

Discussion Paper No. 17-048

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Changing Selection into Full-Time Work**

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Rising Wage Inequality in Germany: Increasing Heterogeneity and Changing Selection into Full-Time Work¹

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September 2017

Abstract: This study revisits the increase in wage inequality in Germany. Accounting for changes in various sets of observables, composition changes explain a large part of the increase in wage inequality among full-time workers. The composition effects are larger for females than for males, and increasingly heterogeneous labor market histories play an important role. Furthermore, we find strong effects of education for males and strong effects of age and experience for females. Changes in industry and occupation explain fairly little. Extending the analysis to total employment confirms the basic findings, while revealing substantial negative selection into part-time work.

JEL-Classification: J31, J20, J60

Keywords: wage inequality, reweighting, composition effects, Germany

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¹We are grateful to the Research Data Center at IAB for useful discussions. We thank Benjamin Bruns, Christian Dustmann, Alexandra Spitz-Oener, as well as participants at the IWH/IAB workshop 2016, the RTG Summer School 2015, the International Conference on 'The German Labor Market in a Globalized World 2015' and the Network Workshops of the DFG priority program 1764 for helpful comments and suggestions. We acknowledge financial support by the German Science Foundation (DFG) through the project 'Accounting for Selection Effects in the Analysis of Wage Inequality in Germany' (Project number: BI 767/3-1 and FI 692/16-1).

1 Introduction

Based on different datasets, it has been widely documented that wage inequality among full-time working males and females in West Germany has been rising strongly from the 1990s onwards (Dustmann et al. 2009, Antonczyk et al. 2010a, Card et al. 2013).² The increase in wage inequality has become a major issue of political concern - and this was a key argument for the introduction of a national statutory minimum wage in 2015 (SVR 2014, chapter 7, Bosch und Weinkopf 2014, Dustmann et al. 2014, p. 185). Most of the existing literature undertakes a statistical decomposition analysis of the increase in wage inequality. This study revisits the analysis of the increase in wage inequality in West Germany among full-time working employees between 1985 until 2010 based on German administrative employment data (SIAB). As a novel aspect, we account explicitly for the increasing heterogeneity of labor market experience regarding part-time work and employment interruptions, and we also extend the analysis to total employment despite the lack of comparable wage information for part-time workers.

Wage inequality has been increasing in many industrialized countries between the 1980s and the 2000s (see the comprehensive survey in Acemoglu and Autor 2011, or the literature discussion in Lemieux 2006, Autor et al. 2008, Dustmann et al. 2009). Skill-biased technical change (SBTC) is the most prominent explanation for the increase in wage inequality. It results in an increasing demand for more highly skilled labor, with the increase in demand being stronger than the parallel increase in supply. The simple SBTC hypothesis predicts rising wage inequality over the entire wage distribution. This is consistent with the evidence for the U.S. for the 1980s but not for the 1990s, as in the 1990s inequality stopped to grow at the bottom of the wage distribution (Autor et al. 2008). Acemoglu and Autor (2011) take the latter as evidence for the task-based approach (see Autor et al. 2003) implying a falling demand for occupations with medium skill requirements (which are relatively more routine intensive and thus easier to substitute by technology) relative to both occupations with high or with low skill requirements, resulting in polarization of employment across occupations. The evidence

²See also (in chronological order) Kohn 2006, Gernandt and Pfeiffer 2007, Antonczyk et al. 2010b, Fitzenberger 2012, Felbermayr et al. 2014, Dustmann et al. 2014, Riphahn and Schnitzlein 2016, and Möller 2016. Most recent studies are based on administrative employment records in the Sample of Integrated Employment Biographies (SIAB) - or earlier versions of the same data source - as provided by the Research Data Center of the IAB and the Federal Employment Agency. Some studies use of the cross-sectional wage surveys in the German Structure of Earnings Survey (GSES) provided by the Research Data Center of the Statistical Offices, the Socio-Economic Panel (GSOEP) provided by DIW or the BIBB-IAB/Bibb-BAuA Labor Force Surveys (BLFS). While the SIAB data only involves earnings, the GSES, the GSOEP, and the BLFS allow for an analysis of hourly wages. Researchers using the SIAB data typically focus on full-time working employees. While the SIAB and the GSOEP provide panel data, the GSES data and the BLFS only involve repeated cross-sections every four to six years and the GSES surveys before 2010 only involve a subset of all industries and they lack very small firms. Compared to the GSOEP and the BLFS, the GSES and the SIAB provide much larger cross-sections on employees and wages. All four data sources document the increase in wage inequality since the mid 1990s, see Dustmann et al. (2009, SIAB), Fitzenberger (2012, SIAB and GSES), Antonczyk et al. (2009, BFLS), and Gernandt and Pfeiffer (2007, GSOEP).

regarding a polarization of wages across the wage distribution in the U.S. seems to be limited to the 1990s and a polarization of wages is not an unambiguous prediction of the task based approach (Autor 2013). A parallel literature for the U.S. emphasizes the role of changing labor market institutions such as de-unionization and falling real minimum wages (see also the discussion in Autor et al. 2003). DiNardo et al. (1996) show that the fall in unionization levels explains an important part of the increase in wage inequality during the 1980s. Furthermore, Lemieux (2006) shows that changes in the composition of the workforce regarding education and experience explains a major part of the increase in wage inequality in the U.S. Also, Autor et al. (2008) find strong composition effects, especially for females, but focus on different explanations for the rise in wage inequality. According to DiNardo et al. (1996) and Lemieux (2006), composition effects also have a strong impact on residual wage inequality, i.e. the wage differences among employees with the same observable characteristics. This evidence of the strong role of composition effects for the U.S. is a starting point for our analysis.

Wage inequality has been rising in West Germany [henceforth Germany] since the 1980s, but until the mid 1990s the increase in wage dispersion was restricted to the top of the wage distribution (Fitzenberger 1999, Dustmann et al. 2009). Since then, wage inequality has been increasing strongly across the entire wage distribution. The evidence until the mid 1990s is consistent with skill biased technological change and the hypothesis that labor market institutions such as unions and minimum wages prevented an increase in wage inequality at the bottom of the wage distribution before the mid 1990s, which resulted in rising unemployment among the low-skilled (Fitzenberger, 1999). The study by Dustmann et al. (2009) shows an increase in wage inequality among full-time workers since the mid 1990s up to 2004 based on SIAB data (see footnote 2). The study uses linked employer-employee data based on the IAB establishment survey combined with individual employment records from SIAB (the LIAB data). The study shows that changes in the composition of workers regarding age and education and the sizeable decline in coverage by collective bargaining both explain a major component of the increase in wage inequality. At the same time, the study provides evidence for a polarization of employment as found previously for the U.S.

Using BLFS data and GSES data (see footnote 2), respectively, Antonczyk et al. (2009) and Antonczyk et al. (2010a) find a strong increase of wage inequality between 1999/2001 and 2006. Changes in task assignments cannot explain this rise (Antonczyk et al. 2009). Accounting for coverage by collective bargaining, firm level characteristics, and personal characteristics, Antonczyk et al. (2010a) show that the decline in coverage by collective bargaining does not explain the rise in wage inequality in the lower part of the wage distribution when firm level characteristics are held constant. Most important are changes in the quantile regression coefficients of firm level variables (firm size, region, industry), which reflect a growing heterogeneity in firm level wage policies. The two studies differ regarding the contribution of changes in

personal characteristics. Also using GSES data, Biewen and Seckler (2017) find that changes in union coverage and personal characteristics are most important for the increase in wage inequality between 1995 and 2010. Note that the GSES data do not cover all industries and that both the BLFS and the GSES data are cross-sectional so that changes in labor market histories cannot be addressed.

Using the population of all social security records (of which the SIAB is a 2% sample), Card et al. (2013) estimate person and firm fixed effects in wages over five-year intervals for full-time working employees. Over time, the study finds a growing heterogeneity of these fixed effects and increasing sorting of workers with high personal fixed effects into firms with high firm fixed effects. Both effects contribute strongly to the increase in wage inequality. Based on linked employer-employee data (LIAB) up to 2010 and aggregate industry data, Felbermayr et al. (2014) find that the decline in coverage by collective bargaining is the most important explanation for the increase in wage inequality, while there is no important role for international trade. Our short survey of the literature shows that the literature has not yet reached a consensus on the mechanisms behind the increase in wage inequality in Germany until 2010.³

The literature on the increase in inequality among full-time employees in Germany has so far not taken into account the increasing heterogeneity in employment histories. Over time, part-time work has increased strongly both among males and females, as well as transitions between part-time and full-time work and employment interruptions have become more frequent, not least as a consequence of rising unemployment (Tisch and Tophoven 2012, Potrafke 2012). Correspondingly, over time full-timers in one year have become much more likely to have experienced part-time work or employment interruptions in the past, i.e. patchier employment histories. Episodes of part-time work and gaps in the labor market history can have negative long term impacts on the career path and therefore on future wages (Burda and Mertens 2001, Arulampalam 2001, Beblo and Wolf 2002, Manning and Petrongolo 2008, Edin and Gustavsson 2008, Schmieder et al. 2010, Edler et al. 2015). Negative long term career effects of transition from full-time to part-time work for women after childbirth have been studied by Connolly and Gregory (2009) and Paul (2016). Recent evidence suggests that the accumulation of human capital is very low in part-time work compared to full-time work (Blundell et al. 2016). Furthermore, conditioning on the employment history will go some way towards controlling for characteristics which are unobservable in cross-sectional data, and which Card et al. (2013) attribute to worker fixed effects.

The recent literature on the increase in wage inequality mostly uses statistical decomposi-

³The recent study by Möller (2016) shows that the increase in wage inequality stopped in 2010 based on a new release of the SIAB data. However, the comparison of the years before and after 2011 is plagued by a structural break in 2011 regarding the distinction between part-time and full-time workers (Möller 2016). Therefore, we abstain from analyzing the SIAB data after 2010.

tion analysis (Fortin et al. 2011). While a standard Blinder-Oaxaca decomposition based on an OLS wage regression decomposes the contribution of changes in average characteristics and changes in coefficients to explaining the changes in average wages (typically average log wages), more sophisticated methods have been developed for the decomposition of changes in the entire distribution. DiNardo et al. (1996) involve the first application of the method of inverse probability weighting (IPW), i.e. reweighting, to decomposing changes in the entire wage distribution. The idea of reweighting is to estimate the counterfactual distribution of wages in one period (say the year 2010) for a population of workers with the distribution of characteristics from another period (say the year 1985) or from another target population (say we estimate the counterfactual distribution of full-time wages for the target population of both full-timers and part-timers).⁴ We apply IPW sequentially over time for increasing sets of covariates to gauge the partial contribution of different covariates.

This paper makes the following contributions. First, extending Dustmann et al. (2009), we estimate the contribution of changes in observable characteristics to the increase in male and female wage inequality in Germany over the recent decades. We find that compositional changes in observable characteristics explain over 50 percent of the increase in male wage inequality and up to 80 percent of the increase in female wage inequality. To the best of our knowledge, the literature has so far not recognized the extremely strong role of composition effects for the rise of female wage inequality. Second, we explicitly account for increasing heterogeneity in labor market experience regarding part-time work and employment interruptions, an issue which has not been addressed so far in the literature. We document that the incidence of previous part-time and non-employment experiences has increased for individuals observed working full-time, and we show that increasing heterogeneity of recent labor market histories plays an important role for both male and female wage inequality. Third, we estimate composition effects with regard to the counterfactual distribution of full-time wages for all employees, which confirms the robustness of our main findings. Furthermore, this shows that part-timers (especially female part-timers) represent a negative selection with respect to observable characteristics. Including part-timers into the analysis also speaks to the role of increasingly heterogeneous labor market histories for the rise in German wage inequality.

The remainder of this paper is structured as follows. Section 2 discusses the data used and presents first descriptive evidence. Section 3 explains our counterfactual analysis. In section 4, we present and discuss our empirical results. Section 5 concludes. The appendix provides information about the imputation procedure used in a prior step of our analysis and presents supplementary empirical results.

⁴A decomposition analysis of wage inequality can also be based on conditional quantile regression (as in Antonczyk et al. 2010a), or on unconditional quantile regression (as in Felbermayr et al. 2014).

2 Data and descriptive evidence

Our analysis uses SIAB data involving a 2% sample of all dependent employees who are subject to social security contributions, i.e. excluding the self-employed and civil servants. We study the period 1985 to 2010. Even though SIAB data are available for earlier years, we do not include them in our analysis for two reasons: Changes in wage inequality across the entire distribution can only be observed after the 1980s, and a structural break in the reporting of the data in 1984 implies that wages from earlier years are not fully comparable to those after 1985 (Fitzenberger 1999). Since we may observe several working spells of various lengths per individual in a given year, all observations are weighted with the share of days worked in a job in the respective year. The sampling weights calculated in this way reflect the relative importance of each wage observation.

We distinguish three educational levels: University degree (including Universities of Applied Sciences/Fachhochschulen), degree from Upper secondary school and/or Vocational Training, No/Other degree. We use 14 aggregated industries based on the German Classification of Economic Activities, Edition 1993 (WZ 93) and 63 aggregated occupations based on the 2-digit level of the KldB 1988 (Klassifikation der Berufe 1988). For interactions between industry and occupation, we aggregate occupations to the 1-digit level in order to avoid problems with empty cells in our logit regressions. The education variable is cleaned and interrupted measurements are imputed for consistency (Fitzenberger et al. 2006).

We account for an individual's labor market history using four measures. The first two involve the number of days spent in full-time and in part-time employment during the last five years. The residual category is the number of days spent in non-employment during the last five years, which may be times of unemployment, education, or any other type of non-employment. In addition, we use two dummy variables, indicating whether a person had a full-time or a part-time spell at any point during the previous year. This information captures individual short-term employment dynamics. Wages are daily wages in Euros deflated by the CPI to 1990. Since we use administrative data on employment spells, the measures are very precise. While our dataset does not contain information on hours worked, we are confident that daily wages among full-time employees are comparable (note that the literature on Germany using SIAB data or other samples drawn from social security records focuses on daily wages). Our sample also includes individuals with part-time employment. However, without information on working hours, the wage data for part-timers are not comparable across observations and jobs. Our analysis therefore only uses full-time wages. In section 4.3, we estimate the counterfactual distribution of full-time wages for all workers also including part-timers.

All wages above the contribution threshold for social security are censored in the SIAB. These

Table 1: Variable Classification

Variable group	Short	Content
Education	Ed	3 categories (<i>ed</i>): University, Upper secondary High-School and/or Vocational Training, No/Other Degree
Experience	Ex	Potential experience (age - years of schooling - 6) (<i>ex</i>)
Labor market history	Hist	Number of days in full-time (<i>ft5</i>), or part-time (<i>pt5</i>) over the last 5 years. Indicators for: full-time job in previous year (<i>ft</i>), part-time job in previous year (<i>pt</i>)
Occupation	Occ	Job classification by KldB 2-digit levels (<i>occ</i> , 63 categories)
Industry sector	Ind	Industry classification by WZ93 (<i>sec</i> , 14 categories)

censored observations lie above the yearly 85% wage quantile. Therefore, we compare the 85/15, the 85/50 and the 50/15 quantile gaps in the wage distribution. In those cases, where we cannot restrict our analysis to values below the 85% quantile (in particular when analyzing developments in wage residuals), we impute wages above the threshold according to individual characteristics. Details of the imputation procedure can be found in appendix section 5. Additionally, unless noted otherwise, we restrict our analysis to individuals aged 20 to 60 years, in order to focus on the working age population. Table 1 summarizes the covariates used.

2.1 Trends in wage inequality

Figure 1 shows the development of log wage quantiles (cumulative changes) from 1985 onwards. Our primary measures of wage inequality are the gaps between the 85th, 50th and 15th percentiles of log wages. Until about 1991, the different wage quantiles move upward and largely in parallel. After 1991 median wages of male full-timers stagnate (recall that we analyze real wages). For female full-timers, there is a continuous but decelerating rise until 2003, and a subsequent decline until 2008. For both genders, we observe a widening of the wage distribution beginning just at the time when median wages start stagnating. Wages at the 85th percentile continue to increase, while wages at the 15th percentile decline. For males, this decline is moderate until the early 2000s, but accelerates afterwards. By 2010, male wages at the 15th percentile even lie below their 1985 level. For females, we observe different developments of the three quantiles already in the late 1980s. However, inequality only increases in a more substantial way in the late 1990s, several years later than for males. After 1998, female median wages stagnate, while the 85th percentile rises and the 15th percentile declines rapidly. The corresponding trends in inequality as measured by the 85/50 and 50/15 gaps are depicted by the solid lines in figures 8 to 11.

2.2 Trends in labor market histories

Part-time work in Germany has grown substantially over the last decades (figure 2). While this may reflect secular trends in labor market participation, part of the increase may be linked to political reforms promoting part-time work. Over our observation period, several changes in legislation were targeted at the part-time sector. In 1985, the German government enacted a law (*Beschäftigungsförderungsgesetz*) which granted part-timers the same level of job protection as full-timers. This law increased the acceptance of part-time work on the side of trade unions and in the general population. In 2001, this was followed a law which made it easier for employees to enter voluntary part-time work (*Teilzeit- und Befristungsgesetz*). These changes in legislation had the effect of formally easing the transition between full-time, part-time and non-employment. We observe that not only the yearly stock of part-time employees increased for both genders, but that the frequency of temporary part-time episodes for individuals currently working full-time increased as well (figure 3). Parallel to the rise of part-time work, two changes in legislation between 1985 and 1998 (*Beschäftigungsförderungsgesetz, Arbeitsförderungs-Reformgesetz*) facilitated fixed-term contracts and temporary agency work, which is likely to explain part of the increase in employment interruptions.

Both the intensive and the extensive margin of labor market histories may matter for current wages (Burda and Mertens 2001, Arulampalam 2001, Beblo and Wolf 2002, Manning and Petrongolo 2008, Edin and Gustavsson 2008, Schmieder et al. 2010, Edler et al. 2015, Paul 2016, Blundell et al. 2016). Returns to labor market experience are not uniform across jobs and types of work. Not only is experience in part-time work valued lower than that in full-time work, but part-time spells and non-employment interruptions may slow down career progression and wage growth. For example, Beblo and Wolf (2002) and Edin and Gustavsson (2008) investigate how episodes of non-employment interrupt the accumulation of human capital, and also lead to the depreciation of human capital. When a transition from non-employment back into work involves a job change (no recall), this also implies a loss of job-specific human capital. Beblo and Wolf (2002) note that episodes of part-time work slow down the accumulation of human capital, since part-timers are less likely to receive vocational training and are therefore more vulnerable to skill obsolescence. For females in the UK, Connolly and Gregory (2009) and Blundell et al. (2016) show that part-time employment in the past results in lower earnings trajectories, even when returning to full-time work. For Germany, Paul (2016) finds a substantial negative impact of part-time work on future earnings in full-time work.

In light of the findings in the literature, the rise in part-time employment and employment interruptions is likely to have consequences for the development of wage inequality depending upon the position in the wage distribution. Figure 3 shows increasing average lengths and

also increasing variability of previous part-time episodes for men and females, both above and below the median of the respective wage distribution. The mean and variance of number of days spent in part-time work during the last five years increases over time for those individuals who are in full-time jobs at the time of observation. Male full-timers experience a noticeable increase in past part-time episodes, although the total amount of the time previously spent in part-time is lower than for females. The increasing prevalence and variability of previous part-time experience are considerably stronger for full-time males below the median wage compared to those above. Put differently, there is increasing mobility between part-time and full-time work for male low-wage earners. This may reflect that part-time work acts as a stepping stone towards full-time employment (recall that we analyze full-timers in the observation year) or that workers' preferences may change over time. When individuals move from part-time into full-time work, we expect observed changes in the work history of male workers to drive up inequality in the lower parts of the wage distribution. For female full-timers, we also observe an increase in the length and variability of previous part-time work, both above and below the median of the wage distribution. The initial levels are much higher, but the rise in the amount of time previously spent in part-time work is similar to that of men. Incidentally, the part-time experience of full-time females above the median of the distribution appears to fluctuate more strongly with the business cycle compared to females below the median, whose part-time experience follows more of a secular upward trend. Note that labor supply of females is known to be more elastic than that of men and that the part-time experience of females is often related to career interruptions after child birth (Blundell et al. 2016). After maternity leave, females often re-enter the labor market in part time, but may return to full-time work later on (Fitzenberger et al. 2016, Paul 2016).

Similarly, episodes of non-employment are likely to exert a sizeable influence on wages. Non-employment may involve alternative activities such as education or child care or it may be due to involuntary displacement or unemployment. The literature shows that employment interruptions may involve sizeable wage losses due to displacement (Burda and Mertens 2001, Schmieder et al. 2010, Edler et al. 2015), due to human capital obsolescence (see above), or due to scarring effects of unemployment (Arulampalam 2001). The existing literature has not investigated to what extent the rise in employment interruptions explains the increase in wage inequality. Figure 4 shows the average length and variability of time spent in non-employment over the past 5 years. This includes all activities which do not count as regular employment, such as unemployment, education, marginal employment and absence from the labor market. For individuals above the median wage, these gaps in the labor market history do not show a clear upward or downward trend between 1985 and 2010. By contrast, males and females below the median wage exhibit increasing previous non-employment experiences, which is likely to affect inequality in the lower part of the wage distribution.

2.3 Trends in education, experience and industry structure

In addition to the changes in labor market history, there have been strong extensive changes in the distribution of education, work experience and industry structure. Figure 5 shows the percentage of workers in each education category. The share of workers without an educational degree has declined since the 1980s. This holds in particular for female workers, among whom the percentage of unskilled workers decreases from 32% in 1985 to 18% in 2010. We also observe an increase in the share of university graduates. Again, this is most pronounced for females, as the initial percentage of female university graduates is very small in 1985 but catches up to the male share by 2010. For the medium-skilled, i.e. workers with an upper secondary degree or a vocational degree, we observe a hump-shaped development. The share of medium-skilled rises during the late 1980s and the 1990s, reaches its peak in the late 1990s, and declines in the 2000s, giving way to a rising share of university graduates.

The corresponding trends for the distribution of worker's potential experience are shown in figure 6. Between 1985 and 2010, the percentage of highly experienced workers with 27 or more years of potential experience increases, reflecting the aging of the population. The share of workers with medium levels of experience (between 14 and 26 years) follows a hump shaped trend. The percentage of older workers with 40 or more years of experience did not undergo major changes in our sample, even though the overall population aged considerably. Note that the educational expansion counteracts somewhat the effects of an aging workforce on the share of highly experienced workers. The only major gender difference in potential work experience concerns the share of workers with low experience. Among males, this share is never higher than 20% and it drops to 10% in the late 1990s. Starting at 30% in 1985, the initial share of young female workers is very high, but it converges to the low male level in the late 1990s. This reflects the catching-up of female labor market participation in recent decades. By 2010, the composition of the male and the female working population has become very similar.

Figure 7 shows the development of industry shares for eight aggregated sectors. We observe some sectors with an almost constant share since the 1980s (i.e. transportation and trade), while others experiences strong changes. For males, the largest changes are observed for the construction industry, the manufacturing sector for consumer goods, and the banking and insurance sector. The first two experience a massive decline, while the latter more than doubles its share between 1985 and 2010. Transport and communication, as well as health and social services show small increases, whereas the manufacturing sectors for vehicles and for machinery shrink slightly. The initial sector composition differs strongly by gender, but the dynamics of the different sectors are quite similar. In particular, manufacturing declines strongly, while banking and health services grows. The construction sector, which plays no important role for females, does not change in any substantial way.

For our study of wage inequality, the decline of the manufacturing sector is of special interest. In these industries, the wage level is higher than in the rest of the economy and wage inequality is smaller. Table 5 shows that the log wage gap between the 85th and 15th wage percentile for the non-manufacturing sector was 10 log points higher in 1985 than that of the manufacturing sector across both genders, and 18 log points higher in 2010. Thus, the decline of employment in the manufacturing sector may have had an impact on (residual) wage inequality. Note that the sector variable considerably overlaps with a multitude of firm and job characteristics, which we do not disentangle explicitly.⁵

3 Implementation of counterfactual analysis

3.1 Composition reweighting for full-timers

We account for the selection into full-time work based on the observed composition of workers regarding their socio-economic characteristics. Changes in the composition over time reflect selective movements of individuals into and out of full-time work. Our aim is to quantify the effects of such changes in the composition of full-timers on wage inequality. To do so, we estimate counterfactual wage distributions fixing the composition of a reference group, which, in our case, is the sample of full-timers in a reference year. In the first part of our analysis, we analyze the distribution of full-time wages which would result if the distribution of worker characteristics had not changed over time but only the conditional wage structure (i.e. the wage distribution holding characteristics constant).⁶ Based on these counterfactual wage distributions, we calculate and compare the development of inequality as measured by the gaps between the 85th, 50th and the 15th wage percentiles and the spread of residual wages.

For residual wages, we consider the residuals from a Mincer regression of log wages w on a flexible specification of the characteristics listed in table 1. The dispersion of residual wages represents wage inequality within narrow groups of workers defined by the characteristics given in table 1. Changes in residual wage inequality may also be the result of changes in the composition of the labor force (Lemieux 2006). This will be the case if there is heteroscedasticity, i.e. the conditional residual variance depends on observed characteristics. In this case, shifts in the distribution of characteristics affect residual wage inequality. For instance, overall residual wage inequality will typically rise if there is a rising share of workers with above-average levels

⁵See Card et al. (2013, 2016), for a detail analysis of the role of firm specific effects.

⁶Such an analysis ignores general equilibrium effects, i.e. changes in the conditional wage structure are assumed to be independent of changes in the work force composition.

of within-group inequality.

In order to estimate the counterfactual distributions, we use the reweighting method proposed by DiNardo et al. (1996) and applied among others by Lemieux (2006) and Dustmann et al. (2009). Let $t_x = b$ denote the base year, for which the composition of the work force will be held fixed, and $t_w = o$ the year for which we intend to estimate a counterfactual wage distribution. We call this year the observation year. Here, we only use observations on full-timers in years t_w and t_x .

The counterfactual wage distribution using the conditional wage structure of year $t_w = o$ but the distribution of characteristics x from the base year $t_x = b$ is given by

$$\begin{aligned} f(w|t_w = o, t_x = b) &= \int_x f(w|x, t_w = o) dF(x|t_x = b) \\ &= \int_x f(w|x, t_w = o) \rho(t_x = b) dF(x|t_x = o). \end{aligned} \quad (1)$$

where $f(w|t_w = o, t_x = o)$ is the actual density of wages for characteristics x in year $t_w = o$ and $\rho(t_x = b) = \frac{dF(x|t_x=b)}{dF(x|t_x=o)}$ is the reweighting factor which translates the density of observed wages into the counterfactual density. Note that as a special case $f(w|t_w = o, t_x = o) = \int_x f(w|x, t_w = o) dF(x|t_x = o)$, for which $\rho(t_x = b) \equiv 1$ in equation (1). The reweighting factor can be written as the ratio $\rho(t_x = b) = \frac{P(t=b|x) P(t=o)}{P(t=o|x) P(t=b)}$, where $P(t = o)$ and $P(t = b)$ are the sample proportions of the observation year and the base year when pooling the data for both years.

The proportions $P(t = b|x)$ and $P(t = o|x)$ are estimated by logit regressions of the respective year indicator on flexible specifications of the characteristics shown in table 1. The logit regressions are based on the sample pooling the base year and the observation year. Using the fitted logit probabilities, we then calculate the individual reweighting factors $\rho_i(t_x = b)$ for observations i . All our estimates use the sample weights s_i which compensate for the varying length of employment spells. For robustness reasons, we trim the maximum value of individual observation weights to the value of thirty, in order to prevent extreme values of the reweighting factor, which may occur as a result of extremely rare combinations of characteristics. We tested a range of trimming thresholds, and found that values between 20 and 50 avoid extreme outliers, while at the same time excluding a very small number of observations (details are available upon request).

The reweighting factor can be incorporated into the estimation of counterfactual quantiles based on the sample wage distribution while fixing the composition of full-timers in the base year. Using the abbreviation $\rho = \rho(t_x = b)$, the reweighted (composition adjusted) $p\%$

quantile is given by

$$Q_p(w|t_w = o, t_x = b) = \begin{cases} \frac{w_{[j-1]} + w_{[j]}}{2} & \text{if } \sum_{i=1}^{j-1} (s\rho)_{[i]} = \frac{p}{100} \sum_{i=1}^n (s\rho)_{[i]} \\ w_{[j]} & \text{otherwise} \end{cases}, \quad (2)$$

where

$$j = \min \left(k \mid \sum_{i=1}^k (s\rho)_{[i]} > \frac{p}{100} \sum_{i=1}^n (s\rho)_{[i]} \right),$$

$w_{[i]}$ is the i th order statistic of wages, and $(s\rho)_{[i]}$ is defined accordingly (i.e. the order statistic of the compound individual weights $s\rho$, combining the sample weight s with the reweighting factor ρ).

As inequality measures, we use the quantile gaps (differences in quantiles of log wages) between the 85th and 50th, the 85th and 15th as well as between the 50th and 15th counterfactual percentile, i.e.

$$QG_{85/50}(w|t_w = o, t_x = b) = Q_{85}(w|t_w = o, t_x = b) - Q_{50}(w|t_w = o, t_x = b) \quad (3)$$

$$QG_{85/15}(w|t_w = o, t_x = b) = Q_{85}(w|t_w = o, t_x = b) - Q_{15}(w|t_w = o, t_x = b) \quad (4)$$

$$QG_{50/15}(w|t_w = o, t_x = b) = Q_{50}(w|t_w = o, t_x = b) - Q_{15}(w|t_w = o, t_x = b). \quad (5)$$

In addition to a graphical comparison of the actual and counterfactual development over time, we also contrast the increase in the counterfactual quantile gaps with the actual increase between 1985 and 2010. This allows us to quantify the share of the increase in inequality associated with composition changes (where $g \in \{85/50, 85/15, 50/15\}$)

$$\begin{aligned} \text{share}QG_{g,x}(w|t_w = 2010, t_x = 1985) = & \quad (6) \\ \frac{(QG_g(w|t_w = 2010, t_x = 2010) - QG_g(w|t_w = 2010, t_x = 1985))}{(QG_g(w|t_w = 2010, t_x = 2010) - QG_g(w|t_w = 1985, t_x = 1985))}. \end{aligned}$$

For the logit regression, we use a sequence of specifications adding covariates in order to investigate the incremental composition effect on wage inequality. We divide the vector of characteristics into five groups of variables, namely educational outcomes (Ed), labor market experience (Ex), labor market history (Hist), occupation and industry characteristics (Occ, Ind) (see tables 1 and 2). Among those, we consider potential labor market experience as continuous and all other variables as categorical, leading to a highly flexible specification of the logit model. We calculate four versions of the counterfactual quantile gaps, starting with a

specification only controlling for education (row E in table 2).

Table 2: Specification overview

Label	Covariates	Exact specification
E	Education	ed
EE	Education, Experience	$ed + ex + ed * ex + ex^2 + ed * ex^2$
EEH	Education, Experience, Labor market history	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt + ft + pt5 + ft5 + ed * (pt5 + ft5) + pt5^2 + ft5^2 + ed * (pt5^2 + ft5^2)$
EEHOI	Education, Experience, Labor market history, Occupation & Industry Sector	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt + ft + pt5 + ft5 + ed * (pt5 + ft5) + ex * (pt5 + ft5) + pt5^2 + ft5^2 + ed * (pt5^2 + ft5^2) + occ + occ * ex + occ * ex^2 + sec + sec * ex + sec * ex^2 + sec * ed$

Sequentially adding sets of covariates (characteristics) to our reweighting procedure, we estimate the change in the counterfactual quantile gaps that is associated with the set of covariates considered up to a certain stage. This way, we quantify the incremental contribution of each set of covariates to the increase in wage inequality (this contribution is given by the figures in the columns labeled 'Increment' in tables 6 to 9). By going from one specification to the next, we decompose the difference between the observed and counterfactual rise in inequality into the effects of separate sets of covariates. For example, when adding occupation and industry characteristics (OI) to the reweighting function that already contains education, experience and labor market history (EEH), we measure the incremental composition effect of occupation and industry (OI) net of the composition effects contributed by the set of covariates already included (EEH). We add covariates in the order given in table 2. The incremental effect of each set of covariates depends upon the order in which they are added to the model. Our reasoning behind the choice of the sequence shown in table 2 is that we gradually move from exogenous and predetermined characteristics towards characteristics that are the likely consequence of endogenous decisions of the individual. We start with education because education typically remains fixed after labor market entry. Next, potential work experience is a linear function of time and education. Similarly, labor market history involves characteristics which are affected by education and actual work experience. Finally, occupation and industry can in principle be changed any time conditional on education, experience and labor market history, and we are particularly interested as to whether occupation and industry play a role after accounting for all other individual level characteristics.

3.2 Composition reweighting for total employment

The reweighting can be expanded to take into account selection between full-time work and total employment based on observables, thus addressing the limitation that the SIAB data do not provide comparable wages for part-timers. We first calculate wage distributions for full-timers using the distribution of characteristics in the total employment sample, involving both part-timers and full-timers. Then, in a second step, we reweight these counterfactual wage distribution to the characteristics of a base year, analogous to section 3. The resulting distribution can be interpreted as the wages that would have prevailed had all individuals worked full-time and had their characteristics stayed at the level of the base year.

The first step consists in within-period composition reweighting. We calculate counterfactual wage distributions, which would have prevailed if all individuals had been paid full-time wages. This interpretation holds under the assumption that returns to characteristics for non-full-timers are equal to those for full-timers. The results of Manning and Petrongolo (2008) suggest that hourly wage differentials for (female) part-timers in industrialized countries are not driven by differences in returns to characteristics, which lends credibility to our approach. In order to calculate these distributions, we apply the reweighting technique described in section 3, but instead of the full-time sample in a specific base year, the reference group is total employment in the same year. Let $e \in \{FT, TE\}$ describe the employment group to which each observation belongs, where FT represents full-timers and TE total employment. Full-time workers appear in both FT and TE . The reweighting factor $\rho(FT \rightarrow TE, t_x = o)$ is the probability of characteristics x in the total employment sample in a given year, relative to the probability x in the full-time sample of the same year

$$\rho(FT \rightarrow TE, t_x = o) = \frac{dF(x|e_x = TE, t_x = o)}{dF(x|e_x = FT, t_x = o)} = \frac{P(e = TE|x, t = o) P(e = FT|t = o)}{P(e = FT|x, t = o) P(e = TE|t = o)}. \quad (7)$$

Then, the counterfactual distribution of wages, assuming the entire labor force was working full-time, can be written as

$$\begin{aligned} & f(w|e_w = FT, e_x = TE, t_w = o, t_x = o) \\ &= \int_x f(w|x, e_w = FT, t_w = o, t_x = o) \rho(FT \rightarrow TE, t_x = o) dF(x|e_x = FT, t_x = o). \end{aligned} \quad (8)$$

Here, $P(e = TE|x, t = o)$ is estimated by a weighted logit regression on the pooled sample of the reference group (total employment TE) and the group of interest (full-timers FT), with the employment status indicator e denoting group membership of each observation. In this step, we use the specification from table 3, in order to include the full set of observable

individual characteristics.

Table 3: Specification for counterfactual total employment

Variables	Formula
Education, Experience, Labor market history, Occupation, Industry sector	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt + pt5years + ft + ft5years + ed * (pt5years + ft5) + occ + occ * ex + occ * ex^2 + sec + sec * ex + sec * ex^2 + sec * ed$

In a second step, we analyze the distribution of wages which would have prevailed, had all employees worked full-time, and had their characteristics been fixed at the level of the base year. By holding the composition of total employment constant over time, we control for changes in the wage distribution due to changes in the selection into total employment over time. This counterfactual distribution can be written as

$$f(w|e_w = FT, e_x = TE, t_w = o, t_x = b) = \quad (9)$$

$$\int_x f(w|x, e_w = FT, t_w = o) \rho(e_x = TE, t_x = b) \rho(FT \rightarrow TE, t_x = o) dF(x|e_x = FT, t_x = o),$$

where

$$\rho(e_x = TE, t_x = b) = \frac{dF(x|e_x = TE, t_x = b)}{dF(x|e_x = TE, t_x = o)} = \frac{P(t = b|x, e_x = TE) P(t = o|e = TE)}{P(t = o|x, e_x = TE) P(t = b|e = TE)}. \quad (10)$$

Analogous to section 3, we sequentially add groups of covariates to our logit specifications as described by table 2. This allows us to investigate the incremental changes in inequality associated with the corresponding composition changes.

4 Empirical results

First, we analyze the impact of composition changes on wage inequality among full-timers. Next, we investigate the sensitivity of the findings to the choice of base year and the importance of interaction effects. Finally, we analyze wage inequality for total employment by accounting for composition differences between part-timers and full-timers.

4.1 Wage inequality among full-timers

Starting with *male full-timers*, we first analyze the effect of educational upgrading on male wage inequality. Figure 8 (left panel) shows the evolution of the wage quantile gaps among

males between 1985 and 2010 under the assumption that the 1985 distribution of education is held fixed over time. It turns out that fixing education considerably reduces the increase in inequality, i.e. the observed educational upgrading contributes strongly to the observed increase in wage inequality. Table 6 shows that a share of 17.1% of the increase in overall inequality (as measured by the 85/15 quantile ratio) and 37.5% of the increase in the upper half of the distribution (as measured by the 50/15 quantile ratio) can be explained by changes in education, while these changes did not contribute to rising inequality at the bottom of the distribution (as measured by the 50/15 quantile ratio, see lower part of figure 8). This means that the compositional effects of the educational expansion mostly affected the upper part but not the lower part of the male wage distribution. The contribution of changes in education on residual wage inequality amounts to a moderate 7.1%, i.e. there is no strong shift towards groups of workers with above-average levels of within-group inequality. As a next step, figure 9 extends the reweighting procedure to include changes in work experience (in addition to changes in education). Based on the evidence shown in figure 9 (left panel) and table 6 (columns 4 to 6), the incremental contribution of work experience is very small.

In figure 10, we add changes in recent labor market histories to our reweighting procedure. This considerably changes the results for overall wage inequality, and it affects in particular the lower part of the distribution. The incremental contribution amounts to 16.9% for overall wage inequality, and to some 19.2% for inequality in the lower half of the distribution (column 10 of table 6). This means that increasingly discontinuous labor market histories are important to explain the rise in lower-tail wage inequality. There was also a sizeable contribution to changes in residual wage inequality (10.7%), suggesting that changes in recent labor market histories were associated with shifts towards worker groups with higher levels of within-group inequality. Finally, figure 11 adds changes in occupations and industry structure to our reweighting procedure. This also contributes to the general rise in male wage inequality (13.0% for overall wage inequality, 22.2% to inequality at the bottom and 13.6% to residual wage inequality, see columns 11 to 13 of table 6).

Note that adding this last stage of our reweighting procedure results in the cumulative effect of changing the joint distribution of all our covariates (Ed+Ex+Hist+Occ+Ind). As shown in column 12 of table 6, these compositional changes explain more than half of the increase in male wage inequality over the period 1985 to 2010 (53.0% of overall wage inequality, 54.6% at the top, 51.5% at the bottom, and 34.0% of residual wage inequality). Our results confirm the importance of compositional effects for male wage inequality changes also found by Dustmann et al. (2009) and Felbermayr et al. (2014), but establish the contribution of the additional factor of changes in recent labor market histories. Note that the explanatory power of compositional changes is particularly high between 1985 and 1995 (holding characteristics fixed, there is no increase in inequality at all, see left panel of figure 11), but became somewhat weaker from

1996 onwards. Similar to the findings for the U.S. (Lemieux 2006), the total contribution of the compositional changes considered lies above 50%, which is quite high.

Next, we turn to results for *female full-timers*, see the right hand panels of figures 8 to 11. By contrast to the findings for males, figure 8 shows that the increase in female wage inequality remains largely unchanged, when holding constant the 1985 distribution of education.⁷ Adding changes in work experience (which are mainly driven by age) yields a strong incremental contribution (35.1% to overall inequality, 30.4% to upper half inequality, and 38.2% to lower half inequality, see figure 9 and columns 5 to 7 of table 7). This also differs from the findings for males. In light of figure 6, the findings for females reflect that younger cohorts are much smaller compared to older ones (e.g. the share of females with 0 to 13 years of potential work experience dropped from 30% in 1985 to 10% in 2010). This leads to a rising share of older female full-timers with different wage levels and higher within-group inequality.

In the right hand panel of figure 10, we add recent labor market histories to our reweighting procedure. Again, this explains a considerable, incremental share (18.6% for overall inequality and 17.1% for residual inequality, columns 8 to 10 in table 7). Thus, the impact of part-time episodes and labor market interruptions on the rise of female wage inequality was similar to that on the rise of male wage inequality. Finally, we find that adding changes in occupations and industry structure had negligible further effects on rising female wage inequality (columns 11 to 13 of table 7).⁸

Altogether, we find that compositional changes can account for an even larger share of the rise in female wage inequality than it was the case for men. Column 12 of table 7 shows that 63.6% of the increase in overall inequality, 61.9% of the increase in the upper part, and 64.8% of the increase in the lower part of the distribution can be accounted for the compositional changes considered, in particular by changes in potential work experience and labor market histories. The right hand panel of figure 11 implies that these effects were so strong that, during the period 1991 to 2001, female wage inequality would even have fallen in the absence of such compositional changes in the age and experience structure of the female labor force. Also an important part of these changes has worked through composition changes in residual wages, i.e. shifts between groups of workers with different levels of within-group inequality (51.6% of the changes are accounted for by composition changes, see column 12 of table 7).

⁷However, as to be discussed in section 4.2, holding constant the distribution of education in 2010, suggests a composition effect for education in explaining the increase in wage inequality. This points to interaction effects, see below.

⁸It is not an error that quantile gaps for the overall distribution are unchanged up to the third digit in row 13 of table 7 when adding occupation and industry characteristics. This relates to the fact that daily wages are rounded to full Euros. Therefore, quantiles only change if the change in counterfactual weights are large enough to move the wage quantile to a different Euro integer value.

4.2 Choice of base year and interaction effects

As a robustness check and to account for interaction effects in the counterfactual analysis, we reverse the role of the base year and the target year in our reweighting procedure. So far, we have considered the wage distribution in 2010 and changed the distribution of characteristics back to that of the base year 1985. This is indicative of the part of the inequality increase that could be ‘reversed’ by undoing the change in characteristics. In this case, the inequality change explained by composition effects is $QG(t_w = 2010, t_x = 2010) - QG(t_w = 2010, t_x = 1985)$. Now, we focus on the opposite case in which we start with the wage distribution in 1985 but only change the distribution of characteristics to the level of 2010. This corresponds to the change $QG(t_w = 1985, t_x = 2010) - QG(t_w = 1985, t_x = 1985)$. It is indicative of the part of the inequality increase that can be accounted for by solely changing the distribution of characteristics, holding fixed the conditional wage structure at its 1985 level.

The results of this exercise are given in tables 8 and 9.⁹ For males, the contributions of the different sets of covariates to the overall inequality increase remain qualitatively similar, with a few notable exceptions. The general result is that compositional changes in educational qualifications and in labor market histories provide substantial contributions to the overall inequality increase, while compositional changes related to potential work experience and the occupations/industry structure do so only to a much smaller extent (table 8 vs. table 6). However, the impact of education changes is much stronger in table 8 compared to table 6 (31.9%, 59.4%, 7.4%, 18.6% vs. 17.1%, 37.5%, -1.0%, 7.1%). This means that compositional changes over time would be associated with a stronger increase in wage inequality based on the wage distribution in 1985 compared to 2010.¹⁰ Put differently, the effects of a widening conditional wage structure $f(w|x)$ is stronger when applied to the distribution of characteristics in 1985 than when applied to that in 2010. This would naturally arise if the 1985 distribution of characteristics is more heterogeneous so that applying diverging wage returns to this more heterogeneous population leads to stronger inequality increases. This applies to education: the proportion of low-skilled declines from a high initial level, while the proportion of high-skilled increases (figure 5). Another difference between tables 6 and 8 is that the contribution of occupations/industries falls when the base year 2010 is used (table 8). In contrast to the results for education, the composition of occupation and industry has changed in a way that

⁹More detailed graphs are provided in the appendix.

¹⁰This conclusion is based on the following formal argument ($10 \equiv 2010, 85 \equiv 1985$):

$$QG(t_w = 85, t_x = 10) - QG(t_w = 85, t_x = 85) > QG(t_w = 10, t_x = 10) - QG(t_w = 10, t_x = 85)$$

is equivalent to

$$QG(t_w = 10, t_x = 10) - QG(t_w = 85, t_x = 10) < QG(t_w = 10, t_x = 85) - QG(t_w = 85, t_x = 85).$$

wage inequality increases more strongly for the 2010 composition of occupation and industry compared to the 1985 composition, i.e. in this sense occupation and industry have become more heterogeneous over time.

For females, the contribution of composition changes in work experience and recent labor market histories remains qualitatively unchanged when we change the base year (columns 6 to 10 in tables 7 and 9). However, as for males, the compositional effects of educational upgrading becomes much stronger in table 9. As explained for males, this is the expected consequence of a more heterogeneous distribution of educational qualifications in the year 1985. The only other effect for females, that is not fully robust to the choice of the base year, concerns the changes in occupations and industries. Here, table 9 shows pronounced effects on inequality in the upper and lower part of the distribution, which are not present in the scenario of table 7. Altogether, the overall contribution of compositional effects to rising female wage inequality in table 9 is even larger than for the base year 1985 (table 7). In particular, composition changes can account for 78.4% of the overall rise in female wage inequality between 1985 and 2010. In the lower part of the distribution, such compositional changes even account for the complete change in inequality (103.2%). We conclude that the composition changes would have been associated with a large increase in inequality based on 1985 wages compared to 2010 wages. This suggests that already in 1985 there were 'dimensions of wage inequality', in contrast to the widely held view in the past that Germany used to be a country where institutions strongly limited wage inequality (see Fitzenberger 1999 or Dustmann et al. 2014 for a critical assessment of this view). Incidentally, the changes in the wage structure over time in fact attenuated the inequality increasing effects of the composition changes.

4.3 Counterfactual full-time wages for total employment

This section extends the analysis of full-wage wages to total employment, including those working part-time in the year of observation. As explained above, part-time wages are not comparable because we lack detailed information on hours worked in our data set. However, we observe the personal characteristics of part-timers and we can include this information into our analysis of composition effects. More concretely, we consider the distribution of characteristics in the combined population of full-time and part-timers ('total employment sample').

Our analysis of total employment will be informative in four ways. First, comparing the actual wage distribution of full-timers with the counterfactual wage distribution that assumes that both part-time and full-timers are paid full-time wages will be informative about whether part-timers are a positive or negative selection with respect to their characteristics (compared to full-timers). Second, examining the development of the counterfactual wage distribution for

the total employment sample over time may serve as an estimate for composition effects on wage inequality in a wider population of part-time and full-timers, which we cannot examine directly given that comparable wage information for part-timers is missing. This also serves as a robustness checks of our above findings for full-timers. Third, a major part of the effect of selection into full-time work versus part-time work is accounted for by the employment history both among part-timers and full-timers, see above. Fourth, we net out selective transitions between part-time and full-time work in our analysis of composition effects, in the sense that we measure composition effects net of such (often temporary) movements between part-time and full-time work.

Our analysis of total employment starts out with the estimated counterfactual trends in inequality of full-time wages in a sample sharing the composition of total employment (see section 3.2 for the estimation of the counterfactual distributions). Figure 12 shows the trend in wage inequality if full-timers shared the education composition of total employment. For male workers, the differences between both distributions is very small in 1985. After 2000, we see a slight decline in the 15% quantile of the total employment distribution, relative to the full-time distribution, which leads to slightly wider 50/15 and 85/15 quantile gaps. This suggests a negative selection into part-time work for men. However, the part-time share of male workers already starts rising in the early 1990s, while we only observe negative effects of selection into part-time a decade later. This implies that there is no negative selection associated with the initial expansion of part-time work. Also for females, the initial full-time and total employment distributions for females are quite similar, especially regarding the upper tail. However, the quantiles diverge quickly and by 1990, we see lower wages for the total employment sample over the entire distribution. This means that characteristics that were prevalent among part-time workers involve lower wage returns than those of full-timers, implying negative selection into part-time work. After 1990, the distributional gap between the full-time and the counterfactual total employment sample was almost constant, implying a basically stable positive selection into full-time work.

The differences of the observed female full-time wage distribution in 2010 and the wage distribution for the counterfactual total employment sample are also shown in the right panel of figure 13 (bold vs. dashed line). Considering the total employment sample shifts the distribution to the left, i.e. the full-time sample is positively selected. The dotted lines in figure 13 represent the wage distributions that result when one further changes the characteristics to those of the total employment sample in 1985. For both genders, this results in a considerable compression of the wage distribution, i.e. also in the total employment sample changing characteristics contribute to rising inequality.

Now, we analyze the importance of composition changes for trends in full-time wage inequality

in the total employment sample. Table 10 shows the contributions for different groups of covariates to the increase of wage inequality. We find fairly similar results in comparison to the results for the male full-time sample reported in table 6. In particular, there is an important role for composition changes regarding education (especially at the top) and labor market histories (especially at the bottom). Including part-timers into the analysis makes the contribution of labor market histories to rising inequality much more pronounced at the bottom of the distribution (38.6% in table 10 vs. 22.2% in 6). Thus, the increase in the patchiness of labor market histories is quite relevant for male part-timers. There is only a limited role for changes in occupations and industries. These conclusions are robust to reversing the base year, see tables 10 and 8.

Table 11 presents results for the female total employment sample. Figure 2 shows that the share of part-timers is much higher than among males, which may let one to expect much more pronounced differences between the development of the full-time and the total employment sample. However, comparing the results in table 11 to those on the female full-time sample in table 7 yields qualitatively similar results. As in table 7, the numbers in table 11 show a role for shifts in experience and recent labor market histories, while changes in education and occupations and industries do not contribute much. In table 13, we reverse the base year. As in the female full-time sample, this boosts the role of education changes (particularly at the top of the distribution) and leads to a number of smaller unsystematic changes that point to complex interaction effects of compositional and wage structure effects. Similar to males, extending the analysis to total employment for females also amplifies the importance of recent labor market histories for increasing wage inequality at the bottom of the distribution (20.5% vs. 28.6% in table 7 vs. table 11, and 11.9% vs. 22.7% in table 9 vs. table 13, column 10).

Summing up, the analysis for total employment leads to broadly similar conclusions about the impact of compositional changes on increases in wage inequality. For males, we confirm that education changes and recent labor market histories are important, while we find that changes in age/experience and labor market histories are important for females. Furthermore, extending the analysis to include part-time work amplifies the contribution of recent labor market histories to inequality increases at the bottom of the distribution.

5 Conclusions

The rise in wage inequality has been a major concern in the policy debate in Germany and it was a key argument for the introduction of a national statutory minimum wage. Even though a large literature exists on the topic, no consensus has been reached regarding the driving forces behind the rise in wage inequality. This paper analyzes the time period 1985

to 2010, and we scrutinize the contribution of composition changes in education, potential work experience, labor market history, industry structure, and occupation. We use inverse probability weighting to estimate the counterfactual full-time wage distributions which would have prevailed, had worker characteristics remained fixed at the level of a base year. Our major contribution is that we account explicitly for the increasing heterogeneity of labor market experience regarding part-time work and employment interruptions. We document the strong increase in the incidence of both temporary and permanent part-time employment and the variability of part-time employment over time, both for female and male workers. Furthermore, we estimate the counterfactual full-time wage distribution for total employment.

Our results imply that changes in observables explain a large part of the increase in wage inequality, and that the increasing heterogeneity of labor market experience plays an important role. For males, we find that (depending on the base year) 43 to 53 percent of the increase in wage inequality between 1985 and 2010 can be accounted for by compositional effects of the observables considered. For females, the importance of composition changes is even higher, ranging between 64 and 78 percent. To the best of our knowledge, the literature has so far not recognized the extremely strong role of composition effects for the rise of female wage inequality. For males, composition changes in education (especially in the upper part of the distribution) and changes in recent labor market histories (especially in the lower part of the distribution) are the main contributors to compositional change. The compositional effects of male labor market histories to rising overall wage inequality range from 14 to 17 percent, and from 18 to 23 percent in the lower half of the distribution. For females, we find strong composition effects of changes in age/experience and in labor market histories. The latter contribute 17 to 18 percent to the overall increase in female wage inequality over the period 1985 to 2010. Our further analysis implies that the composition changes would have been associated with a larger increase in inequality based on 1985 wages compared to 2010 wages. Quite similar composition effects also apply for total employment. When including part-timers, the role of recent labor market histories becomes even stronger.

Our results are policy relevant because both changes in the age/education structure and in labor market histories can be predicted fairly well and may therefore inform policy makers. On the one hand, the fact that education and work experience increase among employees implies that the additional relative labor supply is met by rising demand. This is consistent with the SBTC hypothesis which predicts rising demand for education and higher work experience. On the other hand, increasingly patchy and heterogeneous labor market histories may be the result of labor market deregulation, unemployment shocks, and increasing labor market participation, especially of females. Given that wages are influenced by previous employment histories, such changes will continue to influence the wage distribution and wage inequality. Our further analysis including part-timers reveals their negative selection regarding their human capital

characteristics. This implies that selection effects with respect to prior employment at the intensive and extensive margin are important for the analysis of wage inequality.

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Figures

Figure 1: Wage quantiles relative to levels of 1985

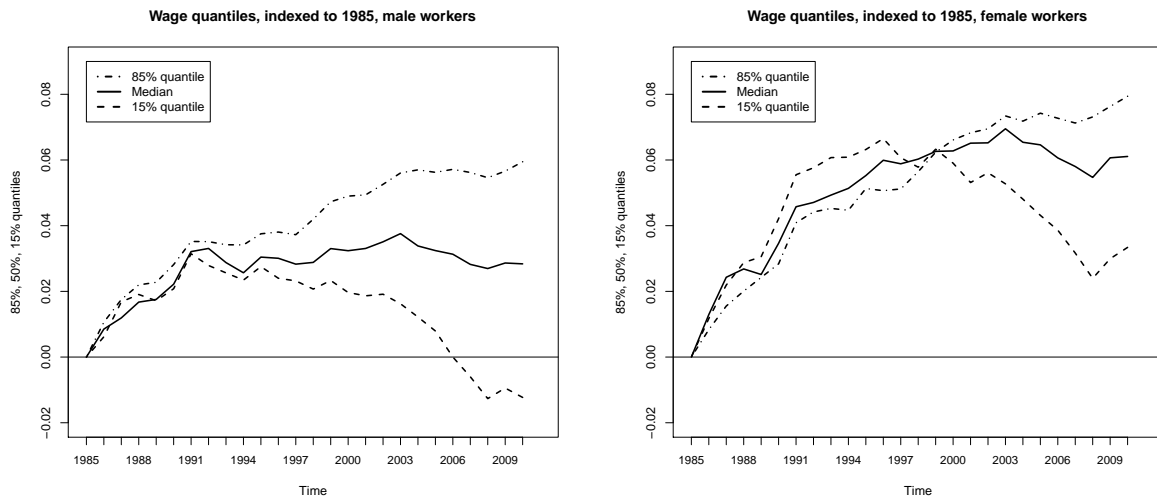


Figure 2: Part-time share over time

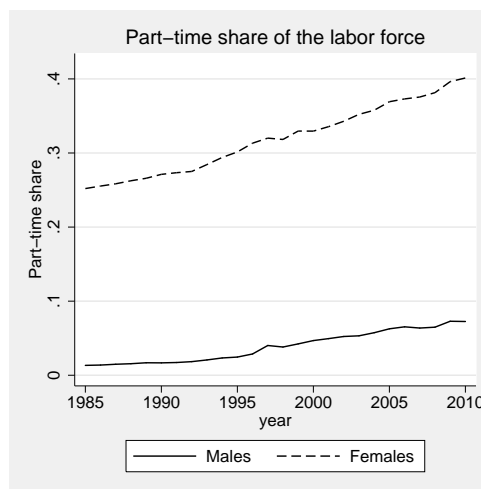
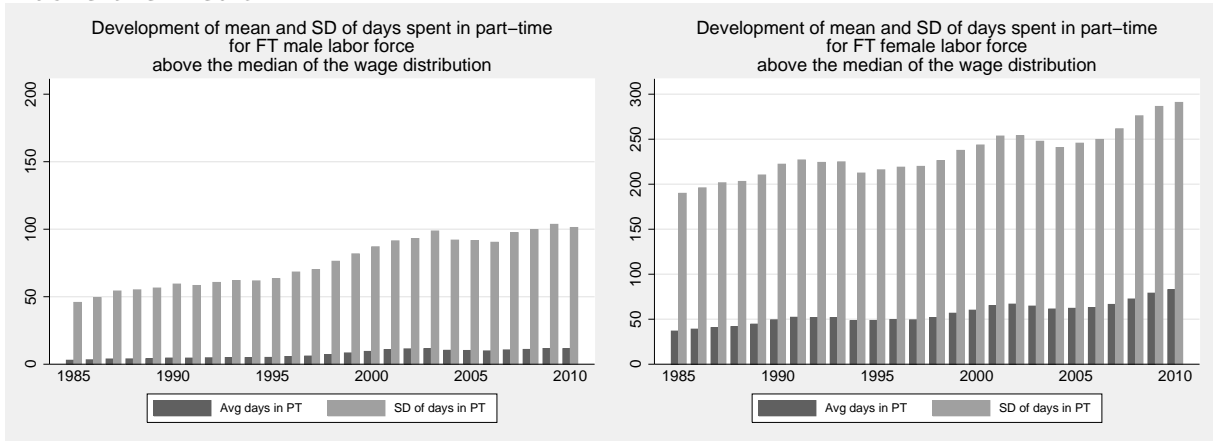


Figure 3: Days spent in part time work during the last 5 years

Above the median



Below the median

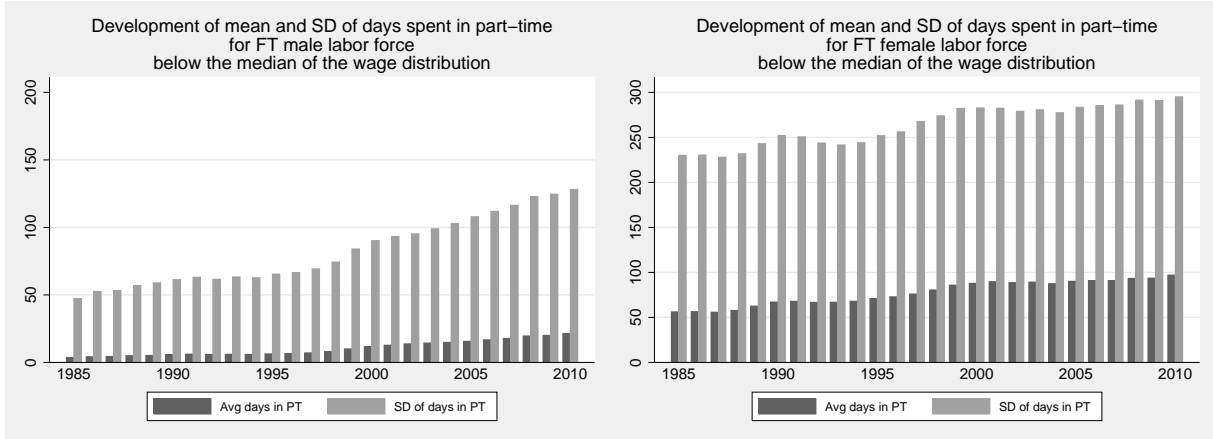
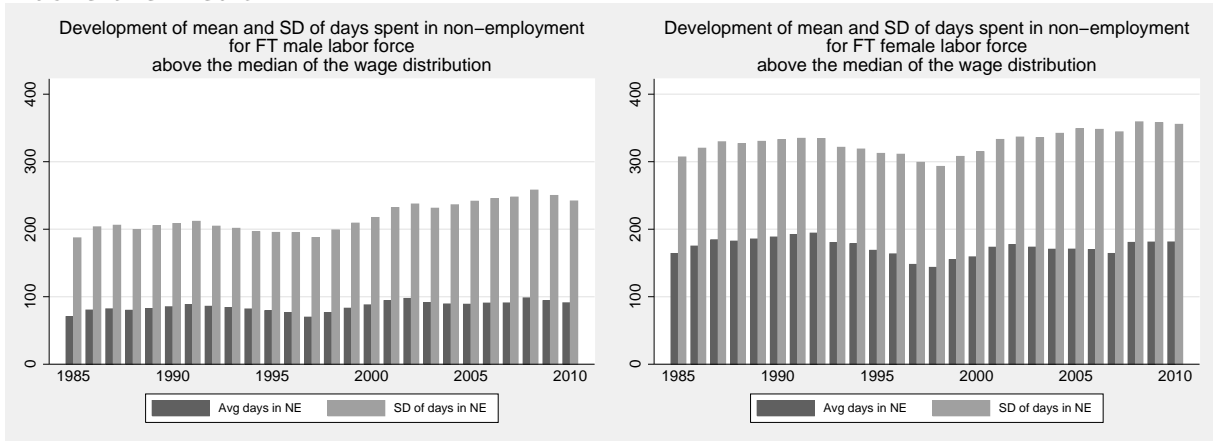


Figure 4: Days spent in non-employment during the last 5 years

Above the median



Below the median

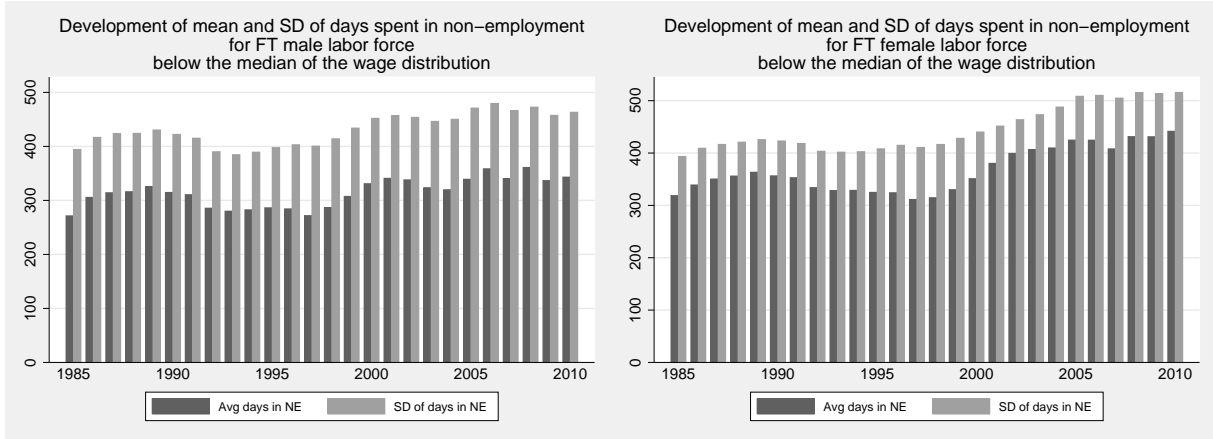


Figure 5: Share of education groups

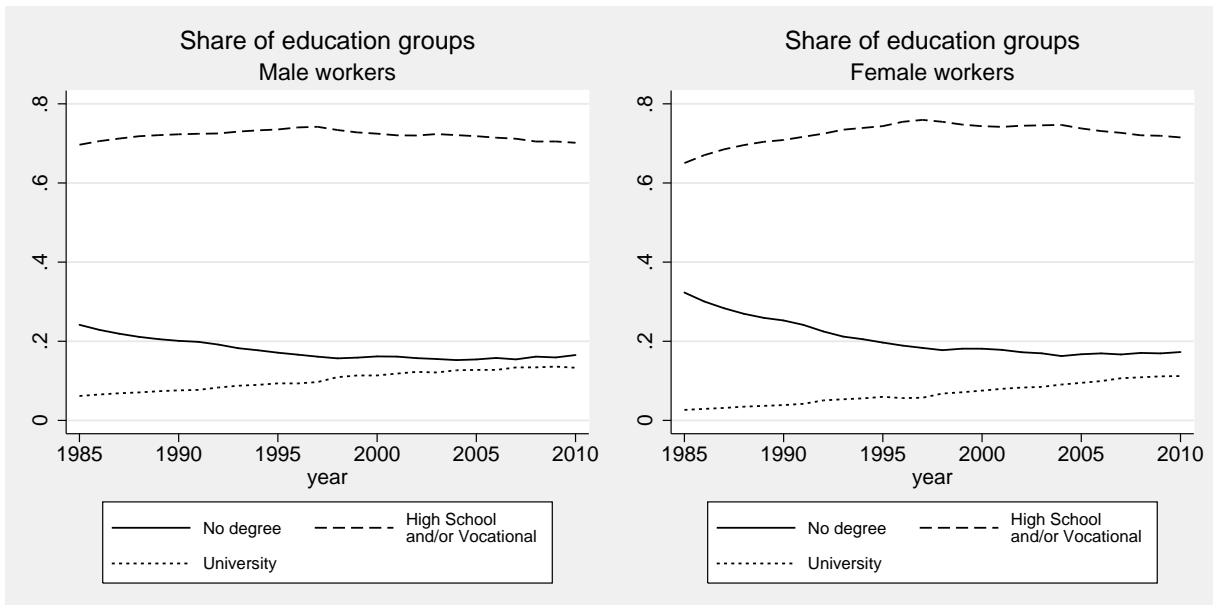


Figure 6: Share of experience groups

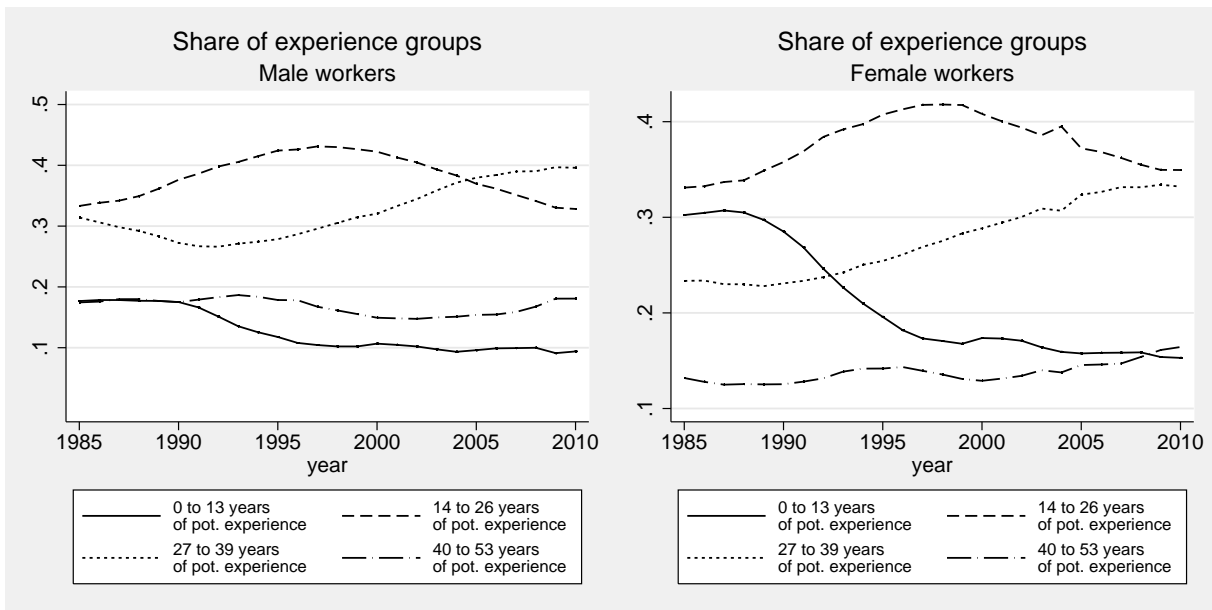


Figure 7: Share of industry sectors

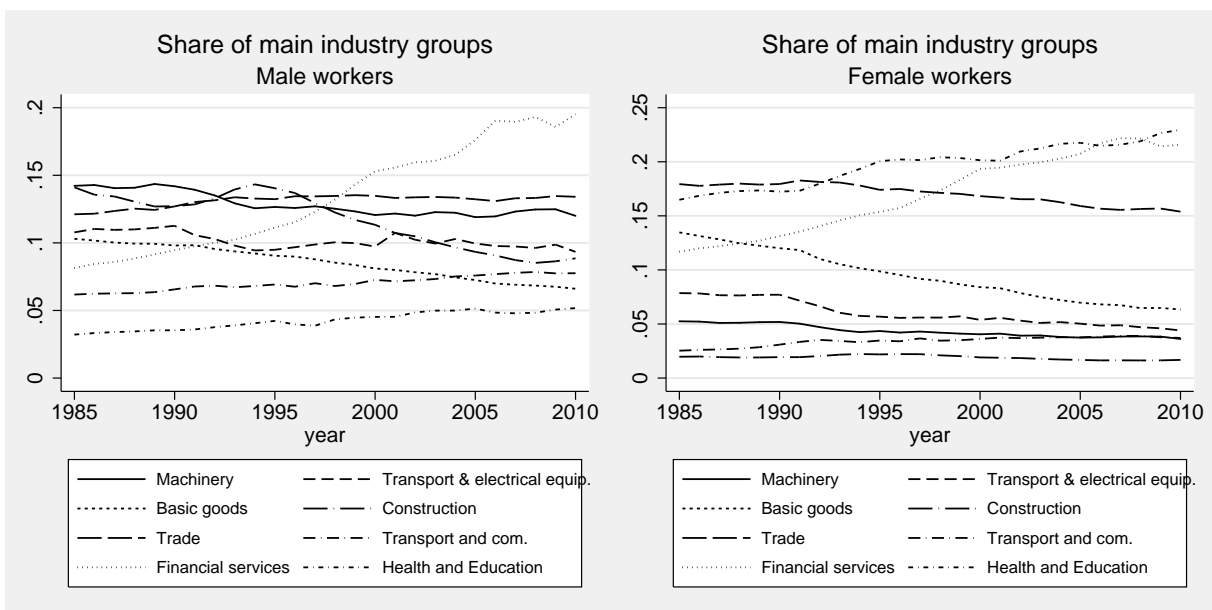


Figure 8: Inequality development base year 1985, specification E (Education)

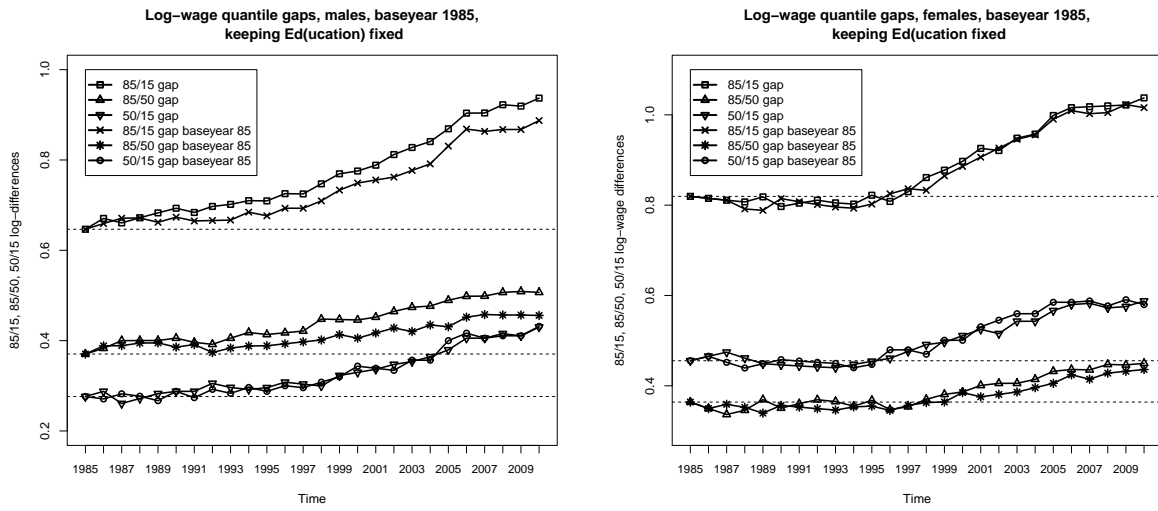


Figure 9: Inequality development base year 1985, specification EE (Education, Experience)

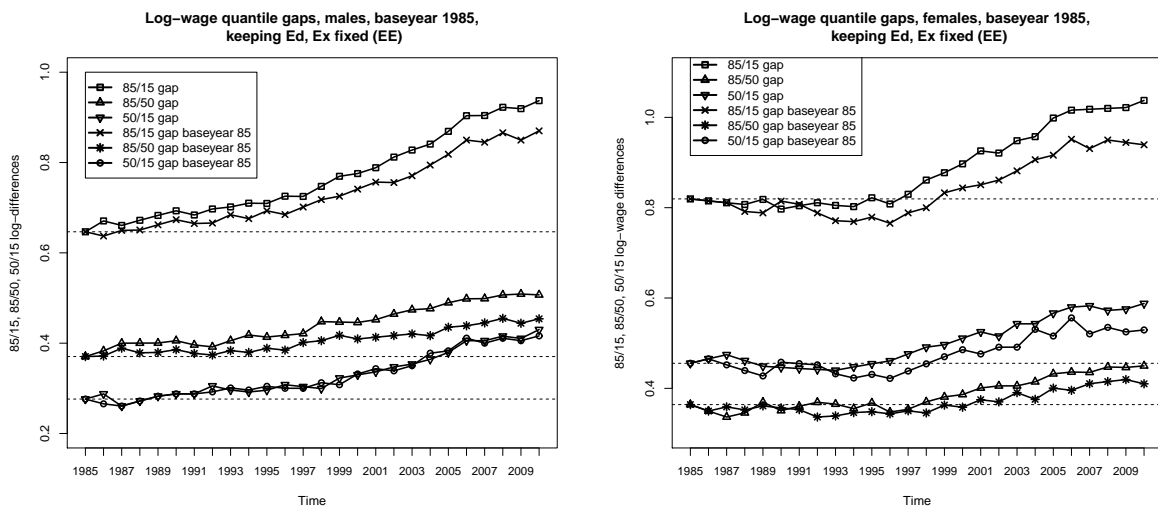


Figure 10: Inequality development base year 1985, specification EEH (Education, Experience, Labor market history)

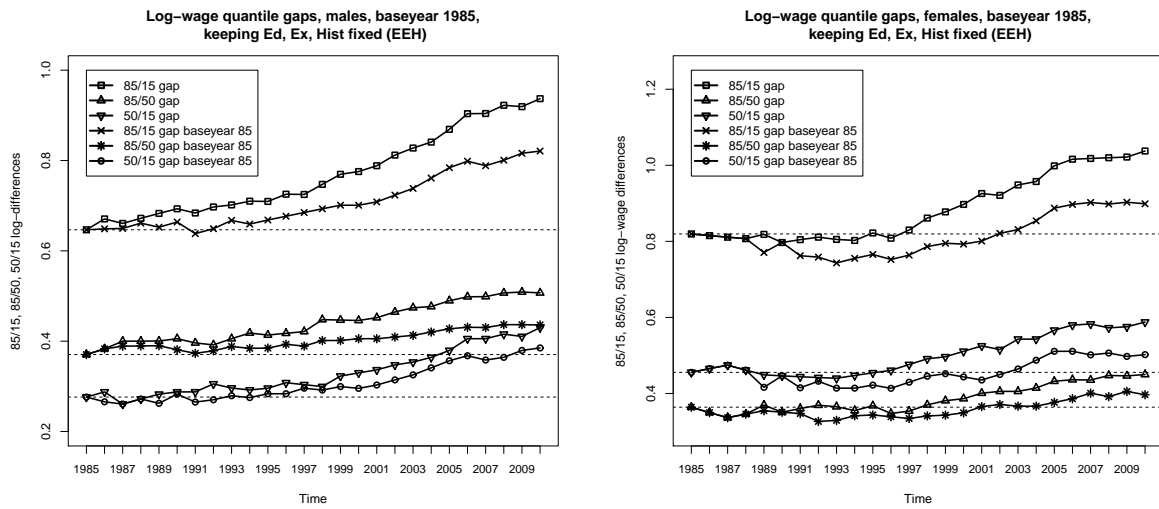


Figure 11: Inequality development base year 1985, specification EEHOI (Education, Experience, Labor market history, Occupation, Industry sector)

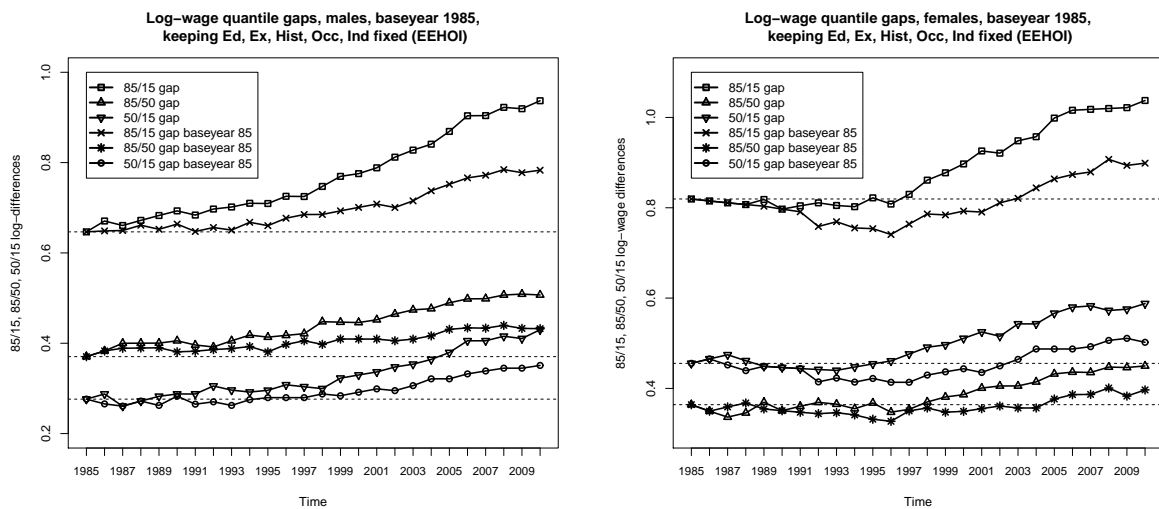


Figure 12: Counterfactual wage distribution, if full-timers had total employment characteristics

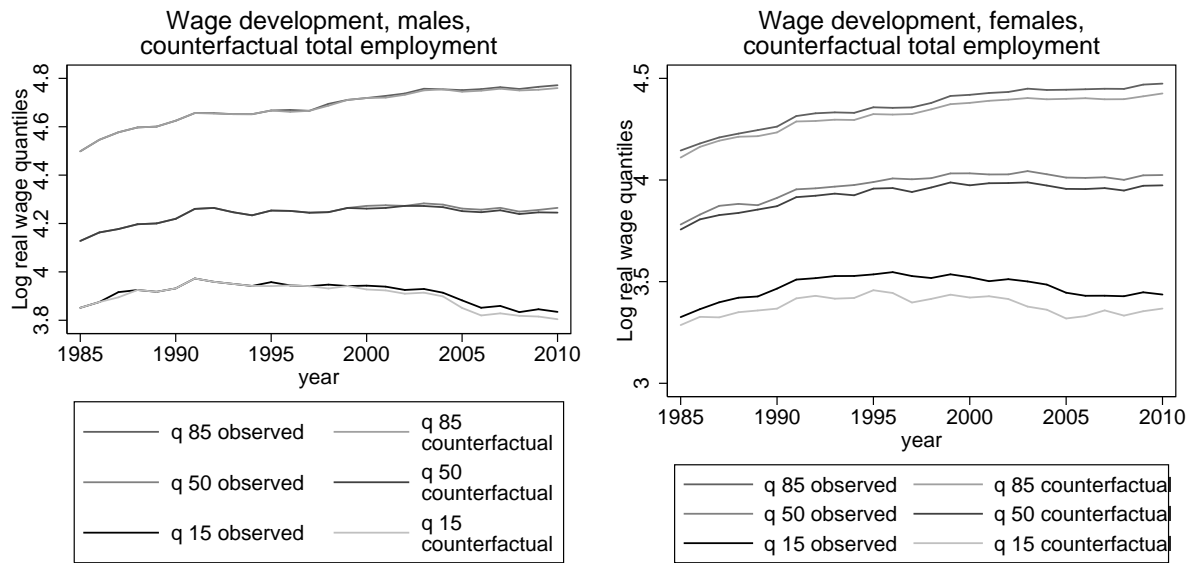
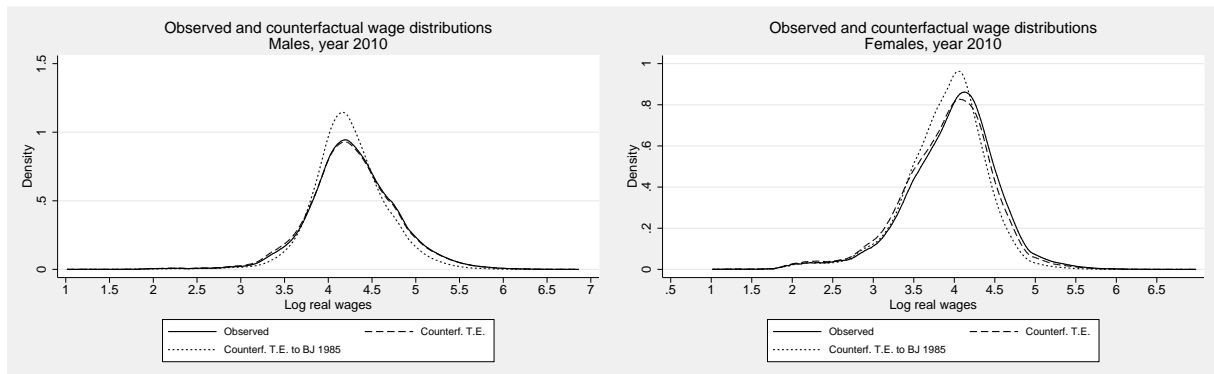


Figure 13: Comparison of observed, counterfactual total employment and reweighted counterfactual total employment sample (specification EEHOI)



Tables

Table 4: Descriptives of full-time samples

	Male full-time sample				Female full-time sample			
	1985		2010		1985		2010	
	mean	sd	mean	sd	mean	sd	mean	sd
Real wage in Euro	70.06	47.53	82.48	48.34	46.24	20.34	61.02	35.16
Log real wage	4.16	0.39	4.28	0.51	3.74	0.44	3.97	0.56
No/other degree indicator	0.19	0.40	0.08	0.28	0.27	0.45	0.08	0.27
Vocational degree indicator	0.71	0.46	0.71	0.45	0.66	0.47	0.73	0.44
University degree indicator	0.07	0.25	0.15	0.36	0.03	0.16	0.12	0.32
Work experience	27.34	11.19	28.98	10.13	24.03	11.90	27.39	11.14
No. of days in full time last 5 years	1546.04	487.51	1523.88	513.84	1356.01	598.16	1327.35	625.94
Fulltime spell in previous year?	0.96	0.19	0.96	0.20	0.93	0.26	0.93	0.26
No. of days in part time last 5 years	3.26	46.49	15.72	113.47	45.97	210.01	88.99	292.80
Part-time spell in previous year?	0.00	0.05	0.01	0.09	0.02	0.15	0.04	0.20
Agriculture and mining	0.03	0.17	0.02	0.13	0.01	0.08	0.01	0.08
Plastics, rubber, mineral products	0.03	0.17	0.03	0.17	0.02	0.14	0.01	0.11
Chemicals	0.03	0.18	0.02	0.15	0.02	0.15	0.02	0.13
Machinery and metal products	0.15	0.36	0.13	0.33	0.05	0.23	0.04	0.19
Transport- and electrical equipment	0.12	0.32	0.11	0.31	0.08	0.27	0.05	0.21
Food and basic consumption	0.10	0.31	0.07	0.25	0.13	0.34	0.06	0.25
Hotels and restaurants	0.01	0.11	0.02	0.13	0.03	0.18	0.03	0.18
Construction	0.12	0.32	0.08	0.28	0.02	0.14	0.02	0.13
Trade	0.12	0.33	0.14	0.35	0.18	0.38	0.16	0.36
Transport and communication	0.06	0.24	0.07	0.26	0.02	0.16	0.04	0.19
Financial and insurance	0.08	0.27	0.18	0.38	0.12	0.33	0.21	0.40
Public services	0.04	0.20	0.05	0.21	0.06	0.23	0.06	0.24
Health and Education	0.03	0.18	0.05	0.23	0.17	0.38	0.24	0.42
Public administration	0.06	0.24	0.04	0.20	0.08	0.27	0.06	0.24

Table 5: Median wages by industry sector

	Sector 1: Non-manufacturing	Sector 2: Manufacturing
1985		
Log median wage, 1985	4.00	4.06
Log 85-15 wagegap, 1985	0.82	0.72
2010		
Log median wage, 2010	4.13	4.30
Log 85-15 wagegap, 2010	1.05	0.87
all years		
Log median wage, all years	4.13	4.22
Log 85-15 wagegap	0.89	0.78

Table 6: Reweighted inequality increase, 1985-2010, males, compositions for base year 1985

Observed Increase	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.290	0.241	17.11%	0.223	23.04%	5.93%	0.174	39.95%	16.92%	0.137	52.97%	13.02%
85/50	0.137	0.085	37.50%	0.084	38.82%	1.32%	0.066	52.00%	13.18%	0.062	54.64%	2.64%
50/15	0.154	0.155	-1.00%	0.140	9.02%	10.02%	0.109	29.25%	19.23%	0.075	51.49%	22.24%
90/10 residual	0.183	0.170	7.07%	0.165	9.71%	2.64%	0.146	20.37%	10.66%	0.121	33.96%	13.59%

Table 7: Reweighted inequality increase, 1985-2010, females, compositions for base year 1985

Observed Increase	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.218	0.196	9.91%	0.120	45.05%	35.14%	0.079	63.64%	18.59%	0.079	63.64%	0.00%
85/50	0.086	0.072	15.90%	0.046	46.30%	30.40%	0.033	61.89%	15.59%	0.033	61.89%	0.00%
50/15	0.132	0.124	6.02%	0.074	44.23%	38.21%	0.047	64.77%	20.54%	0.047	64.77%	0.00%
90/10 residual	0.185	0.193	-4.38%	0.132	28.77%	33.15%	0.100	45.89%	17.12%	0.090	51.56%	5.67%

Table 8: Reweighted inequality increase 1985-2010, males, compositions for base year 2010

Observed Increase	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.198	31.87%	31.87%	0.192	33.87%	2.00%	0.153	47.34%	13.47%	0.167	42.46%	-4.88%
85/50	0.137	59.40%	59.40%	0.039	71.47%	12.07%	0.027	80.17%	8.70%	0.041	69.80%	-10.37%
50/15	0.154	7.43%	7.43%	0.153	0.48%	-6.95%	0.126	18.18%	17.70%	0.126	18.18%	0.00%
90/10 residual	0.183	18.64%	18.64%	0.138	24.62%	5.98%	0.107	41.36%	16.74%	0.094	48.73%	7.37%

Table 9: Reweighted inequality increase 1985-2010, females, compositions for base year 2010

Observed Increase	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.218	27.10%	27.10%	0.099	54.49%	27.39%	0.062	71.79%	17.30%	0.047	78.39%	6.60%
85/50	0.086	30.58%	30.58%	0.044	48.38%	17.80%	0.022	74.01%	25.63%	0.051	40.09%	-33.92%
50/15	0.132	24.85%	24.85%	0.055	58.44%	33.59%	0.039	70.36%	11.92%	-0.004	103.22%	32.86%
90/10 residual	0.185	2.55%	2.55%	0.093	49.56%	47.01%	0.061	66.94%	17.38%	0.046	75.11%	8.17%

Table 10: Change in inequality measures since 1985, for males, composition adjusted to total employment in base year 1985

Observed	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.309	16.90%	16.90%	0.249	19.24%	2.34%	0.174	43.55%	24.31%	0.137	55.79%	12.24%
85/50	0.144	33.72%	33.72%	0.087	39.43%	5.71%	0.076	47.43%	8.00%	0.062	57.11%	9.68%
50/15	0.164	2.14%	2.14%	0.162	1.51%	-0.63%	0.098	40.15%	38.64%	0.075	54.64%	14.49%
90/10	0.195	6.23%	6.23%	0.177	8.92%	2.69%	0.143	26.75%	17.83%	0.117	39.72%	12.97%
residual												

Table 11: Change in inequality measures since 1985, for females, composition adjusted to total employment in base year 1985

Observed	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.234	5.19%	5.19%	0.150	35.72%	30.53%	0.101	56.76%	21.04%	0.101	56.76%	0.00%
85/50	0.098	5.25%	5.25%	0.075	23.16%	17.91%	0.065	33.65%	10.49%	0.051	47.56%	13.91%
50/15	0.136	5.15%	5.15%	0.075	44.74%	39.59%	0.036	73.36%	28.62%	0.050	63.37%	-9.99%
90/10	0.158	-9.09%	-9.09%	0.114	28.31%	37.40%	0.078	50.44%	22.31%	0.069	56.12%	5.68%
residual												

Table 12: Change in inequality measures since 1985, for males, composition adjusted to total employment in base year 2010

Observed	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.222	36.71%	36.71%	0.215	39.24%	2.53%	0.159	58.32%	19.08%	0.166	55.96%	-2.36%
85/50	0.144	60.46%	60.46%	0.051	71.68%	11.22%	0.045	75.67%	3.99%	0.036	81.00%	5.33%
50/15	0.164	10.64%	10.64%	0.164	0.71%	-9.93%	0.114	41.36%	40.65%	0.131	29.29%	-12.07%
90/10 residual	0.195	-4.04%	-4.04%	0.149	4.87%	8.91%	0.056	68.78%	63.91%	0.058	67.67%	-1.11%

Table 13: Change in inequality measures since 1985, for females, composition adjusted to total employment in base year 2010

Observed	Ed			Ed+Ex			Ed+Ex+Hist			Ed+Ex+Hist+Occ+Ind		
	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment	Remaining increase	Explained share	Increment
85/15	0.173	31.10%	31.10%	0.087	68.30%	37.20%	0.035	88.04%	19.74%	0.062	78.15%	-9.89%
85/50	0.098	58.46%	58.46%	0.047	58.46%	0.00%	0.031	73.55%	15.09%	0.039	66.00%	-7.55%
50/15	0.136	8.88%	8.88%	0.041	75.07%	66.19%	0.004	97.73%	22.66%	0.023	86.39%	-11.34%
90/10 residual	0.158	-15.97%	-15.97%	0.077	47.55%	63.52%	0.036	76.60%	29.05%	0.018	88.34%	11.74%

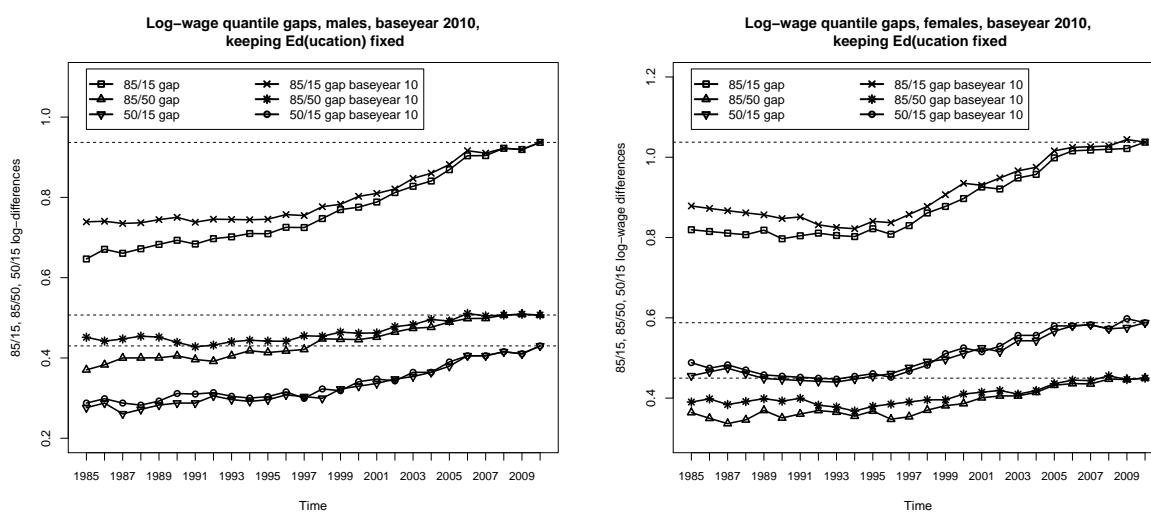
Appendix

Imputation of wages above the censoring threshold

Our imputation procedure for wages above the contribution threshold of social security is loosely based on Gartner (2005). We assume that log-wages are approximately normally distributed and estimate expected wages above the censoring point with a Tobit model. We regress log wages on education, age, nationality and individual labor market history, separately for both genders. Results in the literature suggest that this type of imputation leads to a slight upward bias in the variance of wages each year. Important for our analysis, however, it does not lead to bias in the trend of wage dispersion.¹¹ As we want to take into account that the variance of wages is potentially correlated with individual characteristics, we modify the procedure suggested by Gartner (2005) to explicitly model a heteroscedastic variance for the Tobit regression. A simple imputation of log wages from the Tobit model would exhibit too little variation. We therefore adjust imputed wages by a random draw from a truncated normal distribution, using the predicted heteroscedastic variance from the Tobit model. We impute separately for each year and for male and female workers. Imputation by this method raises the mean wage by 0.8% and the standard deviation 14.6% for males, and by 0.2% as well as 3.2% for females across all years.

Additional Figures and Tables

Figure A1: Inequality development base year 2010, specification E



¹¹Compare the discussion in Card (2013).

Figure A2: Inequality development base year 2010, specification EE

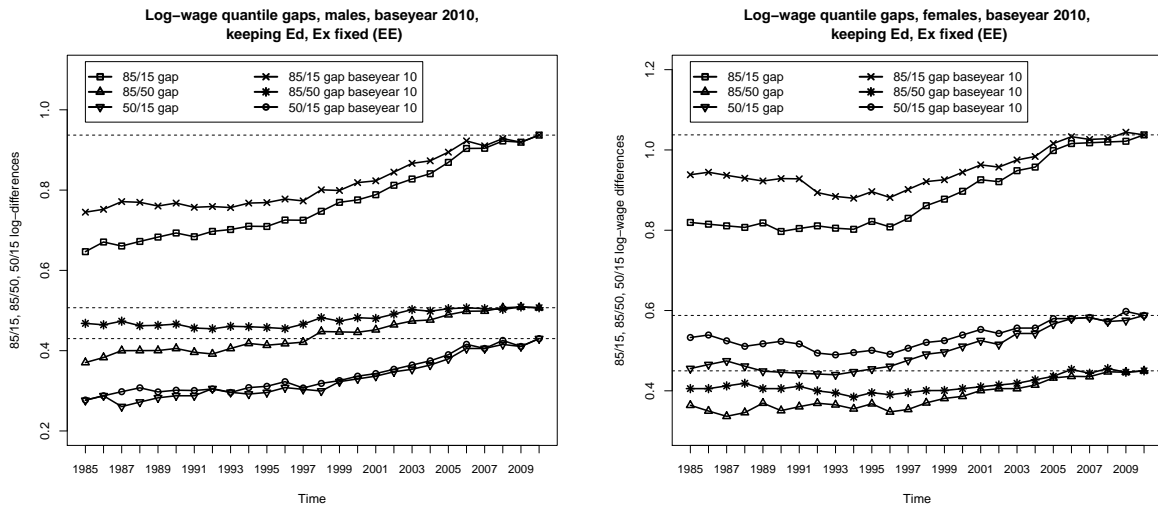


Figure A3: Inequality development base year 2010, specification EEH

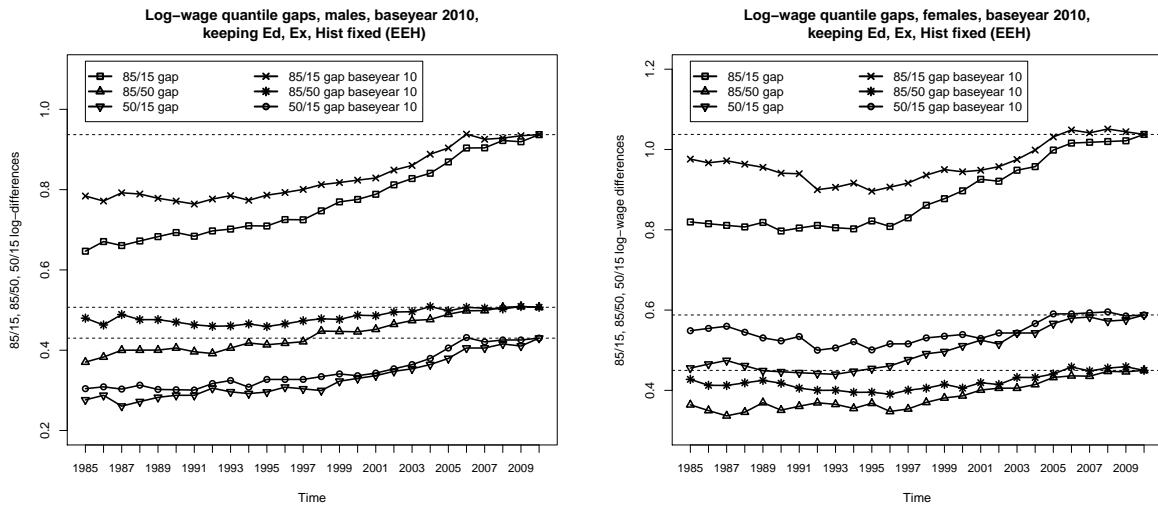


Figure A4: Inequality development base year 2010, specification EEHOI

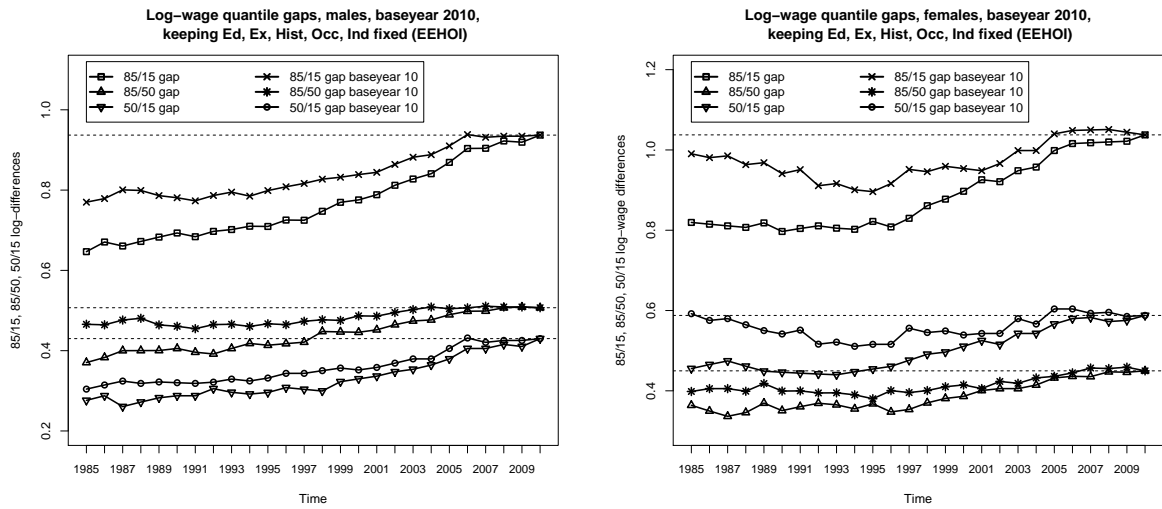


Table A1: Descriptives of combined full-time and part-time samples

	1985		2010	
	mean	sd	mean	sd
Males				
Real wage in Euro	69.89	47.51	81.61	48.15
Log real wage	4.15	0.40	4.27	0.52
No/other degree indicator	0.19	0.40	0.08	0.28
Vocational degree indicator	0.70	0.46	0.71	0.46
University degree indicator	0.07	0.25	0.16	0.36
Work experience	27.32	11.19	29.08	10.23
No. of days in full time last 5 years	1540.45	494.58	1494.81	544.03
Fulltime spell in previous year?	0.96	0.20	0.94	0.24
No. of days in part time last 5 years	6.29	78.41	37.03	203.05
Part-time spell in previous year?	0.01	0.08	0.03	0.18
Agriculture and mining	0.03	0.17	0.02	0.13
Plastics, rubber, mineral products	0.03	0.17	0.03	0.17
Chemicals	0.03	0.18	0.02	0.15
Machinery and metal products	0.15	0.36	0.13	0.33
Transport- and electrical equipment	0.12	0.32	0.10	0.31
Food and basic consumption	0.10	0.31	0.07	0.25
Hotels and restaurants	0.01	0.11	0.02	0.14
Construction	0.12	0.32	0.08	0.27
Trade	0.12	0.33	0.14	0.35
Transport and communication	0.06	0.24	0.07	0.26
Financial and insurance	0.08	0.27	0.18	0.38
Public services	0.04	0.20	0.05	0.21
Health and Education	0.04	0.18	0.06	0.23
Public administration	0.06	0.24	0.04	0.20
Females				
Real wage in Euro	43.64	20.41	55.40	33.52
Log real wage	3.67	0.48	3.85	0.59
No/other degree indicator	0.28	0.45	0.08	0.28
Vocational degree indicator	0.65	0.48	0.73	0.44
University degree indicator	0.03	0.16	0.11	0.32
Work experience	24.99	11.90	28.62	10.99
No. of days in full time last 5 years	1199.98	696.74	1048.65	759.52
Fulltime spell in previous year?	0.81	0.39	0.72	0.45
No. of days in part time last 5 years	209.50	513.80	366.32	642.41
Part-time spell in previous year?	0.14	0.35	0.25	0.43
Agriculture and mining	0.01	0.08	0.01	0.08
Plastics, rubber, mineral products	0.02	0.14	0.01	0.10
Chemicals	0.02	0.14	0.01	0.12
Machinery and metal products	0.05	0.22	0.03	0.18
Transport- and electrical equipment	0.07	0.26	0.04	0.20
Food and basic consumption	0.12	0.33	0.06	0.23
Hotels and restaurants	0.03	0.18	0.03	0.18
Construction	0.02	0.14	0.02	0.13
Trade	0.19	0.39	0.16	0.37
Transport and communication	0.03	0.17	0.04	0.19
Financial and insurance	0.12	0.33	0.19	0.40
Public services	0.06	0.23	0.06	0.24
Health and Education	0.18	0.38	0.26	0.44
Public administration	0.08	0.28	0.07	0.26

Figure A5: Inequality development base year 1985, specification EEHOI of total employment

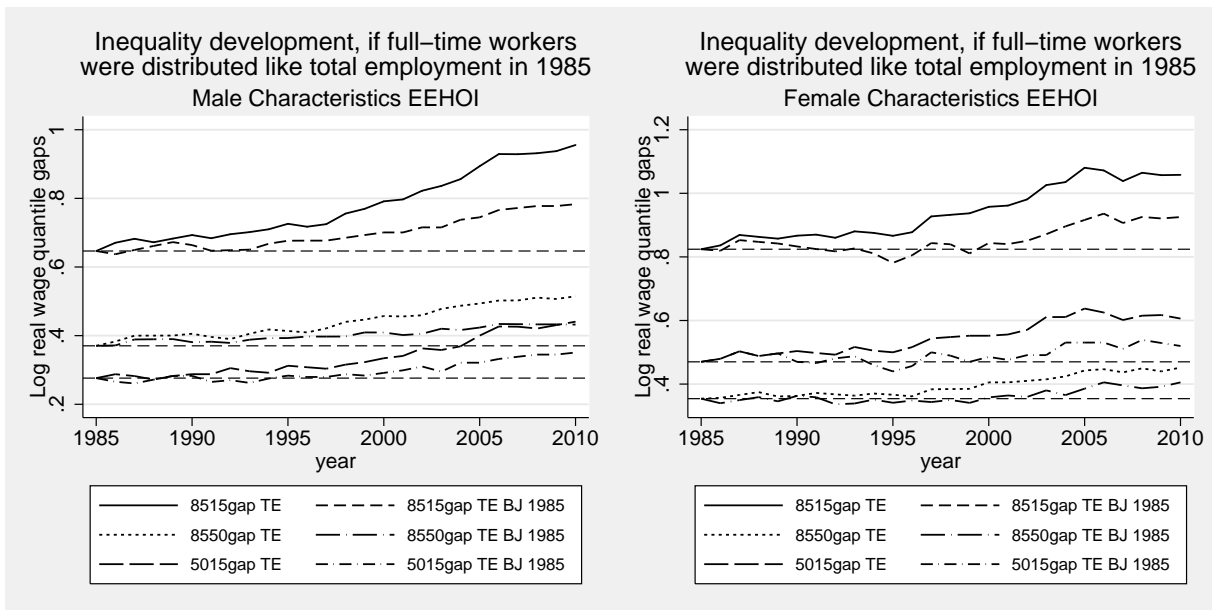


Figure A6: Inequality development base year 2010, specification EEHOI of total employment

