Social Interaction in Regional Labour Markets *

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Abstract

Social interaction, i.e. the interdependence of agents' behaviour via non-market activities, has recently become the focus of economic analysis. Social interaction has been used to explain various labour market outcomes. An important result arising from the literature is the proposition that labour markets are characterised by multiple equilibria. Thus, social interaction is used as an explanation for regional unemployment disparities. Building on this, we construct a Pissarides (2000) type search model with social interaction. Depending on the assumend parameter values, this type of model may be characterised by either a unique equilibrium or by multiple equilibria. Using a unique data set on un-/employment spell data for Germany we analyse whether multiple equilibria in regional labour markets exist. After controlling for structural differences we are able to show that the data supports the assumption of a unique equilibrium. As such, social interaction cannot explain regional unemployment disparities.
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1 Introduction

Differences in the labour market performance (i.e. unemployment) in a cross-section of countries are usually explained by the different institutional settings between these countries, see Nickell and Layard (1999) or, more recently, Nickell et al. (2005) for example. However, we do not only witness large and persistent differences in unemployment rates between countries, but also within countries, i.e. at the regional level, see Elhorst (2003), for example. Since labour market institutions such as unemployment benefit legislations usually do not differ within a jurisdiction, we cannot explain these regional differences.

One possible reason for different regional unemployment experiences which has come under closer scrutiny is the notion of social interaction between agents at the regional level. Social interaction means that there is some (non-market) interdependence between agents (for example preference-based or constraint-based interaction, see Manski (2000)) which shapes agents' behaviour and thus influences the labour market performance.

Using preference-based interaction, Lalive and Stutzer (2004) argue that there is an attitude to the acceptability of living on the dole. This social norm exerts pressure on the unemployed and thus influences the unemployment rate. The strength of this norm, however, might differ across regions which, leads to regional unemployment differentials. They present convincing evidence for Switzerland that there is a correlation between the strength of this social norm and regional labour market performance.

Kolm (2005) puts forward very similar arguments. Her notion of social interaction is that the (dis-)utility of being unemployed depends on the unemployment rate of the region one lives in. This is due to the fact that stigmatisation in a high unemployment environment is lower, for example. Here, the pressure to find a new job is low. This form of social interaction results in persistence of shocks and in multiplicity of equilibria.

The classical reference of the labour market effects of constraint-based social interaction is Diamond (1982). In this paper the probability, of an agent finding a suitable trading partner (which in turn influences the production decision) is a function of the decisions of all other agents in the community. Thus, the decisions of others shape the form of the feasible consumption bundles (=constraint for utility maximisation). Diamond shows that this interaction results in multiple labour market equilibria.

Other constraint-based social interaction models, for example Topa (2001) and Topa and Conley (2002), argue that when searching for new jobs, unemployed agents face the constraint of finding a suitable job. This constraint, however, is affected by the social environment the agent lives in since the majority of jobs are allocated via informal channels. Thus, an agent will ceteris paribus find it easier to get a new job if she lives in a low unemployment environment and vice versa. Similar reasoning is applied by Selod and Zenou (2001), who postulate that the probability of finding a job is a function of the social network one lives in.

An important feature common to many of the models which incorporate social interaction is the existence of multiple equilibria. Regions which are identical in their economic structure (productivity, educational structure and so on) could thus experience different labour market outcomes.[1] In the Kolm (2005) framework, for example (structurally) identical regions could implicitly coordinate on different labour market equilibria.

The question as to whether the root of regional unemployment disparities is the multiplicity of equilibria or structural economic differences is highly important for policy-making. Multiple equilibria offer scope for governmental intervention to coordinate regions on the Pareto dominating labour market equilibrium. In contrast, the "structuralist" view of regional labour market disparities would not be that much in favour of regional policies.

Thus, the question begs whether social interaction inevitably results in multiple labour market equilibria and whether the data support the view of multiplicity of labour market equilibria. This is the starting point of this paper.

We amend a Pissarides (2000) type search model of the labour market with social interaction. We model social interaction as a leisure externality. The idea is that unemployed agents have to invest time in the search process. The opportunity costs of this time investment depend on the time investment of the other agents in the region. This is due to the fact that agents like to spend their leisure time together. Thus, the utility of consuming leisure time will be a function of the leisure time of the other individuals. Although this type of social interaction might lead to self enforcing processes, the number of labour market equilibria in the economy is ambiguous. Depending on the assumed values for the structural parameters of the model, one unique equilibrium or multiple equilibria may be observed. Thus it is not clear whether social interaction modelled as a leisure externality can explain regional differences in unemployment rates.

As the next step we try to empirically detect the uniqueness or multiplicity of regional labour market equilibria using a unique micro-level data set on unemployment spell data for Germany. We estimate the hazard rate

[1] Glaeser and Scheinkman (2003) analyse conditions under which preference-based social interaction generates multiple equilibria. Their model, however, is very general and thus does not directly address problems of search unemployment.

for leaving unemployment, i.e. the probability of leaving unemployment in the next instant of time conditional on being unemployed, from 1999-2001. Controlling for individual and regional heterogeneity we find that the hazard rates do not significantly differ between regions. We regard this as an indication that regional labour markets are characterised by a unique equilibrium and that regional differences in the labour market performance are due to economic differences between individuals living in structurally different regions.

The rest of the paper is organised as follows. The next section derives the first order conditions for the behaviour of individual agents and firms. These building blocks are put together in Section 2.5 to analyse a symmetrical general equilibrium. The empirical analysis follows in Section 3. First, we describe the empirical model and the data set. Second, we present regression results and analyse the regional distribution of the hazard rates. The last section, eventually, summarises our results and concludes.

2 The Theoretical Model

2.1 The Matching Technology

The basic framework for our analysis is the Pissarides (2000) model of frictional unemployment. In this model, (unemployed) workers are searching for jobs and firms are trying to fill vacancies. Both sides of the market are matched via a matching function. The rate m at which matching takes place depends positively on aggregate (=average) search intensity s, and the aggregate rates of unemployment u and vacancies v. We employ the familiar Cobb-Douglas specification of the matching function:

$$m = (u)^{1-\alpha}(v)^{\alpha}s. \tag{1}$$

Search intensity could be interpreted as input-augmenting efficiency of the matching function.[2] The probability of an efficiency unit of unemployment (=su) to be matched to a vacant job is given by:

$$\frac{m}{su} = \theta^{\alpha}, \tag{2}$$

where θ (defined as v/u) reflects labour market tightness.

[2] A similar idea is found in Hosios (1990), for example.

2.2 Individuals' Behaviour

An unemployed individual decides on how much search intensity to "invest". This decision has to be based on the subjective values of being employed or unemployed. The Bellman equations for these states are given by:

$$rW_i = w_i + \lambda(U_i - W_i), \tag{3}$$

$$rU_i = \max_{s_i} \left\{ b + l_i^{\mu} l^{\chi} + q_i(W_i - U_i) \right\}, \tag{4}$$

where W_i is the value of being employed, U_i is the value of being unemployed, r is the rate of time preference (which is equal to the interest rate in a steady state), w_i is the wage the individual earns if employed, λ is the (exogenous) probability of destruction of a matched job and q_i is the individual probability of finding a job.

We assume risk neutrality on the part of the worker, i.e. utility is linear in the unemployment benefit b. The second argument in the flow utility function of unemployed workers captures the novel aspect of this framework: l_i is the amount of leisure the unemployed individual consumes. Individual leisure exhibits decreasing marginal utility (the utility function thus is quasi-linear). Since $l_i = T - s_i$ (so searching for a job is only costly in terms of time, i.e. in terms of foregone utility), the marginal costs of searching are increasing.[3]

In addition to individual leisure l_i, aggregate leisure l also enters the unemployed's utility function. This captures the notion of agents being social individuals who would like to spend their leisure time together, because there is a complementary in the consumption of free time. An agent needs other agents to play football or have a chat with in the pub, for example. We only assume the probability of finding another individual with whom these activities can be shared to increase with the overall leisure of all (unemployed) agents. Thus, leisure exerts a positive externality; χ describes the strength of this effect.[4] The consequence of this externality is that an individual's marginal costs of searching decrease with an increase in overall search intensity.

The probability of an individual's finding a new job is given by:

$$q_i = s_i \theta^{\alpha}. \tag{5}$$

[3] The higher s_i, the lower l_i and hence the higher the marginal value of leisure (=marginal costs of searching). This is a standard assumption in the literature; see Pissarides (2000).

[4] We do not explicitly take into account leisure time of the employed since we assume their leisure time to be exogenously given, due to a fixed work contract. Since the time endowment of all agents is identical, we only have to consider the leisure time the unemployed have in excess of the employed.

When choosing optimal search intensity, the unemployed person has to take the following trade-off into account. A lower s_i increases the flow utility of staying unemployed, but also increases the expected duration of the unemployment spell. The latter effect is negative since the value of being employed is higher than the value of being unemployed. The first order condition of this problem is given by the derivative of equation (4) with respect to s_i (note that the individual agent assumes all aggregate variables to be unaffected by his or her choice):

$$\mu l_i^{\mu-1} l^{\chi} = \theta^{\alpha}(W_i - U_i). \tag{6}$$

In deriving this equation we took advantage of the fact that the value functions U_i and W_i depict values of being unemployed and employed respectively in the case of optimal behaviour of agents (see, for example Dixit and Pindyck (1994) or Shimer (2004) for a detailed argumentation). As such, these are *not* general functions of s_i. Thus, when deriving the condition for the choice of optimal search intensity, we do not have to take changes in the optimal state values into account.

The interpretation of the first order condition is straightforward. The left-hand side of the equation depicts the marginal cost of increasing search intensity which is the loss in flow utility due to less leisure time. The right-hand side, on the other hand, depicts the marginal value of higher search intensity which is equal to the increase in the probability of finding a job multiplied by the (optimal) net value of having a job.

The first order condition of individual search behaviour reveals two important points. First, an increase in labour market tightness θ will ceteris paribus increase individual search intensity.[5] Second, the net value of having a job must exceed some threshold level so that the agents will start investing into search intensity. Throughout the paper we assume this condition to hold.

2.3 Firm Behaviour

Firms choose whether to invest in offering a vacant job slot. The Bellman equations for a vacant and a filled job slot are given by:

$$rV = -cp + m/v(J - V), \tag{7}$$

$$rJ = p - w_i + \lambda(V - J), \tag{8}$$

[5]This is a point Shimer (2004) focuses on. He argues that this is counterfactual in a business cycle context. Note, however, that this result is only of partial equilibrium nature. The aggregate relation between search intensity s and labour market tightness θ will become clearer later on.

where p is the productivity of a worker, cp denotes search costs and m/v is the probability of finding an adequate worker and turning the vacancy into a job. By free entry, the value of a vacancy must be zero. The matching function implies $m/v = s\theta^{\alpha-1}$. So the Bellman equations can be written as:

$$J = cps^{-1}\theta^{1-\alpha} \tag{9}$$

and

$$J = \frac{p - w_i}{r + \lambda}. \tag{10}$$

Combining these two equations gives the job creation curve:

$$\frac{p - w_i}{r + \lambda} - cps^{-1}\theta^{1-\alpha} = 0. \tag{11}$$

2.4 Wage Determination

The last element of our description of the economy concerns the wage equation. We assume the wage to be bargained between a worker and a firm upon meeting. To determine the wage rate the assumed timing structure must be made explicit:

1. Stage:*Agents* choose the amount of search intensity they want to invest rationally anticipating the outcome of the bargain. *Firms* determine the number of vacancies they want to offer, also anticipating the bargained wage.
2. Stage: Agents and Firms meet and bargain over the wage.
3. Stage: Vacancies are filled and production starts.

Thus, in the wage bargain the amount of search intensity has already been invested by agents and is thus fixed. The bargained wage maximises the following Nash product:

$$\Omega = (W_i - U)^{\varphi} J^{1-\varphi}, \tag{12}$$

where φ denotes the bargaining power of the worker. Moreover, we took advantage of the fact that the value of offering a vacancy must be zero by the free entry condition. Solving this wage bargaining problem (see Appendix 5.1) yields the following wage equation:

$$w_i = \varphi p + (1-\varphi)(b + l_i^{\mu} l^{\chi}) + \varphi cp \frac{s_i}{s}\theta. \tag{13}$$

At the individual level, the effect of higher search intensity on the bargained wage is ambiguous. On the one hand, the individual value of being unemployed decreases with s_i, so that the firm can offer a lower wage. On the other hand, the agent has to be compensated for the higher search intensity, because the vacancy costs decrease. Moreover, the individual wage will decrease with an increase in aggregate search intensity in the economy.

Before turning to the determination of the general equilibrium in the economy, we will demonstrate how the endogeneity of the wage influences the decision making of agents concerning search intensity. Using equation (22) from Appendix 5.1 and (9), optimal search behaviour of agents is driven by the following first-order condition:

$$\mu l_i^{\mu-1} l^{\chi} = \frac{\varphi}{1-\varphi} c p s^{-1} \theta. \tag{14}$$

The right-hand side of equation (14) depicts the marginal value of additional search that holds with an endogenous wage. The interpretation is straightforward: $cp\theta s^{-1}$ is the expected search costs the firm would have to bear if it did not fill the vacancy with the worker just met. This is therefore the cost the firm will save if it employs the worker, i.e. the matching rent. The bargained wage is such that the net value of having a job is a fraction of this matching rent. If the costs of filling a vacancy increased, the marginal gain of searching for an unemployed worker would also increase (since the net value of being employed would increase). Thus, their optimal search intensity would increase. The left-hand side is, as before, marginal utility of leisure. This is unchanged in the general equilibrium. The condition for optimal search behaviour of agents leads us to the following:

Proposition 1 *Aggregate search intensity has countervailing effects on the optimal choice of an individual's search behaviour. For small s, individual search intensity will decrease with aggregate search intensity and vice versa.*

Proof 1 *Take the differential of (14) to note:*

$$\begin{aligned}
\left(\mu(1-\mu) l_i^{\mu-2} l^{\chi}\right) ds_i + \left(-\chi \mu l_i^{\mu-1} l^{\chi-1}\right) ds &= \left(-\frac{\varphi}{1-\varphi} c p s^{-2} \theta\right) ds \\
\Leftrightarrow (1-\mu) l_i^{-1} \frac{\varphi}{1-\varphi} c p s^{-1} \theta ds_i - \chi l^{-1} \frac{\varphi}{1-\varphi} c p s^{-1} \theta ds &= \left(-\frac{\varphi}{1-\varphi} c p s^{-2} \theta\right) ds \\
\Leftrightarrow \frac{ds_i}{ds} &= \frac{\chi l^{-1} - s^{-1}}{(1-\mu) l_i^{-1}} \gtreqless 0.
\end{aligned}$$

The ambiguity of this expression is driven by the numerator. With $l = T - s$ the following holds:

$$\frac{ds_i}{ds} \begin{cases} > 0 & \textit{iff} \quad s > \frac{T}{1+\chi} \\ < 0 & \textit{iff} \quad s < \frac{T}{1+\chi} \end{cases}$$

■

An increase in aggregate search intensity has two countervailing effects on an individual's choice. On the one hand, higher s will decrease the matching rent. In this situation firms will find it easier to fill vacancies. As a consequence there will be more firms entering the market with open job slots. However, here the value of a filled job slot must decrease.[6] Thus, the net value of having a job decreases, which in turn discourages individuals from searching intensively. On the other hand, marginal costs will decrease with aggregate search intensity. This is the impact of the leisure externality. With all other individuals searching intensively, it is very unlikely for them to find someone to spend their leisure time with. The marginal value of leisure decreases, i.e. the marginal costs of searching decrease and individuals are tempted to search more intensively. The latter effect will be the stronger, the larger s is(at least for $\chi < 1$ which we assume). So for high values of s, this effect will dominate the former and agents will increase individual search intensity.

2.5 General Equilibrium

We will now derive and analyse the symmetric general equilibrium in the economy, i.e. a situation in which all agents and firms behave identically $s_i = s$ and $w_i = w$. In the symmetric equilibrium, the three equations derived in the previous sections (the first order condition of individual agents (14), the job creation curve of firms (11) and the wage curve (13)) solve the model for the three endogenous variables θ, s and w. The wage is a function of average search intensity and labour market tightness: $w = w(\theta, s)$ with $w_\theta > 0$ and $w_s < 0$, where the subscript denotes the partial derivative with respect to this variable. The economic intuition for these properties is straightforward. The higher search intensity of the unemployed, the lower the value of being unemployed, hence the firm only has to pay a low wage (in the Nash bargaining interpretation: "the outside option of the unemployed decreases"). A tighter labour market increases the wage that firms are willing to pay, since search costs are high.

[6]Since the higher s makes it easier to fill a job slot, the implicit barrier to entry which protects incumbent firms decreases. As such, the value of a filled job slot must decrease.

Using this wage equation, there are two relationships left which determine the equilibrium of the economy, namely the job creation curve and the optimal search behaviour of a representative individual:

$$(1-\varphi)(p-(b+l^{\mu+\chi}))-\varphi c\theta-(r+\lambda)cps^{-1}\theta^{1-\alpha}=0, \tag{15}$$

$$\mu l^{\mu+\chi-1}=\frac{\varphi}{1-\varphi}cps^{-1}\theta, \tag{16}$$

where we used the expression for the bargained wage and the fact that in a symmetric equilibrium every agent will choose the same amount of search intensity, hence $l_i = l$.

In order to derive comparative static results, we have to calculate the slopes of these two equilibrium equations in the θ-s-space. Let us consider the job creation curve first. Totally differentiating equation (15) yields:

$$\begin{aligned}\left((1-\varphi)(\mu+\chi)l^{\mu+\chi-1}\right)ds-\varphi c d\theta-\left((r+\lambda)cps^{-1}(1-\alpha)\theta^{-\alpha}\right)d\theta\\+\left((r+\lambda)cps^{-2}\theta^{1-\alpha}\right)ds=0\end{aligned}$$

From this, the slope of the job creation curve is given by:

$$\frac{d\theta}{ds}=\frac{(1-\varphi)(\mu+\chi)l^{\mu+\chi-1}+(r+\lambda)cps^{-2}\theta^{1-\alpha}}{\varphi c+(r+\lambda)cps^{-1}(1-\alpha)\theta^{-\alpha}}>0. \tag{17}$$

Both the denominator and the numerator are positive, hence, the job creation curve is positively sloped in the θ-s-space. Higher search intensity of unemployed agents makes it ceteris paribus more profitable to offer vacant jobs, since the wage the firm has to pay decreases and the probability of filling a vacancy increases. This effect is also present in Diamond (1982), where more activity on one side of the market (in this case on the side of the unemployed searcher) induces activity on the other side.

Next, we turn to the slope of the curve that describes optimal search behaviour of agents. Totally differentiating (16) yields the following equation:

$$\begin{aligned}\frac{d\theta}{ds}&=\frac{(1-\mu-\chi)\varphi l^{\mu+\chi-2}+\frac{\varphi}{1-\varphi}cps^{-2}\theta}{\frac{\varphi}{1-\varphi}cps^{-1}}\\ \Leftrightarrow\frac{d\theta}{ds}&=((1-\mu-\chi)l^{-1}+s^{-1})\theta.\end{aligned} \tag{18}$$

The slope of the curve depicting optimal search behaviour in the θ-s space is ambiguous. This ambiguity is driven by the fact that $(1-\mu-\chi)$ does not have to be positive (in the aggregate, marginal costs of search intensity need not increase). If the leisure externality is zero or very small, i.e. situations in which $\mu + \chi < 1$, the slope of the curve is strictly positive, i.e. an increase in θ will increase search intensity. As such, the model resembles the results derived in Pissarides (2000) for the leisure externality, χ being small. The economy is characterised by one stable equilibrium.

However, in the following we concentrate on the more interesting case (in our view) in which the leisure externality is strong enough, i.e. we will focus on the case of $\chi + \mu > 1$. Thus, we basically analyse the implication of aggregate increasing marginal utility to leisure for the equilibrium in the economy.

Proposition 2 *Iff $\chi + \mu > 1$, the curve showing optimal (equilibrium) search intensity of agents will be hump shaped.*

Proof 2 *Note that the slope of the curve is driven by:*

$$s^{-1} - (\mu + \chi - 1)l^{-1} \gtreqless 0 \Leftrightarrow \frac{l}{s} \gtreqless (\mu + \chi - 1)$$
$$\Leftrightarrow \frac{T}{\mu + \chi} \gtreqless s.$$

For $\bar{s} = \frac{T}{\mu+\chi} < T$, this expression will hold true with equality and, hence the slope of the curve will be zero. For $s < (>)\bar{s}$ the slope will be positive (negative). ■

The s associated with the positively and negatively sloped part of the curve showing agents optimal behaviour are in the choice set of agents $s \in [0; T]$. As such, both parts of the curve are relevant for the determination of the equilibrium.

The effect of a change in labour market tightness θ on individual behaviour depends on the level of aggregate search intensity. This is due to the fact that by the leisure externality the individual marginal costs of search intensity are a function of search intensity exerted by other agents.

Higher labour market tightness θ will on impact induce agents to increase their level of search intensity independently of aggregate search intensity. This is because marginal gains of search will ceteris paribus increase. However, individual decisions change aggregate behaviour, i.e. aggregate search behaviour changes. This in turn feeds back on the optimal behaviour of the individual. For low-values of s, individual search intensity will decrease with higher s. The second round effect, therefore, dampens the impact effect of a higher θ. But the impact effect will unambiguously dominate this second round effect. Search intensity will increase with higher θ. This is the standard result which is also present in Pissarides (2000). Explaining the negatively sloped part is not straightforward. Technically speaking, the curve depicts combinations of s and θ where the marginal gain of search is equal to the marginal costs. An increase in θ increases the marginal gain of search. As such, s must change in order to equate marginal costs and gains again. But this implies that for high levels of s, search intensity must decrease to close this gap. This reaction is due to the assumption of aggregate decreasing costs of searching.

However, this is only a description of the curve, but not of the behaviour of agents where s is large enough. As before, the increase in θ will increase individual search behaviour s_i and thus, s. For high levels of s, however, this again will increase individual's search behaviour. Thus, any change in θ will lead to an ever increasing search behaviour of agents. This process will not come to an end until all agents have invested their entire time endowment in search. As such, all points depicted by the negatively sloped part of this curve are unstable. This is important for the characterisation of the equilibrium in the economy.

Proposition 3 *Consider an economy in which $\mu + \chi > 1$. If search intensity of agents is already very high, a change in labour market conditions will lead to a corner solution in which all unemployed agents will invest their entire time endowment in search.*

It is important to note that the corner solution is not the result of an explicit choice of agents. Every individual agent's utility function is well-behaved, i.e. at the individual level, agents face increasing costs of search activity. This would usually rule out a corner solution. However, the leisure complementary between individual and aggregate leisure results in the feed-back effect (caused by aggregate decreasing costs of search intensity) described above. This causes the economy to end up in the corner situation.

After having characterised the behaviour of individual agents and firms, we can eventually turn to the equilibrium of the economy. Note that the curve for the search behaviour of agents in (16) is steeper than the curve reflecting the job offer of firms when s converges to zero.[7] Therefore the job creation curve intersects the curve for the search behaviour from below which guarantees the existence of (at least) one equilibrium in the labour market. Figure 1 depicts the equilibrium in the economy for the assumption of a strictly convex job offer curve.

The dashed line corresponds to a situation in which productivity in the economy is large, for example. The thick line delineates a job offer curve for

[7]The proof can be found in the appendix, p. 30.

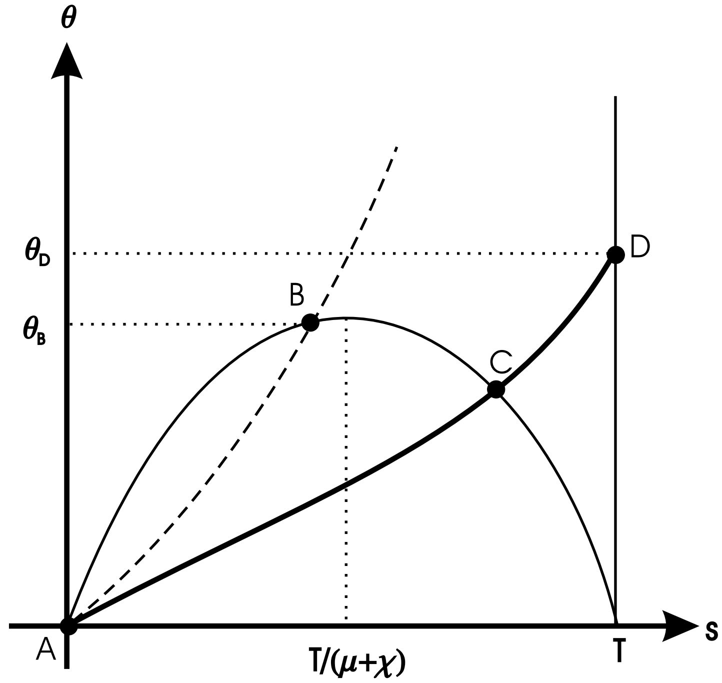

Figure 1: Equilibria in the Economy

different parameter values. By the form of the two equilibrium forming equations (15) and (16) there are at most two (real) solutions for the equilibrium. Since both equations start at the origin, point A is always an equilibrium. This point reflects the "no-action" equilibrium. This equilibrium is basically driven by the interdependence of the actions of agents on both sides of the market. If firms expect agents not to invest in search intensity for instance, they know that no vacancy will be filled. Thus, no vacancies will be offered. But with no vacancies being offered no agent will invest in search intensity. As such, this equilibrium is the result of a coordination failure as described in Diamond (1982), for example.

The "no-action" equilibrium, however, is not stable. A marginal increase in θ will make an individual agent increase search intensity. This in turn makes all agents search more intensively until the new equilibrium is reached. Depending on the form of the job offer curve, this could be a point such as B, which is stable or a point such as C, which is not stable. If the economy is characterised by a job offer curve corresponding to the thick line in Figure 1, the economy will end up in the corner solution D. This is due to the fact that any change in labour market tightness θ in a situation in which $s > \frac{T}{\mu+\chi}$ will kick off a self-amplifying process of ever increasing search intensity until the corner is reached. In this situation firms will offer vacancies such that $\theta = \theta_D$. The equilibrium values of aggregate search intensity and labour market tightness determine the equilibrium (steady state) unemployment rate in the economy. The change of the rate of unemployment in the economy is given by:

$$\dot{u} = \lambda(1-u) - s\theta^{\alpha}u = 0.$$

In a steady state the unemployment rate is thus given by:

$$u^* = \frac{\lambda}{\lambda + s\theta^{\alpha}},$$

which is only a function of s and θ. Thus, the equilibrium derived above unambiguously determines the unemployment rate in the economy. In the case illustrated above the corner solution is associated with a lower rate of unemployment than the "standard" equilibrium, point B, since both search intensity and labour market tightness are larger. However, this does not necessarily hold for all parameter values. If we assume different values for the structural parameters of the model the job creation curve may be no longer characterised by strict convexity. Thus, more than one intersection of the job creation curve with the curve for the individual search behaviour beside point A in figure 1 may exist, indicating multiple equilibria. As before we observe stable equilibria for $s < \frac{T}{\mu+\chi}$. Otherwise a corner solution (point D in figure 1) will be realized.

Due to our theoretical analysis, no clear statement concerning the uniqueness or the multiplicity of equilibria in the labour market can be made. Thus, social interaction has as an ambiguous effect on the existence of differences in regional unemployment rates. In order to discriminate between these two competing views and their policy implications, it is important to understand which of these is reconcilable with the data. In the next section we use unemployment spell data for Germany to analyse whether regional labour markets are characterised by multiple equilibria.

3 Empirical Analysis

3.1 Identification Strategy

3.1.1 General Idea and Procedure

It was shown in the previous section that with social interaction, unique as well as multiple equilibria in the labour market are possible. In this section we try to empirically discriminate between these two cases. There are two huge problems which arise when testing for multiplicity in regional labour markets. First, and this is common to all testing for multiple equilibria, we can only observe the outcome of *one* equilibrium at a time. We tackle this problem by focusing on many regions and arguing that some of them are in the one or the other equilibrium. The second problem is even more severe. Social interaction (at least modelled as preference-based interaction) changes the behaviour of the unemployed, i.e. varying their search intensity, which then possibly gives rise to multiple equilibria. However, we cannot observe the behaviour of agents. We are only able to observe the outcome of this behaviour, for example the length of the unemployment spell an individual faces.

Facing these constraints, we stick to the following identification and estimation strategy. We estimate and analyse the hazard rate for leaving unemployment, i.e. the probability of leaving unemployment conditional to being unemployed. If regional labour markets were characterised by a unique equilibrium, the hazard rates of unemployed agents should be identical across regions. Thus, we would only have to analyse the regional hazard rates and compare their distribution in order to discriminate between models. A drawback of this simple approach, however, is that it totally neglects the differences in hazard rates which are due to regional or individual heterogeneity, e.g. due to self-sorting effects. Let us suppose that the population in region i is better educated than that in region j. If we believe in education as an important determinant for the chances of getting a job, our simple approach would identify significant differences in the hazard rate between the regions. These differences, however, would only be due to composition effects. The same would be true for other differences in structural parameters between regions. Remember that social interaction models which generate multiple equilibria (implicitly) state that regional labour market performance differs although structural characteristics are identical. Comparing hazard rates across regions while controlling for structural influences should indicate whether or not the data are consistent with multiple equilibria. If these regional differences were very small (large) we would conclude that when controlling for structural differences the regional labour markets perform identically (differently). This result would point to a labour market with a unique (multiple) equilibrium (equilibria).[8]

To get estimates of regional baseline hazard rates, we base our examinations on a stratified parametric survival specification. Thus, we assume that

[8]Our identification strategy is very indirect compared to the approach in Manning (1992), for example who directly tests the conditions of his model which generate multiplicity, i.e. increasing returns to scale. Due to data limitations, especially search intensity, we have to stick to an indirect strategy.

social interactions among unemployed individuals could be identified as unobserved regional heterogeneity and are detected by incorporating regional fixed effects. Depending on the assumed distribution for the failure times, we estimate either a Proportional Hazard (PH) or an Accelerated Failure Time (AFT) specification.

Within a PH framework, a stratified specification for the hazard rate of an individual i in region j may be written as:

$$h_{ij}(t_{ij}|x_{ij}, \sigma_j, \gamma_j) = h_0(t_{ij}, \sigma_j) \exp(x_{ij}\beta, \gamma_j), \tag{19}$$

with t_{ij} as unemployment duration of individual i in region j. The baseline hazard in region j, $h_0(t_{ij}, \sigma_j)$, is allowed to depend on the location-specific fixed effect σ_j. Since we use a stratified specification, a location-specific fixed effect γ_j is also included in the rescaling term $\exp(x_{ij}\beta, \gamma_j)$, where x_{ij} is a vector of both individual and regional covariates and β a vector of coefficients to be estimated.

Contrarily, in the case of an AFT model, a separation of the hazard rate into a baseline hazard and a rescaling term is not possible due to the properties of the assumed distribution of the failure times. Therefore, the following specification is used for a stratified estimation:

$$\ln t_{ij} = x_{ij}\beta + \gamma_j + z, \tag{20}$$

where z is the error term and follows the assumed distribution for the failure times.

To calculate regional hazard rates controlling for individual and regional heterogeneities, all covariates are reset to zero, leaving only the regional dummies for the specific region unchanged. Hereafter we refer to these hazard rates as *regional baseline hazard rates* .

3.1.2 Evaluation of the estimated baseline hazards and the Dip-Test

To evaluate and compare regional baseline hazard rates, we decided to calculate the hazards for different durations of unemployment spells. In detail, calculations have been made for unemployment durations of 30, 60, 90, 180, 270, 365, 455, 545, 635, 730, 820, 910, 1000 and 1095 days. For each duration, we evaluate whether there are significant variations among the regional baseline hazards. Remember that a unique regional labour market equilibrium implies that the regional baseline hazards should be more or less identical. To formalise this point, we argue that the distribution of regional baseline hazards should be characterised by a unimodal density function if the equilibrium is unique. On the other hand, if the data do not support the theoretical model, the baseline hazards should be significantly different over regions, leading to a multimodal density/distribution function. To control for such uni-/multimodal distribution of regional baseline hazard rates, we employ the "Dip-test" as proposed by Hartigan and Hartigan (1985).

This procedure is a non-parametric test for the unimodality of probability distributions. The idea is to calculate the minimum of the maximum distances between the empirical distribution and unimodal distribution functions which have to fulfil certain criteria. This minimum is the so-called *Dip*. Comparing the Dip with distances computed under the null-distribution which is the uniform distribution allows us to reject/accept the null-hypothesis that the distribution is unimodal.

3.2 The Data

3.2.1 General Description

To employ the identification strategy described above, we use the IAB employment subsample (IAB-Beschäftigtenstichprobe 1975-2001 [Regionalfile], IABS-R01) provided by the Institut für Arbeitsmarkt- und Berufsforschung (IAB) der Bundesagentur für Arbeit, Nuremberg.

The IABS-R01 is a unique micro-level data set, including the employment history as well as the history of unemployment benefit receipt for two percent of all German employees subject to social insurance contributions for the period 1975 to 2001.[9]

Two different sources of information are used for the creation of this data set. First, the dates concerning the employment history of individuals are generated using information provided by the social insurance institutions to whom employers yearly report the employment status of their employees, including daily dates concerning the beginning and/or ending of an employment spell. The data were amended by the periods of receipt of unemployment benefit[10], as supplied by the German Federal Employment Office ("Bundesagentur für Arbeit" BA). It is important to notice that the data do not include periods of self-employment or employment as civil servants. Moreover, no information on the receipt of social security benefits are included in the data.

The data set contains information on 1,293,819 individuals, including

[9] A basic description of the data can be found in Bender et al. (2003).

[10] Note that the data allows for a distinction to be made between three different types of unemployment benefits. Since a distinction between the transfer payments is not relevant for this empirical investigation, we refer to Fitzenberger and Wilke (2004) for more details.

181,058 in East Germany, since 1992. Both the data on the individual employment status and the data on receipt of benefits are provided in spells with precise dates concerning the beginning and ending of the spell. Since 1980, the data has also allowed for a distinction to be made between 343 regions. These regions roughly correspond to actual German counties ("Kreise"). For purposes of anonymity, the actual counties have been aggregated to regional entities with at least 100.000 inhabitants. Thus, individuals can be assigned to a specific region.

For any individual, the data set includes information on characteristics like age, sex, education, income while employed, occupation, etc. as well as information on the individual employment status (part-time/full-time, internship, apprenticeship, etc.) or sectoral affiliation while employed or before unemployment.

3.2.2 Two Proxies for Unemployment Durations

Though the IABS-R01 provides detailed information both on individual employment and benefit receipt histories, periods of registered unemployment according to the ILO standard cannot be inferred from the data.[11] Interpreting the receipt of periods of unemployment benefit registered in the IABS-R01 as actual periods of unemployment may lead to the incorrect measurement of the time spent in unemployment. To give an example, although transfer payments have expired, an individual might still be unemployed. The consequence would be an underestimation of the actual unemployment duration. On the other hand, an unemployed individual may still receive payment though she has stopped participating in the labour market and has already dropped out of the labour force. Therefore, Fitzenberger and Wilke (2004) suggest two proxies for unemployment durations instead of periods of transfer payments as registered in the IABS-R01. These are operationalised as follows:

- **Nonemployment** (NE):

  The NE proxy consists of the time between two employment spells, containing at least one period of transfer payments by the BA. If no employment spell is registered after a period of benefit receipt, the NE spell is considered to be (right-)censored. Otherwise, a transition from unemployment to employment has occurred.

- **Unemployment Between Jobs** (UBJ):

[11] Fitzenberger and Wilke (2004)

In contrast to the NE proxy, the UBJ proxy is based on the durations of benefit receipt as registered in the IABS-R01. Since interruptions of these payments can be up to four, or in the case of cut off times up to six weeks, UBJ unemployment durations for an individual may be the combination of several spells of transfer payments. UBJ spells will exhibit a failure event, i.e. leaving unemployment, if the last spell of benefit receipt in a UBJ context indicates the end of the payments and the start of new employment.

We perform the empirical analysis using both definitions of individual unemployment duration.

3.2.3 Data in Use and Covariates

Individual unemployment durations from the years 1999 to 2001 were used for the regressions. By restricting the data, the problem of left-censoring could occur. Information on the individual unemployment history prior to 1999 may be lost. To avoid underestimations of unemployment durations due to left-censoring, we only focus on individuals with unemployment spells starting in this period.

For the regressions we focused on prime age males' unemployment spells, i.e. spells of males between the ages of 16 and 50. We concentrate on this subgroup since we want to make sure that the observed NE or UBJ unemployment durations correspond to periods of active participation in the labour market. This may not hold for older males due to generous early retirement schemes in Germany. Additionally, it may also not hold for women, since in most cases men are the breadwinners and women's contribution to the income of the household might be comparatively low.

To control for individual and regional characteristics, we include several covariates in the regressions. Individual characteristics include the age of the person observed as well as variables for educational attainment and sector affiliation before unemployment. For the dummy of individual sector affiliation, we have decided to group the data into three sectors, namely agricultural, industrial, and trade and services. Due to the lack of data [12] concerning the classification of the economic sector, we excluded 20 regions , leaving 323 regions to analyse. In the case of educational attainment, the data allow us to distinguish between four different categories: no professional training,

[12] The excluded regions are the cities of Braunschweig, Oldenburg, Remscheid, Solingen, Offenbach am Main, Heidelberg, Regensburg, Erlangen and Fürth and the following counties: Enzkreis, Vogelsbergkreis, Tuttlingen, Mühldorf am Inn, Erlangen-Höchstadt, Fürth, Aichach-Friedberg, Neu-Ulm, Nürnberger Land, Biberach, Bördekreis and Ohre-Kreis.

secondary school and professional training, university-entrance diploma and university diploma (including degrees from universities of applied sciences).

To measure regional heterogeneity, we also include several regional covariates in the regressions. This includes the average age of all registered individuals in a region, the number of people in each category of educational attainment and the number of employees in each sector (as a proxy for the economic structure of the region). Furthermore, we control for regional labour market conditions by including the regional inflows into unemployment as proposed by Lalive and Stutzer (2004).

The regional inflows and all the other regional covariates are measured on an annual basis. Since both NE and UBJ unemployment spells may start in one year and may not end until the next year, we allow regional covariates and the individual age to change on December 31st. Further, as suggested by Kiefer (1988), all covariates are measured as deviations from their mean. A descriptive summary of the covariates used in the regressions is provided in Table 1 in Appendix 5.3.

3.3 Results

3.3.1 Model selection and Regression Results

In the first step of this empirical analysis, we estimate five stratified parametric survival models for both proxies of unemployment durations.[13] After a check of the Cox-Snell residual plots[14] it turned out that the models based on a Log-Normal distribution provided the best fit for both the NE and the UBJ proxy.

The results for the NE and UBJ proxy are reported in Table 2. We have to keep in mind that survival models based on a Log-Normal distribution belong to the class of AFT models. Therefore, the displayed coefficients report the impact on (the natural logarithm of) the individual unemployment duration and not on the hazard rate.[15]

Table 2 around here

Since the interpretation of the coefficients is not the main concern of this

[13]The estimations were made using the following distributions for the failure times: Exponential, Weibull, Gompertz, Log-Logistic and Log-Normal.

[14]For a description of Cox-Snell residual plots see Klein and Moeschberger (2005).

[15]To avoid downward biased standard errors on regional covariates due to a clustering of individuals within regions (Moulton, (1990)), robust standard errors have been used for all regressions.

empirical analysis, we keep the discussion brief. Let us first take a look at the coefficients on individual characteristics. We find that for both proxies of unemployment durations, age and educational attainment have the expected signs and are significant at the 95% level with the exception of the variable *university entrance-diploma*.[16] Therefore, older individuals will ceteris paribus have more difficulty in finding new employment, while people equipped with a university diploma tend to leave unemployment earlier. Note that these results are by and large in line with the literature,(see for example Steiner (2001) or Biewen and Wilke (2005)).

Both regressions also indicate that an individual who has worked in the agricultural (trade and services) sector will ceteris paribus experience shorter (longer) unemployment durations.

When turning to regional covariates, we observe that in the case of the NE proxy none of them had significant influence. On the other hand, we find significant coefficients for the number of individuals with no professional training, secondary education and university diploma using the UBJ definition. Inspecting the signs of the significant coefficients, the unemployment duration of an individual reduced with a higher number of individuals with no professional training in the region. In contrast, the transition from unemployment to employment is slower the larger the number of individuals in the region with secondary education or university diploma.

Among the proxies for the region's industry structure, only one covariate in the UBJ context turned out to be significant. The larger the number of employed people in the industrial sector, the faster the transition from unemployment to employment.

Besides individual and regional covariates, 322 regional dummies and a constant were used both in the main equation and for estimating of the ancillary parameter of the Log-Normal distribution. We find that most regional dummies for the ancillary parameter, σ_j, turn out to be significant for both definitions of the left hand side variable. The picture changes for the dummies γ_j. Only about 15% (8%) within the NE (UBJ) proxy turn out to be significant.

Investigation of the Baseline Hazards

To calculate the regional baseline hazard rate, we reset the values of the individual and regional covariates to zero, leaving only the regional dummies unchanged. The baseline hazard rate for a region j in the Log-Normal model

[16] We defined *secondary education* and *industry* as reference categories in the context of individual covariates and the *city of Kiel* for the regional dummies.

yields:

$$h_j(t_{ij})|_{x_{ij}=0} = \frac{\frac{1}{(\hat{\sigma}_0+\hat{\sigma}_j)\sqrt{2\pi}} t_{ij}^{-1} \exp[-\frac{1}{2}\left(\frac{\log(t_{ij})-(\hat{\beta}_0+\hat{\gamma}_j)}{\hat{\sigma}_0+\hat{\sigma}_j}\right)^2]}{1-\Phi\left(\frac{\log(t_{ij})-(\hat{\beta}_0+\hat{\gamma}_j)}{\hat{\sigma}_0+\hat{\sigma}_j}\right)}, \tag{21}$$

where Φ is the cumulative distribution of the standard normal distribution, $\hat{\beta}_0$ the constant and $\hat{\gamma}_j$ the regional dummy for region j. Moreover, $\hat{\sigma}_0$ is the constant in the estimation for the ancillary parameter, while $\hat{\sigma}_j$ represents the estimated regional dummy for region j.

Using (21) we calculate regional baseline hazard rates for durations t of 30, 60, 90, 180, 270, 365, 455, 545, 635, 730, 820, 910, 1000 and 1095 days. The means of the baseline hazard rate across the regions diminish, which holds true for the NE as well as the UBJ proxy, see Tables 6 and 5. This fits well with the general intuition that the probability of leaving unemployment decreases with increasing unemployment duration. Considering the resulting variances of the baseline hazard rates across regions, we observe that these tend to diminish, too (as can also be seen from the evolution of the coefficient of variation). Initial differences in the regional baseline hazard rate become smaller for larger unemployment durations. Our identification strategy is the notion that if regional labour markets were characterised by a unique equilibrium, regional baseline hazards should be (randomly) distributed around this equilibrium. This in turn implies that the density function of regional baseline hazard rates should be uni-modal. Therefore, we use kernel density estimations[17] to characterise the density functions of the regional baseline hazards. The relevant plots can be found in Appendix 5.3 in Figures 2-5.

In the case of the NE proxy, none of the density plots apparently exhibits a second mode. Inspecting the plots in more detail reveals the following pattern. The spread of the distribution of regional baseline hazard rates decreases for higher unemployment durations. This is what was already noted after inspecting Table 5. In addition to this, however, the density plots show that for higher unemployment durations a small group of regions emerge whose hazard rates stabilise at a relatively high level. As such, the distribution of regional hazard rates becomes right-skewed. Note that these group of outlier regions is too small to form a second mode.

We apply the Dip-test (as introduced above) as a formal test of the uni-modality of distributions/density functions. If the density functions of the regional baseline hazards are in accordance with the theoretical model, the null-hypothesis (= uni-modal distribution) of the Dip-test should not be rejected. In the following, we present the results of the Dip-test for the particular unemployment durations. In both the NE and the UBJ cases,

[17] A standard Gaussian Kernel has been used for the estimation.

the null-hypothesis of uni-modality for the distributions of regional baseline hazard rates cannot be rejected for any unemployment duration (see Table 7 in Appendix 5.3).[18]

Two consequences may be deduced from this result. First, differences in the individual's probability of leaving unemployment are mainly driven by individual characteristics such as age, education and so on. Regional characteristics basically play no role in the explanation of the hazard rate for leaving unemployment. Second, regional labour markets do not seem to be characterised by multiple equilibria. As suggested by our theoretical model, we find evidence for the uniqueness of regional labour markets. As such, we have to reject the idea that due to social interactions individuals coordinate on different equilibria in different regional labour markets.

3.4 Robustness Check and Discussion

Though the empirical results presented so far support the theoretical model, they might be misleading. For the empirical analysis in the section above, we focused on reunified Germany, including East and West Germany. Despite focusing on periods ten years after the German reunification, the general labour market situation in East Germany is by far worse than the West German labour market. We observe for example differentials of 10 percentage points in the unemployment rates between East and West Germany for the relevant periods. Therefore, a joint examination of East and West German regions may influence the distribution of the regional baseline hazards. Thus, we decided to run the empirical analysis separately for East and West German regions.

3.4.1 West Germany

Model selection and Regression Results

Considering only individuals located in West Germany, we get a sample consisting of 30,859 (38,171) individuals for the NE (UBJ) definition, with 39,671 (51,148) unemployment spells. Beside individual and regional covariates, 247 regional dummies are included. The modell selection by means of Cox-Snell residual plots resulted in the choice of the Log-Normal model for both proxies of unemployment duration.

[18]Both the test-statistic and the plots of the densities are included in the Appendix. All calculations concerning the Dip-test were done with R 1.8.1, while for the survival analysis Intercooled Stata 8.2 was used.

Inspecting the results of the estimations, we find these to be by and large the same as for Germany. Individual age and no professional training turn out to be significantly positive This is also true for the coefficients on university diploma, agricultural sector and trade and services sector. As in the previous section, regional characteristics basically do not play a role in determing the hazard rate. This is at least true for the NE definition. With the UBJ definition, the coefficients on the number of individuals with *no professional training*, the number of individuals working in the *industrial and trade and services sector* are significantly negative and the number of individuals with a *university diploma* is significantly positive. A surprising point is the fact that the UBJ regression indicates a shorter period of unemployment with higher inflows into the regional labour market.

Baseline Hazard Rates and the Dip-Test

When calculating the baseline hazard rates for regions in West Germany, we get a similar picture to before. The means tend to diminish over time, and the variances of the baseline hazards are around zero.

As in the case of Germany, we did kernel densities estimations for various unemployment durations. Within the NE definitions, the plots turn out to be slightly right skewed. Inspecting the plots for unemployment durations equalling or longer than 60 days, we observe a small second peak on the right-hand tail of the densities.

Applying the Dip-test, however, we have to reject the hypotheses of multimodality proxies and for any unemployment duration.[19]

3.4.2 East Germany

Model selection and regression results

For East Germany the sample collapses to 15,486 (18,358) (NE/UBJ) individuals with 21,046 (25,765) unemployment spells in 75 regions. The parametric distribution function is again Log-normal.

The qualitative influence of the individual characteristics on the hazard of leaving unemployment in East Germany is by and large the same as for West Germany and Germany as a whole. Qualitatively some values differ, individuals with no professional training in the East find it harder to get a new job than the same individuals in the West, for example. This reflects the severe problem of low-skilled unemployment in East Germany.

[19]See Appendix 5.3 for the results of the Dip-test. The density plots are available on request.

The impact of regional covariates on the length of the unemployment spell turn out to be slightly different since some of the signs change. The inflow into unemployment has a negative effect on spell length in West Germany, for instance, whereas it is positive in East Germany.

Baseline hazards and the Dip-Test

Evaluating the baseline hazards for the NE and UBJ proxy for the chosen durations, we observe that the means again diminish with higher unemployment durations. In accordance with the results for Germany and West Germany, for both proxies the variances are around zero and decline with higher unemployment durations.

The plots for the NE definition turn out to be quite symmetric, becoming a little left-skewed with higher unemployment durations. We do not observe a clustering of baseline hazards as for Germany and West Germany. The picture changes when turning to the UBJ definition. Here the plots exhibit right skewed densities, and the clustering in regional baseline hazards already observed.

The Dip-test rejects the hypothesis of multi-modality for both proxies. Thus, even when concentrating only on East German regions, no significant differences in regional baseline hazards are detected.

3.4.3 Discussion of the results

We will close the empirical part of the paper with a brief discussion of the results achieved so far. We have seen that with both proxies of unemployment duration, the baseline hazard rates are very similar across regions. Thus, regional labour markets seem to be characterised by one equilibrium, supporting our theoretical model. Though this result turned out to be robust, some topics are left for further discussion.

One point that became apparent in the regressions was the fact that at least with the NE definition hardly any of the regional characteristics had a significant influence on individual unemployment duration. In the case of East Germany, this was also true for the UBJ proxy. Since regional influences seem to be negligible, the location of an individual has no effect on her unemployment duration. To accelerate the transition from unemployment to employment, politics should foster the education of individuals rather than subsidising the economic structure of the region.

Another topic to be mentioned is a comparison of the means for German, West- and East German baseline hazard rates. This is done graphically in Figure 6 for the NE and the UBJ proxy. It turns out that the means of the baseline hazard rates are larger in East Germany than in West Germany, at least for the first 90 days of unemployment. With higher unemployment duration the baseline hazards for the three entities converge. Examining the NE definition, the extent to which East German baseline hazard rates differ in contrast to reunified Germany and West Germany is bigger than for the UBJ proxy.[20] Overall, this result appears to be rather awkward since one would expect a significantly worse labour market performance in East Germany.

One possible explanation for higher baseline hazard rates in East German regions may be work creation schemes (Arbeitsbeschaffungsmaßnahmen) implemented by the German government to improve the labour market situation in East Germany. Examining the figures for 1999, about 1,681,000 individuals in East Germany were employed in these kinds of schemes compared to only 663,000 people in (the much larger) West Germany. Thus, the higher baseline hazard rates for East Germany than for West Germany may be due to a transition of East German unemployed into jobs from state work creation schemes. Unfortunately, we are not able to control for these kinds of governmental programmes within the data.

We also have to address the robustness and the reliability of the Dip-test in identifying multiple equilibria. First, note that the Dip-test by its construction is very conservative, i.e. biased in favour of the null-hypothesis. As Cheng and Hall (1998) state, the use of the uniform distribution as a benchmark for the worst uni-modal distribution is responsible for this distortion. Inspecting the density plots makes us feel comfortable concerning the multimodality results.[21] The Dip-test, however, might be misleading in cases where regional labour markets are characterised by multiple equilibria, but the difference between these equilibria is very small, or in cases where the majority of regions are determined by one equilibrium and only a few regions are from another one. In this case the Dip-test would indicate unimodality since it is not sensitive enough.

[20] One may notice that in Figure 6 with both definitions of unemployment durations the observations for Germany lie above or below the observations for East and West Germany. This may be explained by the fact that the estimations of regional baseline hazards in reunified Germany, East and West Germany are based on different data. Hence, averaging East and West German results does not result in the observations for Germany.

[21] One could also apply other tests for multi-modality, e.g. the excess mass test by Müller and Sawitzki (1991) or the bandwidth test by Silverman (1981). However, according to Cheng and Hall (1998), these may also lead to considerable distortions.

4 Summary and Conclusion

Labour market models which incorporate preference based social interaction are often characterised by multiple equilibria. This is due to the fact that individual behaviour is influenced by the behaviour of others, giving rise to an externality. The consequence of this interdependence may be a coordination failure. Thus, two identical agent would behave differently depending on the environment they live in. Models with social interaction can in principle explain disparities in regional unemployment rates. In this paper, we present a Pissarides (2000) type search model in which we incorporate social interaction. Our notion of social interaction is modelled as a leisure externality. Unemployed agents have to invest time in the search process of finding a new job. The value of this time depends on the time other individuals spend on job search since agents are social individuals who would like to spend their time together. Due to this kind of interaction the results of the theoretical model are ambiguous. The economy is either characterised by a unique (stable) labour market equilibrium or by multiple equilibria. This uniqueness result is due to the existence of a "no action" equilibrium, i.e. if firms expect that agents do not invest time they will not offer any jobs. If on the other hand agents expect firms not to offer jobs, they will not invest time into the search process. On the other hand, multiple equilibria exist if we relax the assumption of strict convexity for the job creation curve.

Whether social interaction leads to multiple equilibria or not has important policy implications since the existence of multiple equilibria will broaden the scope for public regional policies. This begs the question whether we observe multiple equilibria in real world labour markets. Using a micro-level data set on the duration of unemployment in Germany we analyse whether regions are characterised by multiple equilibria. We apply survival analysis to estimate the individual hazard rate of leaving unemployment controlling for structural individual and regional variables.

We find that the overwhelming majority of differences in the hazard rate between individuals can be explained by structural individual characteristics. Structural regional heterogeneity has surprisingly little effect on the duration of unemployment. From this, we conclude that to leave unemployment it does not matter where you are, but who you are. Moreover, we find that the hazard rate controlling for structural variables basically does not differ between regions. This indicates that regional disparities in the unemployment rate cannot be explained by social interaction as sometime suggested in the literature, see Kolm (2005) for example.

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5 The Appendix

5.1 Wage Bargaining

The first order condition for the bargaining wage w_i (using equations (3) and (10)) reads:

$$\varphi J(w_i) - (1-\varphi)(W(w_i) - U) = 0. \tag{22}$$

This simple structure of the wage setting rule is only due to the fact that the value of being employed is linear in the wage, i.e. that workers are risk-neutral. We can rewrite this equation and get a relation between the value of a filled job (which is given by the free entry condition) and the (optimal) net value of being employed: $W(w_i) - U = \frac{\varphi}{1-\varphi} J(w_i)$.

Using (22) we can also derive an explicit solution for the bargained wage. Plugging the expressions for W_i and J from the Bellman equations, (3) and (10), into the rent splitting rule we get:

$$\frac{w_i}{r+\lambda} - \frac{r}{r+\lambda} U_i = \varphi \frac{p - w_i}{r+\lambda} + \varphi \frac{w_i}{r+\lambda} - \frac{r}{r+\lambda} \varphi U_i, \tag{23}$$

which may be simplified to

$$w_i = \varphi p + (1-\varphi) r U_i. \tag{24}$$

By the first order condition of the Nash bargaining solution $W_i - U$ is given by $\frac{\varphi}{1-\varphi} J(w_i)$ so that we can simplify equation (4) to:

$$rU_i = b + l_i^{\mu} l^{\chi} + s_i \theta^{\alpha} \frac{\varphi}{1-\varphi} J. \tag{25}$$

Plugging equation (9) into this equation gives

$$rU_i = b + l_i^{\mu} l^{\chi} + s_i \theta^{\alpha} \frac{\varphi}{1-\varphi} cps^{-1} \theta^{1-\alpha}. \tag{26}$$

Plugging (26) into (24) gives the wage equation (13) stated in the text.

5.2 Limits of the job creation curve and the curve for the first order condition

To consider the behaviour of the slope of the job-creation curve when s converges to zero, we first multiply s on both sides in (15).

$$s(1-\varphi)(p-(b+l^{\mu+\chi}))-s\varphi c\theta-(r+\lambda)cp\theta^{1-\alpha}=0 \tag{27}$$

Totally differentiating yields:

$$\begin{aligned}((1-\varphi)(p-(b+l^{\mu+\chi}))-s(1-\varphi)(\mu+\chi)l^{\mu+\chi-1})ds-\varphi c\theta ds\\ -s\varphi cd\theta-(r+\lambda)cp(1-\alpha)\theta^{-\alpha}d\theta=0\end{aligned} \tag{28}$$

Solving for $d\theta/ds$ and rearranging we get:

$$\frac{d\theta}{ds}=\frac{\theta^{\alpha}((1-\varphi)(p-(b+l^{\mu+\chi}))-s(1-\varphi)(\mu+\chi)l^{\mu+\chi-1}-\varphi c\theta)}{\frac{s\varphi c}{\theta^{\alpha}}-(r+\lambda)cp(1-\alpha)} \tag{29}$$

Taking into account that due to (15) $\theta=0$ if $s=0$ we get the following expression for the limit of (29) when $s\to 0$:

$$\lim_{s\to 0}\frac{d\theta}{ds}=\frac{0}{(r+\lambda)cp(1-\alpha)}=0 \tag{30}$$

To get the limit of the slope of the first order condition in (18) we multiply both sides of the equation with s and than totally differentiate.

$$\frac{d\theta}{ds}=\frac{\mu l^{\mu-\chi-1}-s\mu(\mu+\chi-1)l^{\mu+\chi-2}}{\frac{\varphi}{1-\varphi}cp} \tag{31}$$

When s converges to zero we get:

$$\lim_{s\to 0}\frac{d\theta}{ds}=\frac{\mu T^{\mu+\chi-1}}{\frac{\varphi}{1-\varphi}cp}>0 \tag{32}$$

5.3 Empirical Results

	Germany			West Germany			East Germany		
Year	1999	2000	2001	1999	2000	2001	1999	2000	2001
No. of individuals in a region									
Mean	1771,6280	1801,5290	1790,7240	1851,31	1887,544	1883,508	1508,147	1517,107	1483,92
Std. Deviation	2,1334	2,1376	2,1371	2183,929	2226,613	2220,516	761,7294	775,7916	771,5965
Min	424	421	427	424	421	427	786	793	767
Max	23142	23490	23301	23142	23490	23301	5074	5187	5137
Average age in a region									
Mean	37,9039	38,2494	38,5860	37,64938	37,95497	38,2944	38,74546	39,22284	39,55024
Std. Deviation	0,9829	0,9875	0,9852	0,739586	0,7244424	0,704467	0,5647247	0,6156947	0,5892435
Min	35,22882	35,44238	35,9124	35,22882	35,44238	35,91235	37,31902	37,59844	37,99664
Max	40,02752	40,32589	40,7744	39,70466	39,96109	40,04436	40,02752	40,32589	40,77441
No. of individuals with no professional training									
Mean	272,6811	295,3467	308,9690	320,3871	344,254	357,3387	114,9333	133,6267	149,0267
Std. Deviation	1,7675	1,7779	1,7826	323,1454	343,1382	353,2058	62,82028	74,34993	81,17931
Min	52	58	65	71	77	75	52	58	65
Max	3580	3 811	3969	3580	3811	3969	402	481	534
No. of individuals with secondary education									
Mean	1193,3930	1187,4890	1157,3190	1202,048	1197,492	1172,149	1164,773	1154,413	1108,28
Std. Deviation	2,0222	2,0208	2,0152	1275,048	1265,981	1231,07	512,6318	510,436	497,6756
Min	289	293	294	289	293	294	638	633	613
Max	13909	13752	13289	13909	13752	13289	3350	3336	3244
No. of individuals with university-entrance diploma									
Mean	124,3406	132,8204	137,2539	140,5202	150,8548	156,4274	70,84	73,18667	73,85333
Std. Deviation	1,7146	1,7284	1,7377	246,6044	266,9359	281,6229	56,41378	60,79311	65,43239
Min	13	8	12	13	8	12	27	24	19
Max	2076	2263	2357	2076	2263	2357	355	394	414
No. of individuals with university diploma									
Mean	181,2136	185,8731	187,1827	188,3548	194,9435	197,5927	157,6	155,88	152,76
Std. Deviation	1,7879	1,7939	1,7968	371,9121	385,1015	391,7146	148,5809	149,5441	146,4626
Min	21	23	23	21	23	23	49	50	49
Max	3577	3664	3686	3577	3664	3686	978	1005	975
No. of individuals working in the agricultural sector									
Mean	49,2260	46,9350	43,8855	43,53629	41,55242	38,67339	437	411,76	385,7067
Std. Deviation	1,4852	1,4740	1,4501	56,43568	52,0941	43,55761	168,2661	162,6139	158,1445
Min	4	5	5	4	5	5	165	154	129
Max	526	448	415	526	448	415	1048	993	947
No. of individuals working in the production sector									
Mean	592,1641	582,1517	568,1269	639,0887	633,6815	623,2944	838,2267	815,4133	808,3067
Std. Deviation	1,8436	1,8401	1,8363	500,1462	488,7661	476,4859	551,7198	545,9234	552,9705
Min	111	109	115	111	109	115	355	355	349
Max	4453	4116	3797	4453	4116	3797	3509	3489	3479
No. of individuals working in the trade and service sector									
Mean	1027,5760	1036,1240	1042,9720	1084,839	1102,871	1113,94	68,04	64,73333	61,12
Std. Deviation	2,0640	2,0675	2,0693	1569,119	1595,385	1608,449	27,63685	26,94857	25,08147
Min	219	213	227	219	213	227	15	17	14
Max	16101	16219	16284	16101	16219	16284	136	133	133
Number of in-flows into unemployment									
Mean	148,4985	139,2724	111,0000	124,1653	116,871	94,09274	228,96	213,3467	166,9067
Std. Deviation	1,6504	1,6453	1,5950	155,0126	151,9071	109,7136	95,28456	87,61872	71,52739
Min	26	22	14	26	22	14	119	106	85
Max	2118	2089	1474	2118	2089	1474	608	589	479

Table 1: Descriptive summary for the used covariates.

Germany 1999-2001

Distribution of unemployment durations	Log-Normal	
Individual Characteristics	**NE**	**UBJ**
Age	0.0126601 ***	0.0288007 ***
No professional training	0.6861099 ***	0.7024939 ***
University-entrance diploma	0.0178518	-0.0245373
University diploma	-0.0788928 **	-0.2070774 ***
Agricultural sector	-0.0114872	-0.053354 *
Trade and services sector	0.253012 ***	0.2445984 ***
Regional Characteristics		
Average age	0.0813232	0.0140666
Number of individuals with/working in		
No professional training	-0.0003816	-0.0012692 *
Secondary education	-0.0000443	0.00129 **
University-entrance diploma	0.0010618	-0.0005825
University diploma	-6.09E-06	0.0024291 ***
Agricultural sector	-0.0002963	-0.0000418
Industrial sector	-0.0004269	-0.0010302 **
Trade and services sector	-0.0006407	-0.0006703
Number of inflows into unemployment	0.0001522	-0.0001823
Constant	5.499339 ***	5.304817 ***
Number of regional dummies	322	322
min	-1.767465 ***	-4.423586
max	10.77954 *	0.8396235
Ancillary parameter		
Constant	0.3913959 ***	0.5078563 ***
Number of regional dummies	322	322
min	-0.6220613 ***	-0.5932685 ***
max	0.242695 ***	0.1423117 ***
Number of individuals	45697	55799
Number of unemployment spells	60810	77080
Number of failures	37295	49059
Number of regions	323	323
Log-pseudo-likelihood	-79670.746	-107136.42

significance levels: * 90% ** 95% *** 99%

standard errors are adjusted for clustering on regional level

reference categories: secondary education, industry; city of Kiel

Table 2:

West Germany 1999-2001

Distribution of unemployment durations	Log-Normal	
Individual Characteristics	**NE**	**UBJ**
Age	0,0120409 ***	0,0320974 ***
No professional training	0,6313369 ***	0,6865765 ***
University-entrance diploma	0,0121847	-0,0175913
University diploma	-0,096417 ***	-0,2397993 ***
Agricultural sector	-0,1058374 **	-0,1849751 ***
Trade and services sector	0,2069265 ***	0,1883735 ***
Regional Characteristics		
Average age	0,0256515	0,0541618
Number of individuals with/working in		
No professional training	-0,0004922	-0,0008509
Secondary education	-0,0003226	0,0023811 ***
University-entrance diploma	0,0010758	-0,0000445
University diploma	-0,0005994	0,0038507 ***
Agricultural sector	0,0001124	-0,0002464
Industrial sector	-0,000046	-0,0012849 ***
Trade and services sector	0,0002137	-0,002166 ***
Number of inflows into unemployment	0,0002891	-0,0009186 *
Constant	5,251585 ***	5,701283 ***
Number of regional dummies	247	247
min	-1,061929	-1,471566 ***
max	2,288278	1,015783
Ancillary parameter		
Constant	0,3905041 ***	0,5004467 ***
Number of regional dummies	247	247
min	-0,6049604 ***	-0,5808263 ***
max	0,2377412 ***	0,1453234 ***
Number of individuals	30859	38171
Number of unemployment spells	39671	51148
Number of failures	24023	31513
Number of regions	248	248
Log-pseudo-likelihood	-51056,353	-69445,049

significance levels: * 90% ** 95% *** 99%

standard errors are adjusted for clustering on regional level

reference categories: secondary education, industry, city of Kiel

Table 3:

East Germany 1999-2001

Distribution of unemployment durations	Log-Normal	
Individual Characteristics	**NE**	**UBJ**
Age	0,0146014 ***	0,023792 ***
No professional training	0,9998454 ***	0,7878115 ***
University-entrance diploma	0,0484634	-0,0681372
University diploma	-0,0174711	-0,115908 *
Agricultural sector	0,0994111 **	0,1084606 ***
Trade and services sector	0,3361455 ***	0,3440026 ***
Regional Characteristics		
Average age	-0,00502	0,1331422
Number of individuals with/working in		
No professional training	0,0002197	-0,0011305
Secondary education	0,0000782	0,0006828
University-entrance diploma	-0,004057	0,0052194 *
University diploma	-0,0019	0,0015145
Agricultural sector	-0,0030291	-0,0033742
Industrial sector	-0,0026427 ***	0,0012121
Trade and services sector	-0,0016216 **	0,0006043
Number of inflows into unemployment	0,0001393	0,0018192 **
Constant	3,691068 ***	6,191037 ***
Number of regional dummies	74	74
min	-1,374436 ***	-7,233703 ***
max	8,981759 ***	0,4450857
Ancillary parameter		
Constant	0,3347184 ***	0,4571515 ***
Number of regional dummies	74	74
min	-0,2100894 ***	-0,2438343 ***
max	0,225218 ***	0,0615879 ***
Number of individuals	15486	18358
Number of unemployment spells	21046	25765
Number of failures	13226	17441
Number of regions	75	75
Log-pseudo-likelihood	-28407,996	-37344,327

significance levels: * 90% ** 95% *** 99%

standard errors are adjusted for clustering on regional level

refernce categories: secondary education, industry, city of Cottbus

Table 4:

Germany - NE Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0048156	0,0047335	0,0043738	0,0034694	0,002893	0,0024823	0,0022007
Std. Deviation	0,0019927	0,0017796	0,0015952	0,0012301	0,001015	0,0008649	0,0007631
Coef. of Variation	0,41380098	0,37595859	0,36471718	0,35455698	0,35084687	0,34842686	0,34675331
Min	0,0008819	0,0014295	0,0016202	0,0015504	0,0013371	0,0011749	0,0010591
Max	0,0105059	0,0107484	0,010181	0,0090795	0,0078722	0,0068795	0,0061568

Duration	545	635	730	820	910	1000	1095
Mean	0,0019845	0,0018125	0,0016647	0,0015483	0,0014492	0,0013638	0,0012853
Std. Deviation	0,0006855	0,0006241	0,0005716	0,0005304	0,0004955	0,0004654	0,0004378
Coef. of Variation	0,34542706	0,34433103	0,34336517	0,34256927	0,34191278	0,34125238	0,34062087
Min	0,0009675	0,0008931	0,000828	0,0007759	0,000731	0,0006919	0,0006557
Max	0,0055843	0,0051198	0,0047155	0,004394	0,0041186	0,0038797	0,0036594

West Germany - NE Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0058003	0,005604	0,0051172	0,0039796	0,0032842	0,0027984	0,0024694
Std. Deviation	0,0019166	0,0018629	0,001739	0,0013926	0,0011595	0,0009914	0,0008757
Coef. of Variation	0,33043118	0,33242327	0,33983428	0,34993467	0,35305402	0,35427387	0,35462056
Min	0,0003051	0,0004252	0,0004772	0,000513	0,0005006	0,0004778	0,0004552
Max	0,0115233	0,0129833	0,0126697	0,0106249	0,0089416	0,0076806	0,0068015

Duration	545	635	730	820	910	1000	1095
Mean	0,0022188	0,0020207	0,0018514	0,0017185	0,0016058	0,0015089	0,0014201
Std. Deviation	0,000787	0,0007166	0,0006562	0,0006088	0,0005685	0,0005338	0,000502
Coeff. of Variation	0,35469623	0,35462958	0,35443448	0,35426244	0,35402914	0,35376765	0,35349623
Min	0,0004339	0,0004143	0,0003956	0,0003795	0,0003648	0,0003515	0,0003385
Max	0,0061224	0,0055807	0,0051153	0,0047486	0,004437	0,0041684	0,0039221

East Germany - NE Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0162612	0,0117357	0,0094032	0,0061727	0,0047279	0,0038457	0,0032936
Std. Deviation	0,009635	0,006242	0,004713	0,002818	0,002053	0,001613	0,001349
Coef. of Variation	0,59251470	0,53185579	0,50122299	0,45646152	0,43425199	0,41945550	0,40949113
Min	0,000000001	0,000000004	0,000000010	0,000000071	0,000000108	0,000000303	0,000000500
Max	0,0438819	0,0293966	0,0226497	0,0140201	0,0104231	0,0083091	0,0070193

Duration	545	635	730	820	910	1000	1095
Mean	0,0028943	0,0025903	0,0023383	0,0021452	0,0019847	0,0018488	0,0017261
Std. Deviation	0,001163	0,001025	0,000913	0,000828	0,000759	0,000701	0,000649
Coef. of Variation	0,40185883	0,39570706	0,39036907	0,38607123	0,38237517	0,37911077	0,37610799
Min	0,000000700	0,000000901	0,000001015	0,000001039	0,000001064	0,000001090	0,000002017
Max	0,0061032	0,0054154	0,0048518	0,0044242	0,0040716	0,0037752	0,0035094

Table 5: Descriptive Statistics for the Regional Baseline Hazard Rates – NE Definition

Germany - UBJ Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0063741	0,0055514	0,0048645	0,0036068	0,0029215	0,0024625	0,0021587
Std. Deviation	0,0035841	0,0022783	0,0017619	0,001147	0,0008901	0,0007338	0,0006352
Coef. of Variation	0,56229115	0,41040098	0,36219550	0,31801042	0,30467226	0,29798985	0,29425117
Min	0,0022403	0,0021305	0,0019588	0,0015664	0,0013203	0,0011438	0,0010084
Max	0,040733	0,0256023	0,0192436	0,0115326	0,0084493	0,0066731	0,0056028

Duration	545	635	730	820	910	1000	1095
Mean	0,0019305	0,0017518	0,0016002	0,001482	0,0013822	0,0012966	0,0012185
Std. Deviation	0,0005632	0,0005079	0,0004616	0,0004259	0,000396	0,0003705	0,0003473
Coef. of Variation	0,29173789	0,28993036	0,28846394	0,28738192	0,28649978	0,28574734	0,28502257
Min	0,0009037	0,0008217	0,0007521	0,0006978	0,0006518	0,0006124	0,0005764
Max	0,0048491	0,0042869	0,0038285	0,0034824	0,0031979	0,0029595	0,0027635

West Germany - UBJ Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0063741	0,0055514	0,0048645	0,0036068	0,0029215	0,0024625	0,0021587
Std. Deviation	0,0035841	0,0022783	0,0017619	0,001147	0,0008901	0,0007338	0,0006352
Coef. of Variation	0,56229115	0,41040098	0,36219550	0,31801042	0,30467226	0,29798985	0,29425117
Min	0,0022403	0,0021305	0,0019588	0,0015664	0,0013203	0,0011438	0,0010084
Max	0,040733	0,0256023	0,0192436	0,0115326	0,0084493	0,0066731	0,0056028

Duration	545	635	730	820	910	1000	1095
Mean	0,0019305	0,0017518	0,0016002	0,001482	0,0013822	0,0012966	0,0012185
Std. Deviation	0,0005632	0,0005079	0,0004616	0,0004259	0,000396	0,0003705	0,0003473
Coef. of Variation	0,29173789	0,28993036	0,28846394	0,28738192	0,28649978	0,28574734	0,28502257
Min	0,0009037	0,0008217	0,0007521	0,0006978	0,0006518	0,0006124	0,0005764
Max	0,0048491	0,0042869	0,0038285	0,0034824	0,0031979	0,0029595	0,0027635

East Germany - UBJ Proxy

Duration	30	60	90	180	270	365	455
Mean	0,0062765	0,0054201	0,0047312	0,0034932	0,0028256	0,0023802	0,0020859
Std. Deviation	0,002898	0,001882	0,001423	0,000860	0,000635	0,000505	0,000427
Coef. of Variation	0,46178603	0,34717072	0,30081163	0,24616398	0,22455408	0,21204100	0,20446810
Min	0,0028953	0,0031049	0,0028682	0,0022378	0,0018595	0,0015944	0,0014139
Max	0,0189759	0,0125719	0,0096717	0,0062297	0,0048314	0,0039588	0,0034059

Duration	545	635	730	820	910	1000	1095
Mean	0,0018651	0,0016922	0,0015457	0,0014314	0,001335	0,0012523	0,0011769
Std. Deviation	0,000371	0,000330	0,000296	0,000271	0,000250	0,000232	0,000216
Coef. of Variation	0,19907780	0,19501241	0,19162839	0,18904569	0,18689139	0,18509942	0,18344804
Min	0,0012758	0,0011661	0,0010719	0,0009976	0,0009345	0,00088	0,0008299
Max	0,0030029	0,0026942	0,0024372	0,0022395	0,0020747	0,0019349	0,0018085

Table 6: Descriptive Statistics for the Regional Baseline Hazard Rates – UBJ Definition

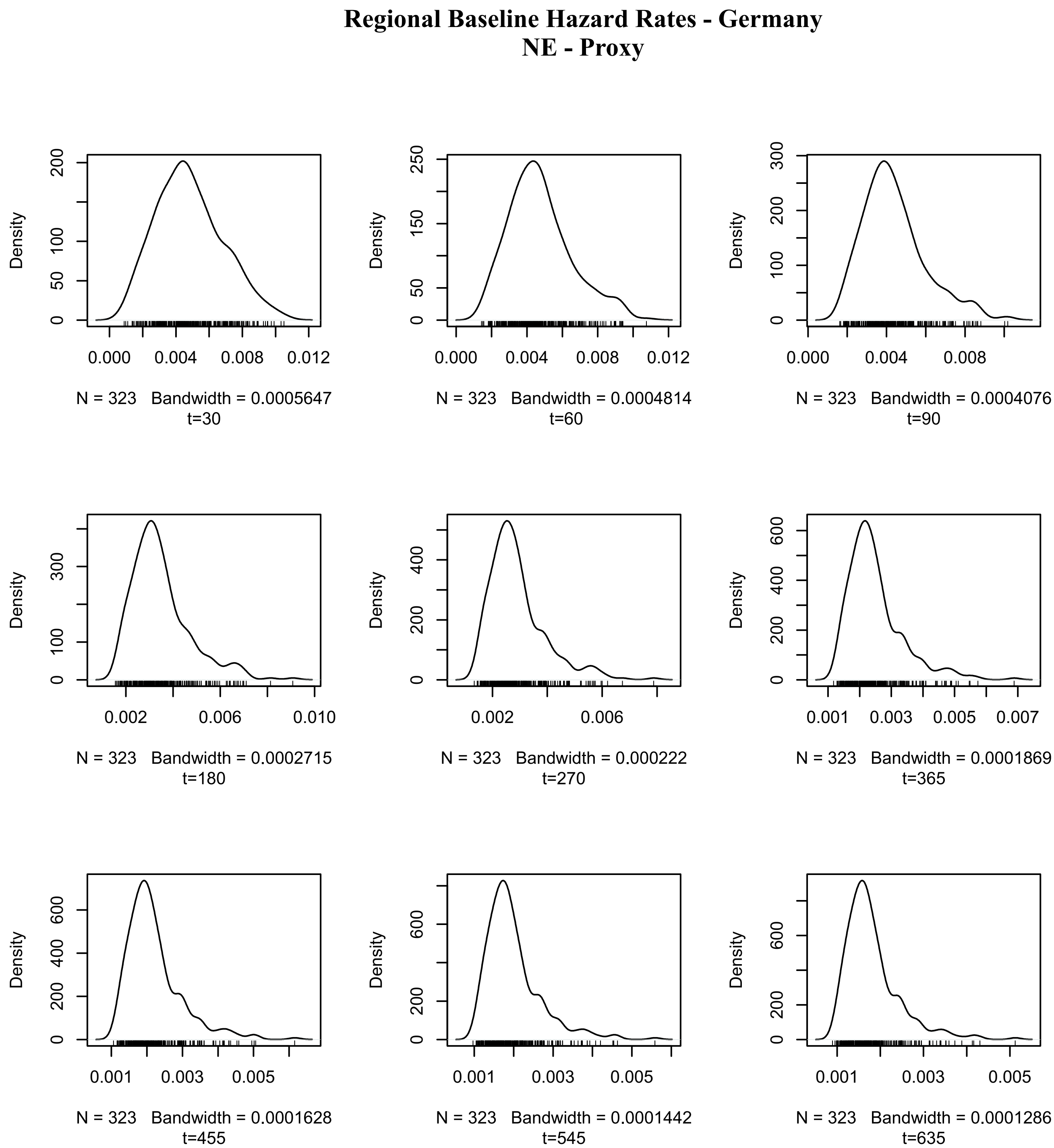
Regional Baseline Hazard Rates - Germany
NE - Proxy
Density
N = 323 Bandwidth = 0.0005647
t=30
N = 323 Bandwidth = 0.0004814
t=60
N = 323 Bandwidth = 0.0004076
t=90
N = 323 Bandwidth = 0.0002715
t=180
N = 323 Bandwidth = 0.000222
t=270
N = 323 Bandwidth = 0.0001869
t=365
N = 323 Bandwidth = 0.0001628
t=455
N = 323 Bandwidth = 0.0001442
t=545
N = 323 Bandwidth = 0.0001286
t=635

Figure 2:

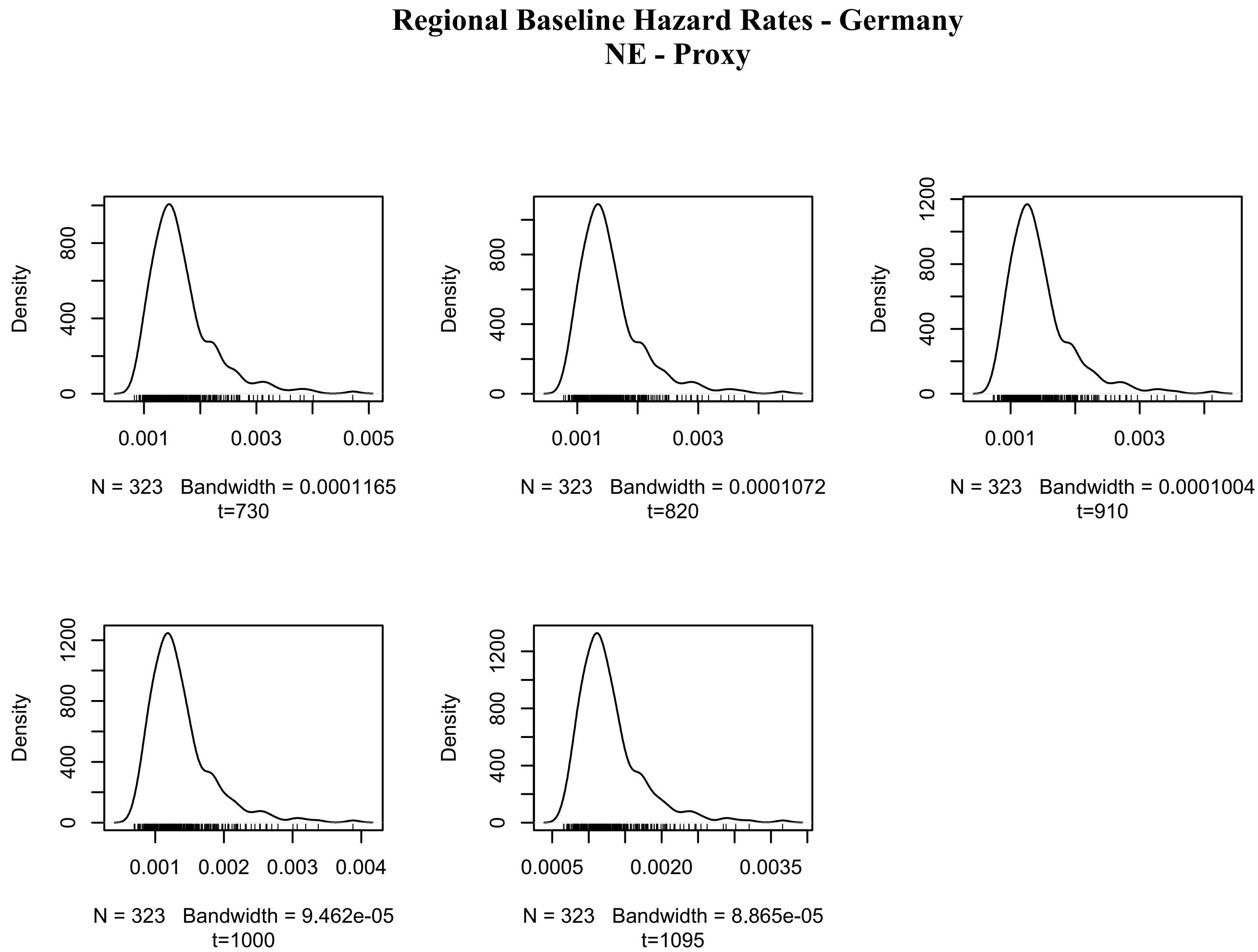
Regional Baseline Hazard Rates - Germany
NE - Proxy
Density
0
400
800
0.001
0.003
0.005
N = 323 Bandwidth = 0.0001165
t=730
Density
0
400
800
0.001
0.003
N = 323 Bandwidth = 0.0001072
t=820
Density
0
400
800
1200
0.001
0.003
N = 323 Bandwidth = 0.0001004
t=910
Density
0
400
800
1200
0.001
0.002
0.003
0.004
N = 323 Bandwidth = 9.462e-05
t=1000
Density
0
400
800
1200
0.0005
0.0020
0.0035
N = 323 Bandwidth = 8.865e-05
t=1095

Figure 3:

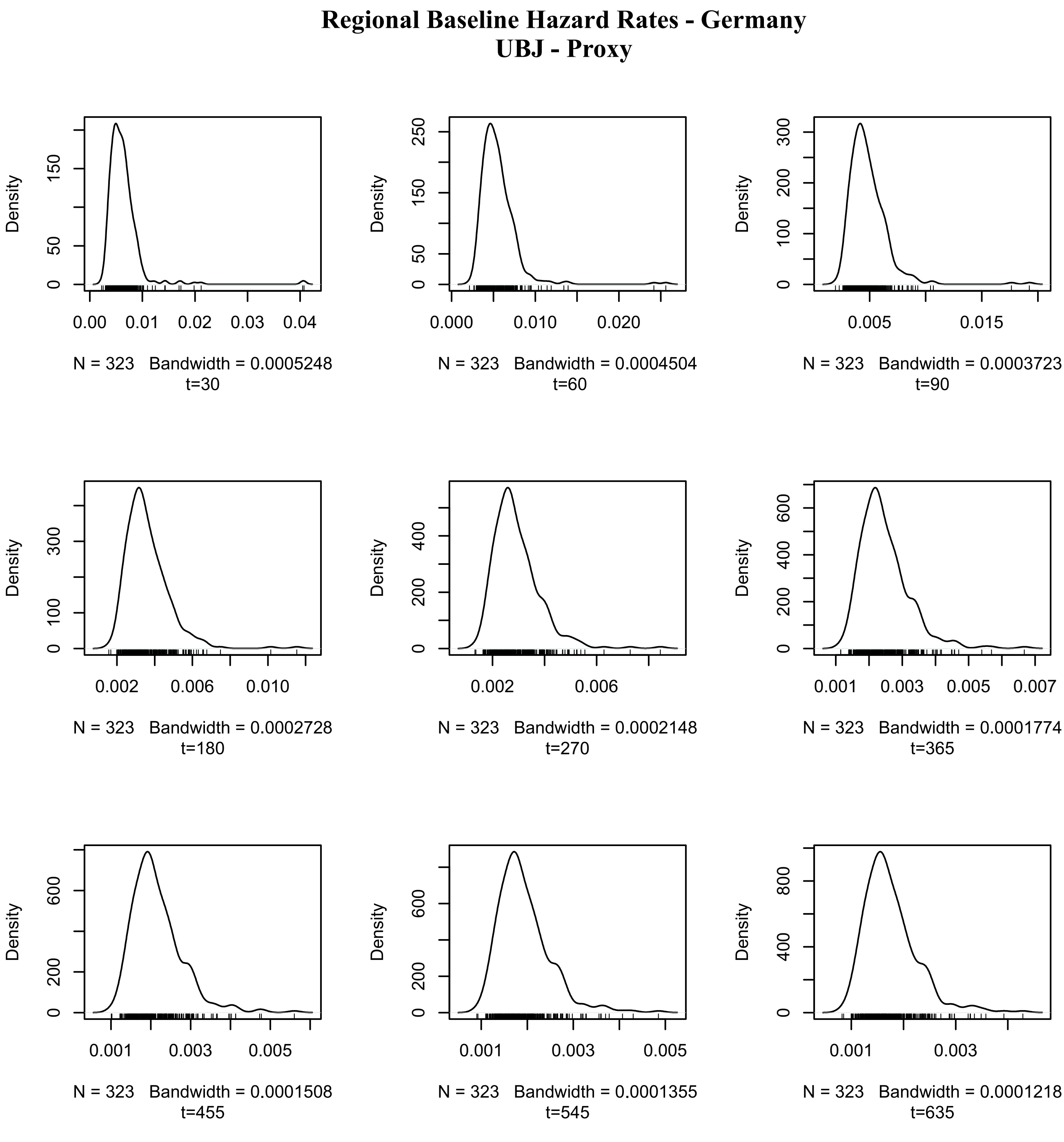
Regional Baseline Hazard Rates - Germany
UBJ - Proxy
N = 323 Bandwidth = 0.0005248
t=30
N = 323 Bandwidth = 0.0004504
t=60
N = 323 Bandwidth = 0.0003723
t=90
N = 323 Bandwidth = 0.0002728
t=180
N = 323 Bandwidth = 0.0002148
t=270
N = 323 Bandwidth = 0.0001774
t=365
N = 323 Bandwidth = 0.0001508
t=455
N = 323 Bandwidth = 0.0001355
t=545
N = 323 Bandwidth = 0.0001218
t=635
Density

Figure 4:

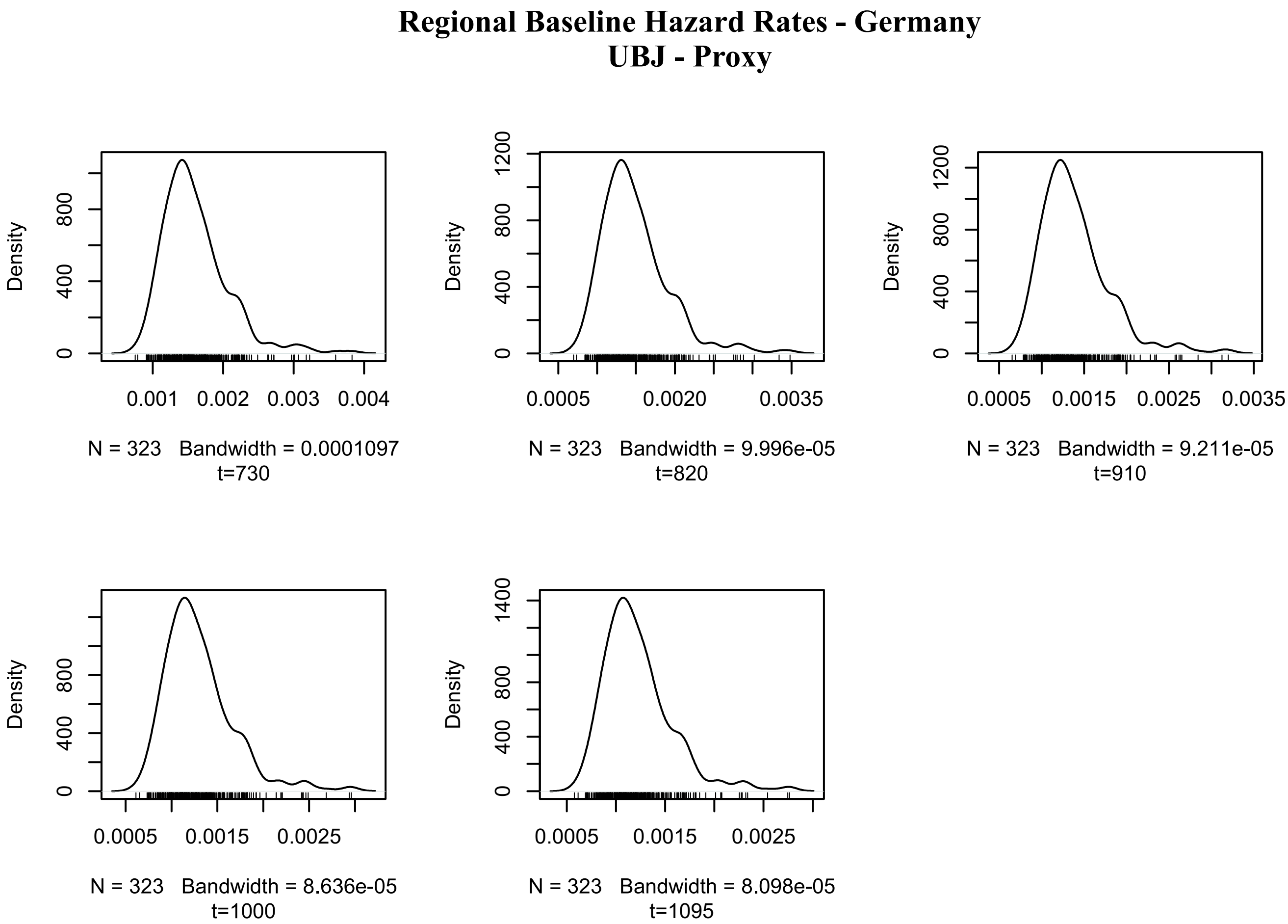
Regional Baseline Hazard Rates - Germany
UBJ - Proxy
Density
N = 323 Bandwidth = 0.0001097
t=730
N = 323 Bandwidth = 9.996e-05
t=820
N = 323 Bandwidth = 9.211e-05
t=910
N = 323 Bandwidth = 8.636e-05
t=1000
N = 323 Bandwidth = 8.098e-05
t=1095

Figure 5:

NE Proxy

	Germany		West Germany		East Germany	
		Uni-modal		Uni-modal		Uni-modal
Duration	Dip	Significance = 99%	Dip	Significance = 99%	Dip	Significance = 99%
30	0,0151052	yes	0,0147519	yes	0,02937652	yes
60	0,01790928	yes	0,01300539	yes	0,02672174	yes
90	0,01289873	yes	0,01375341	yes	0,02512945	yes
180	0,01385845	yes	0,01571918	yes	0,02720139	yes
270	0,01151076	yes	0,0189356	yes	0,0242116	yes
365	0,01258255	yes	0,01439373	yes	0,02523247	yes
455	0,01366336	yes	0,01578179	yes	0,02886098	yes
544	0,01751526	yes	0,01535741	yes	0,02725137	yes
635	0,01531989	yes	0,01528028	yes	0,02642542	yes
730	0,01362229	yes	0,01378019	yes	0,02677622	yes
810	0,01261178	yes	0,01354609	yes	0,02704961	yes
920	0,01302154	yes	0,01514897	yes	0,02704961	yes
1000	0,01195623	yes	0,01668281	yes	0,02955739	yes
1095	0,01136926	yes	0,01602339	yes	0,03002688	yes

UBJ Proxy

	Germany		West Germany		East Germany	
		Uni-modal		Uni-modal		Uni-modal
Duration	Dip	Significance = 99%	Dip	Significance = 99%	Dip	Significance = 99%
30	0,01541311	yes	0,02170949	yes	0,03622034	yes
60	0,01587238	yes	0,02091254	yes	0,03393956	yes
90	0,01258815	yes	0,02010958	yes	0,0255199	yes
180	0,01120743	yes	0,01468738	yes	0,03038955	yes
270	0,01347011	yes	0,02155366	yes	0,03271841	yes
365	0,01317735	yes	0,02023775	yes	0,03288518	yes
455	0,01508845	yes	0,01972749	yes	0,03096421	yes
544	0,01413378	yes	0,0208734	yes	0,03113122	yes
635	0,01193083	yes	0,01934339	yes	0,02993426	yes
730	0,01027185	yes	0,01649127	yes	0,02673475	yes
810	0,0115521	yes	0,01636888	yes	0,02727477	yes
920	0,01195591	yes	0,01717514	yes	0,02566191	yes
1000	0,01053407	yes	0,01642772	yes	0,02944302	yes
1095	0,01134372	yes	0,0165334	yes	0,02709677	yes

Table 7: Results of the Dip-test for Unimodality. The critical values for determining the level of significance have been calculated for $n = 323$ and using the methodology of Hartigan (1985).

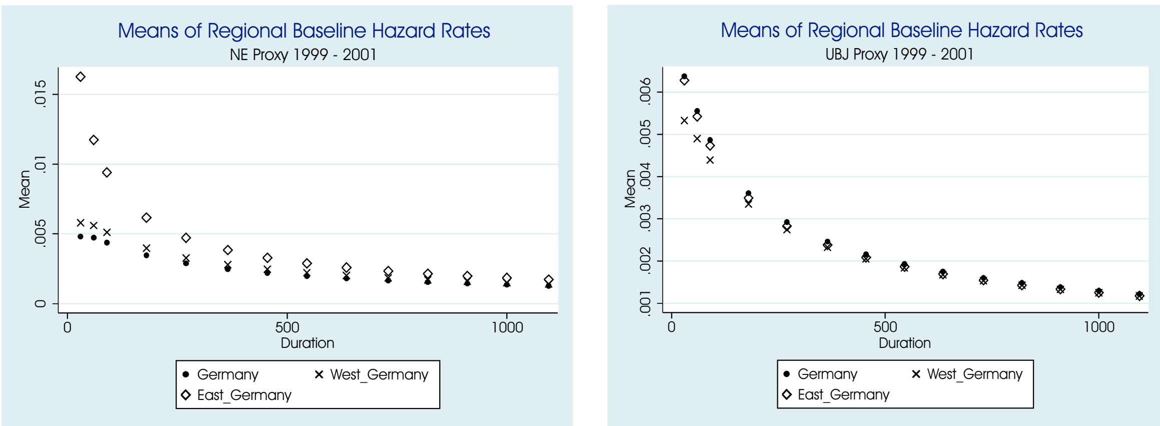

Figure 6: Comparison of the Means