The Impact of International Outsourcing on Individual Employment Security: A Micro-Level Analysis

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Abstract

The paper analyzes how international outsourcing affected individual employment security in German manufacturing industries between 1991 and 2000. The analysis is carried out at the micro-level, combining monthly spell data from the German Socio-Economic Panel and industry-level outsourcing measures. By utilizing micro-level data, problems such as aggregation and potential endogeneity bias, as well as crude skill approximations that regularly hamper industry level displacement studies, can be reduced considerably. The main finding is that international outsourcing significantly lowers individual employment security. Interestingly, the effect does not differ between high-, medium-, and low-skilled workers. With regard to the observed skill upgrading and high relative unemployment rate of low-skilled workers in Germany the impact of international outsourcing is therefore not related to skill biased displacement but to reduced chances for reentering employment.

Keywords: international outsourcing, employment security, duration analysis

JEL classification: F16, F23. J63, J23

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1 Introduction

International outsourcing and its alleged negative labor market effects are raising increasing public concern, especially against the backdrop of the EU's eastern enlargement. In the public debate, the predominant view appears to be that international outsourcing severely threatens domestic jobs, a view supported largely by anecdotal evidence. However, in the academic literature it is far from consensual what the concrete labor market impacts of international outsourcing actually are.

This study focuses on the German labor market, which is an interesting case since it is not only the largest economy in Europe, but also far more open to international trade than, for instance, the US economy. Furthermore, political and economic transition in the former communist Central and Eastern European countries during the 1990s has made possible intensive production-sharing with these economies at Germany's doorstep, with potentially sweeping implications for the German labor market. At the same time, Germany is usually considered to have a labor market with fairly low wage flexibility. In the short-run, international outsourcing therefore would be more likely to have severe employment effects.

Similar to the development that has been reported for other OECD countries (e.g., Berman, Bound and Machin, 1998) Germany has experienced a substantial skill upgrading of employment over the past decades. Reinberg and Hummel (2002) report that employment of low-skilled workers decreased sharply by on average 3.6 percent per year between 1975 and 1990 and continued to fall all through the 1990s by on average 1.3 percent per year. In contrast, employment of the high and medium-skilled increased by, on average, 4.3 and 2.1 percent per year between 1975 and 1990 and continued to rise during the 1990s with average yearly growth rates of 3.6 and 0.2 percent. At the same time, relative wages of low-skilled workers remained fairly stable (see Fitzenberger, 1999 and Christensen and Schimmelpfennig, 1998) which is also reflected in the sharp increase of unemployment rates of low skilled relative to higher skilled workers.[1]

In the literature the role of skill biased technological progress in shaping this development is well established (e.g., Berman, Bound and Griliches, 1994 and Berman, Bound and Machin, 1998). However, over recent years, a number of theoretical contributions such as Feenstra and Hanson (1996a), Arndt (1997, 1999), Deardorff (2001, 2002), Jones and Kierzkowski (2001) and Kohler(2004), to mention only a few, have highlighted the importance of international outsourcing for determining labor demand

[1]Between 1975 and 2000 the unemployment rate among workers in the lowest skill group (without any formal qualification) rose from 6.1% to 19.4% while that among workers with College/University education only rose from 1.7% to 2.6% (see Reinberg and Hummel, 2002).

for different skill groups. However, the theoretical literature is not conclusive with regard to the labor market effects of international outsourcing. Depending on the models' assumptions and framework, international outsourcing can raise or lower relative demand for low-skilled workers.

Furthermore, all of the aforementioned models are general equilibrium models, thus they assume that labor market adjustments are achieved by sufficiently flexible wages. Although this may be justifiable in the long run, in the medium and short run, especially in a country such as Germany, wages might be fairly rigid. If this is the case, then labor market adjustments to international outsourcing have to be achieved mainly through changes in employment (see Krugman 1995). At the same time, the aforementioned models generally abstract from adjustment costs. However, as authors such as Davidson and Matusz (2004) convincingly show, if displaced workers experience spells of unemployment and in some cases have to be re-trained, short-run adjustment costs can consume a significant part of the overall gains from international trade. It is therefore important not to focus solely on the long-run impact of international outsourcing, but to get also a better understanding of its immediate short-run effects in terms of employment.

There exist numerous contributions that empirically analyze the labor market impact of international competition in general (e.g., Revenga, 1992; Sachs and Shatz, 1994 and Greenaway, Hine and Wright, 1999) and more specifically international outsourcing (e.g., Feenstra and Hanson, 1996, 1999;Hsieh and Woo, 2005; Falk and Koebel, 2002; Geishecker, 2006). In this study we are, however, not interested in the partial equilibrium relative employment effects but rather in the dynamics of labor market adjustment to international outsourcing, which are reflected in job turnover. The present study is therefore related to the works of authors such as Kletzer (2000) and Davidson and Matusz (2005) who are concerned with the impact of international trade on job displacement. However, instead of using aggregated industry displacement data we combine monthly employment spell data from the German Socio-Economic Panel and industry level outsourcing measures and address the question of how international outsourcing affects the risk of leaving employment within a micro-level hazard rate model. The main advantage is that we can control for a wide range of person-specific observed and unobserved characteristics and most importantly control for duration dependence. Furthermore, by utilizing micro-level data, potential endogeneity bias, that regularly hampers industry-level studies, can be reduced considerably, since the individual risk of leaving employment and industry-level outsourcing are unlikely to be jointly determined.

Section 2 is concerned with the definition of international outsourcing and its measurement and gives a summary of the recent developments. Section 3 provides a short overview of the previous literature on labor market effects of international outsourcing. The empirical hazard rate model is introduced in Section 4, and Section 5 describes the data set and the empirical strategy. Section 6 gives a detailed description of the empirical results for various model specifications. Section 7 summarizes and discusses the findings in relation to the literature. The general findings are that international outsourcing, defined in a strict, narrow sense, significantly raises the individual risk of leaving employment. However, there are no statistically significant differences in the impact of international outsourcing across skill groups. Thus, with regard to the observed skill upgrading in Germany the impact of international outsourcing is only indirect and related to the obstacles to reentering employment that the different skill groups face after displacement.

2 International Outsourcing

Measuring international outsourcing presents a challenge. Authors such as Yeats (1998) seek to measure international outsourcing by directly quantifying trade with intermediate goods, assessing the intermediate character of the traded goods on the basis of disaggregated goods classifications. Imported parts and components are assumed to be intermediate goods imports of the broader industry that produces them. This procedure abstracts from the possibility that parts and components from one industry can be also used by other industries or by final consumers, thus biasing the measurement.

Other authors such as Campa and Goldberg (1997) and Feenstra and Hanson (1999) quantify international outsourcing by combining input coefficients found in input-output tables and trade data. The estimated value of imported intermediate inputs of an industry thereby largely depends on whether one applies a narrow or wide definition of international outsourcing. Campa and Goldberg (1997) and others assume that the total sum of imported intermediate goods in each industry represents a reasonable indicator for international outsourcing. But according to Feenstra and Hanson (1999) this “definition” might be too broad if one understands international outsourcing as the result of a make-or-buy decision. Following this approach, not the total sum of imported intermediate inputs but only the part that could be produced within the respective domestic industry corresponds to international outsourcing. However, depending on the aggregational level, the range of products that an industry can produce varies. Accordingly, the more highly aggregated the industries, the broader the definition of international outsourcing that is applied to them.

We construct two measures of international outsourcing that largely follow the concepts proposed in Feenstra and Hanson (1999) and Feenstra and Hanson (1996a).

International outsourcing is defined as the shift of a two-digit industry's *core activities* abroad, represented by the value of the industry's imported intermediate inputs from the same industry abroad as a share of the domestic industry's production value. The challenge is now to measure the respective industry's imports of intermediate goods. A simple procedure would be to assume that all imports from a certain industry abroad are directed towards the respective domestic industry and nowhere else. Essentially this would amount to the construction of industry-level import penetration ratios which are, however, rather poor measures of industries' outsourcing activities. Instead input-output data is utilized to allocate imports according to their usage as input factors across industries:

$$OUTS_{it}^{narrow} = \frac{IMP_{i*t} * \Omega_{ii*t}}{Y_{it}} \tag{1}$$

with Imp_{i*t} denoting imported intermediate inputs from industry $i*$ and Y_{it} the production value of industry i at time t. Ω_{ii*t} denotes the share of imports from industry $i*$ abroad that is consumed by the domestic industry i in t with $\sum_{i=1}^{I} \Omega_{ii*t} \times IMP_{i*t}$ =total imports from industry $i*$ that is used in agriculture, manufacturing, services, private and public consumption, investment and exports in t.

Loosening the concept of an industry's *core activities*, wide outsourcing is somewhat less conservatively defined as a two-digit industry's purchase of intermediate goods from abroad represented by the respective industry's sum of imported intermediate goods from all manufacturing industries abroad as a share of the domestic industry's production value:

$$OUTS_{it}^{wide} = \frac{\sum_{j*=1}^{J*} IMP_{j*t} * \Omega_{ij*t}}{Y_{it}} \tag{2}$$

Figure 1 shows the development of international outsourcing for the manufacturing industry as a whole. In general, international outsourcing has grown substantially over recent years. Naturally, wide outsourcing is at a higher level than narrow outsourcing but the development of both appears to by fairly parallel. As can be seen, narrowly defined, international outsourcing (as in Equation 1) increased significantly by around 2.28 percentage points or 46 percent between 1991 and 2000 while, broadly defined, outsourcing (as in Equation 2) increased by around 35 percent or 4.2 percentage points.

Figure 2 shows the evolution of international outsourcing in two-digit NACE industries. Even though international outsourcing differs widely in importance for the separate industries and the dynamic patterns vary considerably, almost every industry shows significant growth in its outsourcing intensity.

3 Previous Literature

There exists a large body of literature, empirically assessing the determinants of job separations. Micro-level studies by authors such as Farber (1999), Beeson Royalty (1998), Zavodny (2003) and Farber (2005) stress the relevance of gender, age, marital status, children, education, unemployment rates and technological change as determinants of job separations. At the same time, authors such as Davidson and Matusz (2005), Klein, Schuh and Triest (2003) and Kletzer (2004) highlight the relevance of export orientation and international competition as determinants of job creation and job destruction. However, the role of international outsourcing has yet remained largely unaddressed in the literature as most empirical studies focus on industry-level relative demand effects of outsourcing (e.g. Feenstra and Hanson, 1996, 1999 ; Hijzen, Görg and Hine, 2005; Egger and Egger, 2003, 2005). Exceptional in this respect are the contributions of Kletzer (2000), Egger, Pfaffermayr and Weber (2006) and Munch (2005).

Kletzer (2000) calculates industry-level displacement rates from the Displaced Workers Survey and regresses them on changes in exports, import penetration and imported intermediate goods, which arguably correspond to international outsourcing. While the author finds overall import penetration to significantly raise industry displacement rates, imports of intermediate goods are rendered insignificant.

Egger et al. (2006) assess the effects of international outsourcing for the transition probabilities of employment. Utilizing a random sample of Austrian social security data and controlling for unobserved heterogeneity, the authors estimate a transition model for multiple states, i.e. employment in the service sector, the trade sector, the manufacturing sector, unemployment and out-of-labor force. Their results suggest that outsourcing significantly reduces the probability of transition into the manufacturing sector, at least into that part of manufacturing that has a revealed comparative disadvantage and, thus, is more affected by international competition. However, as the authors do not control for time-changing individual characteristics other than age, it would be interesting to see whether these results are robust to a less parsimonious model specification.

Munch (2005) analyzes the impact of international outsourcing on job separations using yearly data for a 10% sub-sample of the Danish population within an employment duration model. Estimating a single risk model, his general finding is that international outsourcing, at least when broadly defined, has a significant but small impact on individual job separation risks. Estimating a competing risk model and differentiating between exit into unemployment and changing jobs, he finds that international outsourcing increases the risk of becoming unemployed, but that the effect is only statistically significant for low-skilled workers. For high-skilled workers, international outsourcing increases the probability of changing jobs, but has no significant effect on the individual hazard of becoming unemployed.

4 Modelling employment duration

For the present study the risk of employment loss is captured within a hazard rate model controlling for the duration dependence of separations. Accounting for duration dependence is essential, as one would expect job insecurity to typically decline with job duration as employees accumulate firm-specific human capital.[2] Also, other factors such as labor market institutions that result in lower relative employment protection for employees with short tenure play a role. However, as to the exact functional form that duration dependence takes, little can be known a priori. Accordingly, a semi-parametric characterization of duration dependence is chosen. The underlying assumption is that for each respondent, the hazard rate is constant within a specified time interval, but there are no further constraints on the functional form of the hazard.

The present study utilizes a large sample of monthly spell data from the German Socio-Economic Panel (GSOEP) for the years 1991 to 2000. Although employment transitions can in principle occur in continuous time, in the data one can only observe monthly spells.[3] Accordingly, a discrete time hazard model is specified. The data allows us to estimate employment transitions on a monthly basis and provides a wide array of individual characteristics to control for individual heterogeneity. Nevertheless, unobserved characteristics might be important, resulting in a misspecified model with omitted regressors. Not accounting for this problem potentially yields biased estimates of the duration dependence and the proportionate response of the hazard with respect to other regressors.[4] We control for unobserved heterogeneity following Heckman and Singer (1984) and allow for an unobserved individual effect that is assumed to follow an arbitrary discrete distribution with up to seven points of support.

Furthermore, it is necessary to control for left truncation, which is an inevitable aspect of stock sampling. The sample period for observing employment duration starts

[2]See Farber (1999) for a discussion.

[3]Other authors such as Egger et al. (2006) and Munch (2005) only capture employment transitions that take place between two years and disregard transitions that occur within single years.

[4]However, as Dolton and von der Klaauw (1995) convincingly show, ignoring unobserved heterogeneity results in severe biases when an incorrect functional form for the baseline hazard is chosen. With a flexible characterization of duration dependence, as is applied in this study, ignoring or misspecifying unobserved heterogeneity has almost no consequences. It is, however, not entirely clear how these results transfer to other data sets than the one used by Dolton and von der Klaauw (1995).

in 1991.[5] Naturally, many respondents had already been in continuous employment for some time at that date. Similarly, new respondents that later enter the sample might already have been in employment for a considerable time. Fortunately, the GSOEP provides information about the employment history of each individual. One can therefore derive the duration of current employment spells even if they started before 1991 or even before 1984, the first wave of the GSOEP, and correct for left truncation.

Formally the individual i discrete time hazard rate of leaving employment is defined as the probability of exit in the interval $(t-1,\ t)$ conditional upon survival until $t-1$:

$$\lambda_i(t, X_{it}, \gamma_{it}, \epsilon_i^m) = Pr(t-1 < T \leq t |\ T \geq t-1, X_{it}, \gamma_{it}, \epsilon_i^m) \tag{3}$$

where X_i denotes a vector of individual characteristics, γ_{it} a set of interval dummies flexibly capturing duration dependence and ϵ_i^m a time-invariant individual error component that is distributed such that:

$$E(\epsilon_i^m) = \textstyle\sum_{m=1}^{2} Pr(\epsilon_i^m) \times \epsilon_i^m = 0 \tag{4}$$

$$\textstyle\sum_{m=1}^{2} Pr(\epsilon_i^m) = 1 \tag{5}$$

$$E(\epsilon_i^m, X_{it}) = 0 \tag{6}$$

One can denote the individual probability of leaving employment in period t in terms of the hazard function as:

$$Pr(T = t|X_{it}, \gamma_{it}, \epsilon_i^m)_i = \lambda_i(t, X_{it}, \gamma_{it}, \epsilon_i^m) \times \prod^{t-1}(1 - \lambda_i(t, X_{it}, \gamma_{it}, \epsilon_i^m) \tag{7}$$

Choosing a complementary log-log representation of the hazard rate:

$$\lambda_i(t, X_{it}, \gamma_{it}, \epsilon_i^m) = 1 - exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m)) \tag{8}$$

one can transform Equation 7 into:

$$\begin{aligned} Pr(T = t|X_{it}, \gamma_{it}, \epsilon_i^m) &= \left(\frac{1}{exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m))}\right)^{c_{it}} \\ &\times \prod^{t} exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m)) \end{aligned} \tag{9}$$

with $c_{it} = 1$ if the employment spell of individual i ends in t and $c_{it} = 0$ otherwise.

Now one can also write down the likelihood function that is to be maximized. However, since we want to explicitly allow for repeated spells by individual, one additional integration step is required. If we let k denote the number of employment spells by

[5] The choice of 1991 as the beginning of the sample period is driven by the availability of NACE two-digit input-output data.

each individual, then

$$L = \prod_{i=1}^{n} \sum_{m=1}^{2} Pr(\epsilon_i^m) \prod_{k=1}^{K_i} \left(\frac{1}{exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m))} \right)^{c_{ikt}} \times \prod^{t_i} exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m)) \tag{10}$$

denotes the overall likelihood function.

5 Empirical strategy and data

The empirical analysis is based on monthly individual-level spell data from the German Socio-Economic Panel (GSOEP) for the period 1991 to 2000. In every wave, respondents are asked to give a record of their monthly work status during the previous year. Predefined categories are full and part-time work, unemployment, housework, maternity leave, military service, education or pension. Due to the retrospective nature of the question and related recollection errors, the data might be considerably noisy. Furthermore, workplace-related characteristics are only collected once a year, adding considerable measurement error if an individual has more than one employment spell per year. There is, however, no reason to believe that this process is non-random, at least not after one controls for individual heterogeneity. Thus, one can derive consistent estimates. The data is reorganized as *person-period data* to foster *easy* estimation methods, as discussed in Allison (1982) and Jenkins (1995). Employment spells can start at any time between 1991 and 2000. Employment spells that started before the respondent has entered the sample are left-truncated. We correct for this by using data on individual employment history. The focus of this work lies on work-to-non-employment transitions. An employment spell ends if the respondent ceases to work and reports having become unemployed or engages in housework. Unfortunately, the data does not provide information on job-to-job transitions, at least not on a monthly basis. Employment spells that end for other reasons, i.e education, military service, pension or maternity leave, are censored. The same is true if the respondent drops out of the sample or the sample period ends. Due to the longitudinal character of the data, respondents can have many different employment spells.

The sample is restricted to prime-age (18 to 65 years) respondents who worked in manufacturing (NACE sectors 15-36) at least once during the sample period. In order to avoid selection bias with respect to item non-response, each explanatory variable is supplemented with a dummy for missing values and subsequently recoded to zero.

Duration dependence is captured by a set of dummies γ_{it} that are defined for employment durations of 1 to 6 months ($DD : 0 - 6$), 7 to 12 months ($DD : 7 - 12$), 13 to 36 months ($DD : 13 - 36$), 37 to 96 months ($DD : 37 - 96$) and more than 97 months ($DD :> 97$).

We control for a wide range of time-changing and constant individual, workplace and region-related characteristics. The choice of control variables included builds on a large body of literature that analyzes job turnover. Largely following the works of Beeson Royalty (1998), Zavodny (2003), Farber (1999), Kletzer (1998) and Farber (2005), the vector X_{it} in Equation 10 consists of a set of basic demographic controls such as age ($AGE : 18-29$, $AGE : 30-49$, $AGE : 50-64$), gender ($MALE : Yes$), marital status ($MARRIED : Yes$), children in household ($CHILD : Yes$), nationality ($GERMAN : Yes$), and individual skills. The definition of skills is based on internationally comparable information following the International Standard Classification of Education (ISCED) as described in UNESCO (1997). The data makes it possible to differentiate among respondents according to their educational attainment as follows: (1) primary education, (2) lower secondary education or second stage of basic education, (3) secondary education, (4) post-secondary non-tertiary education, (5) first stage of tertiary education or (6) second stage of tertiary education. In line with ISCED, low-skilled workers ($ED : low$) are defined as individuals with primary education, lower secondary, or the second stage of basic education. Medium-skilled ($ED : med$) workers are individuals with upper secondary education, post-secondary non-tertiary education, or the first stage of tertiary education. High-skilled workers ($ED : high$) are defined as individuals with some form of the second stage of tertiary education.

Other control variables include workplace-related characteristics such as individual occupational placement as a manager, professional, scientist or technician ($OCC : manager$), clerk ($OCC : clerk$), service worker ($OCC : service$, crafts worker ($OCC : craft$), skilled machine operator ($OCC : swork$) or unskilled worker ($OCC : uwork$). We also control for firm size in terms of employees ($FS :< 20$, $FS : 21-199$, $FS : 200-1999$, $FS :>= 2000$) and public ownership of the employer's company ($PUBOWN : yes$). To capture regional differences we control for the unemployment rate at the level of the federal state ($UNEMP$). Furthermore, a dummy variable for whether the place of work is in the former East, a region subject to specific structural changes and related employment fluctuations, is included (*Work in East: yes*).[6]

In the literature, job turnover models sometimes include a wage variable (e.g., Beeson Royalty, 1998). It is, however, questionable whether wages can be considered exogenous in the kind of model applied here. Furthermore, all determinants that are included to explain individual job separation would also be standard control vari-

[6]The region of residence is not necessarily the location of the workplace. Many East Germans commute between their workplace in the West and home.

ables in a wage regression. However, wages can be a powerful predictor of unobserved individual characteristics, which supports their inclusion in the model. We acknowledge the potential endogeneity of wages in such a setting but estimate specifications including and excluding wages for comparison.

An essential part of the analysis is to merge individual-level data with two-digit industry-level information on outsourcing intensity and other industry characteristics. International outsourcing ($OUTS$) is constructed by combining input-output data that are available from the German Statistical Office (Fachserie 18, Reihe 2) and OECD International Commodity Trade Statistics, which was aggregated from five-digit SITC trade figures to the two-digit NACE level applying the concordance table provided by Eurostat.

To capture the effects of technological change, industry research and development expenditure as a share of industry output is included in the model ($\frac{R\&D}{Y}$). Research and development (R&D) expenditure is only a crude measure of technological change. However, it is commonly used in the literature (e.g., Berman, Bound and Griliches and Machin and Van Reenen, 1998) and alternative proxies of technological change are not available for Germany. Data on industry research and development expenditure are provided by the OECD ANBERD database.[7]

Industry-level studies by authors such as Davidson and Matusz (2005), Klein et al. (2003) Kletzer (2000) and Kletzer (2004) highlight the relevance of export orientation and international competition as determinants of job creation and job destruction. Accordingly, a measure of net exports is included in the model: $Exp - Imp$. Again, data on exports and imports are derived from the OECD Commodity Trade Statistics.

In addition to international outsourcing, technological change and net exports, the model includes industry output (Y) and capital intensity differentiated by equipment and plant ($\frac{Equip}{Y}$),($\frac{Plant}{Y}$) to control for time-varying industry characteristics. Data on industry output and capital were provided by the German Statistical Office.

Summary statistics for the untransformed transition variable and the regressors are provided in Table 4.

6 Estimation and results

Column I of Table 1 presents the results of a simple cloglog hazard rate model as a benchmark abstracting from unobserved heterogeneity. To control for unobserved heterogeneity we start by estimating Equation 10 with two mass points and subsequently

[7]Unfortunately, prior to 1995, research and development expenditure is not available at the NACE two-digit level. Missing values are therefore imputed by regressing available data from 1995 to 2003 on a linear trend for each industry.

add additional point of support until the log-likelihood fails to increase significantly. The parameter estimates of the fully specified model as in Equation 10 with seven mass points are presented in Column II of Table 1.[8] Generally, the estimated coefficients have the expected signs and the model parameters of the simple cloglog model are notably close to the estimates of the fully specified model. In both specification the hazard of exiting a job is largest within the first six months, probably reflecting German legislation that allows for a probationary period of up to six months. After that, the hazard of exiting employment monotonically declines with job duration, confirming Farber (1999). Conditional on job duration, the hazard of exiting employment increases with age, most notably with high age. Furthermore, in both model specifications women face a significantly higher risk of leaving employment than men. This result holds after comprehensively controlling for educational attainment and occupational placement. If one, in addition controls for unobserved heterogeneity this effect becomes even larger (Column II of Table 1). Unfortunately it is not possible to reproduce the results of Beeson Royalty (1998), as the sample is too small to be divided into gender education sub-samples.[9] Similar to the findings of Beeson Royalty (1998) for the US, the simple model specification suggests that having children in the household also significantly increases the risk of leaving employment. The effect is, however, rendered insignificant after controlling for unobserved heterogeneity. Furthermore, having children in the household has a significantly different impact on men and women as the positive and statistically significant coefficient of the interaction term indicates. Accordingly, women with children face a significantly higher risk of leaving employment than men with children, a result that also holds after controlling for unobserved heterogeneity. Similarly, marital status has a significantly different impact for men and women. Both model specifications suggest that while men have a significantly lower probability of leaving employment when married, for women the opposite is true.

With regard to nationality our simple model specification suggests that, ceteris paribus, Germans face a significantly higher risk of leaving employment than non-Germans. However, after controlling for unobserved heterogeneity this effect is rendered insignificant. With regard to workplace-related characteristics, our simple model suggest that respondents who's workplace is located in the East face a significantly lower risk of leaving employment. This seems somewhat counterintuitive. However, the result is conditional on unobserved industry and region characteristics and most

[8] All mass point models are estimated using the GLLAMM module for Stata as described in Raabe-Hesketh and Everitt (2004).

[9] In addition our data only allow to identify job-to-nonemployment transitions but not job-to-job transitions.

importantly regional unemployment. Furthermore, after controlling for unobserved heterogeneity the effect is statistically insignificant. Firm size is found to be a significant determinant in both model specifications, with workers in smaller firms facing greater job insecurity in comparison to workers in larger firms, which is in line with Gómez-Salvador, Messina and Vallanti (2004) who find that larger firms have significantly lower job destruction rates. Regarding public ownership of the workplace, we find no significant impact on individual employment security in both specifications.

Occupational placement is another important determinant of individual employment security. In the simple model we find that managers, clerks, crafts and skilled workers face a significantly lower risk of leaving employment than unskilled workers, the default group. However, after controlling for unobserved heterogeneity the effect is only significant for managers, clerks and crafts workers. An important difference between the simple and the fully specified model is found with regard to the parameter estimate son educational attainment. While in the simple model high- and medium-skilled workers have a significantly lower risk of exiting employment than low-skilled workers these effects are insignificant in the fully specified model that controls for unobserved heterogeneity.

As has been discussed previously, various empirical studies of employment transitions include a wage variable (e.g. Royalty, 1998). Although it is questionable whether wages can be considered exogenous in the kind of model applied here and all determinants that are included to explain individual job separation would also be standard control variables in a wage regression we follow the literature and include an individual measure of hourly wages. The main argument in favor of including wages is that they are likely to capture unobserved worker characteristics such as ability or motivation. To prevent estimation bias due to item non-response we included a dummy variable for missing wages as a regressor and recoded missing wages to zero. Hourly wages are found to significantly lower the probability of leaving employment. The same is true for the dummy variable for missing wages, indicating a negative relationship between non-reporting of wages and employment insecurity. In order to check the robustness of our findings we also estimate a fully specified model excluding wages. A comparison between the estimates in Column III and II of Table 1 reveals that excluding wages from the model results in only modest parameter alterations. One notable difference exists with respect to educational attainment which is a standard control variable in any wage regression, and thus is typically highly correlated with wages. While in the fully specified model that includes wages, educational attainment is rendered insignificant, it is found to be negative and significant in the model specification that omits wages. However, with regard to the outsourcing variable, which is most interesting for this analysis, whether or not wages are included in the model does not significantly alter the results. Outsourcing significantly increases the individual risk of leaving employment.

Regarding the regional and industry-level variables, regional unemployment, ceteris paribus, is not found to significantly alter individual employment security which somewhat contrasts earlier findings of Zavodny (2003) for involuntary job separations in the US. However, technological progress, as captured by industry-level research and development expenditure, appears to be an important factor shaping individual employment security regardless of whether or not one controls for unobserved heterogeneity.[10] With regard to net exports, we find no support for the findings of industry-level studies for the US by authors such as Kletzer (2000) and most notably Davidson and Matusz (2005) with our data. Our simple model specification provides some weak evidence that net exports in fact raise individual employment insecurity. However, this is effect is rendered insignificant after we control for unobserved heterogeneity.

With regard to the industry-level capital intensity, the picture is somewhat mixed. While in the simple model specification equipment intensity is related to higher job insecurity, indicating a substitutability between labor and capital, capital in the form of plant increases employment security. However, after controlling for unobserved heterogeneity neither equipment nor plant intensity are statistically significant.

Regarding industry output, the coefficient is only weakly significant in the simple and insignificant in the fully specified model. However, one has to differentiate the whole equation with respect to output to obtain its marginal effect. Accordingly, the coefficients on Y, $R\&D/Y$, $Equip/Y$, $Plant/Y$ and $OUTS$ are relevant.[11] Looking at the fully specified model the coefficients on output and capital intensity are insignificant and the coefficients on $R\&D/Y$ and $OUTS$ are positive and significant. The partial deviations of $R\&D/Y$ and $OUTS$ with respect to Y are, however, negative. Accordingly the marginal effect of output on employment insecurity must be negative. Thus, increases in industry output raise individual employment security.

For this analysis, the most interesting variable is, of course international outsourcing ($OUTS$). Both model specifications yield a positive and highly significant coefficient which is fairly similar in size. Ceteris paribus, a one percentage point increase in an industry's outsourcing intensity increases the hazard of leaving employment by about 7 percent (Simple model: $exp(0.067) - 1 = 0.069$, Full model:$exp(0.064) - 1 = 0.066$). Thus, industry level international outsourcing is in-

[10] Zavodny (2003) finds that in the US technology, measured by computer usage, is negatively related to job separation. However, this result is driven by voluntary job separations. Involuntary job separations in manufacturing are positively related to technology.

[11] Outsourcing is constructed as the ratio between an industry's imported intermediate inputs and industry output (Equations 1 and 2).

deed an important determinant of individual employment security.

In order to assess the extent to which international outsourcing affects employment security for different skill groups and whether there are significant differences between them, international outsourcing and education are interacted.[12] Similarly, we loosen the poolability constraint on $R\&D/Y$ to allow for skill-specific differences in the impact of technological change. Column IV of Table 1 presents the coefficient estimates for this specification. Again, technological progress results in reduced employment security. The same is true with regard to outsourcing; the respective coefficients are positive and statistically significant for all skill groups. The effect of international outsourcing appears to be strongest for medium-skilled followed by high-skilled workers. However, when testing for the significance of parameter differences, Wald and likelihood ratio tests firmly reject the interaction model.[13] The effects of international outsourcing and technological progress do not differ significantly between skill groups.[14]

In addition, the model is estimated using the somewhat less conservative wide definition of international outsourcing as in Equation 2. Applying the wide definition, international outsourcing is rendered only weakly significant (Column I of Table 2). When interacting outsourcing with skill, we find a significant positive coefficients for medium-skilled workers. However, as the Wald and likelihood ratio test statistics in Column II of Table 2 indicate, we can not reject the hypothesis that broadly defined outsourcing (as well as technological progress) has a uniform impact on employment security for all skill groups.

Overall, the support for a significant role of broadly defined outsourcing is much weaker than that for narrowly defined outsourcing. The diverging results highlight the importance of precisely defining the outsourcing phenomenon. As has been discussed previously in Section 2, narrowly defined, outsourcing can be understood as the outcome of a make or buy decision. Wide outsourcing, however, encapsulates all intermediate goods imports of an industry and therefore may be less correlated with an industry's outsourcing activities explaining the lower statistical significance in the model.

To ease the interpretation of the estimated coefficients and to asses the economic

[12]Preferably, one would estimate the model separately for sub-samples of different skill groups in order to loosen the poolability constraint. Unfortunately, the number of job exits is too low to identify the model parameters for smaller sub-samples.

[13]The Wald test is based on a quadratic approximation of the likelihood function and therefore less precise than the likelihood ratio test.

[14]To assess the robustness of the above results, the model was also estimated interacting gender, education and outsourcing. However, the impact of international outsourcing does not differ markedly by gender.

relevance, one can simulate the effect of international outsourcing on the employment hazard over the sample period. Focusing on narrowly defined international outsourcing, we know from Figure 1 that it increased by 2.28 percentage points between 1991 and 2000. Accordingly, using the coefficients from Column IV in Table 1 the model predicts that between 1991 and 2000 international outsourcing increased the hazard of existing employment by approximately 16 percent ($exp(0.064 * 2.28) - 1 = 0.1571$). In comparison the effects of technological progress, at least as captured by R&D expenditure, are fairly modest. Between 1991 and 2000 research and development expenditure as a share of aggregate output increased from 2.58 percent to 2.64 percent. Accordingly, technological progress raises the hazard of leaving employment by about one percent ($exp(0.165 * 0.06) - 1 = 0.0099$).

On the basis of the estimated coefficients from Column IV of Table 1 one can also calculate the predicted hazard rate at the sample mean. Figure 3 shows the predicted hazard rate and provides a visualization of the impact of international outsourcing. Within the first six months of employment, international outsourcing raises the hazard of leaving employment by more than one percentage points. With higher employment duration, the absolute changes in the hazard rate due to outsourcing are much smaller, as the hazard rate model is proportional and the hazard of leaving employment monotonically declines.

Finally it is important to stress, that the results should by interpret with some caution as combining micro-level and more aggregated industry-level data could give rise to contemporaneous correlation in the error terms and thus result in biased standard errors. Within the context of linear models, this problem has been stressed forcefully by Moulton (1986, 1990). He suggests addressing the issue by multiplying the standard errors with a common factor that reflects the average intra-cluster residual correlation. However, Angrist and Lavy (2002) stress that the equi-correlated error structure imposed by this method is inappropriate in the context of models with binary outcomes and suggest to apply the Generalized Estimation Method (GEE) instead. Again the idea is to multiply the standard errors by a factor reflecting the intra cluster residual correlation, which is, however, allowed to vary between clusters. The main problem with such an approach is that it is only valid for a large number of clusters (see e.g., Thornquist and Anderson, 1992) casting doubt on the applicability within our model.

Authors such as Donald and Lang (2001) and Angrist and Lavy (2002) propose an alternative estimation strategy that assesses the effects of higher aggregated variables within a two-step procedure. Basically, this amounts to using the micro-level information to construct adjusted means of the dependent variable at the higher aggregational level (i.e., industry or region) in the first step. In the second step the means are regressed on the aggregated covariates (e.g., industry or region characteristics).

However, this method is very restrictive as it disposes of all within-cluster variation.

In the literature on duration analysis and job displacement the problem of contemporaneous correlation has, to the best knowledge of the author, remained unaddressed, although the combination of micro and more aggregated data is not uncommon. For example, authors such as Beeson Royalty (1998) and Steiner (2001) combine micro-level data with regional unemployment figures, while Zavodny (2003) combines micro-level data on job separation and industry-level technology measures. We largely follow these examples, but in addition control for unobserved industry and region-specific characteristics by within-transforming the data with respect to region and industry.[15] Thus, contemporaneous correlation in the residual is considerably reduced as the constant residual correlation within clusters due to unobserved heterogeneity is accounted for. Nevertheless, we recognize that the standard errors are still potentially biased as we fail to correct for potential serial correlation within clusters. In order to address this problem we propose bootstrapping to obtain consistent standard errors. However, in the context of our fully specified model, including seven mass points that control for unobserved heterogeneity, bootstrapping is computationally prohibitive. Instead, we present bootstrapped standard errors for a simple cloglog hazard model that delivers parameter estimates which are notably close to the ones estimated by the fully specified model, particularly with regard to the outsourcing variable. Table 3 again presents the model parameters of the fully specified and simple cloglog model with bootstrapped standard errors. As expected, the standard errors of the original cloglog model are indeed downward biased. However, the bias is small enough so that when correcting for contemporaneous correlation by bootstrapping the standard errors our general findings still hold. Most importantly, we still find the coefficients on technological progress and international outsourcing to be significant.

7 Discussion

The paper expands the existing literature by analyzing the effects of international outsourcing for individual job security in a micro-econometric framework utilizing a large panel of individual monthly employment spell data and controlling for the duration dependence of employment security. The approach is suitable to considerably reduce the aggregation and potential endogeneity bias that hampers existing industry-level displacement studies. Furthermore, individual-level data is arguably better suited to describe individual skills than the manual vs. non-manual worker skill approximation that is commonly used in the literature. To address problems of contemporaneous

[15] This corresponds to estimating a unconstrained model including a full set of interacted industry and region dummies.

correlation that arise through the combination of micro and more aggregated industry level data we calculate bootstrapped standard errors.

Our main findings are that workers with less than seven months of employment duration face the highest risk of leaving employment. Afterwards, job security monotonically increases over time. Furthermore, international outsourcing, when narrowly defined, is found to have a marked impact on individual employment security. Remarkably, the effect does not differ statistically between high-, medium- and low-skilled workers. This is an interesting result as it poses a contrast to the findings of industry-level studies that typically identify low-skilled workers to be more adversely effected than high skilled workers by outsourcing (e.g., Feenstra and Hanson, 1996; Egger and Egger, 2003). Similarly, with regard to technological progress we find only uniform negative effects for individual employment security across different skill groups. At first sight our findings therefore appear to not correspond well with the observed overall skill upgrading and the high relative unemployment rate of low-skilled workers in Germany that have been discussed in Section 1. However, authors such as Swaim and Podgursky (1989) and Farber (1997) show that the probability of finding reemployment is increasing in the level of educational attainment. A finding that is also confirmed for Germany by authors such as Hunt (1995), Steiner (2001) and Uhlendorff (2004). This suggests that the skill-biased effects of technological change and international outsourcing are indirect and related to the lower probability of low-skilled workers to reenter employment. This is not to downplay the role of international outsourcing and technological progress - it is well shown that they reduce relative demand for lower skills (e.g., Feenstra and Hanson, 1996; Berman, Bound and Machin, 1998). However, our micro analysis shows that in Germany skill upgrading works not through a direct displacement effect but is the result of reduced reemployment chances for low-skilled workers.

Active labor market policies such as retraining programs principally could help to ease the transition into employment for low-skilled workers. In practise, examples of effective retraining programs are, however, rare.

Authors such as Podgursky and Swaim (1987), Hamermesh (1987), Farber (1993), Kletzer (1989, 1996), Neal (1995) and Haynes, Upward and Wright (2002) in unison demonstrate that post displacement earnings have to significantly fall to allow for reemployment. However, for Germany Burda and Mertens (2001) find much lower wage losses after displacement. Workers that formerly were in the lowest earnings quartile - thus are more likely to be low skilled - were even found to have slightly higher post displacement wage growth. Naturally, for reemployment chances this is fatal. If wages do not adjust downwards, displaced low-skilled workers tend to be driven out of the labor market permanently.

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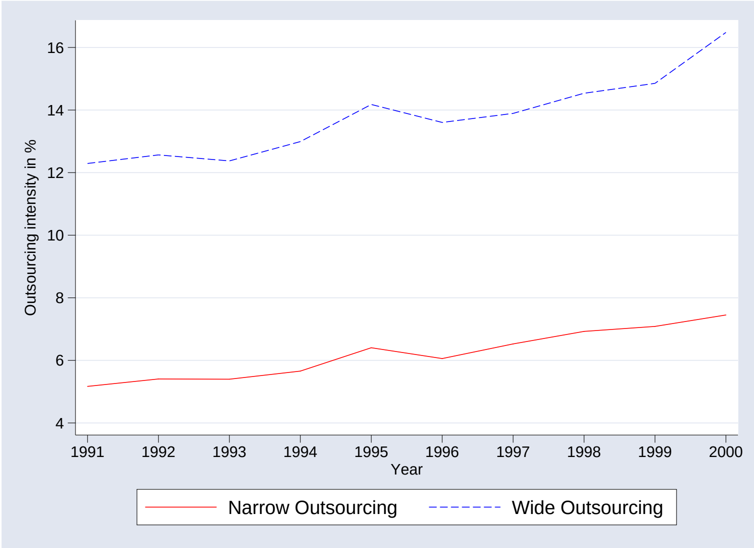
Figure 1: Outsourcing over time



Figures and Tables

Figure 2: Outsourcing over time by industry

Figure 3: Prediction of hazard rate, cumulated effect of international outsourcing

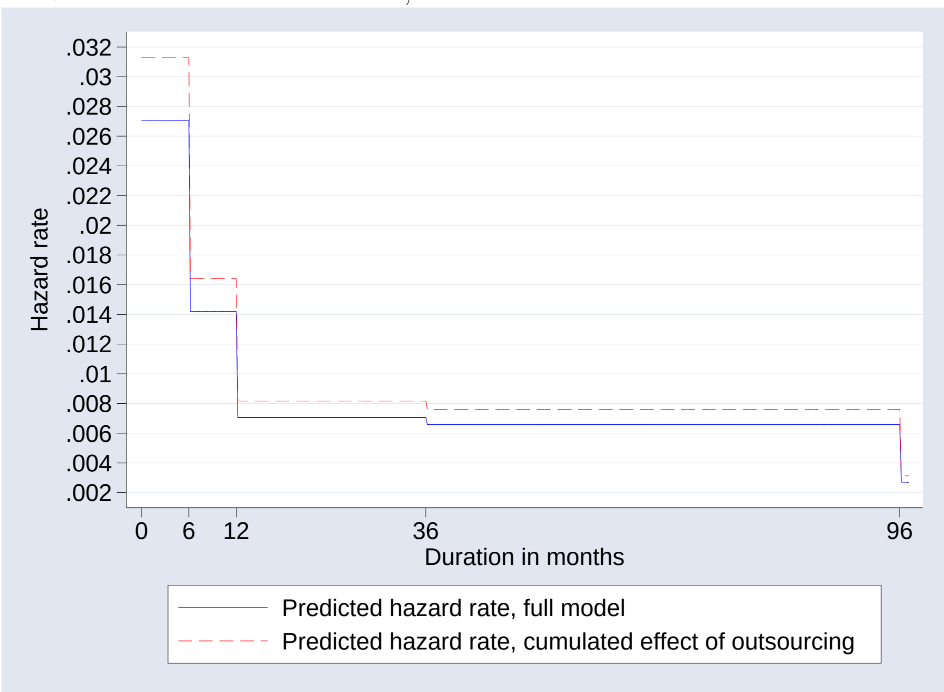


Table 1: Hazard Rate Model - Narrow Outsourcing

	I		II		III		IV	
$DD: 0-6$	2.929	[0.146]***	2.315	[0.206]***	2.425	[0.206]***	2.323	[0.206]***
$DD: 7-12$	1.557	[0.157]***	1.663	[0.212]***	1.747	[0.213]***	1.673	[0.213]***
$DD: 13-36$	0.711	[0.155]***	0.962	[0.210]***	1.034	[0.210]***	0.974	[0.210]***
$DD: 37-96$	0.562	[0.156]***	0.891	[0.212]***	0.935	[0.215]***	0.903	[0.212]***
$AGE: 30-49$	0.339	[0.060]***	0.142	[0.085]*	0.125	[0.088]	0.136	[0.087]
$AGE: 50-64$	0.950	[0.075]***	0.707	[0.118]***	0.639	[0.141]***	0.696	[0.122]***
$MALE: Yes$	-0.377	[0.097]***	-0.710	[0.145]***	-0.700	[0.149]***	-0.695	[0.147]***
$CHILD: Yes$	0.259	[0.081]***	-0.003	[0.115]	0.066	[0.118]	-0.013	[0.117]
$CHILD: Yes * FEMALE$	0.693	[0.093]***	0.697	[0.142]***	0.646	[0.140]***	0.711	[0.143]***
$MARRIED: Yes$	-0.228	[0.088]***	-0.262	[0.127]**	-0.439	[0.128]**	-0.257	[0.129]**
$MARRIED: Yes * FEMALE$	0.813	[0.109]***	0.711	[0.157]***	0.820	[0.158]***	0.709	[0.159]***
$GERMAN: Yes$	0.475	[0.062]***	0.132	[0.103]	0.045	[0.115]	0.118	[0.109]
$WorkinEast: Yes$	-0.305	[0.136]**	-0.112	[0.201]	-0.006	[0.196]	-0.113	[0.201]
$Wage$	-0.059	[0.007]***	-0.057	[0.008]***			-0.056	[0.008]***
$Wageismissing$	-0.260	[0.084]***	-0.423	[0.109]***			-0.426	[0.110]***
$FS: < 20$	0.025	[0.070]	0.098	[0.114]	0.278	[0.148]	0.098	[0.119]
$FS: 21-199$	-0.089	[0.066]	0.058	[0.095]	0.268	[0.118]	0.061	[0.097]
$FS: 200-1999$	-0.180	[0.066]***	-0.212	[0.095]**	-0.097	[0.105]	-0.223	[0.096]**
$PUBOWN: Yes$	-0.175	[0.222]	0.364	[0.294]	0.392	[0.294]	0.366	[0.296]
$OCC: Manager$	-0.488	[0.075]***	-0.316	[0.114]***	-0.518	[0.109]***	-0.320	[0.117]***
$OCC: Clerk$	-0.219	[0.072]***	-0.360	[0.104]***	-0.518	[0.101]***	-0.347	[0.105]***
$OCC: Service$	-0.031	[0.098]	-0.111	[0.150]	-0.172	[0.173]	-0.098	[0.149]
$OCC: Craft$	-0.423	[0.070]***	-0.367	[0.101]***	-0.417	[0.097]***	-0.368	[0.103]***
$OCC: Swork$	-0.340	[0.073]***	-0.177	[0.109]	-0.245	[0.105]	-0.170	[0.110]
$ED: High$	-0.187	[0.086]**	-0.160	[0.128]	-0.188	[0.131]**	-0.138	[0.195]
$ED: Med$	-0.162	[0.071]**	-0.135	[0.107]	-0.061	[0.102]***	-0.363	[0.156]**
$UNEMP$	-0.019	[0.028]	0.054	[0.038]	0.034	[0.037]	0.054	[0.038]
$R\&D/Y$	0.105	[0.056]*	0.165	[0.071]**	0.167	[0.074]**		
$R\&D/Y * ED: High$							0.111	[0.087]
$R\&D/Y * ED: Med$							0.156	[0.083]*
$R\&D/Y * ED: Low$							0.167	[0.072]**
$(Exp - Imp)$	0.025	[0.012]**	0.017	[0.016]	0.016	[0.016]	0.017	[0.016]
$Y * 10^{-3}$	-0.010	[0.005]*	-0.004	[0.007]	-0.005	[0.008]	-0.004	[0.007]
$Equip/Y$	0.034	[0.019]*	0.021	[0.023]	0.019	[0.023]	0.020	[0.023]
$Plant/Y$	-0.062	[0.031]**	0.000	[0.037]	0.004	[0.039]	0.004	[0.037]
OUT	0.067	[0.023]***	0.064	[0.025]**	0.054	[0.029]**		
$OUT * ED: High$							0.079	[0.039]**
$OUT * ED: Med$							0.106	[0.038]***
$OUT * ED: Low$							0.057	[0.026]**
$Year = 1992$	1.280	[0.112]***	0.921	[0.122]***	0.918	[0.122]***	0.922	[0.122]***
$Year = 1993$	1.163	[0.148]***	0.784	[0.167]***	0.810	[0.171]***	0.785	[0.168]***
$Year = 1994$	1.110	[0.161]***	0.645	[0.192]***	0.701	[0.193]***	0.646	[0.193]***
$Year = 1995$	1.222	[0.155]***	0.737	[0.189]***	0.804	[0.189]***	0.741	[0.190]***
$Year = 1996$	1.369	[0.177]***	0.794	[0.214]***	0.834	[0.216]***	0.796	[0.215]***
$Year = 1997$	1.362	[0.203]***	0.867	[0.245]***	0.933	[0.246]***	0.874	[0.245]***
$Year = 1998$	1.247	[0.192]***	0.708	[0.232]***	0.808	[0.232]***	0.716	[0.233]***
$Year = 1999$	1.390	[0.183]***	0.861	[0.217]***	0.960	[0.221]***	0.866	[0.218]***
$Year = 2000$	1.309	[0.171]***	0.886	[0.202]***	0.962	[0.204]***	0.899	[0.203]***
$Constant = \epsilon_i^{m=1}$	-5.470	[0.036]***	-7.282	[0.266]***	-7.212	[0.428]***	-7.288	[0.275]***
$P(\epsilon_i^{m=1})$			0.625	[0.195]	0.602	[0.270]	0.622	[0.196]
$\epsilon_i^{m=2}$			-0.769	[0.124]***	-0.708	[0.124]***	-0.740	[0.127]***
$P(\epsilon_i^{m=2})$			0.002	[0.001]	0.002	[0.001]	0.002	[0.001]
$Constant = \epsilon_i^{m=3}$			-2.817	[0.121]***	-3.417	[0.110]***	-2.808	[0.120]***
$P(\epsilon_i^{m=3})$			0.010	[0.003]	0.069	[0.031]	0.010	[0.003]
$\epsilon_i^{m=4}$			-2.060	[0.153]***	-2.337	[0.123]***	-2.009	[0.163]***
$P(\epsilon_i^{m=4})$			0.002	[0.001]	0.006	[0.003]	0.002	[0.001]
$Constant = \epsilon_i^{m=5}$			-5.273	[0.220]***	-5.499	[0.468]***	-5.294	[0.220]***
$P(\epsilon_i^{m=5}$			0.212	[0.066]	0.207	[0.093]	0.214	[0.068]
$\epsilon_i^{m=6}$			-4.186	[0.201]***	-4.418	[0.286]***	-4.184	[0.209]***
$P(\epsilon_i^{m=6})$			0.066	[0.021]	0.077	[0.034]	0.071	[0.022]
$Constant = \epsilon_i^{m=7}$			-3.638	[0.112]***	-3.906	[0.307]***	-3.628	[0.116]***
$P(\epsilon_i^{m=7})$			0.083	[0.022]	0.038	[0.044]	0.080	[0.022]
Log likelihood	-10538.305		-9174.418		-9203.551		-9171.368	
Observations	213750		213750		213750		213750	
Waldtest:OUT*ED:High,MED,LOW equal, $\chi^2(2)$							2.960	
p-value							0.228	
Waldtest: R&D/Y*ED:High,MED,LOW equal, $\chi^2(2)$							1.200	
p-value							0.550	
LR Test, Pooled vs. interacted model : $\chi^2(4)$							6.100	
p-value							0.192	

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
All data are within transformed by industry/region.
Default categories: $DD :> 97$, $AGE: 18-29$, $FS :>= 2000$, $OCC: Uwork$, $ED: Low$; significance of probabilities of masspoints not reported as original coefficients were transformed

Table 2: Hazard Rate Model - Wide Outsourcing

	I		II		III		IV	
$DD: 0-6$	1.929	[0.122]***	1.932	[0.122]***	1.854	[0.122]***	1.857	[0.122]***
$DD: 7-12$	1.283	[0.126]***	1.285	[0.126]***	1.220	[0.126]***	1.222	[0.126]***
$DD: 13-36$	1.119	[0.125]***	1.123	[0.125]***	1.070	[0.124]***	1.073	[0.125]***
$DD: 37-96$	0.938	[0.127]***	0.943	[0.127]***	0.919	[0.126]***	0.923	[0.126]***
$AGE: 30-49$	-0.025	[0.046]	-0.027	[0.046]	0.016	[0.047]	0.015	[0.047]
$AGE: 50-64$	0.212	[0.065]***	0.215	[0.065]***	0.223	[0.065]***	0.225	[0.065]***
$MALE: Yes$	-0.490	[0.080]***	-0.482	[0.080]***	-0.473	[0.080]***	-0.463	[0.080]***
$CHILD: Yes$	0.157	[0.062]**	0.159	[0.062]***	0.135	[0.062]**	0.137	[0.062]**
$CHILD: Yes * FEMALE$	0.187	[0.077]**	0.190	[0.077]***	0.187	[0.077]**	0.192	[0.077]**
$MARRIED: Yes$	-0.282	[0.069]***	-0.287	[0.069]***	-0.245	[0.069]***	-0.248	[0.069]***
$MARRIED: Yes * FEMALE$	0.530	[0.087]***	0.534	[0.088]***	0.448	[0.088]***	0.450	[0.088]***
$GERMAN: Yes$	0.005	[0.050]	0.001	[0.050]	-0.013	[0.050]	-0.018	[0.050]
$WorkinEast: Yes$	-0.194	[0.114]*	-0.191	[0.114]*	-0.254	[0.114]**	-0.252	[0.114]**
$HourlyWage$					-0.037	[0.005]***	-0.038	[0.005]***
Wage is missing					-0.198	[0.063]***	-0.212	[0.064]***
$FS :< 20$	0.193	[0.057]***	0.191	[0.057]***	0.069	[0.059]	0.065	[0.059]
$FS: 21-199$	0.185	[0.054]***	0.183	[0.054]***	0.101	[0.055]*	0.100	[0.055]*
$FS: 200-1999$	-0.042	[0.055]	-0.047	[0.055]	-0.101	[0.055]*	-0.105	[0.055]*
$PUBOWN: Yes$	-0.380	[0.203]*	-0.376	[0.203]*	-0.413	[0.204]**	-0.406	[0.204]**
$OCC: Manager$	-0.178	[0.061]***	-0.183	[0.061]***	-0.086	[0.061]	-0.094	[0.061]
$OCC: Clerk$	-0.199	[0.061]***	-0.199	[0.061]***	-0.142	[0.060]**	-0.142	[0.060]**
$OCC: Service$	0.032	[0.077]	0.026	[0.077]	0.053	[0.078]	0.049	[0.079]
$OCC: Craft$	-0.085	[0.057]	-0.085	[0.057]	-0.059	[0.057]	-0.062	[0.057]
$OCC: Swork$	0.065	[0.062]	0.064	[0.062]	0.070	[0.061]	0.068	[0.061]
$ED: High$	-0.164	[0.071]**	-0.345	[0.149]**	-0.052	[0.072]	-0.186	[0.151]
$ED: Med$	-0.137	[0.061]**	-0.309	[0.143]**	-0.099	[0.061]	-0.298	[0.142]**
$UNEMP$	0.086	[0.023]***	0.085	[0.023]***	0.092	[0.023]***	0.091	[0.023]***
$R\&D/Y$	0.123	[0.043]***			0.131	[0.043]***		
$R\&D/Y * ED: High$			0.120	[0.047]***			0.147	[0.047]***
$R\&D/Y * ED: Med$			0.152	[0.048]***			0.157	[0.048]***
$R\&D/Y * ED: Low$			0.119	[0.044]***			0.124	[0.043]***
$(Exp-Imp)$	0.004	[0.009]	0.004	[0.009]	0.006	[0.009]	0.006	[0.009]
$Y * 10^{-3}$	-0.002	[0.004]	-0.002	[0.004]	-0.002	[0.004]	-0.002	[0.004]
$Equip/Y$	0.013	[0.015]	0.012	[0.015]	0.024	[0.015]	0.023	[0.015]
$Plant/Y$	-0.034	[0.025]	-0.030	[0.025]	-0.045	[0.025]*	-0.041	[0.025]*
OUT	0.022	[0.015]			0.027	[0.015]*		
$OUT * ED: High$			0.033	[0.018]*			0.030	[0.018]*
$OUT * ED: Med$			0.027	[0.019]			0.035	[0.018]*
$OUT * ED: Low$			0.018	[0.015]			0.024	[0.015]
$Year = 1992$	0.886	[0.077]***	0.888	[0.077]***	0.877	[0.077]***	0.880	[0.077]***
$Year = 1993$	0.733	[0.101]***	0.734	[0.101]***	0.705	[0.101]***	0.707	[0.101]***
$Year = 1994$	0.488	[0.118]***	0.492	[0.118]***	0.457	[0.118]***	0.461	[0.118]***
$Year = 1995$	0.531	[0.117]***	0.542	[0.117]***	0.480	[0.118]***	0.491	[0.118]***
$Year = 1996$	0.550	[0.131]***	0.560	[0.131]***	0.519	[0.132]***	0.526	[0.132]***
$Year = 1997$	0.192	[0.153]	0.208	[0.153]	0.164	[0.154]	0.178	[0.154]
$Year = 1998$	0.095	[0.148]	0.115	[0.148]	0.048	[0.149]	0.065	[0.149]
$Year = 1999$	0.139	[0.142]	0.160	[0.142]	0.098	[0.143]	0.118	[0.143]
$Year = 2000$	0.223	[0.137]	0.245	[0.138]*	0.163	[0.139]	0.186	[0.139]
$Constant = \epsilon_i^{m=1}$	-4.906	[0.058]***	-4.907	[0.058]***	-4.934	[0.060]***	-4.938	[0.060]***
$P(\epsilon_i^{m=1})$	0.898	[0.009]***	0.898	[0.009]***	0.895	[0.009]***	0.894	[0.009]***
$\epsilon_i^{m=2}$	2.512	[0.046]***	2.511	[0.046]***	2.511	[0.047]***	2.509	[0.047]***
$P(\epsilon_i^{m=2})$	0.102	[0.009]***	0.102	[0.009]***	0.105	[0.009]***	0.106	[0.009]***
Observations	213750		213750		213750		213750	
$Wald-Chi^2$	1694.37***		1698.34***		1775.21***		1778.52***	
OUT*ED:High,MED,LOW equal			Chi^2 =1.900 $p-value$ =0.387				Chi^2 =0.870 $p-value$ =0.646	
R&D/Y*ED:High,MED,LOW equal			Chi^2 =1.900 $p-value$ =0.386				Chi^2 =2.720 $p-value$ =0.257	

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
All data are within transformed by industry/region.
Default categories:$DD :> 97$, $AGE: 18-29$, $FS :>= 2000$, $OCC: Uwork$, $ED: Low$

Table 3: Hazard Rate Model - with bootstrapped standard errors

	Full Model		Simple Cloglog		Bootstrapped SE
$DD : 0-6$	2.315	[0.206]***	2.929	[0.146]***	[0.151]***
$DD : 7-12$	1.663	[0.212]***	1.557	[0.157]***	[0.163]***
$DD : 13-36$	0.962	[0.210]***	0.711	[0.155]***	[0.161]***
$DD : 37-96$	0.891	[0.212]***	0.562	[0.156]***	[0.151]***
$AGE : 30-49$	0.142	[0.085]*	0.339	[0.060]***	[0.075]***
$AGE : 50-64$	0.707	[0.118]***	0.950	[0.075]***	[0.086]***
$MALE : Yes$	-0.710	[0.145]***	-0.377	[0.097]***	[0.103]***
$CHILD : Yes$	-0.003	[0.115]	0.259	[0.081]***	[0.090]***
$CHILD : Yes * FEMALE$	0.697	[0.142]***	0.693	[0.093]***	[0.115]***
$MARRIED : Yes$	-0.262	[0.127]**	-0.228	[0.088]***	[0.095]**
$MARRIED : Yes * FEMALE$	0.711	[0.157]***	0.813	[0.109]***	[0.113]***
$GERMAN : Yes$	0.132	[0.103]	0.475	[0.062]***	[0.084]***
$WorkinEast : Yes$	-0.112	[0.201]	-0.305	[0.136]**	[0.155]**
$Wage$	-0.057	[0.008]***	-0.059	[0.007]***	[0.008]***
$Wageismissing$	-0.423	[0.109]***	-0.260	[0.084]***	[0.112]**
$FS :< 20$	0.098	[0.114]	0.025	[0.070]	[0.077]
$FS : 21-199$	0.058	[0.095]	-0.089	[0.066]	[0.071]
$FS : 200-1999$	-0.212	[0.095]**	-0.180	[0.066]***	[0.073]**
$PUBOWN : Yes$	0.364	[0.294]	-0.175	[0.222]	[0.266]
$OCC : Manager$	-0.316	[0.114]***	-0.488	[0.075]***	[0.102]***
$OCC : Clerk$	-0.360	[0.104]***	-0.219	[0.072]***	[0.090]**
$OCC : Service$	-0.111	[0.150]	-0.031	[0.098]	[0.129]
$OCC : Craft$	-0.367	[0.101]***	-0.423	[0.070]***	[0.094]***
$OCC : Swork$	-0.177	[0.109]	-0.340	[0.073]***	[0.086]***
$ED : High$	-0.160	[0.128]	-0.187	[0.086]**	[0.105]*
$ED : Med$	-0.135	[0.107]	-0.162	[0.071]**	[0.084]*
$UNEMP$	0.054	[0.038]	-0.019	[0.028]	[0.030]
$R\&D/Y$	0.165	[0.071]**	0.105	[0.056]*	[0.059]*
$(Exp - Imp)$	0.017	[0.016]	0.025	[0.012]**	[0.014]*
$Y * 10^{-3}$	-0.004	[0.007]	-0.010	[0.005]*	[0.007]
$Equip/Y$	0.021	[0.023]	0.034	[0.019]*	[0.020]*
$Plant/Y$	0.000	[0.037]	-0.062	[0.031]**	[0.040]
OUT	0.064	[0.025]**	0.067	[0.023]***	[0.031]**
$OUT * ED : High$	0.921	[0.122]***	1.280	[0.112]***	[1.489]
$Year = 1992$	0.784	[0.167]***	1.163	[0.148]***	[0.714]
$Year = 1993$	0.645	[0.192]***	1.110	[0.161]***	[0.755]
$Year = 1994$	0.737	[0.189]***	1.222	[0.155]***	[0.838]
$Year = 1995$	0.794	[0.214]***	1.369	[0.177]***	[0.869]
$Year = 1996$	0.867	[0.245]***	1.362	[0.203]***	[0.784]*
$Year = 1997$	0.708	[0.232]***	1.247	[0.192]***	[0.776]
$Year = 1998$	0.861	[0.217]***	1.390	[0.183]***	[0.780]*
$Year = 1999$	0.886	[0.202]***	1.309	[0.171]***	[0.778]*
$Year = 2000$					
$Constant = \epsilon_i^{m=1}$	-7.282	[0.266]***	-5.470	[0.036]***	[0.049]***
$P(\epsilon_i^{m=1})$	0.625	[0.195]			
$\epsilon_i^{m=2}$	-0.769	[0.124]***			
$P(\epsilon_i^{m=2})$	0.002	[0.001]			
$Constant = \epsilon_i^{m=3}$	-2.817	[0.121]***			
$P(\epsilon_i^{m=3})$	0.010	[0.003]			
$\epsilon_i^{m=4}$	-2.060	[0.153]***			
$P(\epsilon_i^{m=4})$	0.002	[0.001]			
$Constant = \epsilon_i^{m=5}$	-5.273	[0.220]***			
$P(\epsilon_i^{m=5}$	0.212	[0.066]			
$\epsilon_i^{m=6}$	-4.186	[0.201]***			
$P(\epsilon_i^{m=6})$	0.066	[0.021]			
$Constant = \epsilon_i^{m=7}$	-3.638	[0.112]***			
$P(\epsilon_i^{m=7})$	0.083	[0.022]			
Log likelihood	-9174.418		-10538.305		
Observations	213750		213750		1000 repetitions

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
All data are within transformed by industry/region.
Default categories:$DD :> 97$, $AGE : 18-29$, $FS :>= 2000$, $OCC : Uwork$, $ED : Low$; significance of probabilities of masspoints not reported as original coefficients were transformed

Table 4: Summary statistics

	Mean	Standard Deviation
$Transitionoutofemployment : Yes$	0.012	[0.109]
$DD : 0 - 6$	0.189	[0.392]
$DD : 7 - 12$	0.134	[0.341]
$DD : 13 - 36$	0.281	[0.450]
$DD : 37 - 96$	0.295	[0.456]
$DD :>= 97$	0.101	[0.301]
$AGE : 30 - 49$	0.578	[0.494]
$AGE : 30 - 49$	0.194	[0.395]
$AGE : 18 - 29$	0.228	[0.420]
$MALE : Yes$	0.736	[0.441]
$CHILD : Yes$	0.511	[0.500]
$MARRIED : Yes$	0.741	[0.438]
$GERMAN : Yes$	0.779	[0.415]
$WorkinEast : Yes)$	0.174	[0.379]
$HourlyWage$	11.637	[5.856]
Wage is missing	0.089	[0.285]
$FS :< 20$	0.149	[0.356]
$FS : 21 - 199$	0.284	[0.451]
$FS : 200 - 1999$	0.314	[0.464]
$PUBOWN : Yes$	0.010	[0.101]
$FS :> 2000$	0.250	[0.433]
$OCC : Manager$	0.272	[0.445]
$OCC : Clerk$	0.086	[0.281]
$OCC : Service$	0.016	[0.125]
$OCC : Craft$	0.358	[0.479]
$OCC : Swork$	0.183	[0.387]
$OCC : Uwork$	0.073	[0.261]
$ED : High$	0.138	[0.345]
$ED : Med$	0.134	[0.340]
$ED : Low$	0.729	[0.445]
$UNEMP$	9.880	[3.929]
$\frac{R\&D}{Y}$	2.356	[2.846]
$(Exp - Imp)$	11.250	[15.796]
$Y * 10^{-3}$	79.393	[42.226]
$\frac{Equip}{Y}$	29.057	[8.650]
$\frac{Plant}{Y}$	17.307	[5.480]
$OUTS^{narrow}$	5.566	[4.684]
$OUTS^{wide}$	12.184	[5.870]
$Year = 1991$	0.114	[0.318]
$Year = 1992$	0.105	[0.307]
$Year = 1993$	0.095	[0.294]
$Year = 1994$	0.093	[0.290]
$Year = 1995$	0.096	[0.294]
$Year = 1996$	0.089	[0.284]
$Year = 1997$	0.086	[0.280]
$Year = 1998$	0.093	[0.290]
$Year = 1999$	0.091	[0.287]
$Year = 2000$	0.139	[0.346]
Observations	213750	