

Schimmelpfennig, Axel

Working Paper — Digitized Version

Structural change of the production process and unemployment duration in Germany

Kiel Working Paper, No. 959

Provided in Cooperation with:

Kiel Institute for the World Economy – Leibniz Center for Research on Global Economic Challenges

Suggested Citation: Schimmelpfennig, Axel (1999) : Structural change of the production process and unemployment duration in Germany, Kiel Working Paper, No. 959, Kiel Institute of World Economics (IfW), Kiel

This Version is available at:

<https://hdl.handle.net/10419/47007>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Kieler Arbeitspapiere

Kiel Working Papers

Kiel Working Paper No. 959

**Structural Change of the Production Process
and Unemployment Duration in Germany**

by

Axel Schimmelfennig



Institut für Weltwirtschaft an der Universität Kiel
The Kiel Institute of World Economics

Kiel Institute of World Economics

Duesternbrooker Weg 120

24105 Kiel (Germany)

Kiel Working Paper No. 959

**Structural Change of the Production Process
and Unemployment Duration in Germany**

by

Axel Schimmelpfennig

December 1999

373 783 256

The responsibility for the contents of the working papers rests with the author, not the Institute. Since working papers are of a preliminary nature, it may be useful to contact the author of a particular working paper about results or caveats before referring to, or quoting, a paper. Any comments on working papers should be sent directly to the author.

Structural Change of the Production Process and Unemployment Duration in Germany

Abstract:

Based on a Cox Proportional Hazard analysis of German unemployment spells, structural change of the production process is identified as a major explanation for long-term unemployment. Other important covariates capture labor market institutions, macroeconomic stress factors, and individual characteristics. Structural change of the production process has resulted in a shift in labor demand across occupations and skills. For individuals laid off from declining parts of the economy, this implies a devaluation of their human capital. They need to acquire new skills for positions in expanding parts of the economy, or spend a longer time in unemployment searching for the few remaining jobs for which they possess adequate skills.

Keywords: Unemployment duration, Cox Proportional Hazard model,
structural change

JEL Classifikation: J62, J64, C41

Axel Schimmelpfennig
Institut für Weltwirtschaft
24100 Kiel

New affiliation
Axel Schimmelpfennig
The International Monetary Fund
700 19th Street, NW,
Washington, DC 20431
e-mail: ASCHIMMELPFENNIG@imf.org

This paper is part of a thesis project on structural change of the production process and unemployment in Germany. (Special thanks to Björn Christensen for his outstanding assistance in generating the data.) The data used in this paper were made available by the German Socio-economic Panel Study (GSOEP) at the German Institute for Economic Research (DIW) Berlin.

1 Structural Change of the Production Process and Unemployment

Long-term unemployment is one of the defining characteristics of the German unemployment problem. Still, its causes are not fully understood. Recent empirical work suggests that neither hysteresis nor the unemployment benefits system can fully explain long-term unemployment in Germany. In particular, Hunt (1995: 91) concludes "... although unemployment insurance plays a role that cannot be ignored, the search for other causes of long German unemployment spells should continue." In this paper, I show that structural change of the production process is another major additional explanation for long-term unemployment in Germany.

Structural change of the production process is an important factor driving labor demand.¹ Consumption expenditure has shifted from standardized mass products to varieties of differentiated goods over the last decades. Thus production has become more intermediate service intensive. For example, management, research and development, or marketing have gained importance. This I call structural change of the production process. As a result, labor demand has shifted across occupations and skills. Jobs in declining parts of the economy require to a large extent physical strength and only few skills. Jobs in expanding parts of the economy require to a large extent analytical problem solving abilities and high skills in general.

Individuals laid-off from declining parts of the economy are faced with a devaluation of their human capital by structural change of the production process. To successfully find a new job in expanding parts of the economy, these individuals need to improve their employability by acquiring new skills or they must accept low paying jobs for example in consumer services. Otherwise, individuals who are negatively affected from structural change of the production process will on average spend more time unemployed because it takes them longer to find one of the few positions left for which their human capital is still adequate.

In this paper, I provide evidence that structural change of the production process explains unemployment duration. In line with existing studies, labor market institutions, macroeconomic stress factors, and individual characteristics are also significant explanatory variables. The evidence is based on a Cox Proportional Hazard model which is estimated for unemployment spells that terminate in employment taken from the German Socio-economic Panel.

¹ Snower (1999) has a similar concept in mind when he talks about the organization revolution.

The remaining part of the paper is organized as follows. Section 2 surveys previous empirical studies of unemployment duration. Section 3 sketches the econometric approach. Section 4 describes the data and section 5 gives the estimation results. Section 6 summarizes the main arguments of the paper.

2 Existing Empirical Studies

Existing empirical studies deal mostly with two broad aspects of unemployment duration: (i) The impact of unemployment benefits, and (ii) the influence of individual characteristics like skill-level or age.² The impact of unemployment benefits on unemployment duration is either based on search theory (e.g. Mortensen 1977, Bloemen 1997) or on a static labor-leisure model (Moffitt and Nicholson 1982). Nickell (1979) is among the first who use survival analysis to investigate the impact of unemployment benefits on unemployment duration. His results for the United Kingdom suggest that unemployment benefits as well as the replacement ratio reduce the hazard rate of leaving unemployment; the effect peters out over the spell. For the United States, Moffitt (1985) has difficulties discerning a clear effect of unemployment benefits on unemployment duration, while Meyer (1990) and Katz and Meyer (1990) find unemployment duration to be influenced by the level and the length of unemployment benefits.

For Germany, Wurzel (1990) finds that eligibility for *Arbeitslosengeld* benefits actually reduces unemployment duration compared to eligibility for *Arbeitslosenhilfe*. He rationalizes this surprising finding by suggesting that eligibility for *Arbeitslosengeld* is a proxy for past employment experience. Alternatively, eligibility for *Arbeitslosengeld* may provide an unemployed with sufficient resources to actively and successfully search for a new position; this being one of the reasons for providing unemployment insurance in the first place.

Allowing for time-varying covariates, Hunt (1995) finds entitlement periods to increase unemployment duration. As in Wurzel, eligibility for *Arbeitslosengeld* reduces unemployment duration compared to eligibility for *Arbeitslosenhilfe*. Schneider and Hujer (1997) find the level of unemployment benefits to increase unemployment duration. Finally, Steiner (1997) finds both the entitlement period and eligibility for unemployment benefits to increase unemployment duration.

² A third aspect addressed in some studies is the the impact of training. See e.g. Pannenberg (1995), Lechner (1999), or Hujer et al. (1998a).

While most empirical studies include individual characteristics in their list of covariates to control for individual heterogeneity, only few interpret the estimated coefficients in detail. This is unfortunate, because the major advantage of using individual data vs. aggregate data to study unemployment is that the influence of individual characteristic can be analyzed. Individual characteristics can be important explanatory variables, even if the source of unemployment is a macroeconomic phenomenon. A shift in relative labor demand from unskilled to skilled workers, or a shift in labor demand across different types of firms is clearly a macroeconomic phenomenon. The incidence and duration of individual unemployment depends on how well an individual is equipped to adjust to such changes in labor demand.

A higher skill-level is found to be associated with shorter unemployment duration in Germany (e.g. Wurzel 1993, and Fehlker and Purfield (1998a, 1998b)). However, for the United Kingdom, Fehlker and Purfield (1998b) find no impact of the skill-level on unemployment duration. Old age is found to be associated with longer unemployment duration in Germany (e.g. Hujer and Schnabel 1990, Wurzel 1993, and Hujer and Scheider 1996). Comparing the influence of skill-level and age on unemployment duration based on descriptive statistics shows age to be the dominant factor (Karr 1999). Long-term unemployment (>12 months) is most heavily concentrated on individuals aged 55 and older. Differences in the skill-level play only a minor role. If unemployed individuals need to acquire new general or firm-specific skills to compete for new jobs, age is a major determinant of the net present value of such an investment in human capital. The older an unemployed individual is, the less time remains in his active life for the investment to pay off. Hence, older individuals should be less willing to invest in human capital to increase their employability.

Long-term unemployment is also discussed from a different point of view. On the one side, long-term unemployment could be the result of state dependence or duration dependence: An individual's re-employment prospects may deteriorate with the duration of the unemployment spell. Either, individuals lose human capital and hence productivity while unemployed, or firms take unemployment duration as an indicator for productivity that has to match a given rigid wage structure. Lagged duration and occurrence may have similar effects on the hazard rate from unemployment. On the other side, long-term unemployment could be the result of sorting: In a recession, individuals with unobserved poor re-employment prospects are laid-off more often than individuals with good re-employment prospects. Hence, long-term unemployment rises.

Flaig et al. (1993) find a state dependence effects on unemployment duration from past unemployment experiences, controlling for individual heterogeneity. Similarly, Licht

and Steiner (1991) also find a positive effect of past unemployment experience on unemployment duration. However, they interpret the significant effect as capturing some unobserved individual heterogeneity rather than as support for the state dependence hypothesis. Steiner (1994) shows that a sorting effect is responsible for long-term unemployment. He estimates a discrete non-parametric hazard model accounting for individual heterogeneity in a non-parametric way. The individual heterogeneity component divides the unemployed into three groups with different, but constant baseline hazard rates of leaving unemployment. While this finding is interesting, it is unfortunate that the characteristics which divides the unemployed into groups is unobserved and hence not identified. Knowledge of these characteristics is required, if the problem of long-term unemployment is to be addressed by economic policy.

3 Econometric Methodology

To identify the determinants of unemployment duration in Germany, I estimate a continuous Cox Proportional Hazard model (Cox 1972, 1975).³ The hazard rate can be interpreted as the probability of leaving unemployment at unemployment spell length t . For the Cox regression, the hazard rate λ for individual i at spell length t is written as

$$[1] \quad \lambda(t_i) = \lambda_0(t_i) e^{\beta' x_i} \quad \text{with } \lambda_0(t_i) > 0$$

where λ_0 is the baseline hazard of leaving unemployment which is assumed to be identical for every individual. x_i is a vector of individual-specific covariates that influence the individual hazard rate according to the coefficients in β .

Cox (1972, 1975) has suggested an estimation approach based on the so called partial likelihood function. The approach is a way of eliminating the baseline hazard from the equation to be maximized in the estimation procedure. Hence, no functional form needs to be specified for the baseline hazard. The estimation procedure is called partial likelihood (PL) because it uses only part of the full likelihood function. The intuition of the Cox regression is very simple. The partial likelihood function can be thought of as the likelihood that all n spells in the sample are observed.

$$[2] \quad PL = \prod_{i=1}^n L_i$$

³ See Lancaster (1979, 1990), Kalbfleisch and Prentice (1980), Allison (1984, 1995), Blossfeld et al. (1986), Kiefer (1988), and Greene (1997).

where L_i denotes the likelihood of observing spell i .

In t_i , all spells that have not previously ended are at risk of ending, with the risk being given by the hazard rate. These spells can be combined into the risk set R_i . L_i is then the probability that out of the risk set R_i spell i is terminated.

$$[3] \quad PL = \prod_{i=1}^n \frac{\lambda_0(t_i) e^{\beta'x_i}}{\sum_{t_j \in R_i} \lambda_0(t_i) e^{\beta'x_j}}$$

Since the baseline hazard λ_0 depends only on the spell length and not on individual characteristics, the partial likelihood simplifies to

$$[4] \quad PL = \prod_{i=1}^n \frac{e^{\beta'x_i}}{\sum_{t_j \in R_i} e^{\beta'x_j}}$$

The partial likelihood approach does not make use of the full likelihood function; not all available information is used for estimation. Hence, the estimator is no longer efficient. However, Bailey (1984) has shown that the PL estimator is consistent and asymptotically normal. In addition, the PL estimator is asymptotically equivalent to the ML estimator of the full likelihood function. See Moffitt (1985: 96) for a brief discussion.

A spell can be terminated for more than just one reason, this is referred to as competing risks. Unemployment can be terminated with an individual finding a new job, dropping out of the labor force into retirement, or dropping out of the labor force and relying on some other form of income. Assuming that the different risks of spell termination are stochastically independent, the risk-specific hazard rates can be treated separately. For each risk, a separate proportional hazard model⁴ is estimated where spells that are terminated due to a different risk are treated as right-censored.

An issue that has received wide attention in the literature is the problem of unobserved individual heterogeneity. The proportional hazard model, as well as most other hazard models, assumes a constant baseline hazard across individuals. Still individuals can have different individual hazards. The difference between the baseline hazard and the

⁴ Depending on the empirical problem at hand, any other type of hazard model can also be estimated.

individual hazard should be accounted for by the vector of covariates. If some variables are omitted from the vector of covariates, one is faced with the problem of unobserved individual heterogeneity.

As a result of unobserved individual heterogeneity the estimated baseline hazard can be downward sloping, even though the true baseline hazard is constant (e.g. Allison 1995: 235). But unobserved individual heterogeneity does not only bias the slope of the baseline hazard, it can also bias the coefficient estimates. Two cases can be distinguished: Either the unobserved heterogeneity component is orthogonal to the included covariates, or the unobserved heterogeneity component is not orthogonal to the included covariates.

If the unobserved individual heterogeneity component is orthogonal to the covariates, Gail et al. (1984) have shown the estimated coefficients to be biased towards zero.⁵ However, standard errors and tests statistics are unbiased. Hence, qualitative inference can be drawn even when the estimation suffers from unobserved individual heterogeneity. If quantitative inference is of interest, it is necessary to somehow control for the unobserved individual heterogeneity component. This is usually done by introducing a multiplicative individual heterogeneity component in the model (e.g. Lancaster 1990: pp. 263). In the case of the proportional hazard model, the hazard rate becomes

$$[5] \quad \lambda(t_i) = \lambda_0(t_i) e^{-\beta'x_i} \varepsilon_i \quad \text{with } \lambda_0(t_i) > 0$$

where ε is a stochastic variable for which it is usually assumed that

$$\varepsilon_i > 0 \quad \text{and} \quad E(\varepsilon_i) = 1$$

The stochastic variable needs be positive so that the hazard rate is always positive. An expected value of one implies that on average, individual heterogeneity does not affect the hazard rate. There is no clear consensus in the literature whether a parametric distribution or a non-parametric distribution should be used for the random variable. See Heckman and Singer (1982, 1984a, and 1984b) or Hujer and Schneider (1996) for a discussion.

⁵ This result is common for models that do not contain an explicit error component, but rather introduce the stochastic component through the dependent variable. The logit model is one example (e.g. Shabbir 1993).

If the unobserved individual heterogeneity component is not orthogonal to the covariates, the problem of biased estimates is aggravated. In analogy to the linear regression model, the influence of the unobserved individual heterogeneity component is picked up in the coefficients of the covariates. In many empirical applications, this type of unobserved individual heterogeneity comes in the form of a selectivity bias. To overcome a potential selectivity bias, matching procedures have been used in several studies (e.g. Lechner 1996 or Hujer et al. 1998a, 1998b, 1998c).⁶

Unobserved heterogeneity is simply a problem of omitted covariates. Failing to control for time-invariant unobserved heterogeneity leads to a downward bias of the estimated hazard rate and the coefficient estimates. However, using a wrong functional form for the unobserved heterogeneity component may also lead to biased estimates with the direction of the bias being unknown. Moreover, accounting for unobserved individual heterogeneity by adding a stochastic component to the hazard rate does not necessarily remove a potential omitted variable bias (cf. Blossfeld et al. 1986: 100); the stochastic component controlling for unobserved individual heterogeneity is very unlikely to capture the exact influence of the omitted covariates.

Given the potential problems of accounting for individual heterogeneity and the little improvement in the coefficient estimates, not accounting for unobserved heterogeneity can be viewed as a superior approach (e.g. Thoursie 1997). Wurzel (1990) finds that accounting for individual heterogeneity does not change the coefficients of a log-logistic hazard model significantly. Narendranathan et al. (1985) actually reject the results obtained from a hazard model with individual heterogeneity in the shape of the gamma-mixing distribution specification because they appear implausible when compared to other studies and their own results obtained from a hazard model without individual heterogeneity.

Empirically, the coefficients on the covariates change little when individual heterogeneity is included in the econometric model, if the baseline hazard is specified nonparametrically (cf. Meyer 1990: 769 or Hunt 1995: 97). It follows that ignoring possible effects from individual heterogeneity when estimating a proportional hazard model is a sensible approach. Lechner (1996: 4) even argues that controlling for individual heterogeneity is not necessary when using data from the German Socio-economic Panel because the panel contains a sufficient number of socio-economic

⁶ See Heckman et al. (1998) for a discussion of alternative statistical methods to control for this sample selectivity problem. Although commonly used, the authors do not find the matching procedure to be the best method.

variables for explicitly controlling for individual heterogeneity. Since the baseline hazard is not at the center of interest in this study, and a the presence of individual heterogeneity is rejected by a score test⁷, I do not control for unobserved individual heterogeneity.

4 The Data

The unemployment spell data is generated from the calendar information in the German Socio-economic Panel (GSOEP).⁸ For each month in the year preceeding the interview, the respondent is asked to enter his employment status. An individual is defined as unemployed in a particular months, if he has reported to be registered as unemployed at the employment office (*Arbeitsamt*).⁹ The first months an individual reports to be unemployed is counted as the spell begin, the last months an individual reports to be unemployed is counted as the spell end. If the spell end is not observed, a spell is treated as right-censored. Left-censored spells are not included in the sample.

Unemployment spells that start after an individual has turned 58 are dropped from the sample, since most of these spells are merely a transition into early retirement. Individuals previously employed in seasonal industries like construction, agriculture, fishing, and forestry are dropped from the sample. In these industries, unemployment is to a large extent driven by seasonal factors not modelled here.

Wurzel (1993: 119) finds unemployment spells shorter than 9 months to be under-represented in the GSOEP by almost 16 percent. Since this is a general caveat associated with retrospective data, the problem cannot be easily overcome. For example, if an individual experiences two short unemployment spell between two interviews, only one of them can be included in the sample because there is only one vector of covariates for the two spells. The results presented here should therefore be

⁷ See Appendix I.

⁸ In identifying unemployment spells from the data in the GSOEP and generating the list of covariates, I follow the conventional approach used, for example, by Steiner (1997) and Hunt (1995). SAS programs for generating all variables and more detailed definitions are provided by the author upon request.

⁹ In addition, an individual defined as unemployed may not have reported to be full-time employed in the same months. Since the data is survey data, such contradictory entries are possible. However, individuals who report to have a minor employment while being unemployed are counted as unemployed because German law allows for such minor employment (*630-Mark Job*) during unemployment.

viewed as referring more to medium- and long-term unemployed than short-term unemployed.¹⁰

Between 1985 and 1996, 2210 unemployment spells can be identified in the GSOEP with valid information for at least some covariates (Table 1).¹¹ 1173 of these spells are experienced by males, the remaining 1037 spells are experienced by females. For the regression, 1497 spells with valid information for all included covariates remain in the sample, of which 774 refer to males and 723 refer to females. 17.5 percent of all spells are right-censored, 18.5 percent for males and 16.3 percent for females. Unemployment spells that end with a transition into the mandatory military service are treated as right-censored, too.

Based on the calendar information, the exit state for each unemployment spell can be determined. Spells can terminate with a transition into employment or with a transition out of the labor force. Employment is defined as a full-time or part-time job. Out of the labor force is defined as retired or a withdrawal from the labor market. 59 percent of all spells end with a transition into employment. This figure is higher for males at 66.5 percent and lower for females at 50.7 percent. The remaining 41 percent of all spells end with a transition out of the labor force, where this figure is lower for males at 33.5 percent and higher for females at 49.3 percent.

For the competing risks analysis, unemployment spells that end with a transition out of the labor force are treated as right-censored when analyzing the transition into employment. Hence, 42 percent of all spells are treated as right-censored in the estimation presented here. Vice versa, unemployment spells that end with a transition into employment would have to be treated as right-censored when analyzing the

¹⁰ Short-term unemployment may not be as susceptible to influences from structural change in the first place. At least very short-term unemployment of less than three months is probably better analyzed in terms of frictional unemployment between two jobs, or with particular emphasis on seasonal industries that are not included in my sample.

¹¹ I cannot use unemployment spells from 1984 because I require information on covariates before the spell started. This information is taken from the interview preceeding the begin of the unemployment spell. Hence, for spells that started in 1985, information on the covariates is taken from the interview in 1984. For unemployment spells that started in 1984, there is no preceeding interview available. 1996 is the last year for which calendar information is available in the 1998 GSOEP release in which the last interview refers to 1997.

Table 1 – Descriptive Statistics for Unemployment Duration

	Both Sexes	Males	Females
Mean	14.80	14.84	14.76
Standard Deviation	14.03	15.88	11.59
Median	12.00	11.00	12.00
Minimum	1	1	1
Maximum	144	144	81
Right-Censored (percent)	17.47	18.50	16.30
Transition into Employment (percent) ^a	59.06	66.49	50.68
Spells Starting in January (percent)	31.04	31.63	30.38
Spells Ending in December (percent)	26.20	24.21	28.45
Observations	2210	1173	1037

^aThis information is not available for 36 spells.

Source: GSOEP (1998); own calculations.

transition out of the labor force. This implies that more than 80 percent of all observations would have to be treated as right-censored for analyzing the transition out of the labor force. Since this is not meaningful, I estimate the proportional hazard model for only one of the competing risks, namely the transition into employment.

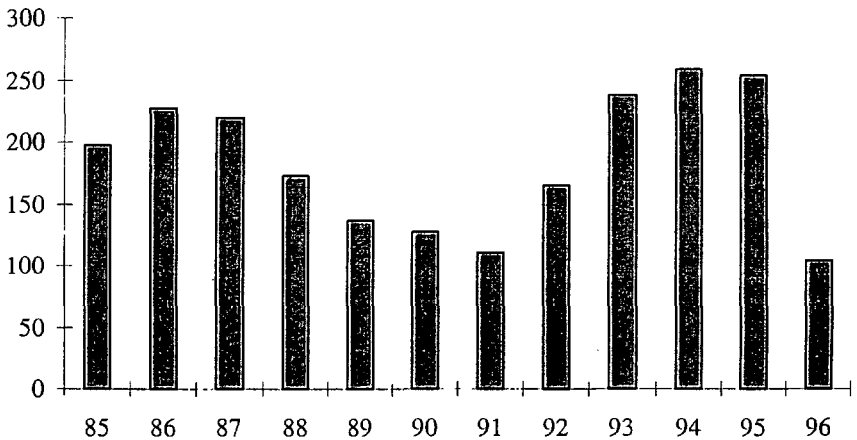
The mean spell is 14 months long, 16 for males and 12 for females. Since the sample includes right-censored spells, it is informative to also look at the median spell. For both sexes, the median spell length is 12 months, 11 for males and 12 for females. Compared to other studies, the average spell length is rather long in my sample. For example, Hunt (1995) finds a mean spell duration of 9.5 months for both sexes, assuming an exponential distribution for the spell length. Her sample ends in 1988, though, and therefore does not include the significant rise in unemployment at the beginning of the nineties. Steiner (1994) finds a mean spell length of 6.2 months for males and 8.3 months for females. He includes individuals who work in seasonal industries like construction which are often characterized by regular, short unemployment spells.

Spell data from retrospective interviews is known to suffer from recollection errors. These errors in recollection and sample attrition, lead to many spells being misreported to have started in January and ended in December, or being right-censored in December. Kraus and Steiner (1998) have shown that controlling for such heaping

effects with dummies is sufficient. For the estimation of the hazard model, I therefore include a begin-in-January dummy and an end-in-December dummy.

Macroeconomic factors are to a large extent responsible for fluctuations in the entrance rate into unemployment over time in the sample (Figure 1). Entrance into unemployment fell since the mid-eighties to a minimum during the unification boom after. The 1993 recession saw entrance rates climbing up again. This temporal pattern suggests that the sample is fairly representative for the aggregate economy. It also suggests that the rise in the aggregate unemployment rate over the nineties is to some extent caused by a corresponding rise in the entrance rate.

Figure 1 – Start Years of Unemployment Spells (Number of Spells)



Source: GSOEP (1998); own calculations.

The covariates used here to explain unemployment duration can be grouped into four categories (Table 2). First, there are covariates that capture the influence of structural change. Second, there are covariates that capture the influence of labor market institutions. Third, there are covariates that account for individual heterogeneity. Fourth, there are covariates that capture the influence of macroeconomic and regional factors. Since the focus here is on the impact of structural change on unemployment duration, the discussion concentrates on these variables. The impact of labor market institutions is, for example, discussed in more detail in Hunt (1995) and Steiner (1997). Descriptive statistics for all covariates are provided in Appendix 2.

Table 2 – Description of the Data

Variable	Description
Unemployment Duration	Number of months an individual is registered as unemployed at the employment office.
Start January	Dummy for spells beginning in January.
End December	Dummy for spells ending in December.
Structural Change	
Expected Income Loss	Inferred loss of income (difference in hourly wage including benefits) associated with immediately taking on a new job after having become unemployed.
Low Formal Skill	Basic schooling (<i>Hauptschule, Realschule</i>) and no vocational training.
Medium Formal Skill	Basic vocational training (<i>Lehre, Ausbildung</i>).
High Formal Skill	Advanced vocational training (<i>Meister, Berufsfachschule, etc.</i>) or university entrance certificate (<i>Abitur, Fachhochschulreife</i>). University degree or equivalent (<i>Universität, Fachhochschule, etc.</i>).
Skill-Specific Unemployment Rate	Within-group unemployment rate matched by formal education for individuals with no vocational training (<i>ohne Ausbildung</i>), vocational training (<i>Lehre, Berufsfachschule</i>), advanced vocational training (<i>Fachschule</i>), technical college (<i>Fachhochschule</i>), and university degree (<i>Universität</i>). Data taken from Reinberg and Rauch (1998).
Physical Production Activity	Last employment was in physical production.
Consumer Service Activity	Last employment was in consumer services.
Intermediate Service Activity	Last employment was in intermediate services.
Secondary Sector	Last employment was in the secondary sector.
Tertiary Sector	Last employment was in the tertiary sector.
Age	An individual's age at the beginning of the unemployment spell.

Table 2 – continued

Variable	Description
Institutions	
Unemployment Insurance	Dummy for receiving unemployment insurance (<i>Arbeitslosengeld</i>) in the first months of being unemployed.
Unemployment Assistance	Dummy for receiving unemployment assistance (<i>Arbeitslosenhilfe</i>) in the first months of being unemployed.
Social Aid	Dummy for receiving social aid (<i>Sozialhilfe</i>) in the first months of being unemployed.
Level of Benefits	The level of benefit transfer received in 1990 prices.
Replacement Ratio	The ratio of benefit received to income in the last job.
Minor Job	Dummy for holding a minor job (e.g. 630-Mark Job) while being unemployed.
Individual Heterogeneity	
Male	Dummy for being male.
Time Since Last Unemployment Spell	Time in months between the begin of the present unemployment spell and the end of the last unemployment spell observed.
Duration of Last Unemployment Spell	Duration of last unemployment spell observed in months.
Foreigner	Dummy for foreigners.
Number of Children under 16 in Household	Number of children under 16 in the household.
Partner	Dummy for having a partner or being married.
Partner Employed	Dummy for having a partner who is full-time / part-time employed.
Partner Income	Income of partner in 1990 prices.
Disabled	Dummy for being handicapped.
Degree of Disability	Percentage scale for severity of handicap.
Does Housework While Unemployed	Dummy for performing household chores (<i>Hausfrau/-mann</i>).
In the Labor Force Before Unemployment Spell	Dummy for being in the labor force, working full-time or part-time before the unemployment spell started.
Parents with Advanced Skill Level	Dummy for having parents with an advanced formal or professional skill level.

Variable	Description
Stress Factors	
Annual Dummies	Dummy for year of spell begin.
Capacity Utilization	Utilization of the production capacity in the aggregate economy in percent from Sachverständigenrat (1998: 285).
Region	Dummy for the region (<i>Bundesland</i>) where an unemployed lives.
Regional Unemployment Rate	Aggregate unemployment rate by region (<i>Bundesland</i>).

Structural change can influence unemployment duration because it can devalue an individual's human capital and thereby influence his employability. An individual laid off in a declining sector or from a declining occupation may not possess the particular skills required in expanding sectors and expanding occupations. The impact of structural change can be proxied by several related covariates. First, I infer an expected wage loss from information on individuals who found a new job immediately after having been laid off. The expected wage loss is estimated as a function of formal skill, type of activity in the last job, sector of the last job. See Appendix 3 for details. This covariate should best capture the effect of structural change on unemployment duration through the loss in human capital.

Second, I include dummies for an individual's skill level, measured by the highest formal degree held, dummies for the type of occupation pursued in the last job, dummies for the last sector of employment, and age dummies. The age dummies are important covariates in the context of structural change because investment in human capital to compensate a loss from structural change is a decreasing function of age. Individuals who are close to the official retirement age have little incentive to invest into new skills because they will not be in the labor force long enough to recoup the investment.

Labor market institutions are included in the regression equation as dummies for receiving unemployment benefits (*Arbeitslosengeld*), unemployment aid (*Arbeitslosenhilfe*), social aid, housing aid, a transfer from the labor office, or an income from a

minor job in the first month of the unemployment spell.¹² Alternatively, the amount of benefits in constant prices could have been used. However, the dummies had a higher explanatory power. I chose not to include the replacement ratio in the regression equation because that would have reduced the sample to only 703 observations due to missing information. The covariates associated with labor market institutions are best thought of as control variables that are not explicitly interpreted.

Individual heterogeneity is controlled for by including dummies for being a foreigner, having a partner, doing housework while unemployed, having been in the labor force before becoming unemployed. In addition, the degree of disability, the number of children in the household, and the duration of the last unemployment spell are included. The duration of the last unemployment spell is particularly important because it accounts for multiple spells per individual in the sample.

5 Regression Results

Using the data on unemployment spells and potential covariates from the GSOEP, I estimate a Cox Proportional hazard model with competing risks. The two competing risks are transition into employment and transition out of the labor force. Results are presented only for transition into employment because for the case of transition out of the labor force more than 80 percent of all observations would have to be treated as right-censored. The model is estimated jointly for both sexes and separately for both sexes. For the joint sample, the estimation is stratified by sex.

The regression equation was specified as follows. As a starting point, an equation containing covariates from all four categories was estimated. Next, covariates were dropped and added within each category according to their explanatory power. This was done first, for covariates referring to individual heterogeneity, second for covariates referring to labor market institutions, and third for covariates referring to structural change. For example, the impact of labor market institutions could either be captured by dummies for receiving various transfers or by the amount of transfer from the different sources. The dummies turned out to have a higher explanatory power. Other possible covariates that were not of central interest here like the replacement ratio were dropped from the regression equation because they reduced the sample by too many observations due to missing information.

¹² I do not account for a possible switch from unemployment benefits to unemployment aid after the former has expired, since labor market institutions are not at the center of interest here.

The model for both sexes has 1497 observations of which 41.6 percent are treated as right-censored (Table 3). All covariates are jointly significant; the likelihood ratio deviance statistic is 848.2, with the critical value at the five percent level being $\chi^2(46) = 62.5$. Based on the test suggested by Blossfeld and Hamerle (1987), the null hypothesis of no individual heterogeneity is not rejected. Hence, I do not need to explicitly model an individual heterogeneity component.

Table 3 – Regression Results^a – Goodness-of-Fit: Transition into Employment, Both Sexes

Observations	1497	Percent Censored	41.62
Log Likelihood	-2958.67	Deviance $\chi^2(46) =$	848.20
Test for Individual Heterogeneity ^b		0.0090	
Exclusion of Covariates	LR χ^2 -Statistic	Degrees of Freedom	Critical Value (5 percent)
Structural Change	30.29	9	16.92
Expected Wage Loss	10.82	1	3.84
Skill	8.04	3	7.82
Activity	4.62	3	7.82
Sector	12.70	2	5.99
Age	24.82	3	7.82
Institutions	25.42	6	12.59
Individual Heterogeneity	89.46	8	15.51
Annual Dummies	59.26	11	19.68
Regional Dummies	31.51	7	14.07
Heaping Effects	251.60	2	5.99

^aCox Proportional Hazard model. Ties treated in the exact manner. Baseline hazard stratified by sex. Transition out of the labor force is treated as right-censored. – ^bTest suggested by Blossfeld and Hamerle (1987). The null hypothesis is no individual heterogeneity. The test statistic is asymptotically normal distributed.

Source: GSOEP (1998); own calculations.

A likelihood ratio test can be used to test for exclusion of groups of covariates. The group of covariates referring to structural change are jointly significant. The likelihood ratio statistic is 30.29, with the critical value at the five percent level being $\chi^2(9) = 16.92$. Within the group of covariates referring to structural change, the skill dummies and the skill-specific unemployment rate are jointly significant at the five

percent level. The activity dummies are jointly insignificant. The sector dummies and the age dummies are again jointly significant at the five percent level. Taken together, these results suggest that structural change has a significant impact on unemployment duration. The other groups of covariates referring to labor market institutions, individual heterogeneity, stress factors, and heaping effects are also jointly significant.

The estimated coefficients from the model for both sexes are reported in Table 4. The coefficient estimates themselves are difficult to interpret because they do not constitute an elasticity or a marginal effect as in most ordinary least squares regressions. Recall that the hazard rate was given by

$$[1] \quad \lambda(t_i) = \lambda_0(t_i) e^{\beta' x_i}$$

The so-called risk ratio lends itself better for interpretation. The risk ratio is given by e^{β} . For continuous covariates, the risk ratio gives the change in the baseline hazard rate, if the covariate is changed by one unit. For example, the risk ratio for the expected wage loss is 0.84. This implies that a one unit increase in the expected wage loss leads to a fall in the hazard rate of leaving unemployment by 16 percent.

For dummy variables, the risk ratio gives the difference in the hazard rate compared to a reference category. For example, having a medium skill level is associated with a risk ratio of 0.78. This means that an individual with a medium skill level has a hazard rate of leaving unemployment that is 22 percent lower than an individual belonging to the reference category high skill. Reference categories are defined as follows. If the dummy variable of interest belongs to a group of dummy variables that are mutually exclusive like the skill level, one of these variables is dropped from the estimation equation and thereby defined as the reference category. For example, the dummy for a high skill level is the reference category for the other two skill dummies. If the dummy variable of interest does not belong to a group of mutually exclusive dummy variables, like receiving unemployment benefits, the baseline hazard is the reference category.

Of the covariates referring to structural change, the expected wage loss and the age dummies stand out. A one unit increase in the expected wage loss is associated with a fall in the hazard rate of leaving unemployment by 16 percent. The expected wage loss was constructed to measure the loss in human capital due to structural change by comparing the hourly wage rate including benefits of displaced workers before and after displacement. The regression result, therefore, suggests that individuals who are negatively affected by structural change and experience a loss in their human capital have a significantly lower probability of finding a new job.

Table 4 – Regression Results^a – Coefficients: Transition into Employment, Both Sexes

	Coefficient	Std. Error	Risk Ratio	Wald $\chi^2(1)^b$
Structural Change				
Expected Wage Loss	-0.1725	0.0524	0.8420	10.8244
Low Skill Level	0.2452	0.2786	1.2780	0.7744
Medium Skill Level	-0.2496	0.1523	0.7790	2.6865
High Skill Level	-	-	-	-
Skill-Specific Unemployment Rate	-0.0392	0.0200	0.9620	3.8348
Physical Production Activity	0.0437	0.1128	1.0450	0.1497
Consumer Service Activity	0.1291	0.1361	1.1380	0.9002
Intermediate Service Activity	0.2996	0.1409	1.3490	4.5187
No Information on Activity	-	-	-	-
Secondary Sector	-0.1934	0.1108	0.8240	3.0463
Tertiary Sector	-0.5138	0.1489	0.5980	11.9036
No Information on Sector	-	-	-	-
16–29 Years	0.6127	0.2122	1.8450	8.3407
30–39 Years	0.6346	0.1673	1.8860	14.3829
40–49 Years	0.6916	0.1428	1.9970	23.4624
50–58 Years	-	-	-	-
Institutions				
Received Unemployment Benefits	0.1718	0.0983	1.1870	3.0557
Received Unemployment Aid	-0.1193	0.1245	0.8880	0.9177
Received Social Aid	-0.2171	0.1591	0.8050	1.8637
Received Housing Aid	-0.1799	0.1261	0.8350	2.0352
Received Transfer from Labor Office	0.7988	0.2731	2.2230	8.5582
Received Income from Minor Job	0.3095	0.1751	1.3630	3.1246
Individual Heterogeneity				
Duration Last Unemployment Spell	-0.0141	0.0050	0.9860	7.9490
Foreigner	-0.3942	0.0821	0.6740	23.0691
Children under 16 in Household	0.0665	0.0383	1.0690	3.0191
Living with Partner	0.2306	0.1067	1.2590	4.6756
Partner Employed	-0.2746	0.1061	0.7600	6.7029
Degree of Disability	-0.0063	0.0024	0.9940	6.7364
Does Housework While Unemployed	-0.6537	0.1308	0.5200	24.9793
Labor Force Before Unemployment	0.4305	0.0900	1.5380	22.8798

^aCox Proportional Hazard model. Ties treated in the exact manner. Baseline hazard stratified by sex. Transition out of the labor force is treated as right-censored. The model also includes annual and regional dummies, as well as dummies controlling for heaping effects. ^bCritical values: 10 percent level: 2.706, 5 percent level: 3.841, 1 percent level: 6.635.

Source: GSOEP (1998); own calculations.

The influence of the age dummies is also supportive of the structural change story. Workers who are in their fifties have only half the hazard rate of leaving unemployment into employment than younger workers. Entering a new job is often associated with acquiring new human capital. This investment can only be recouped, if the individual remains in the labor force for a sufficient number of years. For individuals above fifty who are approaching retirement age, investments in human capital are no longer profitable. Therefore, their probability of leaving unemployment into employment are significantly lower than the probability for younger individuals.

Workers who come from an intermediate service activity have a significantly higher hazard rate of leaving unemployment into employment than workers who come from a physical production activity or a consumer service activity.¹³ These results support the hypothesis of a structural change of the production process: Intermediate service activities have experienced an increase in labor demand while other activities have experienced stagnant or falling labor demand.

After controlling for the expected wage loss, age, and type of activity, coming from the tertiary sector is associated with a significantly lower hazard rate of leaving unemployment into employment. This result is unexpected given that the tertiary sector has experienced a strong increase in employment. However, the structural change towards more service-intensive production is more adequately captured in the activity dummies. The dummy for coming from the tertiary sector may then capture low re-employment possibilities for individuals from stagnant consumer services. In any case, this result questions the idea that a mere expansion of the tertiary sector is a solution to the German unemployment problem.

The skill-specific unemployment rate reflects the relative scarcity of a particular skill at the time an individual becomes unemployed. It is therefore a good indicator of the value assigned to an individual's skill by the labor market. A one unit increase in the skill-specific unemployment rate is associated with a 4 percent fall in the hazard rate of leaving unemployment. Hence, falling demand for an individual's skill leads to a longer unemployment duration.

The coefficient on the low skill dummy is unexpected: A low skilled individual has a higher hazard rate of leaving unemployment than a high skilled individual. However, first this coefficient is not significant. Second, the impact of skill-specific labor

¹³ The dummy for coming from an intermediate service activity is individually significant while the group of activity dummies is insignificant (Table 3).

demand is already more adequately captured by the skill-specific unemployment rate. Given that the impact of labor demand is already controlled for, the dummy for being low skilled could account for low skilled individuals switching frequently between short unemployment and employment spells. The dummy for medium skill is expected: A medium skilled individual has a lower hazard rate of leaving unemployment.

Of the covariates referring to labor market institutions, three deserve special mentioning. First, receiving unemployment benefits instead of other transfers which are typically lower like unemployment aid in the first months of the unemployment spell increases the hazard of leaving unemployment. This result contradicts the consensus view that the unemployment benefits system reduces job search activity. However, the finding is common to all studies on German unemployment. It can be explained as follows. Individuals who are eligible for unemployment benefits differ from individuals who are only eligible for other benefit transfers in some unobserved characteristic that is positively related to their employability, for example effort.

The second interesting covariate is the dummy for receiving a transfer from the labor office. This transfer is paid to individuals who participate in training schemes (*Fortbildung, Umschulung*). Receiving such a transfer doubles the hazard of leaving unemployment into employment. Hence, training schemes appear to be successful at assisting unemployed individuals to find a new job. From the results presented here, it cannot be inferred whether this effect is due to a training effect or whether it is due to a selectivity bias. See the studies by Hujer et al. (1998a, 1998b, and 1998c).

Third, individuals who receive income from a minor job while unemployed also have an increased hazard rate of leaving unemployment into employment. Taking on a minor job (e.g. *630-Mark Job*) while unemployed is legal in Germany. It is sometimes argued that this opportunity reduces the incentive to actively look for a regular employment because individuals can earn some extra money without losing parts of their transfers. Based on the results presented here, it seems more likely that individuals who take on a minor job while being unemployed are better equipped or better motivated to find a regular employment.

The covariates controlling for individual heterogeneity all have the expected influence of the hazard rate of leaving unemployment into employment. An individual who has experienced a longer unemployment spell in the past is more likely to stay unemployed in the present spell.¹⁴ Foreigners are more likely to remain unemployed. The presence

¹⁴ This covariate is included to control for repeated spells.

of children under 16 in the household increases the hazard of leaving unemployment. Living with a partner increases the hazard of leaving unemployment while living with a partner who is employed lowers the hazard of leaving unemployment. A higher degree of disability is associated with a lower hazard of leaving unemployment. Finally, individuals who perform housework have a lower hazard rate and individuals who have been in the labor force before registering as unemployed have a higher hazard rate of leaving unemployment into employment.

Labor market behavior and outcomes differ between males and females. The Cox Proportional Hazard model has therefore been estimated for males and females separately. The results for males are documented in Tables 5 and 6. The results for females are documented in Tables 7 and 8. The fundamental results remain unchanged.

Table 5 – Regression Results^a – Goodness-of-Fit: Transition into Employment, Males Only

Observations	774	Percent Censored	34.88
Log Likelihood	-1623.57	Deviance $\chi^2(46) =$	531.84
Test for Individual Heterogeneity ^b	0.0080		
Exclusion of Covariates	LR χ^2 -Statistic	Degrees of Freedom	Critical Value (5 percent)
Structural Change	19.65	9	16.92
Expected Wage Loss	4.40	1	3.84
Skill	2.88	3	7.82
Activity	3.82	3	7.82
Sector	16.69	2	5.99
Age	8.71	3	7.82
Institutions	33.05	6	12.59
Individual Heterogeneity	60.07	8	15.51
Annual Dummies	31.95	11	19.68
Regional Dummies	32.87	7	14.07
Heaping Effects	142.87	2	5.99

^aCox Proportional Hazard model. Ties treated in the exact manner. Transition out of the labor force is treated as right-censored. –^bTest suggested by Blossfeld and Hamerle (1987). The null hypothesis is no individual heterogeneity. The test statistic is asymptotically normal distributed.

Source: GSOEP (1998); own calculations.

Table 6 – Regression Results^a – Coefficients: Transition into Employment, Males Only

	Coefficient	Std. Error	Risk Ratio	Wald $\chi^2(1)^b$
Structural Change				
Expected Wage Loss	-0.1558	0.0743	0.8560	4.3974
Low Skill Level	-0.0710	0.3252	0.9310	0.0476
Medium Skill Level	-0.3162	0.2032	0.7290	2.4222
High Skill Level	-	-	-	-
Skill-Specific Unemployment Rate	-0.0130	0.0234	0.9870	0.3081
Physical Production Activity	0.1032	0.1387	1.1090	0.5544
Consumer Service Activity	0.3528	0.1929	1.4230	3.3467
Intermediate Service Activity	0.2954	0.2304	1.3440	1.6433
No Information on Activity	-	-	-	-
Secondary Sector	-0.3115	0.1421	0.7320	4.8035
Tertiary Sector	-0.8057	0.2077	0.4470	15.0462
No Information on Sector	-	-	-	-
16-29 Years	0.5441	0.2845	1.7230	3.6582
30-39 Years	0.5032	0.2106	1.6540	5.7064
40-49 Years	0.5291	0.1869	1.6970	8.0125
50-58 Years	-	-	-	-
Institutions				
Received Unemployment Benefits	0.4107	0.1372	1.5080	8.9673
Received Unemployment Aid	-0.0043	0.1639	0.9960	0.0007
Received Social Aid	-0.4769	0.2089	0.6210	5.2131
Received Housing Aid	-0.1177	0.1671	0.8890	0.4958
Received Transfer from Labor Office	1.8714	0.4878	6.4970	14.7158
Received Income from Minor Job	0.0735	0.2491	1.0760	0.0871
Individual Heterogeneity				
Duration Last Unemployment Spell	-0.0150	0.0067	0.9850	4.9568
Foreigner	-0.4457	0.1135	0.6400	15.4275
Children under 16 in Household	0.0918	0.0491	1.0960	3.5009
Living with Partner	0.3998	0.1382	1.4920	8.3710
Partner Employed	-0.3323	0.1340	0.7170	6.1481
Degree of Disability	-0.0094	0.0030	0.9910	10.1020
Does Housework While Unemployed	-0.0001	0.2943	1.0000	0.0000
Labor Force Before Unemployment	0.4682	0.1271	1.5970	13.5685

^aCox Proportional Hazard model. Ties treated in the exact manner. The model also includes annual and regional dummies, as well as dummies controlling for heaping effects. ^bCritical values: 10 percent level: 2.706, 5 percent level: 3.841, 1 percent level: 6.635.

Source: GSOEP (1998); own calculations.

Structural change significantly influences unemployment duration for males and females. The expected wage loss significantly lowers the hazard rate of leaving unemployment into employment for both males and females. Likewise, males and females who are in their fifties have a significantly lower hazard rate than those who are younger. A higher skill-specific unemployment reduces the hazard of leaving unemployment for both sexes; the coefficient is only significant for females. Similar remarks apply to the covariates referring to labor market institutions and individual heterogeneity. In their general thrust, the estimated models do not differ much between the sexes. Hence, I do not elaborate the results further.

Table 7— Regression Results^a – Goodness-of-Fit: Transition into Employment, Females Only

Observations	723	Percent Censored	48.82
Log Likelihood	-1301.42	Deviance $\chi^2(46) =$	383.71
Test for Individual Heterogeneity ^b	-0.0013		
Exclusion of Covariates	LR χ^2 -Statistic	Degrees of Freedom	Critical Value (5 percent)
Structural Change	25.88	9	16.92
Expected Wage Loss	8.47	1	3.84
Skill	7.98	3	7.82
Activity	1.37	3	7.82
Sector	0.84	2	5.99
Age	16.63	3	7.82
Institutions	6.60	6	12.59
Individual Heterogeneity	39.66	8	15.51
Annual Dummies	44.83	11	19.68
Regional Dummies	14.76	7	14.07
Heaping Effects	109.84	2	5.99

^aCox Proportional Hazard model. Ties treated in the exact manner. Transition out of the labor force is treated as right-censored. –^bTest suggested by Blossfeld and Hamerle (1987). The null hypothesis is no individual heterogeneity. The test statistic is asymptotically normal distributed.

Source: GSOEP (1998); own calculations.

Table 8 – Regression Results^a – Coefficients: Transition into Employment, Females Only

	Coefficient	Std. Error	Risk Ratio	Wald $\chi^2(1)^b$
Structural Change				
Expected Wage Loss	-0.2487	0.0854	0.7800	8.4719
Low Skill Level	0.6933	0.5674	2.0000	1.4928
Medium Skill Level	-0.3519	0.2761	0.7030	1.6246
High Skill Level				
Skill-Specific Unemployment Rate	-0.0824	0.0404	0.9210	4.1647
Physical Production Activity	0.1553	0.2194	1.1680	0.5012
Consumer Service Activity	0.0035	0.2188	1.0040	0.0003
Intermediate Service Activity	0.1834	0.2088	1.2010	0.7716
No Information on Activity				
Secondary Sector	-0.0356	0.2004	0.9650	0.0316
Tertiary Sector	-0.2265	0.2475	0.7970	0.8375
No Information on Sector				
16–29 Years	0.5803	0.3598	1.7870	2.6014
30–39 Years	0.6823	0.2943	1.9780	5.3747
40–49 Years	0.9375	0.2447	2.5540	14.6826
50–58 Years				
Institutions				
Received Unemployment Benefits	-0.0115	0.1553	0.9890	0.0055
Received Unemployment Aid	-0.1069	0.2108	0.8990	0.2572
Received Social Aid	-0.0134	0.2666	0.9870	0.0025
Received Housing Aid	-0.1241	0.2075	0.8830	0.3576
Received Transfer from Labor Office	0.5340	0.3515	1.7060	2.3079
Received Income from Minor Job	0.4831	0.2632	1.6210	3.3688
Individual Heterogeneity				
Duration Last Unemployment Spell	-0.0170	0.0084	0.9830	4.0952
Foreigner	-0.3307	0.1274	0.7180	6.7360
Children under 16 in Household	0.0204	0.0679	1.0210	0.0900
Living with Partner	-0.0742	0.2205	0.9280	0.1134
Partner Employed	0.0101	0.2153	1.0100	0.0022
Degree of Disability	-0.0066	0.0046	0.9930	2.0603
Does Housework While Unemployed	-0.7443	0.1542	0.4750	23.2923
Labor Force Before Unemployment	0.3433	0.1384	1.4100	6.1510

^aCox Proportional Hazard model. Ties treated in the exact manner. The model also includes annual and regional dummies, as well as dummies controlling for heaping effects. ^bCritical values: 10 percent level: 2.706, 5 percent level: 3.841, 1 percent level: 6.635.

6 Summary

Traditionally, unemployment duration is modelled as a function of labor market institutions that reduce an individual's search intensity and covariates controlling for individual heterogeneity as well as macroeconomic factors. Here, the traditional approach was extended to explicitly model the impact of structural change on unemployment duration. It was argued that structural change increases unemployment duration, if it devalues the human capital of displaced workers. Such a devaluation of human capital results, when the skills that were required in declining activities and sectors differ from the skills required in expanding activities and sectors.

The effect of structural change on unemployment duration was captured through a set of covariates. First, an expected wage loss was inferred for all individuals who became unemployed, based on a sample of displaced workers who immediately found a new job. Second, age dummies were used to account for the remaining time in the labor force left to recoup investments in human capital to make up for the loss in human capital through structural change. Third, a skill-specific unemployment rate and skill dummies were used to account for the changes in labor demand for different skill groups. Fourth, dummies for the activity performed in the last job and the sector of the last job were used to discriminate between a structural change of the production process and sectoral structural change.

The estimated Cox Proportional Hazard model for a sample of 1497 unemployment spells in Germany experienced by males and females between 1985 and 1996 provides support for the hypothesis that unemployment duration is influenced by the recent wave of structural change in the production process. Unemployment duration is longer for individuals with a higher expected wage loss, for individuals above fifty years, for individuals with skills for which labor demand is falling, and for individuals who were formerly engaged in declining or stagnant production activities.

The estimation results have also shown that labor market institutions, individual characteristics, and macroeconomic stress factors determine unemployment duration. Hence, structural change is not the sole culprit for explaining unemployment in Germany. Nevertheless, structural change constitutes one significant source of unemployment in Germany. And since the last decade has been characterized by a major wave of structural change towards more service intensive production, it can be speculated that the increase in unemployment is at least to some extent the direct result of this structural change.

Appendix

Appendix 1 – Score Test for Individual Heterogeneity

When estimating a hazard model without controlling for unobserved heterogeneity, it is possible to test for the presence of unobserved individual heterogeneity. Several statistics have been suggested in the literature to test for unobserved individual heterogeneity (cf. Blossfeld and Hamerle 1987, Wangler 1997). All statistics are based on the score principle since this only requires estimating the model under the null hypothesis. Hence, a test for unobserved individual heterogeneity can be conducted based on an estimated model without unobserved individual heterogeneity.

Starting point for the construction of a test statistic is equation [5]. The null hypothesis of no unobserved individual heterogeneity can be written as

$$H_0: \sigma_\varepsilon^2 = 0$$

$$H_1: \sigma_\varepsilon^2 > 0$$

For a zero variance, the stochastic variable always takes on the value one, and therefore, the hazard rate with unobserved individual heterogeneity [5] equals the hazard rate without unobserved individual heterogeneity [1].

The test statistic H used here is the one suggested by Blossfeld and Hamerle (1987). It is given by

$$[A1] \quad H = \frac{S}{\sqrt{\hat{\text{var}}(S)}}$$

$$\text{where} \quad S = \frac{1}{2n} \sum_{i=1}^n \left[\Lambda^2(t_i | x_i, \hat{\theta}) - 2\delta_i \Lambda(t_i | x_i, \hat{\theta}) \right]$$

$$\text{and} \quad \hat{\text{var}}(S) = \frac{1}{4n^2} \sum_{i=1}^n (s_i - \bar{s})^2$$

$$\text{with} \quad s_i = \Lambda^2(t_i | x_i, \hat{\theta}) - 2\delta_i \Lambda(t_i | x_i, \hat{\theta}) \quad \text{and} \quad \bar{s} = \frac{1}{n} \sum_{i=1}^n s_i$$

H is asymptotically standard normal. The test is one-sided by way of the alternative hypothesis.

Appendix 2 – Tables

Table A1 – Descriptive Statistics for the Covariates Capturing Structural Change

	Both			Males		Females	
	Mean / Share ^a	Std. Dev.	Obs.	Mean / Share ^a	Std. Dev.	Mean / Share ^a	Std. Dev.
Low Skill Level	0.43	0.49	2160	0.40	0.49	0.45	0.50
Medium Skill Level	0.45	0.50	2160	0.46	0.50	0.44	0.50
High Skill Level	0.12	0.33	2160	0.13	0.34	0.11	0.31
Skill-Specific Unemployment Rate	10.41	6.12	2158	10.18	6.13	10.68	6.09
Expected Wage Loss	4.67	2.09	1911	4.61	2.10	4.74	2.08
Physical Production Activity	0.19	0.39	1953	0.26	0.44	0.11	0.32
Consumer Service Activity	0.14	0.34	1953	0.12	0.33	0.15	0.36
Intermediate Service Activity	0.11	0.31	1953	0.05	0.21	0.17	0.37
No Information on Activity	0.57	0.50	1953	0.57	0.50	0.57	0.50
Secondary Sector	0.23	0.42	1953	0.27	0.45	0.18	0.38
Tertiary Sector	0.24	0.43	1953	0.19	0.40	0.29	0.46
No Information on Sector	0.53	0.50	1953	0.53	0.50	0.53	0.50
Age	35.19	12.27	2210	35.86	12.60	34.44	11.85
16–29 Years	0.42	0.49	2210	0.42	0.49	0.43	0.50
30–39 Years	0.22	0.41	2210	0.21	0.41	0.24	0.42
40–49 Years	0.17	0.37	2210	0.17	0.37	0.17	0.38
50–58 Years	0.19	0.39	2210	0.21	0.41	0.16	0.37
Experience	19.19	12.27	2210	19.86	12.60	18.44	11.85

^aMean for continuous covariates, share for discrete covariates.

Source: GSOEP (1998); own calculations.

Table A2 – Descriptive Statistics for the Covariates Capturing Labor Market Institutions

	Both			Males		Females	
	Mean / Share ^a	Std. Dev.	Obs.	Mean / Share ^a	Std. Dev.	Mean / Share ^a	Std. Dev.
Received Unemployment Benefits	0.62	0.48	2150	0.64	0.48	0.61	0.49
Received Unemployment Aid	0.11	0.31	2150	0.13	0.33	0.09	0.29
Received Social Aid	0.09	0.28	2070	0.10	0.30	0.08	0.26
Received Housing Aid	0.13	0.33	2065	0.14	0.34	0.12	0.32
Received Transfer from Labor Office	0.01	0.10	2150	0.01	0.08	0.01	0.12
Received Income from Minor Job	0.04	0.19	2150	0.04	0.20	0.04	0.19
Unemployment Benefits ^b	654.06	679.22	2012	787.09	789.98	504.77	486.78
Unemployment Aid ^b	102.83	300.30	2152	128.64	341.01	73.65	243.20
Transfer from Labor Office ^b	24.93	180.76	2161	23.09	187.33	27.02	173.10
Social Aid ^b	19.93	85.71	1407	21.15	85.08	18.51	86.48
Income from Minor Job ^b	28.52	191.94	2158	34.51	235.71	21.73	124.69
Replacement Ratio for Household Income ^b	0.97	0.43	1706	0.95	0.40	1.00	0.45
Replacement Ratio for Individual ^b	0.60	0.55	703	0.61	0.58	0.60	0.52

^aMean for continuous covariates, share for discrete covariates. – ^bIn 1990 prices.

Source: GSOEP (1998); own calculations.

Table A3 – Descriptive Statistics for the Covariates Capturing Individual Heterogeneity

	Both			Males		Females	
	Mean / Share ^a	Std. Dev.	Obs.	Mean / Share ^a	Std. Dev.	Mean / Share ^a	Std. Dev.
Time Since Last Unemployment Spell	9.78	19.60	2210	10.18	18.86	9.33	20.41
Duration of Last Unemployment Spell	4.15	8.51	2210	4.47	9.01	3.78	7.90
Foreigner	0.43	0.50	2210	0.44	0.50	0.42	0.49
Number of Children under 16 in Household	0.76	1.06	2210	0.78	1.11	0.74	1.00
Living with Partner	0.65	0.48	2210	0.64	0.48	0.67	0.47
Partner Employed	0.38	0.49	2050	0.26	0.44	0.52	0.50
Income of Partner ^b	873.09	1303.04	2064	404.77	794.99	1406.45	1542.38
Disabled	0.09	0.29	2206	0.11	0.31	0.07	0.26
Degree of Disability	4.45	16.04	2191	5.46	17.89	3.33	13.57
Does Housework While Unemployed	0.13	0.34	2210	0.03	0.16	0.25	0.43
In the Labor Force Before Unemployment Spell	0.71	0.45	2111	0.77	0.42	0.65	0.48
Parents with Advanced Skill Level	0.21	0.41	2149	0.23	0.42	0.19	0.40
Capacity Utilization	95.54	1.86	2210	95.53	1.84	95.54	1.88
Regional Unemployment Rate	8.64	2.43	2210	8.67	2.44	8.60	2.42

^aMean for continuous covariates, share for discrete covariates. – ^bIn 1990 prices.

Source: GSOEP (1998); own calculations.

Appendix 3 – Estimation of the Expected Wage Loss

The estimated wage loss equation for individual i is given by

$$[A2] \quad \Delta y_i = z_{\Delta y, i} \beta_{\Delta y} + v_{\Delta y, i}$$

where Δy is difference between the hourly wage including benefits before being laid-off and the wage in the new job. The wage loss is computed from the hourly wage rate including benefits described in section B.I. $z_{\Delta y}$ is a vector of individual characteristics, $\beta_{\Delta y}$ the vector of coefficients, and $v_{\Delta y}$ is a Gaussian error term.

Using the difference of two wages as the left-hand side variable removes a possible fixed effect present in a simple wage equation. However, there is a possible selection bias when inferring the expected wage loss for individuals who have become unemployed. Individuals who transfer directly to a new job after having been laid-off may differ in some unobserved characteristic from individuals who become unemployed after having been laid-off. For example, Steiner (1997) finds such sample selectivity when estimating an expected wage for females, while he does not find sample selectivity for males. Wurzel (1993: 160) finds no sample selectivity in his expected wage equation.

The Heckman 2-stage estimator is a standard tool for testing and controlling for sample selectivity. (Heckman 1979, Greene 1997: 978, or Johnston and DiNardo 1997: pp. 446). The selection equation is given by

$$[A3] \quad r_i = z_{r, i} \beta_r + v_{r, i}$$

where r is a binary variable that takes on the value one, if an individual immediately finds a new job, z_r is the vector of covariates, β_r the vector of coefficients, and v_r a Gaussian residual. If there is sample selectivity, the residuals of equations [A2] and [A3] are correlated.

In order to identify the parameters in the unemployment duration equation, the wage loss equation, and the selection equation, each equation must contain at least one identifying variable that is not present in the other two equations. For the selection equation, the identifying regressors are a dummy for being a foreigner, the parental skill level, a dummy for living together with a spouse, and a dummy for having a spouse who is employed. In addition, the selection equation contains a dummy for being male, the number of children under 16 in the household, the regional unemployment rate, and a skill-specific unemployment rate.

For the wage loss equation, the identifying regressors are the labor market experience measured as age minus 16, the labor market experience squared, and the capacity utilization in the economy taken from Sachverständigenrat (1998: 285). The regression results are presented in Table A4.¹⁵ The estimated coefficients from the Heckman 2-stage procedure were used to infer an expected wage loss for all unemployment spells where the regressors were available.

Table A4 – Estimation Results for the Wage Loss Equation

	Ordinary Least Squares			Heckman 2-Stage		
	Coefficient	Standard Error	t-value	Coefficient	Standard Error	t-value
Male	-0.106	0.740	-0.144	-0.564	0.697	-0.809
Experience	0.215	0.141	1.529	0.202	0.132	1.531
Experience ²	-0.003	0.003	-0.810	-0.002	0.003	-0.611
Low Skill	4.748	3.470	1.368	5.431	3.116	1.743
Medium Skill	4.122	3.469	1.188	4.392	3.101	1.416
High Skill	5.969	3.491	1.710	6.625	3.130	2.116
No information on activity	-0.539	0.992	-0.544	-0.529	0.895	-0.591
Primary activity	-	-	-	-	-	-
Secondary activity	0.372	0.943	0.395	0.435	0.863	0.504
Tertiary activity	-0.684	1.400	-0.489	-0.373	1.296	-0.288
No information on sector	-	-	-	0.000	19.326	0.000
Secondary sector	0.291	1.053	0.276	0.190	19.372	0.010
Tertiary sector	-1.644	1.078	-1.525	-1.914	19.385	-0.099
Capacity utilization rate	-0.409	0.212	-1.933	-0.515	0.195	-2.639
Constant	32.477	20.816	1.560	46.961	0.000	0.000
Mill's ratio	-	-	-	-2.564	-0.787	3.259
Observations	221			2146		
Specification	F(12, 208) = 2.84			$\chi^2(22) = 48.78$		
R ²	0.141			-		

Source: GSOEP (1998); own calculations.

¹⁵ All estimations were carried out in Stata.

References

- Allison, P.D. (1984). *Event History Analysis. Regression for Longitudinal Event Data*. Newbury Park, CA: Sage Publications.
- (1995). *Survival Analysis Using the SAS System. A Practical Guide*. Cary, N.C.: SAS Institute, Inc.
- Bailey, K. (1984). Asymptotic Equivalence Between the Cox Estimator and the General Maximum Likelihood Estimator of Regression and Survival Parameters. *Annals of Statistics* 12 : 730–736.
- Bloemen, H.G. (1997). Job Search Theory, Labour Supply and Unemployment Duration. *Journal of Econometrics* 79 (2): 305–325.
- Blossfeld, H.-P., and A. Hamerle (1987). Unobserved Heterogeneity in Hazard Rate Models: A Test and Illustration from a Study of Career Mobility. Working Paper 253. Sonderforschungsbereich 3. Mikroanalytische Grundlagen der Gesellschaftspolitik. Universität Frankfurt and Universität Mannheim, Frankfurt.
- Blossfeld, H.-P., A. Hamerle, and K.U. Mayer (1986). *Ereignisanalyse. Statistisches Theorie und Anwendung in den Wirtschafts- und Sozialwissenschaften*. Frankfurt/New York: Campus Verlag.
- Cox, D.R. (1972). Regression Models and Life Tables. *Journal of the Royal Statistical Society Series B* 34 (2): 187–220.
- (1975). Partial Likelihood. *Biometrika* 62 (2): 269–276.
- Fehlker, C., and C. Purfield (1998a). Unemployment Duration: Its Determinants and Evolution. An Empirical Analysis on German Unemployment Duration Using the Socio-economic Panel. Kiel Advanced Studies Working Papers 321. Kiel Institute of World Economics, Kiel.
- (1998b). A Tale of Two Countries. A Comparison of UK and German Unemployment Spells. Kiel Advanced Studies Working Papers 331. Kiel Institute of World Economics, Kiel.
- Flaig, G., G. Licht, and V. Steiner (1993). Testing for State Dependence Effects in a Dynamic Model of Male Unemployment Behavior. In H. Bunzel, P. Jensen, and N. Westergaard-Nielsen (ed.), *Panel Data and Labour Market Dynamics*. Amsterdam: North-Holland.
- Gail, M.H., S. Wieand, and S. Piantadosi (1984). Biased Estimates of Treatment Effect in Randomized Experiments with Nonlinear Regression and Omitted Covariates. *Biometrika* 71 (58): 431–444.
- Greene, W.H. (1997). *Econometric Analysis*. Upper Saddle River, N.J.: Prentice-Hall, Inc.
- GSOEP (1998). *German Socio-economic Panel (Sozio-ökonomisches Panel)*. Berlin: Projektgruppe Sozio-ökonomisches Panel am DIW.

- Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica* 47 (1): 153–161.
- Heckman, J.J., H. Ichimura, J. Smith, and P. Todd (1998). Characterizing Selection Bias Using Experimental Data. NBER Working Paper 6699. National Bureau of Economic Research, Cambridge, Mass.
- Heckman, J.J., and B. Singer (1982). Population Heterogeneity in Demographic Models. In K.C. Land, and A. Rogers (ed.), *Multidimensional Mathematical Demography*. New York: Academic Press.
- (1984a). Econometric Duration Analysis. *Journal of Econometrics* 24 (1/2): 63–132.
- (1984b). A Method for Minimising the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica* 52 (2): 271–320.
- Hujer, R., K.-O. Maurer, and M. Wellner (1998a). The Effects of Public Sector Sponsored Training on Unemployment Duration in West Germany. *Frankfurter Volkswirtschaftliche Diskussionsbeiträge* 94. Universität Frankfurt, Frankfurt.
- (1998b). Kurz- und langfristige Effekte von Weiterbildungsmaßnahmen auf die Arbeitslosigkeitsdauer in Westdeutschland. In F. Pfeiffer, and W. Pohlmeier (ed.), *Qualifikation, Weiterbildung und Arbeitsmarkterfolg*. Baden-Baden: Nomos Verlagsgesellschaft.
- (1998c). Analyzing the Effects of On-the-Job vs. Off-the-Job Training on Unemployment Duration in West Germany. *Frankfurter Volkswirtschaftliche Diskussionsbeiträge* 96. Universität Frankfurt, Frankfurt.
- Hujer, R., and R. Schnabel (1990). Analyse von Beschäftigung und Erwerbslosigkeit anhand des Sozio-ökonomischen Panels. *Allgemeines Statistisches Archiv* 74: 98–116.
- Hujer, R., and H. Schneider (1996). Institutionelle und strukturelle Determinanten der Arbeitslosigkeit in Westdeutschland: Eine mikroökonomische Analyse mit Paneldaten. In B. Gahlen, H. Hesse, and H.J. Ramser (ed.), *Arbeitslosigkeit und Möglichkeiten ihrer Überwindung*. Tübingen: J.C.B. Mohr.
- Hunt, J. (1995). The Effect of Unemployment Compensation on Unemployment Duration in Germany. *Journal of Labor Economics* 13 (1): 88–120.
- Johnston, J., and J.E. DiNardo (1997). *Econometric Methods*. New York: McGraw-Hill.
- Kalbfleisch, J.D., and R.L. Prentice (1980). *The Statistical Analysis of Failure Time Data*. New York: John Wiley and Sons.
- Karr, W. (1999). Kann der harte Kern der Arbeitslosigkeit durch einen Niedriglohnssektor aufgelöst werden? Eine Analyse der Arbeitslosen nach Verweildauer und Reintegration. *IAB Kurzbericht* (3): 1–7.
- Katz, L.F., and B.D. Meyer (1990). The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment. *Journal of Public Economics* 41 (1): 45–72.

- Kiefer, N.M. (1988). Economic Duration Data and Hazard Functions. *Journal of Economic Literature* XXVI (2): 646–679.
- Kraus, F., and V. Steiner (1998). Modelling Heaping Effects in Unemployment Duration Models – With an Application to Retrospective Event Data in the German Socio-Economic Panel. *Jahrbücher für Nationalökonomie und Statistik* 217 (5): 550–573.
- Lancaster, T. (1979). *Econometric Methods for the Duration of Unemployment*. *Econometrica* 47 (4): 939–956.
- (1990). *The Econometric Analysis of Transition Data*. Cambridge: Cambridge University Press.
- Lechner, M. (1996). An Evaluation of Public Sector Sponsored Continuous Vocational Training Programs in East Germany. *Beiträge zur angewandten Wirtschaftsforschung* 539–96. Institut für Volkswirtschaftslehre und Statistik Universität Mannheim, Mannheim.
- (1999). Earnings and Employment Effects of Continuous Off-the-Job Training in East Germany After Unification. *Journal of Business and Economic Statistics* 17 (1): 74–90.
- Licht, G., and V. Steiner (1991). Abgang aus der Arbeitslosigkeit, Individualeffekte und Hysteresis. In C. Helberger, L. Bellmann, and D. Blaschke (ed.), *Erwerbstätigkeit und Arbeitslosigkeit. Analysen auf Grundlage des Sozio-ökonomischen Panels*. Nürnberg: Institut für Arbeitsmarkt- und Berufsforschung.
- Meyer, B. (1990). Unemployment Insurance and Unemployment Spells. *Econometrica* 58 (4): 757–782.
- Moffitt, R. (1985). Unemployment Insurance and the Distribution of Unemployment Spells. *Journal of Econometrics* 28: 85–101.
- Moffitt, R., and W. Nicholson (1982). The Effect of Unemployment Insurance on Unemployment: The Case of Federal Supplemental Benefits. *The Review of Economics and Statistics* LXIV (1): 1–11.
- Mortensen, D.T. (1977). Unemployment Insurance and Job Search Decisions. *Industrial and Labor Relations Review* 30 (4): 505–517.
- Narendranathan, W., S.J. Nickell, and J. Stern (1985). Unemployment Benefits Revisited. *The Economic Journal* 95 (June): 307–329.
- Nickell, S.J. (1979). The Effect of Unemployment and Related Benefits on the Duration of Unemployment. *The Economic Journal* 89 (1): 34–49.
- Pannenberg, M. (1995). *Weiterbildungsaktivitäten und Erwerbsbiographien*. Frankfurt/New York: Campus.
- Reinberg, A., and A. Rauch (1998). Bildung und Arbeitsmarkt: Der Trend zur höheren Qualifikation ist ungebrochen. IAB-Werkstattbericht 15. Institut für Arbeitsmarkt- und Berufsforschung der Bundesanstalt für Arbeit, Nürnberg.

- Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (1998). Vor weitreichenden Entscheidungen. Stuttgart: Metzler-Poeschel.
- Schneider, H., and R. Hujer (1997). Wirkungen der Unterstützungsleistungen auf die Arbeitslosigkeitsdauer in der Bundesrepublik Deutschland: Eine Analyse der Querschnitts- und Längsschnittsdimension. Sonderhefte zum Allgemeinen Statistischen Archiv 30: 71–88.
- Shabbir, T. (1993). Multinomial Logit Model of Occupational Choice: A Latent Variable Approach. *The Pakistan Development Review* 32 (4): 687–698.
- Snower, D.J. (1999). Causes of Changing Earnings Inequality. IZA Discussion Papers 29. Institut zur Erforschung des Arbeitsmarkts, Bonn.
- Steiner, V. (1994). Labour Market Transitions and the Persistence of Unemployment — West Germany 1983 – 1992. ZEW Discussion Paper 94–20. Zentrum für Europäische Wirtschaftsforschung, Mannheim.
- (1997). Extended Benefit-Entitlement Periods and the Duration of Unemployment in West Germany. ZEW Discussion Paper 97–14. ZEW, Mannheim.
- Thoursie, A. (1997). Effects of Renewable Benefit Periods on Exits from Unemployment. Working Paper 1997/1. Institutet för Social Forskning, Stockholm University, Stockholm.
- Wangler, A. (1997). Heterogenitätsprobleme in der Verlaufsdatenanalyse. Frankfurt: Peter Lang.
- Wurzel, E. (1990). Staggered Entry and Unemployment Durations: An Application to German Data. In J. Hartog, J. Ridder, and J. Theeuwes (ed.), *Panel Data and Labor Market Studies*. Amsterdam: North-Holland.
- (1993). *An Econometric Analysis of Individual Unemployment Duration in West Germany*. Heidelberg/New York: Physica.