several studies have indentified business cycle effects on the hazard rate, as illustrated in the introduction.

Labour market segmentation

As discussed earlier the labour market in urban Ethiopia is rather polarized, with the majority of jobs either having high or low earnings attached to them. The largest group, the self employed, have the lowest earnings, while the second largest group, public sector employees, have the highest earnings. Private sector employees, who form a minority, earn somewhere in-between, as discussed in Section 3. [34] Not surprisingly this co-existence of well paid and poorly paid jobs seems to affect the nature of unemployment, as indicated by the difference in duration for different groups. Table 8 shows that those who are in a 'good' job typically had longer spells in unemployment than those who are in 'bad' jobs, and that the unemployed searching for a 'good' job also have longer durations than those searching for a 'bad' job. To test more formally whether the type of job searched for affects the hazard after controlling for changes in the vacancy rate, proxied by GDP growth (GDPg), we test (25) by estimating

$$\lambda_i = \alpha_3 t_i + \beta_3^G \left(G_i * t \right) + \delta_3 \left(GDPg_i * t_i \right) + \Gamma_3 X_i \text{ with } H_0 : \beta_3^G < 0 \tag{29}$$

and

$$\lambda_i = \alpha_3 t_i + \beta_3^B \left(B_i * t \right) + \delta_3 \left(GDPg_i * t_i \right) + \Gamma_3 X_i \text{ with } H_0 : \beta_3^B > 0 \tag{30}$$

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and was expectated to boost the private sector and attract foreign investors. We therefore also try an alternative estimation strategy where we proxy economic change by a step dummy for the year 1992, but its effect is also insignificant. Because our data was collected in 1994, it may have been too soon to see the full effects of the regime change.

[34]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-employment and informal private employment are considered to be 'bad' jobs This is a stylized picture and in reality some of the self-employed may be good jobs as well.

Where G_i (B_i) indicates that the unemployed is looking for a good (bad) job. As before we use an exponential model that controls for unobserved heterogeneity and where X_i is the same vector as before. We interpret support of either null as supporting evidence for segmented labour market. First, as reported in Table 9a we find that, after controlling for observed and unobserved characteristics, on its own searching for a good job has a negative effect on the hazard (Column 1), which becomes more negative when we restrict good jobs to public sector jobs (Column 2), while searching for a bad job has a positive effect (Column 3). The unemployed who are searching for a good job thus have a lower probability to leave unemployment than those searching for a bad job. To find the effect of the type of job one is looking for over time we estimate the interaction with time in unemployment as presented in (29) and (30). In Table 9b we find that while searching for a good job has a negative but insignificant effect on the hazard over time (Columns 1 and 2), searching for a bad job has a significant positive effect over time (p=0.001), providing evidence that the type of job one looks for is important.

To test whether reservation wages fall more for those who are searching for a good job, after controlling for changes in vacancies, using (26), we estimate

$$x_i = \beta_4 (G_i * t_i) + \alpha_4 (GDPg_i * t_i) + \Gamma_4 X_i \text{ with } \qquad H_0 : \beta_4 < 0 \tag{31}$$

and interpret evidence in support of the null as supporting evidence for labour market segmentation. The result, reported in Table 10, shows that we cannot reject the null hypothesis. Using OLS we find that β_4 is negative and significant at the p=0.03 level, whether we control for GDP growth (Colum 1), for time in unemployment (Colum 2) or for both (Column 3). But reservation wages do not fall significantly with time in unemployment for those searching for a bad job (Column 4).[35] Reservation wages thus fall with time in unemployment after controlling for observed characteristics - like education – as well as unobserved characteristics, for those who are searching for a good job, but not for those searching for a bad job, providing supporting evidence for segmentation of the labour market.

Summary and conclusion

The common theoretical assumption that the chances to find a job fall with time in unemployment is intuitively appealing but is not systematically confirmed by empirical evidence, and there is no evidence for developing countries. Using unique data for urban Ethiopia we examine the course of the hazard and establish that it follows an inverse U-shaped course that is not significantly different from a horizontal line, except in the long run, implying that duration dependence is non-

[35] We reach the same concusion, when we estimate the model seperately for those searching for a good job and those searching for a bad job, as .

negative for most of the time spent in unemployment. Making use of a classic job search model we then test the two common explanations why we may observe non-negative duration dependence while genuine duration dependence is negative: financial support of the unemployed over time and changes in the economy that affect the vacancy rate. We also consider a third explanation, namely segmentation of the labour market in good and bad jobs. As the unemployed who started out searching for a good job see their chance to leave unemployment drop, they lower their reservation wage to also consider bad jobs. We extend the classic search model to allow for segmentation and develop a way to test this.

We then test the three explanations empirically and find supporting evidence only for labour market segmentation to explain a non-decreasing hazard. Regarding household support we find that those from richer households do not stay longer in unemployment, indicating that financial support is not a good explanation for observing a non-decreasing hazard. Regarding a change in vacancies driven by changes in the economy over the business cycle, we find that the growth in GDP has no significant effect on the hazard once we control for unemployment duration itself. Finally, as far as labour market segmentation is concerned, we find that searching for a bad job has a significant positive effect on the hazard over time, while searching for a good job has an (insignificant) negative effect, and this helps to explain a non-decreasing hazard. We also find strong evidence that reservation wages fall with time in unemployment for those searching for a good job, but not for those searching for a bad job, which we interpret as further supportive evidence that the unemployed switch from searching for a good to searching for a bad job. Our findings underline the potential importance of labour market segmentation, especially for developing countries, and in particular in the presence of a large public sector. It also calls for further extensions of the classic job search model in this direction.

Bibliography

Abbring, J., G. J. v. d. Berg, et al. (2002). "The anatomy of unemployment dynamics." European Economic Review 46: 1785-1824

Abbring, J. H., G. J. van den Berg, et al. (2001). "Business Cycles and Compositional Variation in U.S. Unemployment." Journal of business and economic statistics 19: 436-448

Addison, J. T. and P. Portugal (1998). "Some specification issues in unemployment duration analysis." Labour Economics 5: 53-66

Alba-Ramirez, A. (1998). "Re-Employment Probabilities of Young Workers in Spain." Investigaciones Economicas 22(2): 201-24

Alba-Ramirez, A., J. M. Arranz, et al. (2007). "Exits from unemployment: Recall or new job." Labour Economics 14: 788-810

Appleton, S., J. Knight, et al. (2001). Labour Retrenchment in China: Determinants and Consequences. mimeo

Arulampalam, W. and M. Stewart (1995). "The Determinants of Individual Unemployment Durations in an era of High Unemployment." Economic Journal 105(321-332)

Atkinson (1999). The Economic Consequences of Rolling Back the Welfare State. Cambridge, Massachusetts; London, England, MIT Press

Atkinson, A. B. and J. Micklewright (1985). Unemployment Benefits and Unemployment Duration

Bienvenue, J.-Y., L. Carter, et al. (1997). "Differential Analysis of Unemployment Duration with Emphasis on Long-Term Unemployment." Labour 11(1): 53-81

Blanchard, O. J. and P. Diamond (1994). "Ranking, Unemployment Duration, and Wages." Review of Economic Studies 61: 417-434

Bulow, J. I. and L. H. Summers (1986). "A Theory of Dual Labour Markets with Application to Industrial Policy, Discrimination, and Keynesian Unemployment." Journal of Labour Economics 4(3): 376-414

Cleves (2000). Weibull duration model with gamma heterogeneity

Cockx, B. and M. Dejemeppe (2005). "Duration dependence in the exit rate out of unemployment in Belgium: is it true or spurious?" Journal of Applied Econometrics 20: 1-23

Coviello (2000). goodness of fit programme written for Stata, see http://fmwww.bc.edu/repec/bocode/s/stcoxgof.ado

Cox, D. R. and E. J. Snell (1968). "A general definition of residuals." Journal of Royal Statistical Society B 30: 248-275

CSA (1987). 1984 Census Report. Addis Ababa, Central Statistical Authority

Dickens, W. T. and K. Lang (1996). "An Analysis of the Nature of Unemployment in Sri Lanka." Journal of Development Studies 31(4): 620-636

Dynarski, M. and S. M. Sheffrin (1987). "Consumption and Unemployment." Quarterly Journal of Economcis 102(2): 44-28

Edin, P. A. (1989). "Unemployment Duration and Competing Risks: Evidence from Sweden." Scandinavian Journal of Economics 91(4): 639-53

Elbers, C. and G. Ridder (1982). "True and Spurious Duration Dependence: The Identifiability of the Proportional Hazard Model." Review of Economic Studies 49(3): 403-09

Flinn, C. J. and J. J. Heckmann (1983). "Are Unemployment and Out of the Labour Force Behaviorally Distinct Labour Force States?" Journal of Labour Economics 1(1): 28-42

Foley, M. C. (1997). "Determinants of Unemployment Duration in Russia." Yale Economic Growth Center Discussion Paper 779: 39

Frijters, P. and B. v. d. Klaauw (2006). "Job search with nonparticipation." Economic Journal 116: 45-83

Grambsch, P. M. and T. M. Therneau (1994). "Porportional hazard tests and diagnostics based on weighted residuals." Biometrika 81: 515-526

Greene, W. H. (1997). Econometric Analysis. New Jersey, Prentice-Hall

Gronau, R. (1971). "Information and Frictional Unemployment." The American Economic Review 61(3): 290-301

Ham, J. C. and S. A. Rea, Jr. (1987). "Unemployment Insurance and Male Unemployment Duration in Canada." Journal of Labour Economics 5(3): 325-53

Heckman, J. J. and V. J. Hotz (1986). "An Investigation of the Labour Market Earnings of Panamanian Males - Evaluating the Sources of Inequality." Journal of Human Resources 21(4): 507-542

Heckman, J. J. and G. Sedlacek (1985). "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labour Market." Journal of Political Economy 93(6): 1077-1125

Hernaes, E. and S. Strom (1996). "Heterogeneity and Unemployment Duration." Labour 10(2): 269-96

Hirschman, C. (1982). "Unemployment among Urban Youth in Peninsular Malaysia, 1970: A Multivariate Analysis of Individual and Structural Effects." Economic Development and Cultural Change: 391-412

Hui, W. T. (1986). "State Dependence and Youth Unemployment in Australia: A Survival Analysis." Australian National University Working Paper in Economics and Econometrics 138: 43

Imbens, G. W. and L. M. Lynch (2006). "Re-employment probabilities over the business cycle." Portuguese Economic Journal 5(2): 111-134

Jackman, R. A. and R. Layard (1991). "Does Long-Term Unemployment Reduce a Person's Chance of a Job? A Time-Series Test." Economica 58: 93-106

Katz, L. F. (1986). "Layoffs, Recall and the Duration of Unemployment." National Bureau of Economic Research Working Paper 1825 47: 47

Katz, L. F. and L. H. Summers (1989). "Industry Rents: Evidence and Implications." Brooking Papers on Economic Activity: 209-75

Kerckhoffs, C., C. de Neubourg, et al. (1994). "The Determinants of Unemployment and Jobsearch Duration in the Netherlands." De Economist 142(1): 21-42

Kiefer, N. (1988). "Economic Duration Data and Hazard Function." Journal of Economic Literature 26(646-679)

Kingdon, G. and J. Knight (2004). "Unemployment in South Africa; the nature of the beast." World Development 32(3)

Korpi, T. (1995). "Effects of Manpower Policies on Duration Dependence in Re-employment Rates: The Example of Sweden." Economica 62(247): 353-71

Kupets, O. (2006). "Dterminants of unemployment duration in Ukraine." Journal of Comparative Economics 34: 228-247

Lancaster, T. (1990). The Econometric Analysis of Transition Data. Cambridge, Cambridge University Press

Lancaster, T. and S. Nickell (1980). "The Analysis of Re-employment Probabilities for the Unemployed." Journal of R. Statist. Soc. A. 1980(143): 141-165

Lang, K. and W. T. Dickens (1992). Labour Market Segmentation, wage Dispersion and Unemployment. NBER Working Paper

Layard, R., S. Nickel, et al. (1991). Unemployment

Macroeconomic Performance and the Labour Market. London, Oxford University Press

Lee, E. T. and J. W. Wang (2003). Statistical Methods for Survival Data Analysis. New York, Wiley

Ljunqvist, L. and T. Sargent (1998). "The Europen unemployment dilemma." Journal of Political Economy 106(3): 514-50

Lubyova, M. and J. C. van Ours (1998). Unemployment Durations of job Losers in a Labour Market in Transition. Working Paper: 309-27

Lynch, L. M. (1984). "State Dependency in Youth Unemployment: A Lost Generation?" CLE Discussion Paper 184: 25

Lynch, L. M. (1989). "The Youth Labour Market in the Eighties: Determinants of Re-employment Probabilities for Young Men and Women." Review of Economics and Statistics 71(1): 37-45

Magnac, T. (1991). "Segmented or Competitive Labour Markets." Econometrica 1991(1): 165-187

Meghir, C., Y. Ioannides, et al. (1989). "Female Participation and Male Unemployment Duration in Greece: Evidence from the Labour Force Survey." European Economic Review 33: 395-406

Meyer (1986). SemiParametric Estimation of Hazard Models, see http://harrisschool.uchicago.edu/faculty/web-pages/bruce-meyer.asp

Micklewright, J. and G. Nagy (1996). "Labour market policiy and the unemployed in Hungary." European Economic Review 40: 819-828

Moffitt, R. A. (1985). "Unemployment Insurrance and the Distribution of Unemployment Spells." Journal of Econometrics 28(1): 85-101

Mortensen, D. T. (1986). Job Search and Labour Market Analysis. Handbook or Labour Economics. O. Ashenfelter and R. Layard, Elsevier Science, North Holland. 2

Myrdal, G. (1968). An Inquiry into the Poverty of Nations. New York, Patheon

Nickel, S. (1979). "Estimating the Probability of Leaving Unemployment." Econometrica 47(5): 1249-1266

Rama, M. (1998). "How Bad is Unemployment in Tunisia? Assessing Labour Market Efficiency in a Developing Country." The World Bank Observer 13(1): 59-77

Rama, M. (1999). The Sri Lanka Unemployment Problem Revisited. Washington DC, The World Bank, Devlopment Reserach Group: 45

Ridder, G. (1987). "The Sensitivity of Duration Models to Misspecified Unobserved Heterogeneity and Duration Dependence." University of Amsterdam Actuarial Science and Econometrics Report 7(87): 41

Ridder, G. and W. Verbakel (1983). On the estimation of the proportional hazard model in the presence of heterogeneity. Amsterdam, University of Amsterdam, Faculty of Actuarial SCience and Econometrics

Roed, K. and M. Nordberg (2003). "temporary layoffs and the duration of unemployment." Labour Economics 10: 381-398

Roed, K. and T. Zhang (2005). "Unemployment duration and economic incentives - a quasi random-assignment approach." European Economic Review 49: 1799-1825

Rosholm, M. (2000). "Observed and unobserved heterogeneity in the duration dependency parameter." Economics Letters 66: 347-351

Saint-Paul, G. (1996). Dual Labour Markets, MIT Press

Serneels, P. (2007). "The Nature of Unemployment among Young Men in Urban Ethiopia." Review of Development Economics 11(1): 170-186

Sheehan, M. and M. Tomlinson (1998). "Unemployment Duration in an Unemployment Blackspot." Labour 12(4): 643-73

Stata (1999). Stata Reference Manuals, Stata Press

Steiner, V. (2001). "Unemployment persistence in the West German labour market: negative duration dependence or sorting?" Oxford Bulletin of Economics and Statistics 63(1): 91-113

Stiglitz, J. E. (1982). Alternative Theories of Wage Determinantion and Unemployment in LDC's: The Efficiency Wage Model. The Theory and Experience of Economic Development: Essays in Honor of Sir W. Arthur Lewis. M. G. e. al. London, Allen & Unwin: 78-106

Torelli, N. and U. Trivellato (1989). "Youth unemployment duration from the Italian Labour Force Survey." European Economic Review 33: 407-415

Trivedi, P. K. and W. T. Hui (1985). "An Empirical Study of Long-Term Unemployment in Australia." Australian National University Working Papers in Economics and Econometrics 124: 31

Udall, A. T. and S. Sinclair (1982). "The Luxury Unemployment Hypothesis: A Review of Recent Evidence." World Development

van den Berg, G. J. (2001). Duration models: specification, identification, and multiple durations. Handbook of Econometrics. J. J. Heckman and E. Leamer. North-Holland, Amsterdam. V

van den Berg, G. J. and B. van der Klaauw (2000). Combining Micro and Macro Unemployment Duration Data. Discussion paper N0 109, IZA. 12: 273-85 van den Berg, G. J. and J. C. van Ours (1994). "Unemployment Dynamics and Duration Dependence in France, the Netherlands and the United Kingdom." Economic Journal 104(423): 432-43

van den Berg, G. J. and J. C. van Ours (1996). "Unemployment Dynamics and Duration Dependence." Journal of Labour Economics 14(1): 100-125

Vodopovic, M. (1995). Unemployment Insurrance and Duration of Unemployment: Evidence from Slovenia's Transition, The World Bank

Figures and Tables

Figure 1: Kaplan Meier survival function

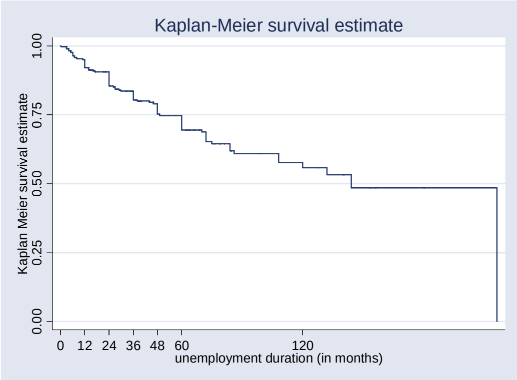


Figure 2: Hazard rate estimated from a Kaplan-Meier survival function

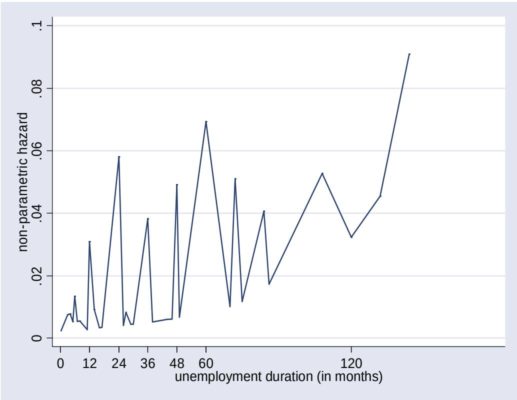
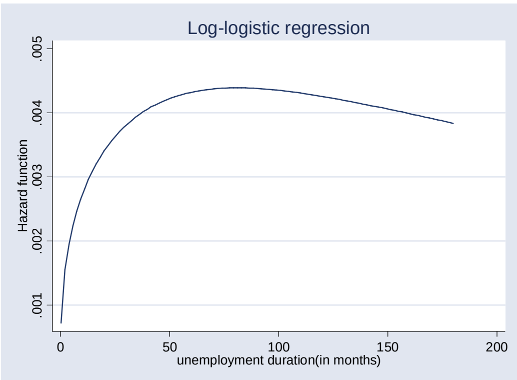


Figure 3: Predicted hazard rates allowing for inverse Gaussian heterogeneity

(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)
Sweden, 1976-1977	positive	Edin (1989)
Australia, early 80's, young	positive	Hui (1986)
US, 1980 – 1981, unemp insurance recipients	positive	Katz (1986)
Denmark, 1981-1990	weakly positive	Rosholm (2000)
US, 1983, male benefit recipients	weakly positive	Meyer (1986)
US, 1980-82, household heads	weakly positive	Dynarski and Sheffrin (1987)
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)
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)
Norway, 1989-1998, experience in a 'recall sector'[36]	inverse u-shaped	Roed and Nordberg (2003)
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	inverse u-shaped	Bienvenue, Carter et al. (1997)

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

unemployed		
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.

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

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

Dummy for year 2	0.13583
	(0.29402)
Dummy for year 3	-0.26181
	(0.37805)
Dummy for year 4	-0.02808
	(0.39256)
Dummy for year 5	-0.02340
	(0.43137)
Dummy for year 6	0.12948
	(0.47318)
Dummy for year 7	-0.24914
	(0.62702)
Dummy for year 8	-0.93149
	(1.06089)
Dummy for year 9	-0.55166
	(1.03304)
Dummy for year 10	-0.24466
	(1.04644)
Dummy for year 11	-0.08302
	(1.04830)
Dummy for year 12	0.31444
	(0.92275)
Dummy for year 13	-27.88370
	(0.48946)***
Dummy for year 14	-27.91665
	(0.54207)***
Dummy for year 15	-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: Unemployment duration by household wealth and performance of the economy

	Mean duration (in months)
Poorest quartile of young men (using consumption)	34.94
Richest quartile of young men (using consumption)	19.57
Lowest quartile of GDP	74.08
Highest quartile of GDP	0.62
Lowest quartile of GDP growth	55.04
Highest quartile of GDP growth	49.73

Table 6a: The effect of household wealth on the hazard using per capita consumption

	(1)	(2)	(3)	(4)
Consumption per hh member	0.00208	0.00039		0.00116
	(0.00034)***	(0.00042)		(0.00088)
Time in unemployment		-0.03482	-0.03524	-0.03088
		(0.00616)***	(0.00634)***	(0.00824)***
Consumption x time in unemployment			-0.00001	-0.00004
			(0.00002)	(0.00005)
Constant	8.15348	0.93698	0.80346	1.63590
	(7.33157)	(5.46306)	(5.42088)	(5.50336)
Parameter for unobserved heterogeneity	-13.40885	-16.08579	-16.10016	-16.11103
	(0.65523)***	(0.21969)***	(0.22463)***	(0.21932)***
Observations	342	342	342	342

Table 6b: The effect of household wealth on the hazard using per capita asset value

	(1)	(2)	(3)	(4)
Value of hh assets per hh member	0.00009	0.00002		0.00011
	(0.00004)**	(0.00003)		(0.00008)
Time in unemployment		-0.03530	-0.03542	-0.03314
		(0.00597)***	(0.00602)***	(0.00671)***
Hh assets x time in unemployment			-0.00001	-0.00001
			(0.00001)	(0.00001)
Constant	7.68732	1.01520	0.78158	1.99692
	(7.65080)	(5.43590)	(5.43282)	(5.66124)
Parameter for unobserved heterogeneity	-14.35341	-14.87646	-16.60992	-14.86790
	(0.82405)***	(0.21737)***	(0.23948)***	(0.21458)***
Observations	342	342	342	342

* 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 wealth, a constant, and unobserved heterogeneity, which is assumed to be inverse Gaussian distributed.

Table 7: Effect of a change in the economy on the hazard

	(1)	(2)	(3)	(4)
GDPg	1.45374	0.63696		0.58190
	(0.59632)**	(0.91600)		(1.50649)
Time in unemployment		-0.04153	-0.04120	-0.04150
		(0.00514)***	(0.00502)***	(0.00543)***
GDPgxt			0.00850	0.00110
			(0.01422)	(0.01711)
Constant	13.11692	3.59056	3.53455	3.59179
	(6.44728)**	(4.76828)	(4.75055)	(4.76796)
Parameter for unobserved heterogen.	-13.61058	-14.95231	-15.45170	-14.95240
	(1.49162)***	(0.19801)***	(0.19772)***	(0.19844)***
Observations	378	378	378	378

* 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 wealth, a constant, and unobserved heterogeneity, which is assumed to be inverse Gaussian distributed.

Table 8: Unemployment duration by type of job

	Mean duration (in months)
'Good' jobs	
Civil servant	11.13
Public enterprise employee	9.18
Private enterprise employee	11.57
'Bad' jobs	
Self employed	8.28
Casual job	7.16
Domestic servant	6.28
Unemployed	
Searching for a Good job	
Searching for a civil service job	30.87
Searching for a public enterprise job	26.17
Searching for a private enterprise job	28.53
Searching fo a 'Bad' job	
Searching for self-employment	19.44
Searching for casual work	18.56
Searching for domestic work	12.73

Table 9a: The effect of job type on the hazard

	(1)	(2)	(3)
Searching for a good job	-0.46868		
	(0.22995)**		
Searching for public sector job		-0.72641	
		(0.27775)***	
Searching for a bad job			1.30303
			(0.26643)***
GDPg x time in unemployment	-0.01789	-0.01623	-0.01502
	(0.01419)	(0.01416)	(0.01475)
Parameter for unobserved heterogeneity	-14.04395	-14.29947	-13.65350
	(0.98076)***	(0.85540)***	(0.97745)***
Observations	332	332	332

* 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, a constant, and unobserved heterogeneity, which is assumed to be inverse Gaussian distributed.

Table 9b: The effect of job type interacted with time in unemplopyment on the hazard

	(1)	(2)	(3)
Searching for a good job x time in unemployment	-0.00784		
	(0.00550)		
Searching for public sector job x time in unemployment		-0.00610	
		(0.00641)	
Searching for a bad job x time in unemployment			0.02339
			(0.00708)***
GDPg x time in unemployment	0.01124	0.01216	0.01514
	(0.02156)	(0.02213)	(0.02215)
Time in unemployment	-0.04238	-0.04415	-0.05726
	(0.00585)***	(0.00595)***	(0.00769)***
Parameter for unobserved heterogeneity	-15.05977	-15.05190	-16.48617
	(0.21164)***	(0.21108)***	(0.21270)***

* 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, a constant, and unobserved heterogeneity, which is assumed to be inverse Gaussian distributed.

Table 10: The effect of job type and time in unemployment on reservation wages

	(1)	(2)	(3)	(4)
Searching for a good job x time in unemployment	-0.59262	-0.62710	-0.67250	
	(0.28186)**	(0.28712)**	(0.31077)**	
Searching for a bad job x time in unemployment				0.22950
				(0.34301)
GDPg x time in unemployment	-0.71652		-0.85473	-0.56583
	(1.41756)		(1.43507)	(1.43413)
Time in unemployment		0.12526	0.26686	-0.40327
		(0.46232)	(0.49854)	(0.45933)
R-squared	0.23	0.23	0.23	

* 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, and a constant.

Appendix

Description of the sample and the survey

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. [37] 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

[37] 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.

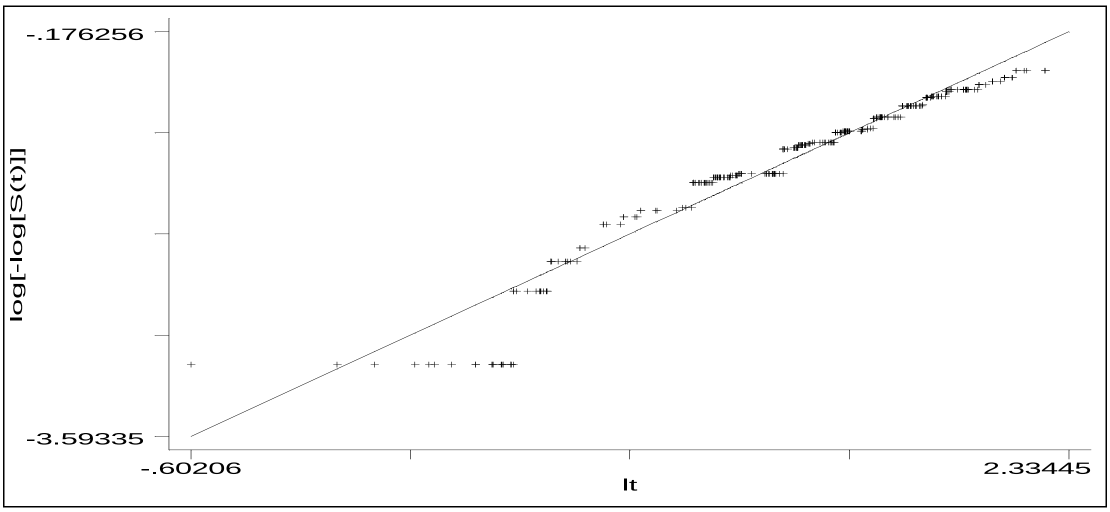
The survey has rich information on the labour market state of the individual, including unemployment duration, the type of job looking for and the reservation wage for the unemployed. The survey also devoted great care to collecting detailed information on household consumption and the assets owned by the household, including their sales value. The instruments were pre-tested in several pilots and were revised wgere needed in order to guarantee high quality data.

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 $\hat{e} = \frac{1}{n}\left[\sum_{j=1}^{n}\left(\hat{\eta}_j - 1\right)^2 - \sum_{j=1}^{n}\left(1-\delta_j\right)\right]$ 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).

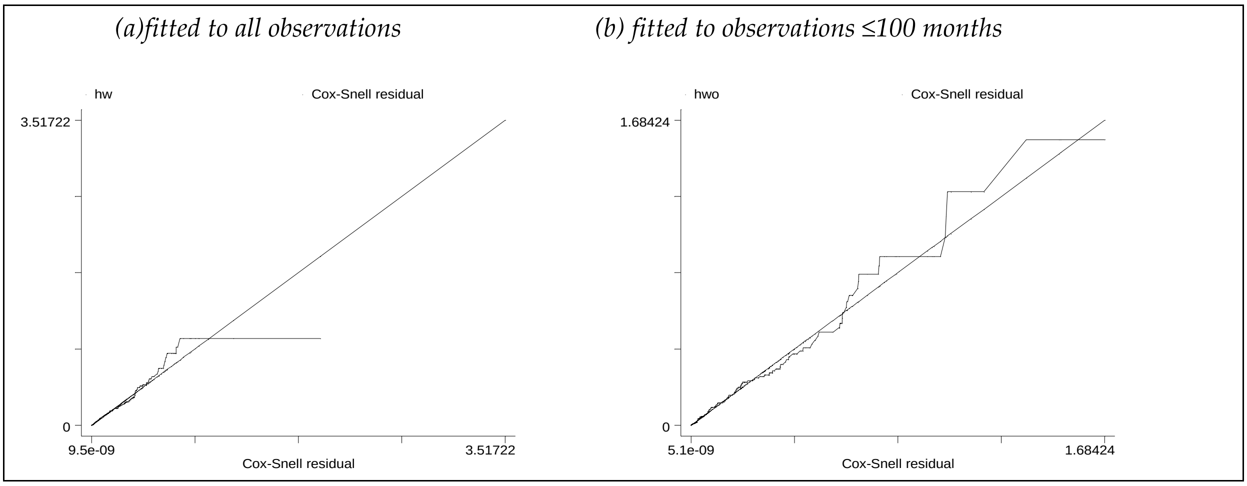
2. A second test we apply is a simple visual test described by Lancaster (1990). Figure A.1 plots the logarithm of integrated hazard against the logarithm of duration. If the Weibull is the appropriate distribution, the result should be a linear curve. Indeed, under the assumption of Weibull distributed 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 <u>Cox-Snell residuals</u> 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



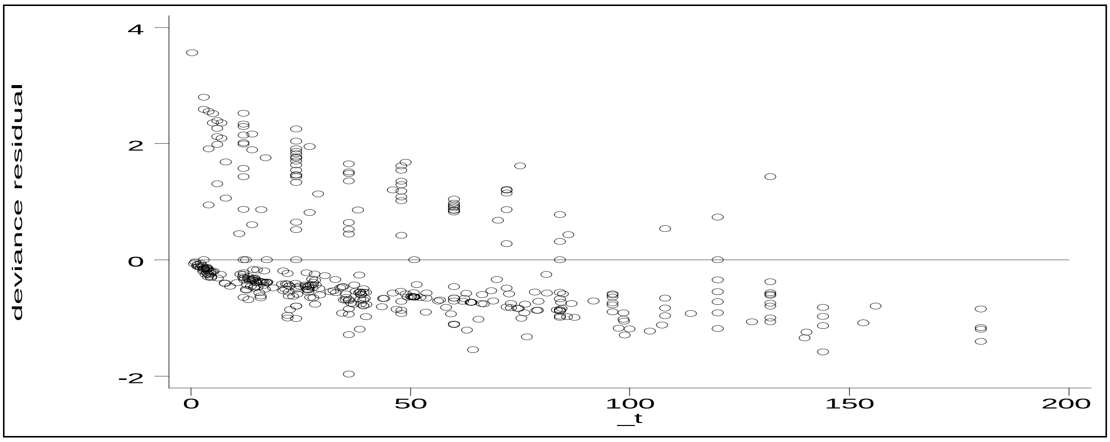
4. Another diagnostic test is to plot the <u>deviance residuals</u>. We first define Martingale-like residuals as the difference over time between the actual number of those leaving unemployment and the expected number based on the model. They are derived from Cox-Snell residuals and are defined as:

$M_j(t) = \delta_j - CS_j(t_j)$, 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 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 (≥ 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.

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