Diskussionsbeiträge des Fachbereichs Wirtschaftswissenschaft
der Freien Universität Berlin

Volkswirtschaftliche Reihe

2006/17

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3-938369-42-6

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November 2006

Abstract

The paper analyzes how international outsourcing affected individual employment security. The analysis is carried out at the micro-level, combining monthly spell data from household panel data 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, however, not differ between high-, medium-, and low-skilled workers but only varies with job duration.

Keywords: outsourcing, displacement, duration analysis, mass points

JEL classification: F16, F23. J63, J23

*The author is particularly grateful to Holger Görg, Peter Egger, Stephen Jenkins, Arne Uhlendorff, Richard Upward and Katharina Wrohlich for their helpful comments. Furthermore, the author gratefully acknowledges financial support by the German Science Foundation (DFG).

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 employment security particulary for low-skilled workers, 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, being not only the largest economy in Europe, but also far more open to international trade than, for instance, the US. Furthermore, political and economic transition in the formerly communist Central and Eastern European countries during the 1990s now allows for intensive production-sharing with these economies at Germany's doorstep, with potentially sweeping implications for the German labor market.

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 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 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, thus labour can move costlessly between different areas of economic activity in response to international outsourcing. 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. Accordingly, albeit unquestioned efficiency gains, what also matters for the welfare effects of international outsourcing is how, and how fast the labour force adjust to changing patterns of international specialisation. The focus of the present paper is therefore on the impact of international outsourcing on the short run labour markets dynamics. More specifically, the paper will address the questions of how international outsourcing affects the individual risk of leaving employment and of how the impact of outsourcing may vary with skill and employment duration.

Section 2 provides some descriptive analysis on the development of employment security, discusses the definition of international outsourcing and its measurement and gives a summary of recent developments. Section 3 gives 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. However, irrespective of educational attainment the outsourcing related risk of leaving employment increases with employment duration.

2 Descriptive Analysis

Table 1 shows calculations based on data from the German Socio Economic Panel (GSOEP) of how employment security of manufacturing employees has developed over the 1990s.[1] While over all individuals in 1991 the unconditional risk of leaving employment was 0.79 percent it increased by about 100% to 1.59 percent in 2000. Furthermore, it becomes apparent that the risk of leaving employment grew for all skill-groups, with particularly steep increases for medium and high-skilled workers. This development is also reflected in individually reported fear of job loss. In the GSOEP respondents each year are asked how worried they are to to loose their present job over the next year. Table 2 presents summary statistics for different categories of worry.[2] When pooling over all skill groups the share of respondents that is not worried at all about the prospects of losing the present job has been declining sharply from 51% to 34% which is mirrored in a significant increase of the share of respondents that are somewhat or very worried. Again, this development is not confined to only one skill-group but can be observed across high, medium and low-skilled workers alike. Obviously, the fear of job loss not only depends on the probability of losing a job but

[1]The figures are calculated using monthly employment data for prime age males and females in the manufacturing industry, the sample is identical with the one used in the econometric analysis in Section 6.

[2]Naturally, it is difficult to compare these worry scores across individuals. To ensure comparability of these scores over time, calculations are based on a balanced sample of 418 individuals in manufacturing employment. Thus, changes in the distribution of the different worry categories have to be due to changes in the individual fear of job loss.

e.g., also one the prospects of finding a new job after displacement or the generosity of the unemployment insurance scheme. Whatever the underlying reasons are, these figures, however, clearly correspond to a considerable increase in individually perceived insecurity.

To clarify to what extent international outsourcing may be indeed responsible for decreased objective employment security, one first has to quantify international outsourcing which 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 also be 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 are utilized to allocate imports according to their usage as input factors across industries:

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

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 j abroad as a share of the domestic industry's production value:

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

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. However, one has to bare in mind that the level of international outsourcing is only secondary. It is the development of outsourcing over time that indicates important underlying structural changes.[3] 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 manufacturing industry shows significant growth in its outsourcing intensity.

In a first analytic step one can now relate the change in industry-level outsourcing to industry-level employment security. As becomes evident in Figure 3 one can observe a positive correlation between changes in international outsourcing and the individual risk of leaving employment in 15 out of 21 industries. However, such an analysis needs to be considerably refined to establish any causal relationship between international outsourcing and employment security.

[3] Accordingly, in the econometric analysis presented in Section 6 the effects of international outsourcing are only identified through changes over time as the model includes industry fixed effects.

3 Previous Literature

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; Ekholm and Hakkala, 2005). However, while the aforementioned studies can quantify the aggregated demand effects of outsourcing the dynamics behind that process remain in the dark.

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 for labor market dynamics has remained largely unaddressed in the literature. 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. However, industry-level results can be severely biased due to the use of aggregated data which impedes controlling for important compositional changes e.g. in the gender or education structure of employment. Furthermore, most industry-level studies assume international outsourcing to be exogenous to labour demand, an assumption that is rarely tested. If international outsourcing is, however, jointly determined with the demand for labour, estimated coefficients suffer from endogeneity bias.

Egger et al. (2006) therefore assess the effects of international outsourcing for the transition probabilities of employment utilizing a random sample of Austrian social security data. By doing so the effects of international outsourcing can be assessed at the individual level avoiding aggregation bias and considerably reducing potential endogeneity bias as individual characteristics are unlikely to affect industry-level aggregates. To control for unobserved individual heterogeneity the authors chose a fixed effects specification applying the estimator proposed by Honoré and Kyriazidou (2000). Although such a fixed effects specification has the clear advantage that no assumptions about the correlation between the unobserved component and the individual time varying variables have to be made, the estimator proposed by Honoré and Kyriazidou (2000) does not allow to compute the probabilities of the transition matrix since no constant can be estimated. The results of Egger et al. (2006) suggest that international 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. More recently, Munch (2005) analyses the impact of industry-level international outsourcing on job separations using yearly data for a ten percent 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.

To the best knowledge of the author the present study is the first empirical analysis of the impact of international outsourcing on employment security for the German labour market. It builds on the contributions of Egger et al. (2006) and Munch (2005) but departs in several important ways. First of all, instead of looking at year to year transitions we use monthly employment data. This allows us to more comprehensively control for the duration dependence of employment loss by taking also short term employment spells into account. Furthermore, we control for a wider range of time changing individual and work-place related characteristics and also include industry and region fixed effects to capture unobserved characteristics thereby avoiding potential endogeneity bias.

4 Modelling employment duration

The present study utilizes a large sample of monthly spell data from the German Socio-Economic Panel (GSOEP) for the years 1991 to 2000.[4] Although employment transitions can in principle occur in continuous time, in the data one can only observe monthly spells. Accordingly, a discrete time hazard model is specified. The data allow 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

[4]The choice of the sample period is determined by the availability of input-output data to construct the outsourcing measure.

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.[5] 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.[6]

Furthermore, accounting for duration dependence is essential, as one would expect employment insecurity to typically decline with job duration as employees accumulate firm-specific human capital.[7] 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.

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 $t-1$:

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

where X_i denotes a vector of individual characteristics and γ_{it} describes set of interval dummies for employment duration. Furthermore, ϵ_i^m denotes a time-invariant individual error component that is distributed such that:

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

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

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

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

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

[5]However, as authors such as Dolton and von der Klaauw (1995) 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.

[6]The availability of repeated spell observations in our sample in principle would also allow for a fixed effects treatment of unobserved heterogeneity. However, as the number of repeated out of employment transitions is very small in our sample fixed effects are not appropriate as the parameters cannot be identified.

[7]See Farber, 1999 for a discussion.

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

$$\lambda_i(X_{it}, \gamma_{it}, \epsilon_i^m) = 1 - exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m)) \tag{8}$$

one can transform Equation 7 into:

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

with $c_i = 1$ if the employment spell of individual i is completed and $c_i = 0$ if it is censored.

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 individuals, one additional integration step is required. If we let k denote the number of employment spells by each individual, then

$$\begin{aligned} L &= \prod_{i=1}^{n} \sum_{m=1}^{M} Pr(\epsilon_i^m) \prod_{k=1}^{K_i} \left(\frac{1 - exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m))}{exp(-exp(\beta' X_{it} + \gamma_{it} + \epsilon_i^m))} \right)^{c_{ik}} \\ &\times \prod_{j=1}^{t} exp(-exp(\beta' X_{ij} + \gamma_{ij} + \epsilon_i^m)) \end{aligned} \tag{10}$$

denotes the overall likelihood function.

5 Empirical strategy and data

The empirical analysis is based on stock-sampled monthly individual-level spell data from the German Socio-Economic Panel (GSOEP) for the period 1991 to 2000. 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.[8]

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 are reorganized as *person-period data* to foster *easy* estimation methods, as discussed in Allison (1982) and Jenkins (1995) yielding a total of 213750 monthly observations for 5431 individuals.

[8]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.

An inevitable aspect of stock sampling is left truncation of ongoing employment spells. The sample period for observing employment duration starts in 1991.[9] 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 by adjusting the employment duration parameters γ_{it} in Equation 10 upwards.

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 do 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, maternity leave or transition into non-manufacturing employment, 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.

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 (e.g. Royalty, 1998; Zavodny, 2003, Farber, 1999, Kletzer, 1998 and Farber, 2005). Accordingly, the vector X_{it} in Equation 10 consists of a set of basic demographic controls, occupational placement, work place characteristics, individual skills and region and industry specific controls. 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 make 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

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

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.

We do not explicitly control for the frequency and duration of past employment spells. As our set of individual control variables already is fairly comprehensive including such additional controls, which are essentially determined by our other explanatory variables (e.g., education), would give rise to multicolinearity and does not improve the model.

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.[10]

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.

Furthermore, we control for unobserved region and industry specific heterogeneity by including a set of industry and region dummies. Accordingly, our outsourcing parameter is only identified trough changes in an industry's outsourcing intensity.

[10]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.

Together with our time varying firm level variables (e.g., firm size), industry and region dummies should ensure that our outsourcing coefficient is not merely a result of firm or industry specific unobservable characteristics that are correlated with the outsourcing measure.[11]

A comprehensive list of our control variables with corresponding summary statistics is reported in Table 3.

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, as authors such as Angrist and Lavy (2002) stress, the equi-correlated error structure imposed by this method is inappropriate in the context of models with binary outcomes and suggest to apply the Generalised 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 if the number of clusters is large relative to the number of within cluster observations (See e.g. Wooldridge, 2002, Ch. 11 for a discussion.) casting doubt on the applicability within our model. However, through the inclusion of industry and region dummies one can considerably reduce contemporaneous correlation in the residual as the residual correlation within clusters due to time constant unobserved heterogeneity is accounted for. Nevertheless, we recognise that the standard errors are still potentially biased as we fail to correct for potential serial correlation within clusters. We therefore present bootstrapped standard errors in Table 7 to show the robustness of our findings with respect to within cluster serial correlation.[12]

[11] Obviously, an estimation with firm-level fixed effects would be desirable but would require matched employer-employee data with a sufficient number of out-off employment transitions by firm.

[12] Following Greene (2000) we can calculate the standard errors of the estimated parameters according to following formula:

$$\widetilde{Var}(\beta) = \frac{1}{R}\sum_{r=1}^{R}(b_r^{cloglog} - b^{cloglog})(b_r^{cloglog} - b^{cloglog})' \tag{11}$$

where R denotes the number of repetitions (500), $b_r^{cloglog}$ the vector of parameter estimates from the rth regression based on the random sample of 10100 individual spells and $b^{cloglog}$ the vector of parameter estimates for the cloglog model based on the full original sample.

6 Estimation and results

Column I of Table 4 presents the results of a simple cloglog hazard rate model as a benchmark abstracting from individual unobserved heterogeneity. To control for unobserved heterogeneity we start by estimating Equation 10 with two mass points and subsequently add additional masses holding all parameters constant at their previous maximum-likelihood levels until the log-likelihood fails to increase significantly. The parameter estimates of the fully specified model as in Equation 10 with four mass points are presented in Column II of Table 4.[13]

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 specifications the hazard of exiting employment 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 employment duration, confirming Farber (1999).[14] Furthermore, the hazard of exiting employment increases with age, however, not linearly and decreases with higher educational attainment. Women face a significantly higher risk of leaving employment than men. In line with the findings of Beeson Royalty (1998) having children in the household and marital status have a significantly different impact on men and women as the statistically significant coefficients of the interaction terms indicate. Accordingly, women with children face a significantly higher risk of leaving employment than men with children. Furthermore, men have a significantly lower probability of leaving employment when married while for women the opposite is true.

Firm size is found to be positively related to employment security which is in line with Gómez-Salvador, Messina and Vallanti (2004). Public ownership, however has no significant impact on individual employment security. Furthermore higher occupational placement has no clear impact on employment security. After controlling for unobserved heterogeneity we only find negative significant coefficients for clerks and crafts workers.

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 employment loss would also be standard control variables in a wage regression. However, wages can be a powerful predictor of unobserved

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

[14] Note that Farber (1999) is concerned with job duration as opposed to employment duration. The line of argument, however, still applies.

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.[15] 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. However, a comparison between the estimates in Column III and II of Table 4 reveals that excluding wages from the model results in only modest parameter alterations.[16]

Regarding the regional and industry-level variables, regional unemployment, ceteris paribus, is found to significantly raise the risk of leaving employment at least after one controls for unobserved heterogeneity.[17] Furthermore, 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.[18] 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) at least after we control for unobserved individual heterogeneity. With regard to the industry-level capital intensity, only capital in the form of plant is found to increases employment security. Regarding industry output, the coefficient is negative and weakly significant and the overall marginal effect is negative.[19]

For this analysis, the most interesting variable is, of course international outsourcing ($OUTS$). All model specifications reported in Table 4 yield a positive and highly significant coefficient which is fairly similar in size independent of whether one controls for unobserved heterogeneity or one excludes wages from the regressors. Ceteris paribus, a one percentage point increase in an industry's outsourcing intensity increases the hazard of leaving employment by about six percent (Simple model: $exp(0.059) - 1 = 0.061$, Full model:$exp(0.054) - 1 = 0.055$). Thus, industry level in-

[15] 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.

[16] One notable difference exists with respect to educational attainment and occupational placement which are standard control variables in any wage regression, and are typically highly correlated with wages.

[17] Our results are therefore is in line with earlier findings of Zavodny (2003) for involuntary job separations in the US.

[18] 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.

[19] Looking at the fully specified model the coefficients on output and capital intensity are negative 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. Thus, increases in industry output raise individual employment security.

ternational outsourcing is indeed 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.[20] 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 4 presents the coefficient estimates for this specification. Again, technological progress results in reduced employment security, the effect is however only statistically significant for medium- and low-skilled workers. 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 indicate that one cannot reject teh pooled model within reasonable confidence bounds.[21] Accordingly, the effects of international outsourcing and technological progress do not differ significantly between skill groups.[22]

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 insignificant (Column I of Table 5). When interacting outsourcing with skill, we find a significant positive coefficients for medium-skilled workers. However, as the likelihood ratio test statistics in Column II of Table 5 indicates, we again cannot reject the pooled model.

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 assess the economic

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

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

[22]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 II in Table 4 the model predicts that between 1991 and 2000 international outsourcing increased the hazard of existing employment by approximately 13 percent ($exp(0.054 * 2.28) - 1 = 0.131$). In comparison the effects of technological progress, at least as captured by R&D expenditures, 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 less than one percent ($exp(0.140 * 0.06) - 1 = 0.00844$).

In a next step it is interesting to assess how the impact of international outsourcing varies with employment duration shedding light on the role of unobserved firm specific human capital for mitigating the effects of outsourcing. In order to address this issue we simply interact international outsourcing with the duration dummies and re-estimate the model. Table 6 presents the outcome of this exercise for the simple cloglog and the fully specified model. In both models the negative impact of international outsourcing on individual employment security appears to increases with job duration. However, as the likelihood ratio test in Table 6 indicates, in the fully specified model that controls for unobserved heterogeneity we can reject the hypothesis of a uniform impact of international outsourcing over employment duration within reasonable confidence bounds.[23] While the general risk of leaving employment declines with employment duration which is in line with the idea that over time workers accumulate firm-specific capital (see Farber, 1999), the specific impact of international outsourcing follows a different pattern with positive instead of negative duration dependence. We interpret this result as evidence that international outsourcing represents a substantial technological change that leads to a devaluation of firm-specific human capital. Workers then face a situation in which their previous human capital wage premiums are not longer sustainable. In this scenario longer tenured, more experienced workers may be more affected since the discrepancy between the wage that is sustainable under the outsourcing regime and the previous human capital wage premium is particularly large. Accordingly, if wages do not adjust downwards, longer tenured workers are more likely to exit employment due to international outsourcing. To what extent existing German labour market institutions constitute an obstacle to required wage cuts is an

[23] Strictly speaking the standard errors of the interaction parameter estimates could be biased downwards due to within cluster serial correlation as previously discussed. However, when interacting duration dummies and industry level outsourcing the clusters become much smaller which arguably reduces potential distortions in the standard errors.

interesting question for further research.

7 Discussion

The paper expands the existing literature by analyzing the effects of international outsourcing for individual employment 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 are arguably better suited to describe individual skills than the manual vs. non-manual worker skill approximation that is commonly used in the literature.

Our main findings are that workers with less than seven months of employment duration face the highest risk of leaving employment. Afterwards, employment 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).[24] Similarly, with regard to technological progress we find only uniform negative effects for individual employment security across different skill groups. At first sight this stark discrepancy between industry-level findings on relative employment effects of international outsourcing and technological change and our micro-level results is puzzling. However, while industry-level studies are concerned with partial equilibrium net effects we look at the dynamics of the adjustment process in response to international outsourcing (an technological change). 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 that have been found for Germany in aggregated industry-level studies (e.g.,Falk and Koebel, 2002; Geishecker, 2006) are indirect and related to the lower probability of low-skilled workers to reenter employment.

In addition, we find evidence that the impact of international outsourcing varies with employment duration. While we estimate a negative general duration depen-

[24] An exception is Ekholm and Hakkala (2005) for Sweden who find medium-skilled workers to most adversly affected by international outsourcing.

dence we find some evidence that the specific effect of international outsourcing is characterized by positive duration dependence. Thus the risk of leaving employment due to outsourcing increases with employment duration. Although our model is not suited to address this issue directly, this is in line with the idea that international outsourcing represents a major technological shift that leads to a devaluation of firm-specific human capital. Accordingly, the previous human capital wage premium may not be sustainable which is particularly relevant for more experienced, longer tenured workers.

Finally, it is important to stress that the present analysis only focuses on one side of the labour market adjustment process, namely on out of employment transitions. While we can provide evidence that outsourcing uniformly raises the risk of leaving employment, the number of reported transitions in the GSOEP data are to small to analyse whether outsourcing also has a direct effect on the probability of re-entering employment. As has been previously discussed, low-skilled workers face a significantly lower probability of re-entering employment. However, to what extent this lower probability is determined by international outsourcing remains an open question for future research. Ideally, a future study would employ a much larger micro-level data set, such as the social insurance sample provided by the Institut für Arbeitsmarkt und Berufsforschung (IAB) to analyse out-off employment and out-off unemployment transitions simultaneously.

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Figures and Tables

Table 1: Risk of existing employment over time in %

Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	Total
Pooled over all skill groups	0.79	1.07	1.2	1.01	1.18	1.22	1.29	1.18	1.36	1.58	1.2
High-Skilled	0.21	0.58	0.26	0.20	0.69	0.45	0.38	0.25	0.25	1.03	0.49
Medium-Skilled	0.25	0.76	0.70	0.78	0.66	0.74	0.99	1.01	1.34	0.99	0.84
Low-Skilled	0.96	1.20	1.42	1.19	1.37	1.46	1.54	1.40	1.59	1.85	1.39
Number of observations	24,445	22,451	20,362	19,792	20,465	18,940	18,309	19,832	19,400	29,754	213,750

Table 2: Individually reported concern to lose job within the next year, shares in %

Year	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
All Skill Groups										
Very Concerned	13.4	14.35	16.03	21.29	14.59	13.4	21.53	16.03	13.4	15.07
Somewhat Concerned	35.17	46.41	49.52	51.91	50.72	51.67	50.96	49.04	53.83	50.48
Not Concerned At All	51.44	39.23	34.45	26.79	34.69	34.93	27.51	34.93	32.78	34.45
High-Skilled										
Very Concerned	15.00	11.67	16.67	18.33	10.00	10.00	13.33	10.00	13.33	16.05
Somewhat Concerned	23.33	40.00	50.00	55.00	46.67	50.00	58.33	53.33	48.33	46.91
Not Concerned At All	61.67	48.33	33.33	26.67	43.33	40.00	28.33	36.67	38.33	37.04
Medium-Skilled										
Very Concerned	15.52	16.95	13.56	27.12	19.67	12.70	24.19	22.58	11.11	14.04
Somewhat Concerned	32.76	52.54	52.54	44.07	52.46	57.14	43.55	40.32	53.97	56.14
Not Concerned At All	51.72	30.51	33.90	28.81	27.87	30.16	32.26	37.10	34.92	29.82
Low-Skilled										
Very Concerned	12.67	14.38	16.39	20.74	14.48	14.24	22.64	15.88	13.90	15.00
Somewhat Concerned	38.00	46.49	48.83	52.84	51.18	50.85	51.01	50.00	54.92	50.36
Not Concerned At All	49.33	39.13	34.78	26.42	34.34	34.92	26.35	34.12	31.19	34.64

Notes: Calculated based on balanced panel of 418 individuals.

Figure 1: Outsourcing over time

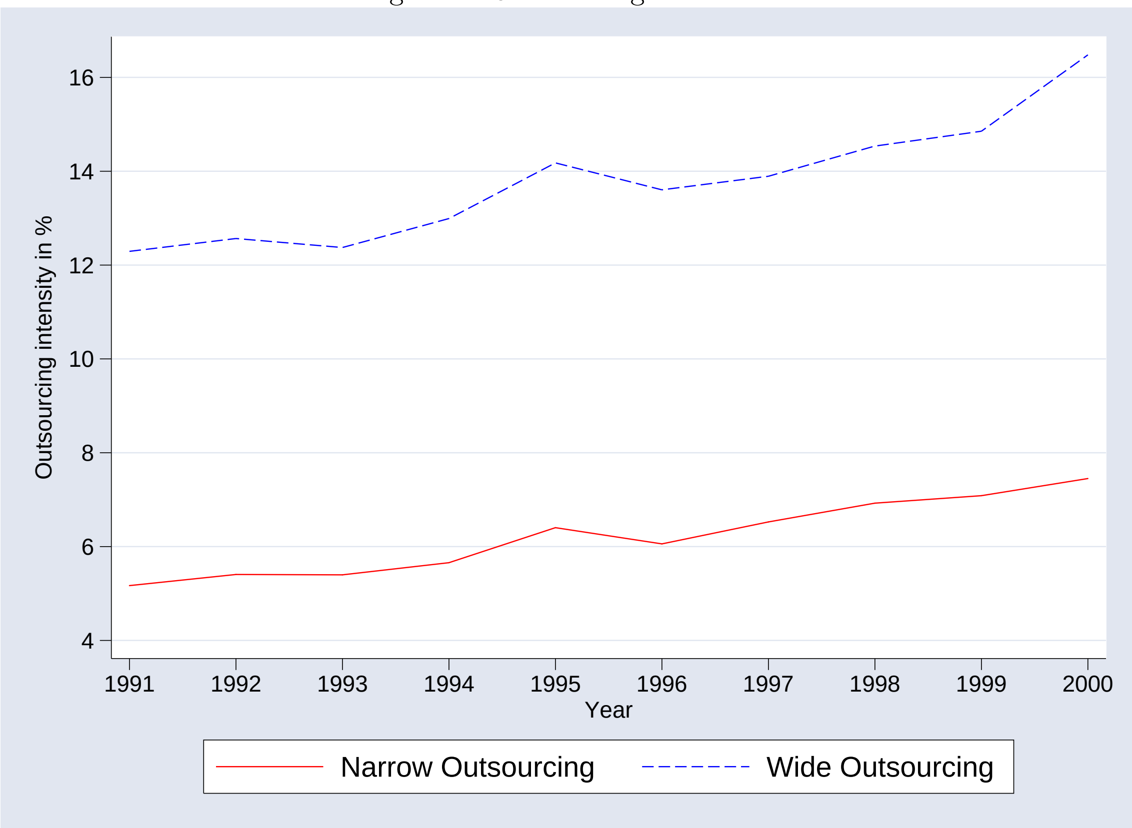

Figure 2: Outsourcing over time by industry

Figure 3: Outsourcing and employment security

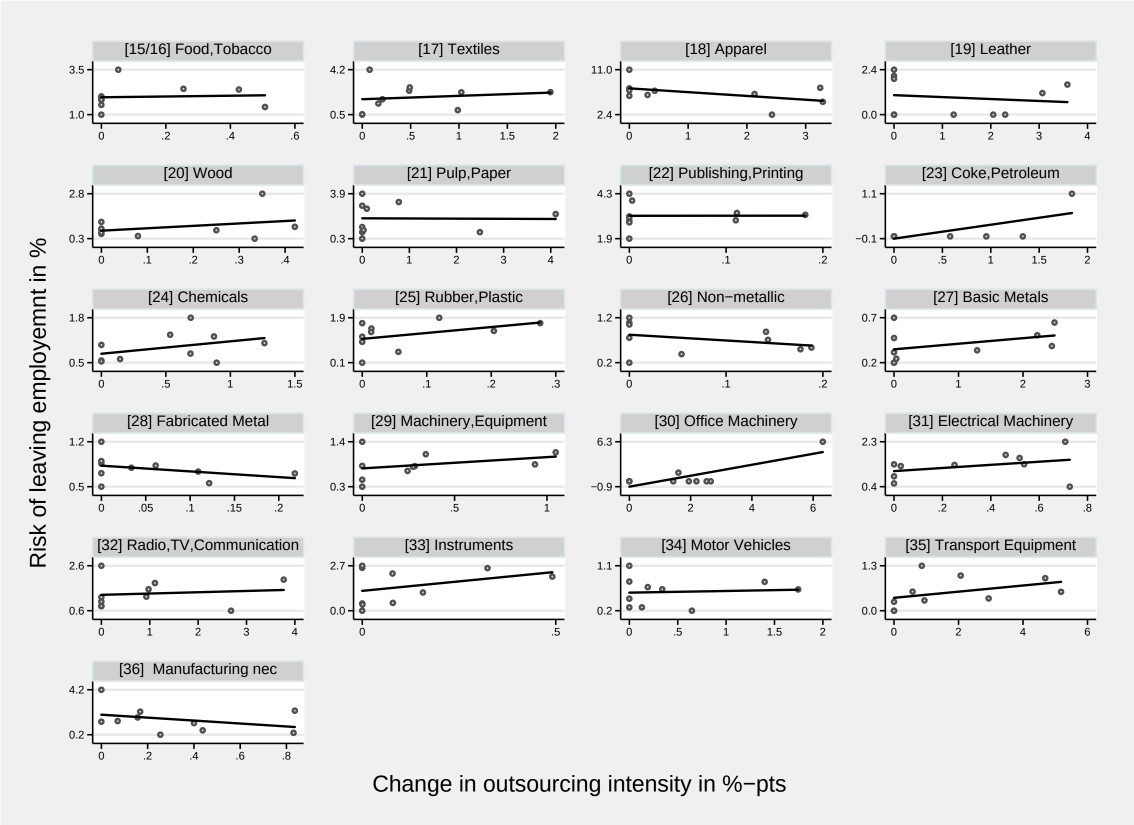

Table 3: Summary statistics

		Mean	Standard Deviation
Transitions out of employment		0.012	[0.109]
Employment duration 0-6 months	$DD : 0-6$	0.189	[0.392]
Employment duration 7-12 months	$DD : 7-12$	0.134	[0.341]
Employment duration 13-36 months	$DD : 13-36$	0.281	[0.450]
Employment duration 37-96 months	$DD : 37-96$	0.295	[0.456]
Employment duration ¿=97 months	$DD :>= 97$	0.101	[0.301]
Age	AGE	39.718	[10.515]
Gender	$MALE : Yes$	0.736	[0.441]
Respondent has children in HH	$CHILD : Yes$	0.511	[0.500]
Marital Status	$MARRIED : Yes$	0.741	[0.438]
Nationality	$GERMAN : Yes$	0.779	[0.415]
Workplace in East Germany	$WorkinEast : Yes)$	0.174	[0.379]
Hourly Wage	$HWage$	11.637	[5.856]
Wage is missing	$MissWage$	0.089	[0.285]
Firm size ¡20 employees	$FS :< 20$	0.149	[0.356]
Firm size 21-199 employees	$FS : 21-199$	0.284	[0.451]
Firm size 200-1999 employees	$FS : 200-1999$	0.314	[0.464]
Firm size ¿=2000 employees	$FS :> 2000$	0.250	[0.433]
Firm public ownership	$PUBOWN : Yes$	0.010	[0.101]
Occupation: manager,technician,scientist	$OCC : Manager$	0.272	[0.445]
Occupation: clerk	$OCC : Clerk$	0.086	[0.281]
Occupation: service worker	$OCC : Service$	0.016	[0.125]
Occupation: crafts worker	$OCC : Craft$	0.358	[0.479]
Occupation: skilled machine operator	$OCC : Swork$	0.183	[0.387]
Occupation: unskilled worker	$OCC : Uwork$	0.073	[0.261]
High education	$ED : High$	0.138	[0.345]
Medium education	$ED : Med$	0.134	[0.340]
Low education	$ED : Low$	0.729	[0.445]
Regional unemployment	$UNEMP$	9.880	[3.929]
R&D intensity	$\frac{R\&D}{Y}$	2.356	[2.846]
Net exports	$(Exp - Imp)$	11.250	[15.796]
Production value	$Y * 10^{-3}$	79.393	[42.226]
Capital intensity:Equipment	$\frac{Equip}{Y}$	29.057	[8.650]
Capital intensity:Plant	$\frac{Plant}{Y}$	17.307	[5.480]
Narrow outsourcing	$OUTS^{narrow}$	5.566	[4.684]
Wide outsourcing	$OUTS^{wide}$	12.184	[5.870]
Year Dummies	$Year = 1991$	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	

Table 4: Hazard Rate Model - Narrow Outsourcing

	I		II		III		IV	
$DD: 0-6$	3.659	[0.218]***	2.726	[0.237]***	2.841	[0.236]***	2.761	[0.238]***
$DD: 7-12$	2.341	[0.226]***	2.047	[0.243]***	2.138	[0.243]***	2.072	[0.243]***
$DD: 13-36$	1.431	[0.226]***	1.323	[0.242]***	1.391	[0.241]***	1.340	[0.242]***
$DD: 37-96$	0.995	[0.230]***	1.127	[0.244]***	1.149	[0.244]***	1.116	[0.245]***
AGE	0.003	[0.016]	-0.023	[0.021]	-0.038	[0.021]*	-0.060	[0.022]***
$AGE^2/100$	0.038	[0.019]**	0.054	[0.026]**	0.071	[0.025]***	0.105	[0.027]***
$MALE: Yes$	-0.342	[0.096]***	-0.849	[0.138]***	-0.823	[0.136]***	-0.766	[0.139]***
$CHILD: Yes$	0.218	[0.091]**	-0.036	[0.110]	-0.037	[0.109]	-0.007	[0.110]
$CHILD: Yes * FEMALE$	0.682	[0.101]***	0.585	[0.129]***	0.698	[0.129]***	0.683	[0.132]***
$MARRIED: Yes$	-0.456	[0.097]***	-0.399	[0.123]***	-0.403	[0.122]***	-0.353	[0.124]***
$MARRIED: Yes * FEMALE$	0.940	[0.112]***	0.731	[0.147]***	0.878	[0.142]***	0.848	[0.147]***
$GERMAN: Yes$	0.371	[0.061]***	-0.029	[0.085]	-0.045	[0.084]	-0.100	[0.088]
$WorkinEast: Yes$	-0.298	[0.148]**	-0.121	[0.173]	-0.058	[0.168]	-0.165	[0.173]
Hourly Wage	-0.049	[0.006]***	-0.052	[0.008]***			-0.049	[0.008]***
Wage is missing	-0.258	[0.081]***	-0.393	[0.096]***			-0.381	[0.100]***
$FS :< 20$	0.258	[0.076]***	0.192	[0.096]**	0.173	[0.092]*	0.015	[0.101]
$FS: 21-199$	0.075	[0.073]	0.230	[0.094]**	0.215	[0.090]**	0.120	[0.092]
$FS: 200-1999$	0.093	[0.073]	0.137	[0.090]	0.043	[0.090]	-0.062	[0.091]
$PUBOWN: Yes$	-0.079	[0.218]	0.269	[0.255]	0.334	[0.254]	0.229	[0.255]
$OCC: Manager$	-0.413	[0.074]***	-0.072	[0.094]	-0.165	[0.092]*	-0.117	[0.097]
$OCC: Clerk$	-0.068	[0.070]	-0.171	[0.087]**	-0.189	[0.083]**	-0.058	[0.090]
$OCC: Service$	-0.141	[0.098]	0.002	[0.133]	-0.037	[0.125]	-0.038	[0.138]
$OCC: Craft$	-0.399	[0.071]***	-0.305	[0.084]***	-0.331	[0.084]***	-0.206	[0.091]**
$OCC: Swork$	-0.282	[0.073]***	-0.049	[0.089]	-0.021	[0.090]	-0.023	[0.101]
$ED: High$	-0.323	[0.093]***	-0.236	[0.123]*	-0.337	[0.123]***	-0.082	[0.192]
$ED: Med$	-0.155	[0.071]**	0.000	[0.117]	-0.184	[0.106]*	-0.159	[0.141]
$UNEMP$	-0.033	[0.031]	0.055	[0.027]**	0.046	[0.027]*	0.057	[0.028]**
$R\&D/Y$	0.173	[0.060]***	0.140	[0.067]**	0.180	[0.068]***		
$R\&D/Y * ED: High$							0.126	[0.084]
$R\&D/Y * ED: Med$							0.167	[0.079]**
$R\&D/Y * ED: Low$							0.207	[0.069]***
$(Exp-Imp)$	0.023	[0.014]*	0.025	[0.016]	0.024	[0.016]	0.018	[0.016]
$Y * 10^{-3}$	-0.012	[0.006]*	-0.012	[0.007]*	-0.008	[0.007]	-0.007	[0.007]
$Equip/Y$	0.033	[0.020]	0.028	[0.023]	0.021	[0.023]	0.024	[0.023]
$Plant/Y$	-0.106	[0.029]***	-0.058	[0.034]*	-0.053	[0.034]	-0.049	[0.035]
OUT	0.059	[0.021]***	0.054	[0.023]**	0.053	[0.023]**		
$OUT * ED: High$							0.066	[0.036]*
$OUT * ED: Med$							0.096	[0.033]***
$OUT * ED: Low$							0.053	[0.025]**
$Year = 1992$	1.270	[0.111]***	0.929	[0.118]***	0.940	[0.121]***	0.917	[0.118]***
$Year = 1993$	1.258	[0.147]***	0.819	[0.153]***	0.867	[0.156]***	0.822	[0.153]***
$Year = 1994$	1.199	[0.166]***	0.704	[0.169]***	0.752	[0.172]***	0.690	[0.170]***
$Year = 1995$	1.230	[0.162]***	0.739	[0.165]***	0.824	[0.168]***	0.748	[0.168]***
$Year = 1996$	1.412	[0.183]***	0.775	[0.182]***	0.844	[0.185]***	0.798	[0.185]***
$Year = 1997$	1.465	[0.207]***	0.800	[0.201]***	0.857	[0.204]***	0.808	[0.204]***
$Year = 1998$	1.238	[0.195]***	0.673	[0.192]***	0.704	[0.196]***	0.653	[0.196]***
$Year = 1999$	1.365	[0.181]***	0.846	[0.181]***	0.895	[0.184]***	0.816	[0.183]***
$Year = 2000$	1.297	[0.163]***	0.832	[0.175]***	0.851	[0.177]***	0.847	[0.178]***
$Constant = \epsilon_i^{m=1}$	-5.649	[1.235]***	-7.124	[1.400]***	-7.657	[1.388]***	-7.203	[1.375]***
$P(\epsilon_i^{m=1})$			0.686	[0.263]	0.693	[0.294]	0.734	[0.107]
$\epsilon_i^{m=2}$			-2.660	[1.417]*	-2.719	[1.399]*	-3.981	[1.369]***
$P(\epsilon_i^{m=2})$			0.003	[0.001]	0.002	[0.001]	0.141	[0.021]
$Constant = \epsilon_i^{m=3}$			-5.174	[1.400]***	-5.631	[1.400]***	-2.145	[1.396]
$P(\epsilon_i^{m=3})$			0.141	[0.054]	0.128	[0.054]	0.001	[0.000]
$\epsilon_i^{m=4}$			-3.854	[1.390]***	-4.361	[1.373]***	-4.810	[1.378]***
$P(\epsilon_i^{m=4})$			0.170	[0.016]	0.177	[0.017]	0.123	[0.025]
Industry Dummies	Yes		Yes		Yes		Yes	
Region Dummies	Yes		Yes		Yes		Yes	
Log likelihood	-9844.67		-9028.67		-9048.63		-9027.62	
Observations	213750		213750		213750		213750	
Waldtest:OUT*ED:High,MED,LOW equal:$\chi^2(2)$							3.44	
p-value							0.18	
Waldtest:R&D/Y*ED:High,MED,LOW equal:$\chi^2(4)$							3.29	
p-value							0.19	
LR Test, Pooled vs. interacted model:$\chi^2(4)$							2.10	
p-value							0.72	

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
Default categories:$DD :> 97$, $FS :>= 2000$, $OCC: Uwork$, $ED: Low$

Table 5: Hazard Rate Model - Wide Outsourcing

	I		II	
$DD: 0-6$	2.726	[0.238]***	2.742	[0.238]***
$DD: 7-12$	2.046	[0.243]***	2.067	[0.244]***
$DD: 13-36$	1.323	[0.242]***	1.345	[0.243]***
$DD: 37-96$	1.126	[0.244]***	1.146	[0.245]***
AGE	-0.025	[0.022]	-0.021	[0.021]
$AGE^2/100$	0.057	[0.026]**	0.053	[0.026]**
$MALE: Yes$	-0.850	[0.138]***	-0.887	[0.140]***
$CHILD: Yes$	-0.035	[0.111]	-0.032	[0.112]
$CHILD: Yes * FEMALE$	0.584	[0.129]***	0.585	[0.130]***
$MARRIED: Yes$	-0.402	[0.123]***	-0.404	[0.124]***
$MARRIED: Yes * FEMALE$	0.731	[0.148]***	0.678	[0.150]***
$GERMAN: Yes$	-0.029	[0.085]	-0.056	[0.088]
$WorkinEast: Yes$	-0.117	[0.173]	-0.120	[0.173]
$Hourly\ Wage$	-0.052	[0.008]***	-0.054	[0.008]***
$Wage\ is\ missing$	-0.390	[0.096]***	-0.388	[0.095]***
$FS: < 20$	0.199	[0.096]**	0.173	[0.097]*
$FS: 21-199$	0.231	[0.094]**	0.183	[0.093]*
$FS: 200-1999$	0.139	[0.090]	0.111	[0.091]
$PUBOWN: Yes$	0.280	[0.255]	0.353	[0.263]
$OCC: Manager$	-0.075	[0.095]	-0.065	[0.096]
$OCC: Clerk$	-0.173	[0.087]*	-0.199	[0.088]**
$OCC: Service$	-0.010	[0.133]	-0.044	[0.130]
$OCC: Craft$	-0.307	[0.084]***	-0.297	[0.084]***
$OCC: Swork$	-0.055	[0.089]	-0.070	[0.089]
$ED: High$	-0.232	[0.123]*	-0.282	[0.268]
$ED: Med$	-0.003	[0.121]	-0.811	[0.213]***
$UNEMP$	0.054	[0.027]*	0.054	[0.027]*
$R\&D/Y$	0.117	[0.067]*		
$R\&D/Y * ED: High$			0.060	[0.078]
$R\&D/Y * ED: Med$			0.158	[0.075]**
$R\&D/Y * ED: Low$			0.114	[0.067]*
$(Exp-Imp)$	0.025	[0.016]	0.028	[0.016]*
$Y * 10^{-3}$	-0.013	[0.007]*	-0.014	[0.007]*
$Equip/Y$	0.026	[0.023]	0.030	[0.023]
$Plant/Y$	-0.057	[0.036]	-0.062	[0.036]*
OUT	0.021	[0.018]		
$OUT * ED: High$			0.032	[0.026]
$OUT * ED: Med$			0.064	[0.024]**
$OUT * ED: Low$			0.019	[0.018]
$Year = 1992$	0.939	[0.119]***	0.935	[0.119]***
$Year = 1993$	0.840	[0.153]***	0.834	[0.151]***
$Year = 1994$	0.739	[0.169]***	0.727	[0.169]***
$Year = 1995$	0.781	[0.168]***	0.794	[0.168]***
$Year = 1996$	0.821	[0.182]***	0.822	[0.183]***
$Year = 1997$	0.850	[0.201]***	0.839	[0.202]***
$Year = 1998$	0.733	[0.195]***	0.723	[0.196]***
$Year = 1999$	0.899	[0.186]***	0.890	[0.187]***
$Year = 2000$	0.891	[0.187]***	0.867	[0.187]***
$Constant = \epsilon_i^{m=1}$	-6.998	[1.416]***	-6.857	[1.422]***
$P(\epsilon_i^{m=1})$	0.686	[0.263]	0.687	[0.235]
$\epsilon_i^{m=2}$	-2.531	[1.431]*	-2.437	[1.434]*
$P(\epsilon_i^{m=2})$	0.003	[0.001]	0.004	[0.001]
$Constant = \epsilon_i^{m=3}$	-5.050	[1.415]***	-4.942	[1.420]***
$P(\epsilon_i^{m=3})$	0.142	[0.054]	0.137	[0.047]
$\epsilon_i^{m=4}$	-3.728	[1.405]***	-3.592	[1.409]**
$P(\epsilon_i^{m=4})$	0.169	[0.017]	0.172	[0.016]
Industry Dummies	Yes		Yes	
Region Dummies	Yes		Yes	
Log likelihood	-9030.67		-9026.92	
Observations	213750		213750	
Waldtest:OUT*ED:High,MED,LOW equal:$\chi^2(2)$			6.820	
p-value			0.033	
Waldtest: R&D/Y*ED:High,MED,LOW equal:$\chi^2(2)$			3.500	
p-value			0.174	
LR Test, Pooled vs. interacted model:$\chi^2(4)$			7.492	
p-value			0.112	

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
Default categories:$DD :> 97$, $FS :>= 2000$, $OCC : Uwork$, $ED : Low$

Table 6: Hazard Rate Model - Narrow Outsourcing interacted with duration

	I		II	
$DD: 0-6$	3.931	[0.340]***	3.173	[0.359]***
$DD: 7-12$	2.793	[0.352]***	2.514	[0.370]***
$DD: 13-36$	1.596	[0.351]***	1.592	[0.369]***
$DD: 37-96$	1.263	[0.358]***	1.427	[0.373]***
AGE	-0.005	[0.015]	-0.022	[0.021]
$AGE^2/100$	0.049	[0.019]***	0.053	[0.026]**
$MALE: Yes$	-0.347	[0.096]***	-0.851	[0.138]***
$CHILD: Yes$	0.231	[0.091]**	-0.032	[0.110]
$CHILD: Yes * FEMALE$	0.667	[0.101]***	0.569	[0.129]***
$MARRIED: Yes$	-0.460	[0.096]***	-0.405	[0.123]***
$MARRIED: Yes * FEMALE$	0.960	[0.112]***	0.741	[0.147]***
$GERMAN: Yes$	0.362	[0.061]***	-0.033	[0.085]
$WorkinEast: Yes$	-0.641	[0.099]***	-0.125	[0.173]
$Wage$	-0.046	[0.006]***	-0.053	[0.008]***
$Wageismissing$	-0.238	[0.080]***	-0.406	[0.096]***
$FS :< 20$	0.241	[0.076]***	0.201	[0.096]**
$FS: 21-199$	0.043	[0.073]	0.233	[0.094]**
$FS: 200-1999$	0.081	[0.073]	0.137	[0.090]
$PUBOWN: Yes$	-0.067	[0.218]	0.283	[0.254]
$OCC: Manager$	-0.429	[0.074]***	-0.076	[0.094]
$OCC: Clerk$	-0.097	[0.070]	-0.171	[0.087]**
$OCC: Service$	-0.117	[0.098]	0.004	[0.133]
$OCC: Craft$	-0.417	[0.070]***	-0.305	[0.084]***
$OCC: Swork$	-0.266	[0.073]***	-0.042	[0.089]
$ED: High$	-0.325	[0.093]***	-0.233	[0.123]*
$ED: Med$	-0.127	[0.071]*	0.008	[0.115]
$UNEMP$	-0.037	[0.010]***	0.055	[0.027]**
$R\&D/Y$	0.159	[0.060]***	0.154	[0.067]**
$(Exp-Imp)$	0.025	[0.014]*	0.023	[0.016]
$Y * 10^{-3}$	-0.013	[0.006]**	-0.012	[0.007]*
$Equip/Y$	0.032	[0.020]	0.026	[0.023]
$Plant/Y$	-0.106	[0.029]***	-0.054	[0.034]
$OUT * DD: 0-6$	0.069	[0.021]***	0.047	[0.024]**
$OUT * DD: 7-12$	0.032	[0.026]	0.043	[0.029]
$OUT * DD: 13-36$	0.087	[0.025]***	0.081	[0.028]***
$OUT * DD: 37-96$	0.066	[0.025]***	0.074	[0.028]***
$OUT * DD :>= 97$	0.102	[0.038]***	0.115	[0.041]***
$Year = 1992$	1.285	[0.106]***	0.937	[0.118]***
$Year = 1993$	1.273	[0.124]***	0.828	[0.153]***
$Year = 1994$	1.207	[0.128]***	0.715	[0.169]***
$Year = 1995$	1.255	[0.126]***	0.745	[0.165]***
$Year = 1996$	1.441	[0.129]***	0.786	[0.182]***
$Year = 1997$	1.487	[0.134]***	0.815	[0.201]***
$Year = 1998$	1.249	[0.133]***	0.685	[0.193]***
$Year = 1999$	1.376	[0.132]***	0.859	[0.181]***
$Year = 2000$	1.300	[0.136]***	0.854	[0.175]***
$Constant = \epsilon_i^{m=1}$	-5.656	[1.181]***	-7.645	[1.425]***
$P(\epsilon_i^{m=1})$			0.691	[0.262]
$\epsilon_i^{m=2}$			-3.150	[1.440]**
$P(\epsilon_i^{m=2})$			0.003	[0.001]
$Constant = \epsilon_i^{m=3}$			-5.685	[1.425]***
$P(\epsilon_i^{m=3})$			0.136	[0.052]
$\epsilon_i^{m=4}$			-4.387	[1.415]***
$P(\epsilon_i^{m=4})$			0.171	[0.017]
Industry Dummies	Yes		Yes	
Region Dummies	Yes		Yes	
Log likelihood	-9877.75		-9024.33	
Observations	231750		231750	
Waldtest:OUT*DD equal, $Chi^2(4)$	9.090		9.000	
p-value	0.059		0.061	
LR Test, Pooled vs. interacted model : Chi2(4)	-		8.690	
p-value	-		0.069	

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
Default categories:$DD :> 97$,$FS :>= 2000$,$OCC: Uwork$,$ED: Low$

Table 7: Bootstrapped Standard Errors

	Full model		Simple model		Bootstrapped SE
$DD : 0-6$	2.726	[0.237]***	3.659	[0.218]***	[0.215]***
$DD : 7-12$	2.047	[0.243]***	2.341	[0.226]***	[0.221]***
$DD : 13-36$	1.323	[0.242]***	1.431	[0.226]***	[0.220]***
$DD : 37-96$	1.127	[0.244]***	0.995	[0.230]***	[0.230]***
AGE	-0.023	[0.021]	0.003	[0.016]	[0.016]
$AGE^2/100$	0.054	[0.026]**	0.038	[0.019]**	[0.000]**
$MALE : Yes$	-0.849	[0.138]***	-0.342	[0.096]***	[0.093]***
$CHILD : Yes$	-0.036	[0.110]	0.218	[0.091]**	[0.095]**
$CHILD : Yes * FEMALE$	0.585	[0.129]***	0.682	[0.101]***	[0.108]***
$MARRIED : Yes$	-0.399	[0.123]***	-0.456	[0.097]***	[0.099]***
$MARRIED : Yes * FEMALE$	0.731	[0.147]***	0.940	[0.112]***	[0.115]***
$GERMAN : Yes$	-0.029	[0.085]	0.371	[0.061]***	[0.067]***
$WorkinEast : Yes$	-0.121	[0.173]	-0.298	[0.148]**	[0.180]*
$Wage$	-0.052	[0.008]***	-0.049	[0.006]***	[0.007]***
$Wageismissing$	-0.393	[0.096]***	-0.258	[0.081]***	[0.090]***
$FS :< 20$	0.192	[0.096]**	0.258	[0.076]***	[0.078]***
$FS : 21-199$	0.230	[0.094]**	0.075	[0.073]	[0.077]
$FS : 200-1999$	0.137	[0.090]	0.093	[0.073]	[0.073]
$PUBOWN : Yes$	0.269	[0.255]	-0.079	[0.218]	[0.251]
$OCC : Manager$	-0.072	[0.094]	-0.413	[0.074]***	[0.078]***
$OCC : Clerk$	-0.171	[0.087]**	-0.068	[0.070]	[0.078]
$OCC : Service$	0.002	[0.133]	-0.141	[0.098]	[0.105]
$OCC : Craft$	-0.305	[0.084]***	-0.399	[0.071]***	[0.078]***
$OCC : Swork$	-0.049	[0.089]	-0.282	[0.073]***	[0.079]***
$ED : High$	-0.236	[0.123]*	-0.323	[0.093]***	[0.100]***
$ED : Med$	0.000	[0.117]	-0.155	[0.071]**	[0.078]**
$UNEMP$	0.055	[0.027]**	-0.033	[0.031]	[0.032]
$R\&D/Y$	0.140	[0.067]**	0.173	[0.060]***	[0.059]***
$(Exp-Imp)$	0.025	[0.016]	0.023	[0.014]*	[0.014]
$Y * 10^{-3}$	-0.012	[0.007]*	-0.012	[0.006]*	[0.006]*
$Equip/Y$	0.028	[0.023]	0.033	[0.020]	[0.021]
$Plant/Y$	-0.058	[0.034]*	-0.106	[0.029]***	[0.030]***
OUT	0.054	[0.023]**	0.059	[0.021]***	[0.023]**
$Year = 1992$	0.929	[0.118]***	1.270	[0.111]***	[0.121]***
$Year = 1993$	0.819	[0.153]***	1.258	[0.147]***	[0.161]***
$Year = 1994$	0.704	[0.169]***	1.199	[0.166]***	[0.178]***
$Year = 1995$	0.739	[0.165]***	1.230	[0.162]***	[0.176]***
$Year = 1996$	0.775	[0.182]***	1.412	[0.183]***	[0.197]***
$Year = 1997$	0.800	[0.201]***	1.465	[0.207]***	[0.224]***
$Year = 1998$	0.673	[0.192]***	1.238	[0.195]***	[0.212]***
$Year = 1999$	0.846	[0.181]***	1.365	[0.181]***	[0.192]***
$Year = 2000$	0.832	[0.175]***	1.297	[0.163]***	[0.174]***
$Constant = \epsilon_i^{m=1}$	-7.124	[1.400]***	-5.649	[1.235]***	[1.020]***
$P(\epsilon_i^{m=1})$	0.686	[0.263]			
$\epsilon_i^{m=2}$	-2.660	[1.417]*			
$P(\epsilon_i^{m=2})$	0.003	[0.001]			
$Constant = \epsilon_i^{m=3}$	-5.174	[1.400]***			
$P(\epsilon_i^{m=3})$	0.141	[0.054]			
$\epsilon_i^{m=4}$	-3.854	[1.390]***			
$P(\epsilon_i^{m=4})$	0.170	[0.016]			
Industry Dummies	Yes		Yes		
Region Dummies	Yes		Yes		
Log likelihood	-9028.67		-9844.67		
Observations	213750		213750		

Notes: Standard errors in parentheses, * significant at 10%, ** at 5%, *** at1%
Default categories:$DD :> 97$,$FS :>= 2000$,$OCC : Uwork$,$ED : Low$