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Working Paper

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Zentrum für Europäische
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Non-technical summary

An increasing number of empirical studies suggests that an individual's work experience is not fully represented by the number of years in employment because career interruptions may have far-reaching consequences and are not appropriately accounted for in the raw sum. Beyond mere stagnation, human capital may decay during an interruption because of technical and organizational progress or due to the fact that the employee's knowledge is not maintained and brushed up during absence. As human capital accumulated on the job is one of the main determinants of an individual's wage rate, wages are likely to be affected by employment breaks. Furthermore, little is known about the wage effects of different types of interruptions such as unemployment, parental leave, additional home time or further education activities. The aim of our paper is to shed light on the long-run wage effects of this variety of career breaks.

For this purpose we consider the timing and duration of non-employment spells for 17 to 40 year old German women and men. We exploit an administrative data set of German social security accounts (IAB employment sample) supplemented with information on the employees' entire working lives (IAB supplement sample I). These data allow us to distinguish between employment breaks due to registered unemployment, formal parental leave, training or other reasons – a distinction which can only be approximated using just the IAB employment sample.

The results show that, for both men and women, job experience accumulated many years ago contributes less to the current income level than recent employment spells. Allowing for unobserved individual heterogeneity and endogeneity of the work history results in lower estimated returns to experience, particularly for women. Furthermore, the wage penalties of discontinuous employment biographies are very different, in sign and in size, for women and men. While men's wages seem to be negatively affected by unemployment and out-of-the-labor-force periods, wage cuts for women are mainly triggered by parental leave and additional home time, even if taken place several years ago. It is interesting to note that unemployed women experience lower wage cuts than those staying out of the labor force for a while. Training, on the contrary, generates positive wage effects for both sexes. A nice by-product of our estimation procedure is that it allows us to disentangle the overall wage cut into two components, the missing experience effect and an additional productivity-related effect, possibly caused by signaling or a stigma imposed by the employer. Wage cuts exceeding the missing experience effect seem to concern mostly unemployed men and women with family-related interruptions. This implies that female wages are primarily determined by the women's attachment to the labor market.

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Centre for European Economic Research (ZEW)

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Abstract

This paper examines the wage effects of different types of career interruptions. We consider the timing and duration of non-employment spells by exploiting an administrative data set of German social security accounts (IAB employment sample) supplemented with information on the employees' entire working lives (IAB supplement sample I). These data allow us to distinguish between employment breaks due to registered unemployment, formal parental leave, training or other reasons – a distinction which can only be approximated using just the IAB employment sample. Our IV fixed effects estimation results suggest that women's labor supply is endogenously determined, whereas men's employment histories can be treated as exogenous. Career interruptions reduce the wage rates of both men and women. Moreover, the wage cuts resulting from unemployment, parental leave and additional home time are larger than the pure human capital effects of missing experience, hinting at a possible stigmatization of workers with discontinuous employment histories.

JEL classifications: J22, J24, J31

Keywords: career interruptions, returns to experience, wage differentials, panel estimation.

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1 Introduction

In most wage estimations job-related human capital is measured by aggregated labor market experience, that is the amount of time spent in (self-)employment. However, an increasing number of empirical studies suggests that the pure sum of years employed does not unveil the whole picture of what determines an individual's work experience, because discontinuities in the employment biography are not explicitly considered. Two people with the same number of years worked may still differ in the frequency of career interruptions. Employment breaks – be they due to childbearing, childrearing, further training, unemployment, illness/disability, or any other out-of-the-labor-force periods – are likely to generate wage effects, presumably mainly negative ones. As a result, discontinuities in the employment pattern do not only imply interruptions in the accumulation of human capital, but possibly a deterioration of the human capital stock in the sequel. In this case, not only the duration, but also the timing of the career interruptions matters. Due to the neglect of these peculiarities in an individual's employment biography, empirical evidence points to the fact that conventional specifications underestimate the return to experience, in particular during the first years of an individual's career (see e.g. Light and Ureta 1995, Murphy and Welch 1990).

One reason why the interruption of employment may not be wage-neutral refers to technical and organizational progress and innovations in the work process. Human capital acquired in previous years of employment may become obsolete after an interruption, if this specific knowledge is not maintained and updated during absence. In the economic literature, the decay of human capital has been neglected for a long time. The effect of employment breaks on earnings was first investigated by Mincer and Polachek (1974) for women in the U.S.. From simple OLS regressions, they conclude that wage cuts due to periods out of work can be attributed to an interruption in the accumulation of human capital as well as a depreciation or atrophy of the human capital stock built up in the past. However, these results are at risk of being biased, because unobserved worker characteristics are expected to be correlated with both intermittent labor force participation and wages.

A number of studies tackle this problem by estimating fixed-effects models using panel data (Mincer and Polachek 1987, Mincer and Ofek 1982, Sundt 1987 as well as Licht and Steiner 1991). More recent analyses on the impact of career interruptions are provided by Kim and Polachek (1994), Light and Ureta (1995), Ferber and Waldfogel (1998) as well as Ureta and Welch (2001) using US data, Gupta and Smith (2000) for Denmark and Albrecht et al. (1999) for Sweden. The impact of employment breaks on the income profile of German women has been investigated among others by Galler (1991), Gerlach (1987), Licht and Steiner (1992), Kunze (2002), Ondrich et al. (2001) and Beblo and

Wolf (2000, 2002). Whereas Gupta and Smith simply use the presence and number of children as a proxy for employment interruptions, Kim and Polachek introduce the number of years spent not working as a home-time variable in the wage equation. After controlling for individual heterogeneity and endogeneity of home time they detect skill atrophy. Licht and Steiner find a catch-up effect of wages following a break that partly offsets the depreciation of human capital. Galler, who considers also the sequence of full-time and part-time periods, observes these wage catch ups only for formerly part-time employees who take up a full-time position again. Full-time experience gathered prior to a break has a weaker impact on the wage rate than that following a discontinuity. Gerlach (1987) found that wages of German women fall with the length of time spent on the job prior to the first leave, using work experience and employment breaks at different points in life as explanatory variables. That is, the wage penalty is most pronounced for later breaks when a higher amount of human capital has already been accumulated, which is then at risk to depreciate. The impact of the exact timing of interruptions in Germany has been investigated explicitly in our preceding study (Beblo and Wolf 2000), where we estimate the depreciation rate on work experience due to non-work and part-time spells in an extension of the Mincer wage equation. A shortcoming of this approach, however, is that the limited number of observations compelled us to impose strong restrictions on the functional form of the human capital depreciation process. Nevertheless, the implications of our specification are consistent with the empirical results of Gerlach (1987).

Light and Ureta (1995) account for intermittency in the work history in the most flexible way. In their wage equation, they include a set of variables that measure the fraction of time worked during each year of a career. They also draw special attention to the timing of interruptions. A major drawback of this very flexible specification, however, is the large number of parameters to be estimated, because this requires a large number of observations. A second shortcoming is that they do not distinguish between the impacts of different types of career interruptions. But there are good reasons to believe that the specific cause of the break may influence the size of the wage penalty. Since participation in vocational training programs is generally much lower among unemployed or young mothers, skill obsolescence may be particularly relevant for these groups. Other reasons for wage penalties to depend on the type of career interruption are potential stigma or signaling effects. Several studies point to the fact that past unemployment spells evoke negative expectations on the side of the employer regarding the productivity of the potential employee. As a consequence, unemployed may be offered lower wages, everything else being equal. Albrecht et al. (1999) argue that parents who take a long employment break after the birth of a child may also be stigmatized as being less motivated and hence less productive.

To date, hardly anything is known about the long-run wage effects of different types of employment breaks. Does, for example, a one-year maternity leave cause the same wage cut as an unemployment spell or a sabbatical? And what kind of training yields higher returns, full-time education in school or learning-by-doing on the job? Taking up these open questions, Kunze (2002) distinguishes between four types of career interruptions, namely unemployment, parental leave or national service and other non-work, using German data. She finds large differences in losses across the variety of career interruptions. Also Albrecht et al. (1999) distinguish various types of career breaks and find different impacts of formal parental leave and additional home care on subsequent labor income. They conclude that the negative wage effect cannot only be attributed to the depreciation of human capital but is also driven by the signal of lacking career orientation.

The aim of our paper is to shed more light on the wage effects of different types of employment breaks of German men and women. Following Light and Ureta's work history specification, we consider the impact of each single year of an individual's career. The work history model is advantageous to conventional specifications of the wage equation by measuring experience more precisely and by imposing less constraints on the shape of the wage-experience profile. We go beyond Light and Ureta in two different respects: As Kunze, we distinguish between several types of non-employment. But in contrast to both studies, we do not only take into account the timing but also the duration of each interruption by calculating the exact length of each employment and non-employment spell. Following Light and Ureta, we consider the endogeneity of individual employment decisions throughout the life cycle by applying the instrumental variable approach following Hausman and Taylor (1981) within a fixed-effects panel estimation to quantify the wage penalties of different career interruptions. We are able to identify time out of work by exploiting extensive and detailed information of individuals' biographies since the beginning of their careers. This information stems from a data set of German social security accounts (IAB employment sample) supplemented with additional administrative data on the individuals' entire working lives.

The paper proceeds as follows: After a description of the data and our sample chosen we illustrate the relevance of different types of career interruptions for women and men. We then present some theoretical considerations regarding the diverse impacts of different types of employment breaks. The estimation procedure is presented in Section 5. Panel estimation results for female and male wages then provide the empirical answers. The last section concludes.

2 Data set and description

The individual information underlying our research is based on the IAB employment sample and additional administrative data assembled at the state pension authorities. The IAB employment sample is a 1 percent random sample of German social security accounts that is available for empirical researchers at the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung IAB) in Nürnberg (see also Bender et al. 2000). These data cover the period between 1975 and 1995, that is, every person who was employed for at least one day from 1975 to 1995 and/or with claims to pension benefits is included in the parent population.[1] During this time, social security contributions were mandatory for all employees who earned more than a lower earnings limit. Civil servants, self employed and people with so-called marginal jobs, that is, jobs with less than 15 hours per week or temporary jobs which last 6 weeks at most, are not covered by this sample.

Altogether, the employment sample represents about 80 percent of all West German employees and provides very precise information about each individual's average daily wage rate. If the wage rate exceeds the upper earnings limit ("Beitragsbemessungsgrenze"), the daily social security threshold is reported instead.[2] Note that the daily wage rate is therefore censored from above and truncated from below. The available wage information refers to employment spells that employers report to the Federal Employment Service.[3] In this study, we use the wage information of those employment spells that include June 30th as the relevant day of each year between 1990 and 1995, that is, we have an unbalanced panel including six waves of subsequent years.

In order to have more details about non-employment spells, we supplemented the employment sample with data from the same administrative process generating the data, the IAB employment supplement sample I. This supplement sample provides information about the individuals' entire working lives and allows us to distinguish between different types of "non-working" periods,

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1 These are people who, as employees, have paid contributions to the pension system or who have been covered by the pension system through contributions by the unemployment insurance or by being a parent (depending on the birth year of the child, a fixed number of years is counted as child caring time during which the non-working parent becomes entitled to receive pension benefits).

2 Fitzenberger and Wunderlich (2000) show that this affects particularly the wage rate of high-skilled employees. According to their results, about 50 percent of high-skilled men earn wages above the upper earnings limit. Among high-skilled full-time females, this share amounts to at least 20 percent.

3 To deal with the problem of overlapping spells, we apply a hierarchical order of activities where employment trumps all other activities.

namely, unemployment, formal parental leave, illness, disability, care for other people, full-time education, military or civil service and simple out-of-the-labor-force spells. Such a distinction can only be approximated with the IAB employment sample. To our knowledge, there is no other large-sample longitudinal data set providing as much and detailed information on individuals' employment histories in Germany. Moreover, as we use administrative data, our results do not rely on self-reported or retrospective wages and biography information. Due to the large number of observations and due to the most accurate and precise information about individual biographies and wage rates, these panel data are very suitable for a comprehensive and exceptionally detailed analysis of heterogeneous employment patterns and wages.[4]

For the purpose of our analysis, we defined four types of non-employment spells. The first category, formal parental leave, accounts for employment breaks due to the birth of a child. These spells include the mandatory employment break of 14 weeks (maternity protection) prescribed by the German law, that is aimed at protecting working pregnant women and mothers of new-born babies, as well as the additional months of parental leave that parents are entitled to by the prevailing law. Non-employment spells due to unemployment are summarized in the second group. A third category captures time spent in school or vocational training. It also includes military service or, alternatively, civil service. All remaining activities other than being employed, such as illness (only if it exceeds 6 weeks), disability or care for other family members including children, are generally not associated with the accumulation of job-related human capital. We define them as out-of-the-labor-force periods. The remaining days of each year which are not reported in the social security records are also added to this category. Since no information is available on the reasons of such drop outs from the records, we cannot prevent that periods of self-employment, marginal employment as well as the temporary status as a civil servant are also treated as work interruptions. Taking into account that these activities are usually associated with human capital accumulation then implies that we are rather underestimating the wage effects of real out-of-the-labor-force periods.

To make sure that the observed non-employment periods truly represent interruptions of the employment biography, we have to identify the starting date of each individual's career. Therefore, we define the beginning of the career as soon as the individual has been reported in employment (and covered by social

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4 For a comparative analysis of the employment penalties for motherhood in West Germany after 1945 see Kohlmann, Bender and Lang (2002).

security) for at least five months during one year.[5] Any spells before the start of the career are ignored. That is, all activity shares performed prior to the first employment enter the wage regression with value zero. Since our current sample provides information about the employment history of the past 23 years, we exclude individuals older than 40 years, so as to have observations for everybody since the very beginning of his or her career. We restrict the analysis to those who are full-time employed at the cross-section dates (June 30th) of the years 1990 to 1995, although sensitivity analyses are performed for part-time working women as well. We limit our analysis to West Germans, since large parts of the human capital stocks accumulated by East Germans before 1990 seem to have become obsolete due to the German reunification (Puhani and Steiner, 1997). As a consequence, employment breaks at the time of the socialist regime in East Germany are likely to be less relevant for the wage rate obtained in a market economy.[6]

In addition to the process-dependent censoring and truncation of the data we chose to trim daily wages at the highest and lowest percentile in order to exclude remaining outliers. The resulting average gross daily wage rate of men is 82.8 Euro and 63.9 Euro for women. Since part-time employees are excluded from the sample, this difference cannot be attributed to differences in the number of working hours. Apart from differences in qualification and sectoral segregation, this wage gap may be partly due to differences in human capital accumulated on the job. In our sample of individuals aged between 19 and 40 years, men have worked 8.2 years on average, whereas women spent 6.7 years in gainful employment.

3 The occurrence of unemployment, formal parental leave and other employment interruptions over the early life cycle

Figures 1 and 2 display the average activity patterns of women and men below age 40 once their career has started. We have chosen the average employment biographies of a 40-year old woman and a 40-year old man. For any given age the graphs show the percentage time per year spent in employment, formal maternity/parental leave, unemployment, schooling or other non-employment

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5 In contrast to Light and Ureta (1995), we choose a less restrictive definition of the starting date of the career, because the employment spells reported in the IAB employment sample are related to social security contributions, which are in general not mandatory for students in temporary or second jobs.

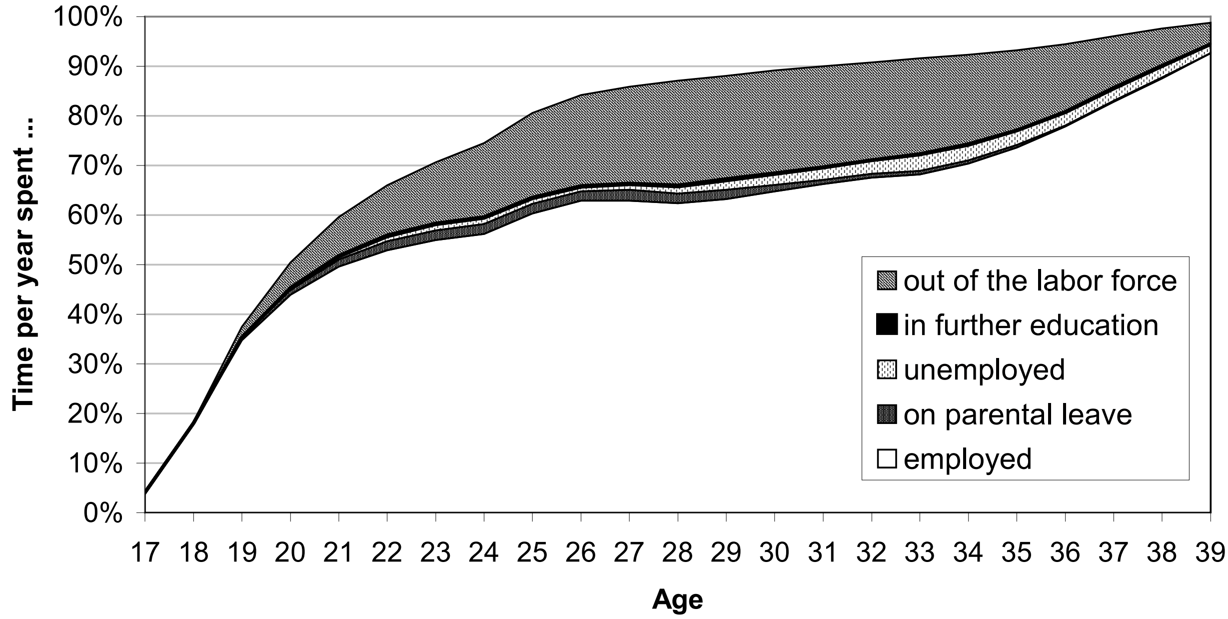
6 Moreover, our observation period just covers the beginning of the fundamental transition process in East Germany when wages were strongly affected by institutional regulations, making the interpretation of wage differentials even more complex.

activities. Note that, as these life cycle illustrations are based on samples of women and men who are employed in either of the years 1990 to 1995, they do not provide a fully representative picture of the biography of an average German man or woman of that age.

One of the most striking differences between the patterns of women and men is that, while gainful employment increases steadily over the life cycle for both sexes, only women have a more or less constant employment share in their late 20s. Female annual labor force participation starts off at zero percent at the age of 17, it levels out at some 60 percent from 26 to 30 and rises to above 90 percent at the age of 39, conditional on being employed at age 40. Figure 1 illustrates that formal maternity leave spells of women occur mainly prior to or during this plateau phase of gainful employment, when they are at the beginning of their twenties up to age 30. Their small magnitude is due to the parental leave legislation up to 1979 that allowed a maternity protection period of 14 weeks only (6 weeks before and 8 weeks after childbirth), which translates into a maternity share per year of about 27 percent. Additional parental leave of 4 months was not introduced before 1979. It was extended to 10 months in 1986 and gradually increased during the following years. Since 1992 parents of a newborn child had the right to interrupt work for a period of three years while they are guaranteed the right to return to their previous employer in a status adequate job. As the majority of our sample already experienced their parenthood before the 1992 extension of the maximum parental leave period, we only observe proportions just above 1 percent between age 21 and 30 and a maximum proportion of 2.2 percent at age 27. That is, the average woman of this age (including mothers and non-mothers) has spent less than a week in maternity leave. If we focus our attention on mothers only, the fraction of maternity leave averages at approximately 40 percent of a year (= 21 weeks).

The proportion of women in further education, on the contrary, is rather small and can be neglected particularly in the early and late years of the career. Female unemployment plays an increasing role with rising age, although it is highest at age 33 and 34 with above 3 percent. There may be two explanations for this finding. First, job changes that are accompanied by search unemployment are likely to occur more frequently around this age and, second, these unemployment spells may be associated with or following a maternity leave.

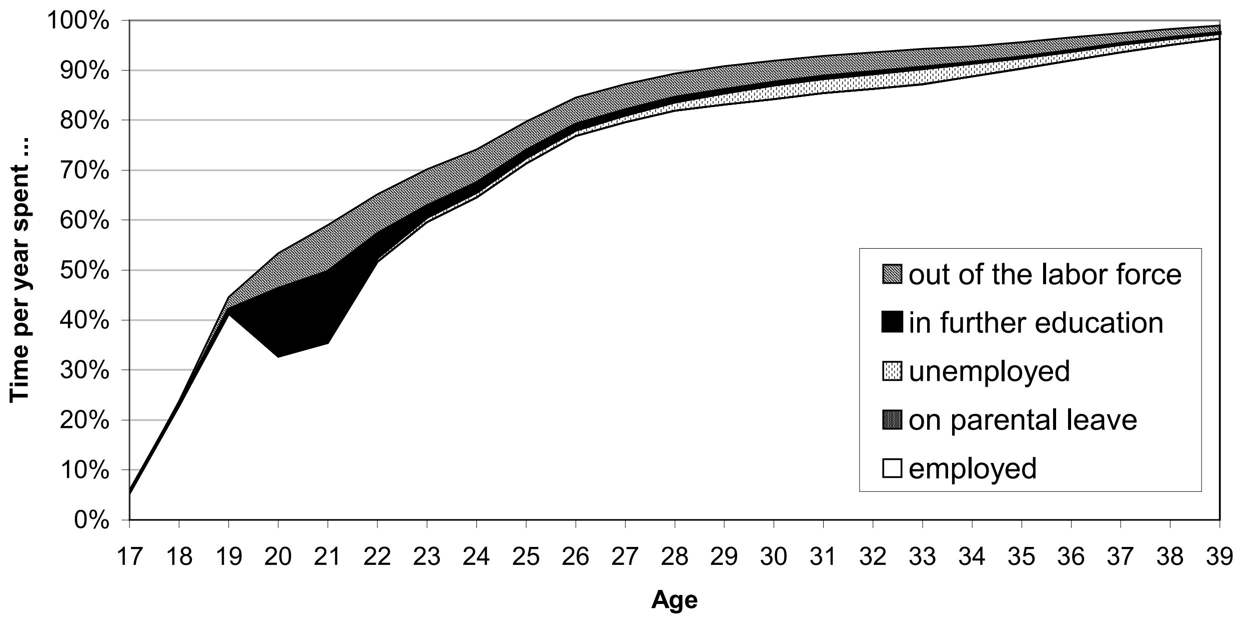
Figure 1: Employment and employment breaks over the early life cycle of women



Note: For a given age the different areas represent the percentage of time per year spent in employment, formal maternity/parental leave, unemployment, further education or other non-employment activities once the career has started.

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-1995 of 40-year-old women, own calculations.

Figure 2: Employment and non-employment states over the early life cycle of men



Note: For a given age the different areas represent the percentage of time per year spent in employment, formal maternity/parental leave, unemployment, further education or other non-employment activities, once the career has started.

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-1995 of 40-year-old men, own calculations.

After considering employment, unemployment, schooling and parental leave, any remaining work interruption of each year is attributed to activities out of the labor force. As mentioned above, these include all states that are not associated with the accumulation of marketable human capital, such as illness, disability or care for other family members including children. Between age 25 and 35 out-of-the-labor-force periods take up about 20 percent of an average woman's year. Naturally, the importance of this status diminishes in the sequel as the graphs are conditioned on women being currently employed.

Male employment increases monotonically with age and levels out above 90 percent from age 35 onwards. Contrary to the female picture, we observe a sharp drop at age 19 caused by compulsory military or civil service. According to our definition this status is included in the training category. Apart from this feature, further education and non-employment spells both decrease with age, whereas unemployment periods only seem to be relevant from the middle of the twenties (with a maximum level around 3 percent at age 31 to 33). We do not observe any family–related pattern in the men's figure. Formal parental leave, though applying also to fathers since 1992, is of such minor importance that we cannot even distinguish the respective area in Figure 2.

4 Why distinguish between career interruptions?

The various non-employment activities described above are likely to influence the sign and the size of the resulting wage penalty. As re-schooling or participation in training programs during the career are supposed to increase an individual's human capital stock, we would expect positive wage effects of these periods. It remains unclear, however, to which extent further training activities pay off later on compared to learning-by-doing on the job.

During an employment break different forces are at work that may result in future wage cuts. In principle, one can distinguish between missing experience, human capital decay and additional, productivity-related effects. Productivity-related effects may either reflect an actual drop in productivity or may be attributed to a stigma imposed by the demand side of the labor market. Apart from missing experience – which is the same for all breaks – the other wage-cutting factors possibly differ by the type of career interruption.

During unemployment or family-related career interruptions, for example, skill obsolescence may be especially harming. Human capital decay is a particular risk also for employees whose work is affected by rapid technological progress (e.g. jobs in the ICT sector). In addition to human capital decay, stigma or signaling effects may cause further wage cuts for re-employed. Due to asymmetric information potential employers may interpret past non-employment as a taint. Particularly the pool of displaced workers may be seen as less productive on average than other groups on the job market, such as new entrants to the labor force or voluntary job changers. Gibbons and Katz (1991), for instance, show that unemployed who have been laid off are offered lower wages because the dismissal is interpreted as a signal of low productivity by prospective employers, that is they are stigmatized.[7] Other empirical studies also point to the fact that past unemployment spells evoke negative expectations on the side of the employer regarding the productivity of the potential employee (Berkovitch 1990). As a consequence, unemployed may be offered lower wages, everything else being equal.

Voluntary non-employment may be interpreted as a "bad" signal as well such that the resulting wage cut goes beyond mere human capital depreciation. There are various reasons. First, individual productivity is lower on return due to lower flexibility in working time. This argument is most relevant for mothers and anyone with caring responsibilities. Second, the individual decision of a woman or a man to take "time out" without being registered unemployed is interpreted as a lack of career commitment by future employers. For this reason, we may also expect different wage impacts from formal parental leave and additional time out of work. A woman who returns to work right after or before the end of her formal leave period is more likely to be seen as a job-oriented employee. A woman who extends her child-related break beyond the legal time frame, on the contrary, may be judged as primarily being a mother who spends less time and less effort on her career.

However, there is less evidence concerning the stigma effects of parental leave and other out-of-the-labor-force periods. For Sweden, Albrecht et al. (1999) find that men face higher wage reductions than women subsequent to parental leave and household time from which they deduce that the signaling function of discontinuous employment profiles with respect to the individual's career orientation hits men in particular. In Germany, only indirect evidence on the potential stigma of being a housewife or househusband is available. In a recent survey, about 3000 mothers were asked whether their male partners had called on (part of) the 3-year formal parental leave as well as for their assessment of the reasons if they had not (see Beckmann 2001). Among the reasons, the men's fear of being stigmatized by superiors and colleagues seemed to be of minor importance. We would therefore expect to find smaller effects of voluntary non-employment periods on male wages in Germany than in Sweden.

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[7] Gibbons and Katz compare the post-displacement wages of laid-off workers and those who have been displaced in a plant closing and find a higher average wage loss for the first group. As the market infers a lower productivity for laid offs whereas no such inference exists for closed-down employees their results can be interpreted as a stigma effect of lay offs.

5 Estimation procedure

To quantify the long-run wage penalties associated with intermittent labor force participation and to identify possible stigma or signaling effects of unemployment, formal parental leave or out-of-the-labor-force periods, we run wage estimations that consider all these activities performed over the life cycle. For this purpose, we apply a work history model first introduced by Light and Ureta (1995) to assess the returns to experience and the wage effects of different employment discontinuities. In order to fully characterize past work experience, they construct an array of variables measuring the fraction of time worked during each year of the career. This set of experience variables is included in the wage equation, together with a set of dummy variables that are supposed to capture the wage effects of non-active spells.

We extend their model by allowing for different types of non-employment. Furthermore, we exploit precise information about the duration of all employment or non-employment states. That is, instead of dummy variables we construct a set of share variables for each activity. Being employed and four non-employment states – that is, unemployment, formal parental leave, further education and out of the labor force – are measured by the fraction of time spent in the specific status during each year of the past career. As a consequence, our wage model is able to capture both, individual differences in the timing of employment and specific non-employment periods as well as variations in the amount of human capital accumulated on the job and the duration of non-employment states.[8] The mean values of all share variables and other explanatory variables used in the regressions are reported in Table 1 and 2 in the Appendix.

We specify three different models. All three models use complete information about the past 20 years of an individual's career.[9] Model 1 is a simple OLS version of the work history model using pooled data. This estimation may, however, suffer from the potential correlation between unobserved individual effects and some explanatory variables. To control for unobserved heterogeneity among individuals, Model 2 applies a fixed effects estimation procedure. In view of a possible endogeneity of the individual employment pattern, Model 3 takes up the instrumental variable approach suggested by Hausman and Taylor (1981). In this last specification all activity shares are instrumented to account

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[8] Multi-collinearity is circumvented because all share variables only become relevant if non-employment spells occurred during the years after the start of a career. The reference group is thus formed by entrants into the labor market.

[9] Since we focus on activities after the start of a career, activity shares referring to 21 to 23 years ago turned out negligible.

for the correlation of intermittent labor force participation and other unobserved worker characteristics.

The general specification of the wage equation nesting the three models described above can be written as follows:

$$
\begin{aligned}
(1) \qquad \ln W_{it} = \alpha + \beta Y_i + \gamma X_{it} + \sum_{j=1}^{20} \psi_j EMP_{t-j} + \sum_{j=1}^{20} \lambda_j UE_{t-j} + \sum_{j=1}^{20} \lambda_j EDU_{t-j} \\
+ \sum_{j=1}^{20} \lambda_j PL_{t-j} + \sum_{j=1}^{20} \lambda_j OLF_{t-j} + \mu_i + \varepsilon_{it}
\end{aligned}
$$

where the dependent variable $\ln W_{it}$ is the logarithm of the average gross daily wage rate deflated with the consumer-price-index of person i at time t $(t = 1990,...,1995)$. The vector Y_i denotes all time-invariant variables, such as education level and job status.[10] X_{it} represent the explanatory variables that vary over the observation period for each individual. EMP_{t-j} is the set of variables describing the employment history of the past j years $(j = 1-20)$. Accordingly, UE_{t-j} denotes the unemployment history, EDU_{t-j} represents time spent in further education, PL_{t-j} describes the use of parental leave and OLF_{t-j} captures periods out-of-the-labor-force. Information from the past 10 years enter as annual variables, whereas data referring to the past 11 to 20 years are aggregated into a single variable.[11] The individual effects μ_i capture wage differentials due to unobserved characteristics. Finally, we have a transitory component ε_{it}, which is assumed to be homoscedastic with mean zero.

If the individual effects are correlated with the explanatory variables, a random effects panel estimation will yield inconsistent results.[12] In Model 2 and 3 we therefore apply a fixed effects approach to estimate the coefficients in equation (1). One drawback of this procedure is that it does not allow to determine the effects of time-invariant variables. Secondly, the within-group estimator is not

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[10] As these variables are time-constant, they have to be excluded from the simple fixed effects estimation.

[11] We also run estimations including different variables for all of the past 20 years. But since the coefficients do not differ significantly from year 11 onwards, we decided to aggregate them in our final specification to keep things as simple as possible.

[12] We applied a Hausman specification test to check the appropriateness of the random-effects estimator. As expected, the hypothesis that the differences in (the subset of) coefficients between the fixed effects and the random effects model are not systematic can be rejected.

fully efficient since it ignores variations across individuals in the sample. Thirdly, the endogeneity of the individual employment pattern is not taken into account adequately. An alternative approach suggested by Hausman and Taylor (1981) is based on the assumption that certain explanatory variables (X_{it} and/or the activity shares) or at least specific transformations of these variables are not correlated with the individual fixed effects μ_i and can therefore serve as instruments for the endogenous variables (e.g. the work history variables). Hausman and Taylor assume that deviations from the individual means of (all) time-varying variables are not correlated with μ_i and produce unbiased estimates of γ. The underlying idea of this approach is that, while the overall level of, for instance, employment is likely to be correlated with the unobserved individual effects, the year-to-year variation of this status is not. In other words, every person has a preference for being employed or taking time out of work that is reflected in the (endogenously determined) individual means of these variables. The annual deviations from these overall levels, that is the exact timing of employment breaks, are then considered as exogenous shocks.[13]

Hausman and Taylor furthermore illustrate that the individual means of other explanatory variables in X_{it}, which are not correlated with μ_i, provide valid instruments for those variables which are correlated with μ_i. Applying this approach to the work history model allows us to estimate the returns to diverse employment patterns, taking into account unobserved heterogeneity and the endogeneity of past experience.

In our specification, the time-invariant exogenous variables include the year of birth, education level and the industry sector of each individual, whereas the observation year and firm size are taken as time-variant exogenous variables. Hence, the richness of our data set allows us to use both individual means and deviations from individual means (where applicable) as instruments for the endogenous work history variables, the activity shares, and the endogenous time-invariant variables. The inclusion of time-constant covariates makes sure that the rank conditions are satisfied. Since our main focus is on the wage effects of discontinuous employment patterns, we confine ourselves to instrumenting the job status (white collar) as the only time-invariant variable in Model 3.

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[13] One may argue that the Hausman and Taylor approach does not lead to the identification of the parameters of interest, because the current level of employment may be correlated with past shocks. Our point is that an event at one point of time (e.g. the birth of a child) does not necessarily affect an individual's annual deviations from mean employment, because this event is already accommodated in the average employment level of that person, representing the individual's preference for work.

6 Estimation results

We run separate regressions for men and women. Due to the minor role of parental leave among men, we combine out-of-the-labor-force and formal parental leave into one set of share variables. The estimation results of Models 1 to 3 are displayed in Tables 3 to 8 in the Appendix, where Table 3 and 4 refer to the pooled OLS wage regression for men and women respectively, Tables 5 and 6 to the fixed effects panel regression and Tables 7 and 8 present the fixed effects specification with instrumented activity shares and job status. Note that our definition of the activity shares (taking values above zero only for activities after the start of the career) implies that all coefficient estimates have to be interpreted with reference to wage rates of new entrants into the labor market.

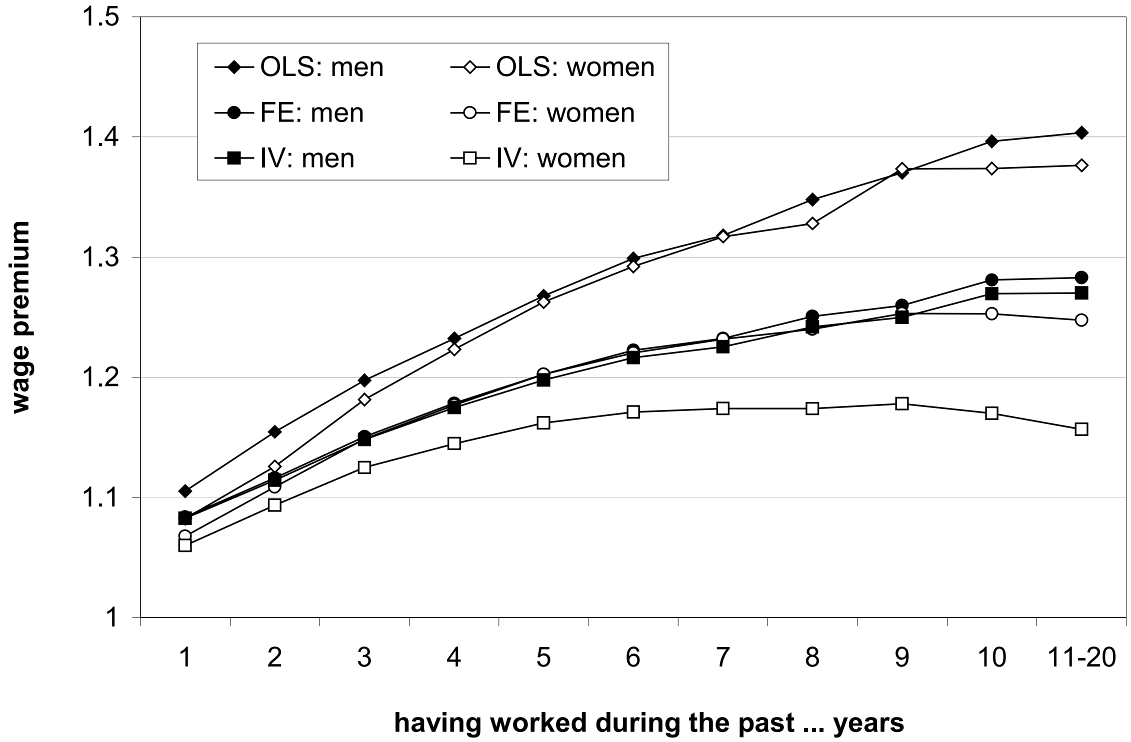
We will first draw our attention to the estimated returns to experience. The results clearly indicate that, for both men and women, job experience that has been accumulated several years ago contributes less to the current income than recent employment spells. The most striking difference between the three models estimated is that the returns for time spent working decrease step by step from Model 1 to Model 3. This is true for both men and women. Also the T-statistics vary remarkably between specifications.[14] The OLS estimates provide by far the largest coefficients for past employment experience (see Figure 3). While a man's wage increases by about 10 percent if he has worked during the preceding year, the respective female wage is only about 8 percent higher than that of a comparable labor market entrant. Over the whole work history, however, marginal returns are more or less the same for women and men. Allowing for unobserved heterogeneity (Model 2) results in lower estimated returns to experience. Hence, the OLS regression is overestimating the true returns to experience due to unobserved heterogeneity among wage earners. If we contrast the estimation results of Model 2 and Model 3, it becomes apparent that both fixed effects equations (with or without instrumented activity shares) yield similar coefficients for men, whereas the regressions for women differ quite substantially by specification. It seems that men's work histories are appropriately treated as being exogenous, for instance determined by social roles.

Estimates for female returns to experience are much lower when we take into account that career breaks, that is intermissions in labor force participation, may be endogenously determined. Table 8 shows that employment spells that took place more than three years ago have no significant effect on the current wage rate. This finding hints at selectivity effects. The lower returns to past experience in the instrumental variable estimation indicate that female workers

[14] Standard deviations for Model 3 are generated by bootstrapping with 200 iterations.

with a high wage potential anticipate their higher returns and self-select into the group of women who are more attached to the labor market and have less career interruptions.

Figure 3: Returns to past employment experience



Note: The wage premium is defined as the quotient of the predicted wage rate for a person who has been working during the past 1, 2, . . ., 20 years relative to the wage rate of a comparable labor market entrant.

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations based on the estimation results of Model 1 to 3.

From Tables 3 to 8 we see that past involvement in further education does not seem to have a statistically significant effect on the current wage rate according to the OLS estimates. Though a positive impact becomes apparent as soon as unobserved individual heterogeneity is captured through individual fixed effects (see Model 2). If we also account for endogeneity of individual employment patterns, the results confirm the significant positive effect of education spells for men's earnings (Model 3). For women, the wage effect becomes insignificant if training took place more than 3 years ago. Remember that all estimation results have to be interpreted with respect to the reference group of new entrants into the labor market. That is, the wage rate of a woman who was engaged in further education several years ago does not differ from the wage rate of a woman who has just entered the labor market but with otherwise same characteristics.

The wage effects of formal parental leave relative to out-of-the-labor-force periods also differ quite substantially across specifications. In the pooled regression parental leave spells are negatively correlated with a woman's wage rate while in the fixed-effects estimation of Model 2 the influence vanishes. In contrast, the wage penalty caused by out-of-the-labor-force periods becomes much more pronounced when unobserved heterogeneity is accommodated. This points to a selection effect in the way that mothers (who are identified by a parental leave spell because the included mother protection period is mandatory for all mothers) are over-represented among low-paid workers – be it because they sort themselves into these jobs ex ante, because they cope with these jobs after childbirth in exchange for more family-friendly working conditions, because of actual productivity effects or due to a stigma effect at work. The lack of statistical significance of wage cuts due to parental leave still holds in Model 3. Having been on formal parental leave does not impair a woman's wage growth on average, whereas out-of-the-labor-force spells significantly decrease her future wage rate compared to someone just starting the career. It is noticeable that for men, no such effects can be observed in cases of "voluntary" non-employment while registered unemployment causes wage losses, particularly if having occurred during the last 2 years.

Figure 4: Wage effects of a one-year break for men

Note: The wage ratio is defined as the quotient of the predicted wage rate after a one-year break that happened a given number of years ago relative to the wage rate of a continuously employed man. Black symbols indicate a statistically significant wage effect of the respective break compared to being employed in the same year at the 5-percent significance level (deviations from the horizontal line at 1).

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations based on the estimation results of Model 3.

In the following, we confine our analysis to the estimation results of Model 3 as we think it represents the most appropriate specification at hand. Figures 4 and 5 illustrate the wage ratio of the predicted wage rate after a one-year break that happened a given number of years ago relative to the wage rate of a continuously employed man or woman. The curves with the squared symbols describe the hypothetical wage penalty caused by the mere lack of experience. We refer to this as the missing experience effect. The vertical difference between this curve and all other lines demonstrates the additional wage effect of the specific non-employment activities. Black symbols indicate non-employment activities which lead to statistically significant wage cuts (or premiums), meaning that the wage ratio of the interrupter and the continuously employed worker is statistically different from one. Transparent symbols reflect that the wage ratio does not differ significantly from one. In this sense, the representation chosen in Figure 4 and 5 differs from that of Figure 3 and Tables 3 to 8 as we now compare our estimated wage effects with respect to continuously employed workers instead of job entrants.

It turns out once more that for men any experience of unemployment or out-of-the-labor-force during the past 20 years yields a lower wage rate than gainful employment. The biggest wage cut stems from unemployment, in particular very recent unemployment spells. Again this wage decrease can be decomposed in two factors. The first one is due to missing experience, which is the same for all types of employment breaks. The remaining wage differential may be interpreted as a stigma effect associated with unemployment. An alternative explanation would be a lower average productivity level of formerly unemployed compared to other break groups. To conclude whether one of the non-employment spells evokes significant wage effects in addition to the missing experience effect, we compare the absolute values of the employment coefficients with the respective set of non-employment coefficients. In the case of unemployment, this test reveals a statistically significant difference between the two coefficients, that is unemployment causes negative wage effects in addition to the lost return to experience. It is noticeable, however, that male wages catch up fairly quickly after re-employment. If unemployment took place more than 4 years ago, the additional effect on the current wage rate is not significant for the most part. In this case, the wage cut of about 3 percent can almost fully be attributed to the missing job-experience. Another interesting finding is that those men who have been out of the labor force also suffer a wage reduction. Although the difference between the missing-experience curve and the out-of-the-labor-force curve seems rather negligible from purely graphical inspection, it proves significant in a statistical sense.

A very intuitive result is that the wage ratio of men in further education remains constantly above the other curves. Provided that the training was completed more than 2 years ago, schooling yields even higher returns than learning-by-doing on the job. But if participation in a training program has taken place very recently, the accompanying human capital effects can only partly compensate the wage reductions due to missing experience. Learning-by-doing on the job still seems more beneficial in this case.

Figure 5: Wage effects of a one-year break for women

Note: The wage ratio is defined as the quotient of the predicted wage rate after a one-year break that happened a given number of years ago relative to the wage rate of a continuously employed woman. Black symbols indicate a statistically significant wage effect of the respective break compared to being employed in the same year at the 5-percent level (deviation from 1 in the graph).

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations based on the estimation results of Model 3.

The financial consequences of employment discontinuities are even more pronounced for women, as apparent from the wider spreading of curves in Figure 5. Unemployment, formal maternity leave as well as employment breaks due to out-of-the-labor-force periods all cause severe wage penalties. In the case of parental leave and additional home-staying these penalties are significantly larger than the pure wage effects due to missing job experience. Contrary to unemployment, there may be a signaling effect accompanied with these types of non-employment. This result is particularly striking as the endogeneity of intermittent labor force participation has been taken into account. Interestingly enough formal parental leave spells only result in a statistically significant additional wage cut if they occurred more than 5 years ago. This implies that there is no catch-up effect. Also the impact of out-of-the-labor-force periods does not seem to level out over time. Even women who stayed out of the labor market more than 10 years ago have to accept significant wage cuts compared to continuously employed women. One explanation may be the relatively long job protection phase of 3 years (from 1992) that guarantees a status-adequate job with the same pay for mothers returning to their former employers. Hence short-run consequences of parental leave are ruled out. Since a large number of mothers does not return directly to the labor market after the end of formal maternity leave, the resulting wage losses only become apparent after these women enter the labor market again, which may not happen before the child has reached school age. Although the analyses presented are based on samples of full-time employed women and men only, we are quite confident that our conclusions concerning the evaluation of the parental leave legislation in Germany apply to all women who are employed at some point in time after child birth.[15] We run several sensitivity analyses – based on a sample including also part-time employed women – and added a dummy variable for working less than half of standard hours and another dummy for working half-time or more hours. The estimation results confirm the wage-reducing effect of out-of-the-labor-force periods, as opposed to unemployment presented above (see the estimation results displayed in Table 9 in the Appendix).

Another interesting finding is that for women, even more than for men, human capital accumulated in training programs pays off better than learning-by-doing on the job. The attendance of a training course or further education immediately results in a statistically significant wage gain. The education curve fluctuates around an average of 1.1. That is to say that the wage rate of a woman who was enrolled in education compared to the wage of an employed woman in that same year is about 10 percent higher, no matter when the schooling activity took place.

7 Discussion

In this paper, we analyze the wage effects of different types of employment breaks for German men and women. Following Light and Ureta's work history specification we consider the impact of each single year of an individual's career on the wage rate. The work history model is advantageous to conventional specifications of the wage equation, because it allows to measure the impact of experience more precisely and imposes less constraints on the shape of the wage-experience profile. We go beyond Light and Ureta in two different

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[15] In fact, many mothers in Germany start off with part-time jobs when returning to work after childbirth and increase work hours only gradually. These women are included in our estimation sample as soon as they have taken up full-time employment (again). Past part-time employment is of course considered as work experience.

respects: First, we distinguish between different types of non-employment spells. Second, we do not only take into account the timing but also the duration of each interruption. We perform fixed-effects panel estimations with instrumented labor force intermissions to quantify the wage penalties of different career interruptions.

The results clearly show that, for both men and women, job experience that has been accumulated several years ago contributes less to the current income level than recent employment spells. Allowing for unobserved individual heterogeneity and endogeneity of the work history results in lower estimated returns to experience, particularly for women. Furthermore, we can show that the wage penalties of discontinuous employment biographies are very different, in sign and in size, for women and men. While men's wages seem to be negatively affected by unemployment and out-of-the-labor-force experience in particular, wage cuts for women are mainly caused by parental leave and out-of-the-labor-force spells even if they occurred several years ago. Our estimation procedure allows us to disentangle the overall wage cut into two components, the missing experience effects and an additional productivity-related effect, possibly caused by signaling or a stigma imposed by employers. We find that productivity or stigma effects associated with unemployment seem to apply mostly to men whereas women are rather stigmatized by family-related interruptions. Training, on the contrary, generates positive wage effects for both women and men.

Our results more or less tally with the findings of other German studies: Ondrich et al. (2001) estimate a reduction in wage growth of 18 percent per year of maternity leave. In accordance with our results they find that staying home after the end of the formal leave period has an even bigger effect on women's wage incomes. Being out of the labor force for only half a year will lower annual wage growth by an additional 15 percent. According to Kunze (2002) , the wage loss for women's wages due to parental leave amounts to 13 to 18 percent per year, depending on the time elapsed since. Although based on the IAB employment sample as well, her estimation results point to a substantially lower wage cut due to residual non-work than ours. There may be various reasons for these differing results. First, Kunze uses a different samples (she restricts herself to 17 to 36 year olds with apprenticeship training at the most whereas we use every person between 17 and 40 in the employment sample). Secondly, the methodologies applied are different (fixed-effects versus IV fixed-effects). And finally, we use a more precise definition of non-work spells due to additional information on non-work activities available only in the IAB supplement sample.

From our results we conclude that for female wages it is primarily the attachment to the labor market that counts. Even women with unemployment experience suffer significantly lower wage penalties than those who stayed out of the labor force for a while. One policy implication resulting from our analyses may then be to get young mothers back to work earlier – right after the end of formal parental leave at the latest. However, one obstacle that prevents women from returning to their jobs in Germany is often seen in the lack of child care facilities, particularly all-day child care. But as we found in a previous study (Beblo and Wolf 2000), even taking up a part-time employment helps to reduce the wage cut substantially.

There are several directions in which our analysis shall be extended. One interesting extension would be the differentiation between industry sectors.[16] In particular we should investigate the difference in wage penalties for workers of more traditional sectors and those working in the information and communication technology where skill obsolescence is expected to be most severe.

[16] The occupation level does not seem to matter with respect to the returns to experience. In a further sensitivity analysis we focussed on high-skill job holders only. The estimated returns to experience and effects of career interruptions did not differ from those of the overall sample.

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Appendix Table 1: Descriptive statistics for the male sample

	Employment		Unemployment		Out-of-the-labor-force		Education		Other control variables		
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.		Mean	Std.dev.
$share_{t-1}$	.9012	.2300	.0170	.0944	.0193	.1039	.0133	.1005	Firm size (number of employees)		
$share_{t-2}$	.8371	.3288	.0205	.1089	.0255	.1295	.0177	.1145	<20	.2982	.4575
$share_{t-3}$	.7809	.3763	.0220	.1128	.0287	.1403	.0181	.1162	20	.0613	.2398
$share_{t-4}$	.7232	.4114	.0233	.1158	.0310	.1470	.0179	.1156	50	.0925	.2897
$share_{t-5}$	.6648	.4371	.0250	.1193	.0315	.1495	.0175	.1142	100	.0693	.2540
$share_{t-6}$	.6069	.4551	.0264	.1221	.0310	.1500	.0177	.1152	500	.1640	.3703
$share_{t-7}$	.5504	.4650	.0276	.1253	.0301	.1484	.0181	.1167	1000	.0645	.2457
$share_{t-8}$	.4983	.4685	.0256	.1203	.0292	.1461	.0178	.1157	>1000	.1491	.3562
$share_{t-9}$	.4482	.4671	.0221	.1116	.0279	.1431	.0181	.1168	Year		
$share_{t-10}$	.4001	.4613	.0182	.1012	.0264	.1400	.0184	.1178	1990	.1584	.3651
$share_{t-11}$	.3550	.4511	.0138	.0877	.0250	.1365	.0179	.1161	1991	.1631	.3694
$share_{t-12}$	.3108	.4363	.0097	.0719	.0235	.1315	.0177	.1157	1992	.1653	.3715
$share_{t-13}$	.2684	.4173	.0058	.0524	.0218	.1266	.0174	.1148	1993	.1658	.3719
$share_{t-14}$	.2256	.3926	.0039	.0400	.0198	.1215	.0176	.1154	1994	.1672	.3731
$share_{t-15}$	.1832	.3617	.0033	.0362	.0182	.1171	.0171	.1136	1995	.1803	.3844
$share_{t-16}$	.1453	.3276	.0026	.0319	.0163	.1109	.0165	.1115	Job status		
$share_{t-17}$	.1125	.2909	.0019	.0279	.0134	.1007	.0158	.1090	Blue coll.	.6352	.4814
$share_{t-18}$	.0822	.2498	.0012	.0220	.0110	.0924	.0154	.1081	White coll.	.3648	.4814
$share_{t-19}$	.0581	.2094	.0006	.0161	.0083	.0812	.0131	.1003	Endogenous variable (in DM)		
$share_{t-20}$	.0432	.1826	.0003	.0106	.0045	.0591	.0065	.0716	wage rate	162.03	44.53
# of observations			143553								

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations.

Appendix Table 2: Descriptive statistics for the female sample

	Employment		Unemployment		Parental leave		Out-of-labor-force		Education		Other control variables		
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.		Mean	Std.dev.
share$_{t-1}$	.8723	.2805	.0155	.0916	.0018	.0338	.0353	.1547	.0027	.0470	Firm size (number of empl.)		
share$_{t-2}$	.7668	.3827	.0189	.1082	.0031	.0434	.0505	.1937	.0040	.0590	<20	.3038	.4599
share$_{t-3}$	.6760	.4330	.0191	.1096	.0043	.0507	.0578	.2097	.0039	.0589	20	.0631	.2431
share$_{t-4}$	.5941	.4592	.0189	.1093	.0053	.0567	.0619	.2179	.0030	.0524	50	.0849	.2787
share$_{t-5}$	.5227	.4705	.0185	.1078	.0062	.0609	.0624	.2204	.0013	.0343	100	.0702	.2555
share$_{t-6}$	.4584	.4721	.0177	.1060	.0059	.0589	.0618	.2214	.0013	.0339	500	.1664	.3725
share$_{t-7}$	.4024	.4664	.0175	.1065	.0058	.0574	.0597	.2186	.0012	.0330	1000	.0593	.2362
share$_{t-8}$	.3568	.4570	.0147	.0976	.0057	.0555	.0567	.2134	.0012	.0327	>1000	.0962	.2949
share$_{t-9}$	.3173	.4447	.0121	.0882	.0055	.0530	.0530	.2065	.0011	.0317	Year		
share$_{t-10}$	.2823	.4308	.0094	.0775	.0060	.0551	.0485	.1976	.0010	.0300	1990	.1424	.3495
share$_{t-11}$	.2521	.4158	.0068	.0652	.0060	.0547	.0433	.1861	.0009	.0278	1991	.1518	.3589
share$_{t-12}$	.2242	.3994	.0048	.0539	.0057	.0533	.0377	.1733	.0007	.0242	1992	.1610	.3675
share$_{t-13}$	.1983	.3817	.0028	.0379	.0051	.0516	.0319	.1584	.0006	.0219	1993	.1700	.3757
share$_{t-14}$	.1717	.3605	.0025	.0356	.0042	.0478	.0266	.1446	.0004	.0190	1994	.1784	.3829
share$_{t-15}$	.1447	.3359	.0022	.0329	.0033	.0423	.0213	.1295	.0004	.0168	1995	.1963	0.3972
share$_{t-16}$	.1198	.3097	.0020	.0315	.0025	.0373	.0163	.1119	.0004	.0169	Job status		
share$_{t-17}$	.0972	.2813	.0016	.0283	.0019	.0324	.0116	.0939	.0003	.0153	Blue coll.	.2096	.4070
share$_{t-18}$	.0749	.2484	.0010	.0215	.0015	.0295	.0083	.0790	.0002	.0125	White coll.	.7903	.4071
share$_{t-19}$	.0544	.2121	.0005	.0156	.0010	.0252	.0053	.0635	.0001	.0089	Endogenous variable (in DM)		
share$_{t-20}$	.0361	.1719	.0002	.0091	.0005	.0172	.0027	.0438	.0000	.0054	wage rate	125.17	43.48
# of observations			74561										

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations.

Appendix Table 3: OLS wage equation for men (Model 1)

	Employment		Unemployment		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
$share_{t-1}$	.1001	15.21	-.0679	-6.16	-.0475	-4.04	.0372	4.23	Firm size (ref. < 20 employees)		
$share_{t-2}$	.0438	6.64	-.0429	-3.84	.0010	0.10	.0020	0.23	20	-.0171	-6.18
$share_{t-3}$	.0364	5.71	-.0258	-2.38	-.0118	-1.11	.0004	0.04	50	.0135	6.07
$share_{t-4}$	.0288	4.54	-.0232	-2.21	-.0055	-0.52	.0034	-0.39	100	.0340	13.66
$share_{t-5}$	.0283	4.39	-.0177	-1.69	.0081	0.77	.0114	1.30	500	.0520	29.92
$share_{t-6}$	.0243	3.68	-.0170	-1.63	-.0034	-0.32	.0093	1.03	1000	.0790	35.43
$share_{t-7}$	.0146	2.20	-.0263	-2.60	.0031	0.29	.0016	0.18	>1000	.1321	81.20
$share_{t-8}$	.0224	3.45	-.0132	-1.33	.0070	0.66	.0080	0.90	Constant	4.6956	1064.88
$share_{t-9}$	.0164	2.64	-.0108	-1.08	-.0049	-0.47	.0057	0.67	Year (ref. 1995)		
$share_{t-10}$	.0189	4.34	-.0157	-1.81	.0032	0.41	.0036	0.56	1990	-.0173	-7.94
$share_{t-11\ 20}$	.0051	15.16	-.0321	-9.58	.0024	2.35	.0011	0.85	1991	.0027	1.25
									1992	.0147	6.92
									1993	.0028	1.34
									1994	-.0060	-2.81
# of observations	143,553										
Adj R^2	0.3725										

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations. Additional control variables include education level and job status. Robust standard errors (White-Huber).

Appendix Table 4: OLS wage equation for women (Model 1)

	Employment		Unemployment		Parental leave		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
share$_{t-1}$	.0790	9.31	-.0556	-2.99	-.2039	-3.68	-.0786	-4.69	.0282	1.08	Firm size (ref. < 20 empl.)		
share$_{t-2}$	.0394	4.52	-.0205	-1.14	-.3140	-7.08	-.0635	-3.81	.0324	1.45	20	-.0052	-0.96
share$_{t-3}$	.0484	5.39	-.0126	-0.69	-.2506	-6.19	-.0196	-1.17	.0032	0.13	50	.0337	7.69
share$_{t-4}$	.0347	3.66	-.0195	-1.06	-.2967	-8.16	-.0379	-2.18	-.0286	-0.96	100	.0886	21.20
share$_{t-5}$	.0317	3.06	-.0174	-0.90	-.2562	-7.35	-.0127	-0.69	.1222	2.26	500	.1539	52.79
share$_{t-6}$	.0232	2.08	-.0236	-1.16	-.2568	-7.38	-.0213	-1.11	.0351	0.47	1000	.2054	52.76
share$_{t-7}$	.0191	1.56	-.0140	-0.67	-.2778	-8.11	-.0242	-1.19	-.0432	-0.51	>1000	.2587	78.36
share$_{t-8}$	.0082	0.61	-.0092	-0.41	-.3046	-8.41	-.0210	-0.99	.0107	0.12	Constant	4.3270	660.94
share$_{t-9}$	.0335	2.42	-.0106	-0.43	-.2079	-5.35	.0109	0.51	.0716	0.77	Year (ref. 1995)		
share$_{t-10}$	.0003	0.03	-.0544	-2.34	-.1938	-5.40	-.0136	-0.77	-.0130	-0.15	1990	-.0410	-10.07
share$_{t-11-20}$	.0019	2.37	-.0264	-2.69	-.0921	-8.43	-.0012	-0.52	.0629	5.24	1991	-.0174	-4.33
											1992	.0090	2.31
											1993	.0015	0.39
											1994	-.0080	-2.14
# of observations			74,561										
Adj R^2			0.3441										

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations. Additional control variables include education level and job status. Robust standard errors (White-Huber).

Appendix Table 5: Fixed effects wage equation for men (Model 2)

	Employment		Unemployment		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
share$_{t-1}$	.0805	23.74	-.0178	-3.30	.0008	0.16	.0677	12.75	Firm size (ref. < 20 employees)		
share$_{t-2}$	.0295	9.01	-.0170	-3.16	.0109	2.14	.0350	6.87	20	.0053	2.56
share$_{t-3}$	.0303	9.15	.0043	0.77	.0051	0.97	.0379	7.17	50	.0159	7.97
share$_{t-4}$	.0238	7.26	-.0007	-0.14	.0023	0.43	.0351	6.39	100	.0273	12.24
share$_{t-5}$	.0202	6.10	-.0031	-0.56	.0057	1.06	.0375	6.57	500	.0425	22.13
share$_{t-6}$	.0167	4.98	-.0044	-0.80	-.0023	-0.43	.0405	6.97	1000	.0547	20.97
share$_{t-7}$	.0080	2.35	-.0159	-2.88	-.0010	-0.18	.0390	6.60	>1000	.0732	28.41
share$_{t-8}$	.0146	4.28	-.0066	-1.19	.0068	1.22	.0440	7.31	Constant	4.8477	235
share$_{t-9}$	.0073	2.16	-.0077	-1.35	-.0064	-1.14	.0429	7.09	Year (ref. 1995)		
share$_{t-10}$	.0167	5.98	-.0059	-1.10	.0029	0.59	.0529	9.52	1990	-.0591	-6.83
share$_{t-11-20}$	.0015	0.82	-.0246	-6.02	-.0048	-1.41	.0378	7.67	1991	-.0307	-4.40
									1992	-.0106	-2.00
									1993	-.0153	-4.23
									1994	-.0175	-8.84

# of observations	143,553
# of groups	32,057
within-group R^2	0.1744
Corr. (μ_i * Xb)	0.0940

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations.

Appendix Table 6: Fixed effects wage equation for women (Model 2)

	Employment		Unemployment		Parental leave		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
share$_{t-1}$	.0656	11.16	-.0088	-0.92	-.0062	-0.20	-.0856	-11.07	.1424	8.09	Firm size (ref. < 20 employees)		
share$_{t-2}$	.0377	6.88	.0047	0.51	-.0152	-0.53	-.0583	-7.85	.1194	7.44	20	.0041	1.18
share$_{t-3}$	.0353	6.15	.0102	1.05	-.0026	-0.09	-.0618	-7.96	.1070	6.54	50	.0335	9.40
share$_{t-4}$	.0243	4.16	.0003	0.03	-.0221	-0.78	-.0603	-7.50	.0820	4.51	100	.0533	13.66
share$_{t-5}$	.0215	3.57	.0146	1.43	-.0279	-0.98	-.0546	-6.48	.1501	4.15	500	.0793	23.88
share$_{t-6}$	.0147	2.35	.0088	0.84	-.0351	-1.22	-.0553	-6.38	.0969	2.59	1000	.0928	19.43
share$_{t-7}$	.0093	1.42	.0184	1.71	-.0483	-1.66	-.0674	-7.44	.0661	1.60	>1000	.1024	21.38
share$_{t-8}$	.0067	0.99	.0116	1.05	-.0532	-1.79	-.0754	-8.08	.1174	2.87	Constant	4.6650	121
share$_{t-9}$	.0104	1.51	.0116	1.01	-.0457	-1.52	-.0664	-6.98	.1011	2.34	Year (ref. 1995)		
share$_{t-10}$	-.0001	-0.02	.0155	1.37	-.0383	-1.28	-.0797	-9.42	.0826	2.16	1990	-.0989	-5.23
share$_{t-11-20}$	-.0043	-1.11	.0062	0.67	-.0249	-0.87	-.0708	-12.51	.0586	2.85	1991	-.0627	-4.12
											1992	-.0271	-2.36
											1993	-.0221	-2.86
											1994	-.0201	-4.88

# of observations	74,561
# of groups	19,132
within-group R^2	0.2054
Corr. (μ_i * Xb)	-0.1308

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations.

Appendix Table 7: IV fixed effects wage equation for men (Model 3)

	Employment		Unemployment		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
share$_{t-1}$	.0793	14.84	-.0259	-2.58	-.0016	-.15	.0649	8.03	Firm size (ref. < 20 employees)		
share$_{t-2}$	.0289	5.72	-.0255	-2.43	.0059	.63	.0337	4.42	20	.0049	1.35
share$_{t-3}$	.0299	7.00	-.0052	-.56	.0001	.01	.0361	4.12	50	.0144	4.20
share$_{t-4}$	.0230	5.22	-.0092	-1.01	-.0019	-.18	.0327	3.92	100	.0254	6.79
share$_{t-5}$	.0193	3.90	-.0108	-1.12	.0019	.20	.0348	3.64	500	.0423	12.24
share$_{t-6}$	.0154	3.58	-.0118	-1.33	-.0065	-.67	.0361	4.18	1000	.0564	13.89
share$_{t-7}$	.0074	1.86	-.0221	-2.67	-.0046	-.49	.0351	3.97	>1000	.0746	17.12
share$_{t-8}$	.0135	3.68	-.0138	-1.50	.0016	.17	.0396	4.18	Constant	4.8238	163.64
share$_{t-9}$	.0064	1.70	-.0141	-1.61	-.0113	-1.17	.0382	4.07	Year (ref. 1995)		
share$_{t-10}$	.0155	4.36	-.0134	-1.43	-.0017	-.20	.0481	4.93	1990	-.0602	-5.61
share$_{t-11-20}$	.0005	.27	-.0299	-3.80	-.0088	-1.14	.0338	3.48	1991	-.0318	-3.75
									1992	-.0116	-1.79
									1993	-.0162	-3.65
									1994	-.0180	-7.71
									Job status (ref. blue collar)		
									White coll.	.1010	5.60
# of observations			143,553								
# of groups			32,057								
within-group R^2			0.1751								
Corr. (μ_i * Xb)			0.2361								

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations. All activity shares and the dummy variable for white collar workers are retrieved by instrumental variable estimation. Standard deviations are generated by bootstrapping.

Appendix Table 8: IV fixed effects wage equation for women (Model 3)

	Employment		Unemployment		Parental leave		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
$share_{t-1}$	.0582	5.52	-.0141	-.63	-.0179	-.23	-.0929	-4.63	.1395	3.35	Firm size (ref. < 20 employees)		
$share_{t-2}$	.0312	2.85	.0009	.05	-.0255	-.36	-.0644	-4.11	.1176	2.91	20	.0043	.62
$share_{t-3}$	.0283	2.77	.0060	.32	-.0141	-.21	-.0685	-3.81	.1045	2.70	50	.0341	4.46
$share_{t-4}$	.0175	1.56	-.0041	-.22	-.0333	-.48	-.0666	-3.50	.0798	1.74	100	.0535	7.15
$share_{t-5}$	.0149	1.37	.0103	.53	-.0389	-.55	-.0608	-3.25	.1510	.85	500	.0789	11.59
$share_{t-6}$	.0079	.64	.0046	.21	-.0464	-.64	-.0619	-3.00	.0952	.63	1000	.0923	10.96
$share_{t-7}$	.0025	.23	.0143	.69	-.0596	-.83	-.0742	-3.62	.0650	.26	>1000	.1016	10.59
$share_{t-8}$	-.0001	-.01	.0076	.37	-.0644	-.82	-.0818	-3.95	.1153	.50	Constant	4.7646	25.24
$share_{t-9}$	.0034	.27	.0073	.35	-.0574	-.73	-.0733	-3.44	.1011	.36	Year (ref. 1995)		
$share_{t-10}$	-.0068	-.66	.0114	.48	-.0499	-.60	-.0858	-3.95	.0824	.47	1990	-.1333	-2.82
$share_{t-11-20}$	-.0113	-1.16	.0016	.08	-.0376	-.47	-.0780	-4.72	.0574	.26	1991	-.0901	-2.37
											1992	-.0477	-1.69
											1993	-.0358	-1.87
											1994	-.0269	-2.78
											Job status (ref. blue collar)		
											White coll.	-.0396	-.30
# of observations			74,561										
# of groups			19,132										
within-group R^2			0.2064										
Corr. (μ_i * Xb)			-0.1038										

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations. All activity shares and the dummy variable for white collar workers are retrieved by instrumental variable estimation. Standard deviations are generated by bootstrapping.

Appendix Table 9: IV fixed effects wage equation for women, full-time and part-time (Model 3)

	Employment		Unemployment		Parental leave		Out-of-the-labor-force		Education		Other control variables		
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.		Coef.	T-Stat.
$share_{t-1}$	.0777	9.57	-.0195	-.96	-.0542	-.91	-.0779	-5.46	.1510	3.26	Firm size (ref. < 20 employees)		
$share_{t-2}$	.0435	5.99	.0104	.59	-.0890	-1.73	-.0490	-3.73	.1302	3.47	20	.0145	2.13
$share_{t-3}$	.0469	6.49	.0120	.62	-.0690	-1.27	-.0461	-3.54	.1188	2.78	50	.0428	5.49
$share_{t-4}$	.0305	3.67	.0068	.35	-.0686	-1.27	-.0520	-3.70	.0974	2.09	100	.0624	7.45
$share_{t-5}$	.0245	2.98	.0177	.95	-.0578	-1.06	-.0450	-2.95	.1756	1.08	500	.0918	13.50
$share_{t-6}$	.0197	2.20	.0085	.43	-.0660	-1.24	-.0547	-3.36	.1276	.69	1000	.1102	11.45
$share_{t-7}$	.0135	1.48	.0217	1.02	-.0714	-1.20	-.0603	-3.55	.1169	.56	>1000	.1111	12.53
$share_{t-8}$	.0113	1.08	.0196	.87	-.0648	-1.14	-.0577	-3.18	.1581	.63	Constant	4.5632	103.44
$share_{t-9}$	.0152	1.45	.0109	.47	-.0550	-.86	-.0556	-3.44	.1303	.34	Year (ref. 1995)		
$share_{t-10}$	.0068	.74	.0187	.79	-.0540	-.87	-.0605	-3.32	.1374	.64	1990	-.0622	-2.85
$share_{t-11-20}$	.0021	.45	.0103	.53	-.0293	-.47	-.0509	-5.20	.1110	.59	1991	-.0316	-1.81
											1992	-.0032	-.24
											1993	-.0053	-.58
											1994	-.0127	-2.62
											Job status (ref. full time)		
											Part time 1	-.7230	-29.03
											Part time 2	-.2289	-31.05
# of observations			95,467										
# of groups			23,452										
within-group R^2			0.3106										
Corr. (μ_i * Xb)			0.1109										

Source: Matched IAB employment sample and supplement sample I, cross sections 1990-95, own calculations. Part time 1 indicates working less than half of standard hours, part time 2 working half-time or more hours All activity shares and the dummy variables for part-time workers are retrieved by instrumental variable estimation. Standard deviations are generated by bootstrapping.