Revisiting Wage Inequality in Germany: Increasing Heterogeneity and Changing Selection into Full-Time Work

Martin Biewen*, Bernd Fitzenberger**, Jakob de Lazzer***

This version: March 2017

Abstract: This study revisits the analysis of the increase in wage inequality in West Germany between 1985 until 2010. The analysis is based on German administrative employment data (SIAB). We are using an inverse probability weighting approach, in the spirit of Lemieux (2006), to account for changes in various sets of observables. In particular, we take account of changes in employment histories and we also estimate the counterfactual full-time wage distributions for all employees. Our findings suggest that changes in observables explain a large part of the increase in wage inequality and the increasing heterogeneity of labor market histories plays a particular strong role. After controlling for education, age, and employment histories, changes in industry and occupation explain very little. The composition effects are larger for females compared to males and when counterfactual wage distributions are estimated for the sample characteristics of employees in 2010 compared to 1985. Put differently, the employees in 2010 would already have experienced noticeably higher levels of wage inequality compared to the workforce in 1985. Our estimation results for the entire labor force show that there is substantial negative selection into part-time work, and that changes in characteristics affect inequality in the full-time workforce to a larger extent than they do for part-time employees.

Keywords: wage inequality, reweighting, composition effects, Germany

JEL-Classification: J31, J20, J60.

* University of Tübingen.
** Humboldt University Berlin, IFS, CESifo, IZA, ROA, and ZEW.
*** Humboldt University Berlin.
Corresponding Author: Bernd Fitzenberger, Humboldt University Berlin, School of Business and Economics, Spandauer Strasse 1, 10099 Berlin, Germany. E-mail: fitzenbb@hu-berlin.de.

We thank the Research Data Center at IAB for useful discussions and for support with the data access through the CADAL project. We are very grateful for helpful discussions and suggestions at the IWH/IAB workshop 2016, at the RTG Summer School 2015, at the International Conference on "The German Labor Market in a Globalized World 2015" and at the Network Workshops of the DFG priority program 1764. We acknowledge financial support of this project 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). The responsibility for all errors is, of course, ours.

Contents

1 Introduction

It has been widely documented that wage inequality among full-time working males and females in West Germany has been rising strongly across the entire wage distribution from the 1990s onwards (e.g. Dustmann et al. (2009); Antonczyk et al. (2010b); Card et al. (2013)).[1] The increase in wage inequality has been documented based on different datasets involving administrative data and survey data.[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 statuatory minimum wage in 2015 (SVR 2014, chapter 7; Bosch und Weinkopf 2014; Dustmann et al. 2014, p. 185). Most of the existing literature (see references above) untertakes 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 compared to the literature, we account explicitly for the increasing heterogeneity of labor market experience regarding part-time work and employment interruptions.

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 Autor et al. 2008, Lemieux 2006, 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 (Autor et al., 2008), as in the 1990s inequality stopped to grow at the bottom of the wage distribution. Acemoglu and Autor (2011) take the latter as evidence for the task-based

[1]See also (in chronological order, not an exhaustive list), Kohn (2006), Gernandt and Pfeiffer (2007), Antonczyk et al. (2010a), Riphahn and Schnitzlein (2011), Fitzenberger (2012), Felbermayr et al. (2014), Dustmann et al. (2014), or Möller (2016).

[2]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 in Nuremberg. 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).

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 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 (see the careful discussion in 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, experience explains a major part of the increase in wage inequality in the U.S.. Both studies emphasize that composition effects (such as de-unionization or changing composition regarding education and experience) can have a strong impact on residual wage inequality, i.e. the wage differences among employees with the same observable characteristics.

Wage inequality has been rising in West 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 (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.Through a labor supply effect, the slow down in skill upgrading between low-skilled and medium-skilled labor contributes also to rising wage inequality in the lower part of the distribution, which dominates a possible positive wage effect at the bottom due to polarization of employment. Using BLFS data (footnote 2), Antonczyk et al. (2009) find a strong increase of wage inequality among full–time working males between 1999 and 2006. The decomposition results show that the changes in personal characteristics explain some of the increase in wage inequality whereas the changes in task assignments strongly work towards reducing wage inequality. Using the GSES data (footnote 2), Antonczyk et al. (2010a) find a strong increase of wage inequality among both full–time working males and females between 2001 and 2006. Accounting for coverage by collective bargaining, firm level characteristics, and personal characteristics, their decomposition analysis finds 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. The main contribution relates to the quantile regression coefficients of firm level variables (firm size, region, industry), thus reflecting a growing heterogeneity in firm level wage policies. Again, changes in personal characteristics work against the increase in wage inequality, especially among female workers. Using the full sample of all SIAB records, Card et al. (2013) estimate person and firm fixed effects in wages both for male and female full-time working employees. Their study shows that the heterogeneity of both firms and workers increases over time and worker with high personal fixed effects sort themselves more strongly over time in firms with high firm fixed effects. Both effects contribute strongly to the increase in wage inequality, whereas the decline in coverage by collective bargaining shows only a negligible effect. The study by Card et al. (2013) emphasizes the role of unobservables through the estimated person and firm fixed effects in explaining the increase in wage inequality. The study by Felbermayr et al. (2014) uses a more recent version (but up to 2010) of the linked employer-employee data (LIAB) as used in Dustmann et al. (2009) and aggregated industry data. This study finds that the decline in coverage by collective bargaining is the most important explanation for the increase in wage inequality up to 2010. At the same time, international trade contributes to the increase in wage inequality. 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 West Germany until 2010. Furthermore, the recent study by Möller (2016) based on a new release of the SIAB data shows that the increase in wage inequality stopped in 2010. However, the comparison of the time periods before and after 2014 is plagued by a structural break in 2011 regarding the variable distinguishing part-time workers from full-time workers.

The literature on the increase in inequality among full-time employees in West Germany has so far not taken into account the increasing heterogeneity in employment histories. Over time, in addition to changes in mincerian characteristics, part-time work has increased strongly both among males and females, transitions between types of work have increased in frequency and employment interruptions have become more common. Thus, over time full-time workers are much more likely to have experienced part-time work or employment interruptions in their employment history. Since the mid 1980s, the labor market histories of workers in West Germany have become more patchy, with shorter average length of employment spells and more frequent switches between full-time, part-time, and non-employment. 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. Negative long term career effects of transition from full-time to part-time work for women after childbirth have been studied in the literature (see e.g. Paul (2016); Connolly and Gregory (2009)). 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 to control for characteristics which are unobservable in cross-sectional data and which Card et al. (2013) attribute to individual fixed effects.

Most of the literature on the increase in wage inequality makes use of methodological advances in decomposition analysis, see Fortin et al. (2011) for a survey of the state-of-the art. While a standard Blinder-Oaxaco 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). DiNardo, Fortin, and Lemieux (1996) involve the first application of the method of inverse probability weighting (IPW) - or reweighting - to decomposing changes in the entire wage distribution. The idea of reweighting is simply 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).[3] The reweighting is based on the estimated probability of a worker with certain characteristics to be observed in either 1985 or 2010. This allows us to estimate the evolution of wage inequality over time that would have been observed if the characteristics of the workers remained as in 1985, see Dustmann et al. (2009) for the first application based on German wage data. By increasing sequentially the set of characteristics whose distribution is held constant, one can estimate the partial contribution of some characteristics while holding other characteristics constant. As pointed out Fortin et al. (2011), the results of a decomposition analysis depends on the counterfactuals estimated (e.g. the base period whose characteristics are held fixed) and a decomposition analysis assumes the absence of general equilibrium effects if coefficients are interpreted as prices in a hedonic wage regression. Note that differences associated with a change in the base period are informative in themselves regarding the way characteristics change over time. For instance, if the composition-constant increase in wage inequality is reduced when a more recent base period is used (as in Dustmann et al. 2009, Table II or in our study) this suggests a positive interaction between the increase in wage inequality holding characteristics constant and the change in characteristics.

[3] A decomposition analysis of wage inequality can also be based on conditional quantile regression (as in Antonczyk et al. 2010) or on unconditional quantile regression (as in Felbermayr et al. 2014 - the method is described in Fortin et al. 2011). In this paper, we use IPW because of the intuitive simplicity of the method and because of the possibility to apply it in two steps and construct counterfactual total employment distributions (see section 3.2.

We follow Dustmann et al. (2009), who estimate the contribution of changes in age and education during the time period 1975 to 2004. We focus on the time period 1985 to 2010 and we scrutinize the contribution of changes in various set of characteristics including education, work experience, labor market history, industry, and occupation. We use IPW to estimate the counterfactual full-time wage distributions holding fixed worker characteristics. Our major contribution is that we account explicitly for the increasing heterogeneity of labor market experience regarding part-time work and employment interruptions. Furthermore, we extend the analysis to estimate the counterfactual full-time wage distributions for the entire labor force including both full-time and part-time workers. Here we differentiate between shifts in the composition of the full-time workforce and of the entire labor force, and find that the contribution of composition changes on WI is higher for full-time workers, than it is for all workers. Our findings suggest that changes in observables explain a large part of the increase in both raw and residual wage inequality and the increasing heterogeneity of labor market experience plays a particular strong role. After controlling for education, age, and employment histories, changes in industry and occupation explain very little. The composition effects are larger for females compared to males and when counterfactual wage distributions are estimated for the sample of employees in 2010. Put differently, the employees in 2010 would already have experienced noticeably higher levels of wage inequality in 1985 compared to the workforce in 1985.

The remainder of this paper is structured as follows: Section 2 describes the data and describes the trend in wage inequality. Section 3 describes our implementation of the decomposition analysis. Section 4 presents the empirical results. Section 5 concludes. The appendix describes the imputation procedure used and it includes further detailed empirical results.

2 Data and trends in wage inequality

For our analysis we use the SIAB administrative dataset which consists of data collected by the German social security services. It is a 2% sample of all dependent employees who are subject so social security, but no self-employed or civil servants. We primarily study the time-frame from 1985 to 2010. Although data is available for earlier years, we do not include them for two reasons: Sizable changes in wage inequality in Germany can be observed since the 80s, and a structural break in the reporting of data in 1984 means that wages from earlier years are not reliably comparable to those after 1985. 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 this job this year. The sampling weights calculated this way reflect the relative importance of each observation.

We aggregate levels of education into three categories: College (University and Technical College/Fachhochschule), High school and/or Vocational Training, and No/Other degree. Industry sectors are classified according to the German Classification of Economic Activities, Edition 1993 (WZ 93) and aggregated into fourteen categories. When analyzing changes in occupations, we aggregate them to the 2-digit level of the KldB 1988 (Klassifikation der Berufe 1988) so that we classify 63 distinct occupations groups. For interaction effects, we aggregate further, to the 1-digit level of the KldB, in order to avoid the problem of empty factor combinations in the logit specification. The education variable is cleaned and interrupted measurements are imputed for consistency (compare Fitzenberger et al. (2006)).

We capture each individual's labor market history by four measurements: The number of days spent in full-time employment and part-time employment, aggregated over the last 5 years, respectively. And two binary variables which indicate if the worker had a full-time or part-time spell at any point during the last year. Wages are available as daily wages in Euros, which we deflate to the level of 1990. Since these wages are collected from administrative data sources, the measurements are very precise and do not suffer from the problems of nonresponse or measurement error commonly associated with wage information in survey data. While our dataset does not contain information on hours worked, we are confident that daily wages among full-time employees are sufficiently comparable. However, without working hours for part-time and marginally employed workers, wage data for those observations is not comparable across observations and jobs. Labor supply decision might vary greatly across time and between individuals, which would create strong confounding effects. In order to avoid these problems, we analyze only the wages of full-time employees. In section 4.2, we study wage developments in counterfactual total employment, where part-time workers are included in the labor force. However, this part of the analysis uses the full-time sample, reweighed with total employment characteristics, and therefore does not rely on the unknown working hours of part-time employees. All wages above the the contribution threshold for social security are censored in the SIAB. These censored observations lie above the yearly 85% wage quantile. Therefore, when looking at quantile gaps in the wage distribution, we compare the 85%/50%, the 85%/15% and the 50%/15% gaps. For those sections where we can not restrict our analysis to below the 85% quantile, for instance 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 6.1. Additionally, unless otherwise noted, we restrict our analysis to individuals of ages 20-60, in order to focuse on the primary working age, before widespread selective attrition due to early retirement sets in. The covariates which we use for the analysis are summarized in Table 1.

Table 1: Variable Classification

Variable Group	Short	Content
Education	Ed	3 categories: College, High-School and/or Vocational Training, No/Other Degree
Experience	Ex	Potential experience (age - years of schooling-6)
Labor Market History	Hist	Number of days in full-time, part-time over the last 5 years. Indicators for: Full-time job in previous year, Part-time job in prev. year
Occupation	Occ	Job classification by KldB 2-digit levels (63 categories)
Industry Sector	Ind	Industry classification by WZ93 (14 categories)

2.1 Trends in wage inequality

Figure 1 shows the development of log wage quantiles, relative to their level at the start of our observation period in 1985. The development path of the different wage quantiles in Germany has been positive and largely parallel until the 90s. However, after 1991 median real wages of male full-time employees have effectively remained stagnant. For female full-time workers we see a continuous, but decelerating, rise until 2003, and a subsequent decline until 2008. At the same time that median wages stop rising, we observe a widening of the wage distribution. Wages at the 85th percentile continue to climb, while real wages at the 15th percentile decline. For male workers, this decline is moderate until the early 2000s, and accelerates afterwards. Their wages at the 15th percentile in 2010 actually lie below the level of 1985. For women, we observe minor differences between the developments of median, upper and lower quantiles as early as 1988. However, strong increases in inequality only start in the late 90s. After 1998, women's median wages stagnate, while those at the 85th percentile rise and those at the 15th percentile rapidly decline. For the rest of the paper, our primary measures of wage inequality are the gaps between the 85th, 50th and 15th percentiles of log-wages. Trends in inequality, as measured by the 85/50 and 50/15 gaps, are plotted in the solid lines of Figure 8

2.2 Trends in labor market history

The prevalence of part-time work in Germany has increased substantially over the last decades (compare Figure 2). The German government has promoted expansions in part-time work as a means to alleviate unemployment, which might have contributed to the increase. Over our observation period, several changes in legislation were targeted at the part-time sector. For example, in 1985, the German government enacted a law (the

Beschäftigungsförderungsgesetz) which granted part-time workers the same level of job protection as full-time workers. This might have increased acceptance of part-time work with unions and in the general population. In 2001 followed another law which made it easier for employees to enter voluntary part-time work (the Teilzeit- und Befristungsgesetz). These changes in legislation had the effect of easing the transition between full-time, part-time and non-employment. We observe that not only has the yearly stock of part-time employees increased for both genders, but that the frequency of temporary part-time episodes for people who otherwise work full-time has increased as well.

In tandem with the increase in part-time work, the frequency of employment interruptions has increased, which is partly associated with the introduction of legislation to liberalize the labor market in Germany. Two changes in legislation between 1985 and 1998 (the Beschäftigungsförderungsgesetz and the Arbeitsförderungs-Reformgesetz) made it easier to employ workers on fixed-term contracts and allowed for extended temporary agency work.

Returns to labor market experience are not uniform across jobs and types of work as discussed, among others, by Manning and Petrongolo (2008). Not only is experience in part-time work valued lower than that from full-time work. It has also been shown that an individual's previous work history, with respect to part-time work or unemployment, influences his career path and the slope of wage progression. Therefore, previous spells in part-time or non-employment affect current full-time wages among full-time employees. Beblo and Wolf (2004) discuss how episodes of non-employment not only interrupt the accumulation of human capital, but also lead to depreciation of human capital through non-use. If transitions from non-employment back into work involve a job change, they also imply a loss of job-specific human capital. The authors note that episodes of part-time work can also slow down the accumulation of human capital, since part-time workers are less likely to receive vocational training and are therefore more vulnerable to skill obsolescence. For women in Great Britain, Connolly and Gregory (2009) show that the presence of part-time episodes in the labor market history lead to lower earnings trajectories when returning to full-time work. For Germany, Paul (2016) finds a substantial negative impact of time spent in part-time work on future earnings in full-time work. Increasing lengths of time spent in part-time work can lead to negative long-term wage effects. These effects can be seen in full-time work wages up several years later. She finds that employment interruptions which are not due to education have even stronger negative long term hourly wage effects than part-time episodes. These effects drive a wedge between the wage developments of those who interrupt their work history, and those who work FT all the time. Episodes of non-employment can also represent periods of additional education or retraining, in which case they will increase human capital.

This has consequences for the development of wage inequality, if changes in the length or frequency of part-time episodes are concentrated in specific regions of the wage distribution. Figure 3 shows increasing average lengths and also increasing variability of previous part-time episodes for both men and women, both above and below the median of the wage distribution. The mean and variance of time spent in part-time work have increased over the years, for those individuals who are working full-time jobs at the time of observation. Male full-time workers, particularly those with below-median wages, have experienced a pronounced increase in historic part-time episodes, although the total amount of time previously spent in part-time is relatively low compared to those of female workers. Striking is the dramatic increase in variability of the time spend in part-time work for males with below-median wages. This indicates increased movement between part-time and full-time work. Such movement is consistent with the idea of part-time work as a stepping stone towards full-time employment. If this is the case and individuals transition from part-time work into entry-level full-time jobs, then we expect observed changes in the work history of male workers to drive up inequality in the lower parts of the wage distribution. Some of the movement between both types of work might also be associated with an increase in the use of part-time work by men during child-rearing periods.

For female full-time workers, 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, while the rise in the amount of time previously spent in part-time work is similar to that of men. Initial variability is also higher for women, but increases more slowly over time. This reflects typical labor market histories of female workers in (West-) Germany, who commonly work full-time until the birth of their first child, and then work part-time or interrupt their career for several years. Eventually they might move back into full-time work. (compare Paul (2016))

The second aspect of mid-run labor market history, which influences wage developments, is time spent without regular employment. Figure 4 shows average lengths and also variability of time spent in non-employment over the past 5 years, for individuals who earn above and below the median of the wage distribution. This includes all activities which do not count as regular employment, such as unemployment, education, marginal employment and absence from the labor market. Different types of non-work will have vastly different implications for future wages. These interruptions in the labor market history do not show a clear upwards or downwards trend betwen 1985 and 2010. If anything, traces of business cycles can be found in the timeline of non-work history. Higher earning men show neither substantially increasing nor decreasing lengths of labor market interruptions over the observation period. Women and lower earning men show a decrease in work interruptions until the mid-90s, and increasing interruptions ever since. Here we might see effects of the expansion of higher education for women, which result in longer breaks due to time spent in education for higher earning individuals. We also observe slight increases in the length of interruptions for lower-earning individuals since the mid-90s, which coincides with high unemployment rates in the early 2000s and the subsequent expansion of marginal employment. Although there is no clear time trend, different types of work interruptions influence the inequality of wages over the observation period.

2.3 Trends in education, experience and industry structure

In addition to the changes in labor market history the German labor force has also experienced strong changes in the distribution of education, work experience and industry structure. Shares of workers in each education category are plotted in Figure 5. The share of workers without an educational degree has declined since the 80s for both genders. This is especially apparent among female workers, where the fraction of degree-less workers decreased from 32% of the workforce in 1985 to 18% in 2010. We also observe a steady increase in the share of university graduates for both genders. Again, this development has the most impact for women, since their initial share of university graduates in the labor force in 1985 is very small and has risen to be roughly equal with the university share of male workers. In the middle of the qualification range, which includes workers with either a high school degree, a vocational degree, or both, we observe a hump-shaped development. The workforce share of those qualifications rose up during the late 80s and early 90s and reached it's peak in the late 90s. After that, the share of these qualifications decreased again, some of this share taken up by university graduates.

In terms of potential experience, we observe similar demographic trends for both male and female workers, as shown in Figure 6. Between 1985 and 2010, the fraction of highly experienced workers with 30 or more years of potential experience has increased, reflecting aging effects of the population. The share of workers with medium amounts of experience (between 14 and 26 years) shows a hump-shape during this time, and is of a similar level at the start and end of our observation period. The share of older workers with 40 or more years of experience has not undergone major changes. For men, this share is at about 18% both in 1985 and 2010, while for women, it increased from 13% to 16%. One major difference between the experience development of men and women is in the share of fresh workers with low experience. Among men, this share has never been higher than 20% and has dropped to 10% in the late nineties, where it has remained ever since. For women, the initial share of fresh workers was higher, starting at ˜30% in 1985, but also decreased in the late 90s. Since then, the share of fresh female workers in the labor force has remained at roughly 15%.

Figure 7 shows the development of industry shares for the eight most common sectors in Germany. While some sectors, i.e. transportation and the trade sector, have not changed much since the 80s with regards to the share of workers they employ, others have seen dramatic increases or decreases in relevance. For male workers, the biggest changes happened to the construction industry, to the sector for manufacture of consumer goods and the banking and insurance sector. The first two experienced massive declines in the share of employed workers, while the latter has more than doubled in worker share between 1985 and 2010. Transport and communication, as well as health and social services show mild increases, while the manufacturing sectors for vehicles and machinery have shrunk slightly.

For women, initial shares of each sector are very different to those of men, but the dynamics of sector changes are relatively similar. Manufacturing has declined strongly, while banking and health services have increased. The main difference is in the construction sector, which employs only a minuscule part of the female workforce and hasn't changed in a substantial way since the 80s. For our study of wage inequality, the decline of the manufacturing sector is of special interest. Wages in this sector are less heterogeneous and more heavily clustered around the median, compared to other sectors. The log wage gap between the 85% and 15% quantile for the non-manufacturing sector was 14% higher in 1985 across both genders, and 20.6% higher in 2010. Therefore, we expect the receding share of the manufacturing sectors to have a substantial effect on wage inequality. The sector variable overlaps heavily with a multitude of firm and job characteristics, which we do not explicitly disentangle. [4]

3 Method

3.1 Composition adjustment for full-time workers

While we do not observe the decision process of selection into the labor force or between full-time and part-time work, we can observe the composition of the labor force with respect to socioeconomic characteristics and their distribution across occupations and industries. Changes in this composition over time can be interpreted as selective movements of individuals into and out of the labor force, or in and out of full-time work. Our aim is to quantify the effects of selection of worker types into states of work on wage inequality measures. To this end, we create counterfactual wage distributions which would have prevailed, had the composition of worker characteristics remained fixed at the levels of a reference group. In our analysis, the reference group is the sample of full-time workers at specific point in time. In the first part we analyze the distribution of full-time wages, which would have prevailed if the characteristics of workers had not changed over

[4]See Card 2013 and Card 2016 for a detailed exploration of the role of the firm in the development of German wage inequality.

time. On these counterfactual wage distributions, we can calculate and compare the development of inequality measures such as the gaps between the 85%, the 50% and the 15% quantiles and quantile gaps residual wages. One aspect which can not be accounted for, and which might potentially influence wage inequality, are general equilibrium effects which arise from differences in the relative supply of skills, compared to the levels of the observed year.

In order to estimate the counterfactual distributions, we use the reweighting method proposed by DiNardo et al. (1996) and applied (among many 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 is fixed, and $t_w = o$ the year of interest, for which we intend to estimate the counterfactual wage (w) distribution based on the composition of the employees (regarding observable characteristics x) in the base year. The year of interest will subsequently be called the observation year. For the first part of the analysis, we only use observations on full-time employee in years t_w and t_x. Then, the unconditional pdf of the actual wage distribution in the observation year is given by

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

which is the density of wages for characteristics (x) being distributed as observed in year o. Analogously, the unconditional counterfactual wage distribution for characteristics x being distributed as in the base year b is given by

$$(2) \qquad \begin{aligned} f(w|t_w = o, t_x = b) &= \int_x f(w|x, t_w = o) dF(x|t_x = b) \\ &= \int_x f(w|x, t_w = o) \rho(t_x = b) dF(x|t_x = o) \ . \end{aligned}$$

Here, $\rho(t_x = b) = \frac{dF(x|t_x=b)}{dF(x|t_x=o)}$ is the reweighting factor which transforms the observed density into the counterfactual density. This reweighting factor can be written as the ratio $\rho(t_x = b) = \frac{P(t=b|x)}{P(t=o|x)} \frac{P(t=o)}{P(t=b)}$, where $P(t = o)$ and $P(t = b)$ are the sample proportions of the year of interest and the base year when combining data for both years. The proportions conditional on x are estimated by a logit regression.

Specifically, we pool (stack) the observations of the base year and the observation year and we define an indicator variable denoting that a data point belongs to $t = o$. Based on this pooled sample, we estimate a flexible logit model of $P(t = b|x) = 1 - P(t = o|x) = L(\beta v(x))$, where $v(x)$ is a polynomial in x. We can then calculate the individual reweighting factors $\rho_i(t_x = b)$ for observations i. All our calculations, including the logit estimates, take account of the sample weights s_i which compensate for the varying length of employment spells. [5] The counterfactual weights obtained with the reweighting factor can be incorporated in the calculation of quantiles of the sample wage distribution, in order to construct the counterfactual wage quantiles for a labor force composition fixed at the level of the baseyear. Abbreviate $\rho_i(t_x = b) = \rho_i$. Then the reweighted pth percentile is:

$$Q_p(w|t_w = o, t_x = b) = \begin{cases} \frac{w_{(j-1)}+w_j}{2} & \text{if } \sum_{i=1}^{j} s_i\rho_i = \frac{p}{100}\sum_{i=1}^{n} s_i\rho_i \\ w_j & \text{otherwise} \end{cases},$$

where

$$j = min(k|\sum_{i=1}^{k} s_i\rho_i > \frac{p}{100}\sum_{i=1}^{n} s_i\rho_i)$$

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. Therefore:

$$\begin{aligned} QG_{85/50}(w|t_w = o, t_x = b) &= Q_{85}(w|t_w = o, t_x = b) - Q_{50}(w|t_w = o, t_x = b) \\ QG_{85/15}(w|t_w = o, t_x = b) &= Q_{85}(w|t_w = o, t_x = b) - Q_{15}(w|t_w = o, t_x = b) \\ QG_{50/15}(w|t_w = o, t_x = b) &= Q_{50}(w|t_w = o, t_x = b) - Q_{15}(w|t_w = o, t_x = b) \end{aligned}$$

We plot the development of these counterfactual quantile gaps over the observation period, in order to display the divergent paths of observed and composition-adjusted inequality over time.

We also contrast the increase in the counterfactual quantile gaps with the increase in observed quantile gaps between 1985 and 2010. This allows us to quantify the share of the increase in inequality which is associated with changes in the distribution of characteristics:

$$\begin{aligned} & shareQG_{g,x}(w|t_w = 2010, t_x = 1985) \\ = & \left[\frac{(QG_g(w|t_w=2010,t_x=2010) - QG_g(w|t_w=2010,t_x=1985))}{(QG_g(w|t_w=2010,t_x=2010) - QG_g(w|t_w=1985,t_x=1985)}\right.,] \end{aligned}$$

where $g \in \{85/50, 85/15, 50/15\}$. For the logit regression, we use a sequence of specifications for $v(x)$. We divide the vector of characteristics into five groups of elements which are educational outcomes, labor market experience, labor market history, occupational choice

[5] We restrict the maximum value of individual observation weights to the value of thirty, in order to prevent extreme weights which can occur as a result of extremely rare combinations of characteristics. We tested a range of trim values, and found that trim values between 20 and 50 prevent outliers, while simultaneously trimming a minimum number of observations.

and industry characteristics (see Tables 1 and 2). Among those, we consider potential labor market experience as continuous and all other variables as categorial, leading to a highly flexible specification of the logit model.

We calculate four versions of the counterfactual quantile gaps, starting with a specification of $v(x)$ which only contains the educational characteristics of row E in 2. We then sequentially expand the specification of $v(x)$ with the characteristics described in 2 and calculate the increase in the counterfactual quantile gaps. The counterfactual rise in inequality of each specification is displayed in the respective columns in Tables 7 to 10, along with the share of the observed rise in inequality which is associated with the respective characteristics.

By sequentially adding more characteristics, we can quantify the additional contribution of each characteristics group to the increase in wage inequality. By going from one specification to the next, we implicitly decompose the difference between the observed and counterfactual rise in inequality into the effects of separate characteristics groups. For example, when adding occupation and industry characteristics to the reweighting function, we measure the cumulative explanatory effect of these characteristics on the rise in the quantile gaps, after controlling for the previous characteristics:

$$
\begin{aligned}
(3) \qquad & QG_g(w|t_w = o, Ed_o, Ex_o, H_oO_o, I_o) && -QG_g(w|t_w = b, Ed_b, Ex_b, H_bO_b, I_b) \\
= (\quad & QG_g(w|t_w = o, Ed_o, Ex_o, H_o, O_o, I_o) && -QG_g(w|t_w = o, Ed_b, Ex_b, H_b, O_o, I_o)) \\
+(\quad & QG_g(w|t_w = o, Ed_b, Ex_b, H_b, O_b, I_b) && -QG_g(w|t_w = b, Ed_b, Ex_b, H_b, O_b, I_b))
\end{aligned}
$$

We add characteristics in the order given in Table 2. As with any sequential method, the incremental effect of each characteristic depends on the order in which they are added to the model. The reasoning behind our choice of sequence is that we move from exogenous and predictable characteristics gradually towards those properties which are more likely subject to endogenous changes due to actions of the individual. Reweighting is performed separately for subsamples of male and female employees and for two separate baseyears, 1985 and 2010.

3.2 Composition adjustment for total employment

This method can be expanded to take into account selective shifts between full-time work and total employment, while mitigating the limitation that the SIAB dataset does not provide comparable wages for part-time employees. We do this by first calculating counterfactual wage distributions for full-time workers, but using the characteristics distribution of all individuals in employment (=total employment). Then, in a second step,

Table 2: Specification overview

Label	Variables	Exact specification
E	Education	ed
EE	Education, Experience	$ed + ex + ed * ex + ex^2 + ed * ex^2$
EEH	Education, Experience, Labor Market History	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt1 + ft1 + pt5 + ft5 + ed * (pt5 + ft5) + pt5^2 + ft5^2 + ed * (pt5^2 + ft5^2)$
EEHOI	Education, Experience, Labor Market History, Occupation & Industry Sector	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt1 + ft1 + pt5 + ft5 + ed * (pt5 + ft5) + ex * (pt5 + ft5) + pt5^2 + ft5^2 + ed * (pt5^2 + ft5^2) + occ + occ * ex + occ * ex^2 + sec + sec * ex + sec * ex^2 + sec * ed$

we reweight these counterfactual wage distribution to the characteristics of a baseyear, 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 baseyear.

The first step is a within-period composition adjustment. We calculate counterfactual wage distributions, which would have prevailed if all individuals in the labor force were employed in full-time jobs in the respective year. This interpretation of the counterfactual wage density holds under the assumption that returns to characteristics for non-full-time workers are equal to those for full-time workers. The results of Manning and Petrongolo (2008) suggest that hourly wage differentials for (female) part-time workers 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 baseyear, the reference group is total employment in the same year. Let $e_i \epsilon \{FT, TE\}$ describe the employment group to which each observation belongs. FT is the group of full-time employment spells, and TE is the total employment group. Full-time observations appear in both FT and TE. The reweighting factor $\rho(FT \to TE, t_x = o)$ 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:

(4)
$$\rho(FT \to TE, t_x = o) = \frac{dF(x|e_x = TE, t_x = o)}{dF(x|e_x = FT, t_x = o)} = \frac{P(e = TE|x, t = o)}{P(e = FT|x, t = o)} \frac{P(e = FT|t = o)}{P(e = TE|t = o)}$$

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

$$
\begin{aligned}
(5) \qquad & f(w|e_w = FT, e_x = TE, t_w = o, t_x = o) \\
(6) \quad = \; & \int_x f(w|x, e_w = FT, t_w = o, t_x = o) dF(x|e_x = TE, t_x = o) \\
= \; & \int_x f(w|x, e_w = FT, t_w = o, t_x = o) \rho(FT \to TE, t_x = o) dF(x|e_x = FT, t_x = o)
\end{aligned}
$$

Here $P(e = TE|x, t = o) = L(\beta v(x))$ is estimated by weighted logit on the pooled sample of the reference group (total employment) and the group of interest (full-time employment), with the employment status indicator e denoting group membership of each observation. In this step, we use the specification from Table 3 for $v(x)$, in order to include the full set of observable individual characteristics. By applying $\rho(FT \to TE, t_x = o)$ to

Table 3: Specification for counterfactual total employment

Variables	Formula
Education, Experience, Labor Market History, Occupation, Industry Sector	$ed + ex + ed * ex + ex^2 + ed * ex^2 + pt1 + pt5years + ft1 + ft5years + ed * (pt5years + ft5years) + occ + occ * ex + occ * ex^2 + sec + sec * ex + sec * ex^2 + sec * ed$

the group of full-time employees, for which we have interpretable wages, we can calculate quantile gaps of the counterfactual wage distribution of total employment:

$$
(7) \qquad QG_g(w|x, e_w = FT, e_x = TE, t_x = o)
$$

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 unchanging over time. By holding the composition of the labor force fixed over time, we control for changes in the wage distribution due to changes in selection into the labor force between periods. Therefore we perform the analysis, as described in Section 3, on the counterfactual total employment sample which we have just constructed. This distribution can be written as:

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

with

(9)
$$\rho(e_x = TE, t_x = b) = \frac{dF(x|e_x = TE, t_x = b)}{dF(x|e_x = TE, t_x = o)} = \frac{P(t = b|x, e_x = TE)}{P(t = o|x, e_x = TE)} \frac{P(t = o|e = TE)}{P(t = b|e = TE)}$$

In practice, we pool the counterfactual total employment samples of the year of interest and the baseyear. On this pooled sample, we estimate $P(t = b|x, e_x = TE)$ by weighted logit, using $\rho(FT \to TE, t_x = o)$ as weights for the regression. Then a counterfactual percentile gap, e.g. the 85/50 gap, is:

$$QG_{85/50}(w|e_w = FT, e_x = TE, t_x = b) =$$

$$Q_{85}(w|e_w = FT, e_x = TE, t_x = b, t_x = b) - Q_{50}(w|e_w = FT, e_x = TE, t_x = b, t_x = b)$$

The counterfactual weights calculated this way can also be incorporated in a standard kernel density estimator by multiplying the kernel function $K(.)$ with $\rho(t_x = b)$, to obtain counterfactual wage densities for total employment and for total employment with labor force composition fixed at the level of the baseyear :

(10)
$$f(w_i|x, e_w = FT, e_x = TE) = \frac{1}{h \sum_{i=1} s_i \rho_i} \sum_i s_i \rho_i (FT \to TE, t_x = o) K\left(\frac{w_i - W}{h}\right)$$

with h denoting the bandwidth and s_i the sample weights. Plotting the counterfactual distribution of total employment at a baseyear and comparing it to the counterfactual total employment distribution at the observation year shows to what extent shifts in inequality due to characteristics are caused by selection into the labor force in general, as opposed to selection solely in to full-time work.

In analogy to Section 3, we perform a series of reweightings, by estimating the logit model with the specifications from Table 2. This provides a sequence of total employment wage distributions where each one shows the changes in inequality associated with the change in the respective characteristics.

4 Empirical Results

We discuss the long run trends in reweighted wage inequality from 1985 to 2010, which reflect systematic changes in composition due to changes in demographics, educational institutions, technology and labor market histories. We also discuss differences in composition-adjusted wage inequality between the sample of full-time employees, and the counterfactual total employment sample.

We show results for two alternate baseyears, 1985 and 2010, and for the sequence of decompositions described in Table 2. The explanatory effect of composition changes on wage inequality differs to some degree between both baseyears, which has important implications for the interpretation of wage inequality. A stronger effect to baseyear 2010 means that if the labor force back in 1985 had had today's characteristics, inequality would have risen to a lesser extent than it would have, if the labor force had always had characteristics of 1985. Which means that between-group and within-group inequality is higher for those characteristics groups which are over-represented in 2010, compared to 1985. This can occur if measures of skill, like education levels and potential experience, are higher in 2010. Higher skill groups show greater within-group inequality, and the skill distribution has become more evenly spread over the skill-spectrum, leading to higher overall between-group inequality. Conversely, a weaker effect to baseyear 2010 shows that inequality is higher for those groups which are under-represented in 2010, relative to 1985.

4.1 Counterfactual inequality of full-time workers

4.1.1 Counterfactual inequality of men

From the results in Table 7 and Figures 8 to 11, it is apparent that substantial amounts of the rise in wage inequality can be attributed to changes in labor force composition. For male employees, if we keep education, experience, labor market history, occupation and industry characteristics fixed at the 1985 level, the gap between the 85th and 15th quantile only rises by 0.137 log points, which is 52.97% of the observed 0.290 log points rise. The magnitude of this effect is larger than the effects found in Dustmann et al. (2009); Felbermayr et al. (2014), due to the larger set of characteristics which we take into account and the longer timeframe which we observe. The strength of the contribution to inequality varies between characteristics groups and is not uniform across the wage distribution. Subsequently, we analyze the sequential contribution of each characteristics group. We start with educational characteristics, which, by the time an individual enters the labor market are unchanging for the vast majority of the labor force. If we keep the male worker's educational composition fixed at the 1985 level, the gap between the 85% quantile and 50% quantile only rises by 0.085 log points, instead of 0.137 log points without composition adjustment. The observed and education reweighted 85/50 gaps move in parallel during the late 80s, but start diverging in 1991. This means that the expansion of higher education, which we observe since the 90s, is associated with 37.5% of the rise in upper-tail wage inequality for men. But the same expansion shows no effect on inequality in the lower half of the wage distribution, where highly educated individuals are rare. When we add potential labor market experience to the decomposition, the effect on upper tail inequality hardly changes, but we see a reduction by 0.014 log points in lower-tail wage inequality, which amounts to 9% of the total increase. Therefore composition effects of the mincerian characteristics education and experience play only a minor role in the lower tail of the male wage distribution. The 50/15 wage gap is affected only to a small extent by the first two steps of the reweighting procedure, regardless of the baseyear chosen. As we have seen in Figure 5, the share of male workers without an educational degree has markedly decreased, but this development is not reflected in changes in lower tail wage inequality. This part of the distribution was not affected by the replacement (in terms of labor force composition, not necessarily replacement within jobs) of untrained workers with trained workers.

In this respect, our findings are consistent with the results in Dustmann et al. (2009) and Card et al. (2013), who similarly report weak composition effects of education and experience on lower tail inequality. They come to the conclusion that labor market institutions and the matching of employees to firms play a more important role in explaining this part of the wage structure. However, subsequently, we show that there are other composition effects which are associated with lower tail inequality, primarily the effect of employment history and of industry composition. When additionally accounting for changes in temporary part-time and full-time history, we observe that overall inequality would have risen by 0.174 log points, which is 39,95% lower than the factual increase. Lower tail inequality would have risen by only 0.109 log points, or 29.3% less. The substantial size of this effect for male workers is of special interest because only a small fraction of the male labor force is working part-time at any given point in time. However, there has been increasing movement between part-time and full-time work over the last decades, as we have seen in Figure 4 and discussed in section 2.2. If long term wage effects of a part-time history lead to lower wages and primarily affect workers in already lower paying jobs, this would be consistent with a widening of the wage distribution below the median. In Figure 10 we see a first divergence between observed and counterfactual lower tail inequality in 1988, but this difference disappears shortly afterwards. Briefly, lower tail inequality in 1997 and 1998 is almost identical for the observed and the counterfactual distribution. Between 1998 and 2010, composition effects of labor market history are increasingly relevant for lower tail inequality, especially after 2005. In the upper part of the distribution, changes due to labor market history are smaller, still account for 0.01 additional log points, or an additional explanatory fraction of 13% of the 85/50 gap. The changes in education, experience and labor market history since 1985 have widened the distribution of real wages, and have done so by shifting the upper part of the distribution to the right, while keeping the lower tail, below the first quintile, relatively stable. This is illustrated in figure 12, where the density of counterfactual wages to baseyear 1985 is overlaid on the observed density. We also find a substantial contribution of occupation and industry composition to inequality for male workers. By including industry characteristics, we partially capture the contribution of firm specific effects on wage inequality, as long as the distribution of high-wage firms is not homogeneous across industry sectors. Occupational and industry sector characteristics reduce the counterfactual 85/15 gap to 0.137 log points, or 53% lower than observed, when controlling for education, experience and labor market history. The importance of industry and occupation varies depending on the position in the wage distribution. Composition changes in industry and occupation account for 0.037 additional log points of the 85/50 gap. In the lower part of the distribution 0.034 log points of the 50/15 gap can be attributed to industry changes. Most of this effect can be traced to a decreasing share in the manufacturing sector, a sector that has been characterized by wages which cluster close to the center of the distribution (compare Section 2.3).

Following Lemieux (2006) we also analyze residual wage gaps with counterfactual characteristics distributions. Row 4 of table 7 shows the residual 90/10 gap while holding compositions fixed at the level of 1985. These results reinforce our conclusions for the non-residual wage gaps. The unmodified rise in the 90/10 gap of residual wages amounts to 0,183 log points and is reduced considerably when keeping composition fixed. Therefore, a substantial fraction of inequality within skill groups is associated with the labor force composition. When holding the education, experience, history and industry characteristics fixed, the residual 90/10 gap is lower by 33,96%. As with non-residual inequality, changes in individual labor market history play an important role in explaining the rise of within-group inequality in Germany since the 80s.

4.1.2 Counterfactual inequality of women

For female employees in full-time jobs, inequality development with counterfactual characteristics are shown in Table 8 and Figures 8 to 11. We observe distinct differences in comparison to their male counterparts. Unadjusted increases in wage inequality are lower for women than for men, with a rise of 0,218 log points in the 85/15 gap, 0.086 log points in the 85/50 gap and 0.132 log points in the 50/15 gap between 1985 and 2010. Changes in educational composition have relatively weak effects on inequality measures, even though the educational composition of women in 2010 is distinctly different from that of 1985 (compare Figure 5). In a pattern similar to that of the male workers, education affects the upper half of the wage distribution more strongly than the lower half. Only 0.022 log points, or 9,9% of the increase in inequality as measured by the 85/15 gap is associated with the composition of education. Once we extend the reweighting procedure to include potential work experience, we see substantial composition effects. For all parts of the distribution, education and experience combined account for 45% of the increase in inequality, divided equally among the upper and lower half of the distribution. This stands in contrast with the results for full-time men, for whom changes in work experience are primarily relevant for upper tail inequality, but not in the lower part of the distribution.

In addition to work experience, labor market histories play an important role for women in both the lower and upper part of the wage distribution. Changes in labor market-history are associated with an additional 18,59% of the inequality increase, which means that the cumulative effect of labor market history, after controlling for education and experience, is a reduction of the rise in inequality by 63,64%. This effect is of roughly the same relative strength in both the upper part and the lower part of the wage distribution. This implies that the effects of increasingly temporary part-time episodes and labor market interruptions are equally relevant for women in low-wage and in high wage jobs. Those movements might be linked to changes in child-rearing behavior of mothers across the entire wage distribution. We contrast the observed and counterfactual distributions in Figure 12. In a pattern similar to that of male employees, the widening of the wage distribution due to changes in characteristics shifts the upper parts of the distribution to the right while keeping the lower tail largely untouched.
Occupational and Industry composition changes have negligible effects on the wage distribution.[6] This result is not entirely unexpected, since the biggest changes in industry and occupation composition of the workforce happened in the manufacturing sector, which is dominated by male workers. Substantial divergence between observed and counterfactual wage distributions, and therefore composition effects, for both education and experience starts in the early nineties. In the upper half of the distribution, we only see divergence between observed and counterfactual quantile gaps after 1992 and as late as 1998 in the lower half.

4.1.3 Choice of the baseyear

Results for counterfactual wage inequality with characteristics distribution of the baseyear 2010 show two important features. They indicate that the strong explained share of the rise in wage inequality due to individual characteristics does not depend on the choice of 1985 as the baseyear. They also show specific differences in the size of the contribution for some characteristics, which gives insight into the distribution of returns to those characteristics in both years. Similar to baseyear 1985, changes in education, experience, labor market history, occupation and industry composition have contributed strongly to

[6] In rows 8 an 9 of table 7 , quantile gaps are unchanging up to the third digit for the addition of occupation and industry characteristics, except for the residual gap. This is not an error. Our daily wage data is rounded to full Euros, therefore quantiles will only change value if the change in counterfactual weights is large enough to move the wage quantile to the next discrete Euro value. While counterfactual weights change with the addition of industry and occupation characteristics, this change is not strong enough to shift the quantiles of the wage distribution.

the increasing spread between quantiles of the wage distribution. Keeping all characteristics fixed at the level of 2010, the counterfactual rise in the 85/15 gap is 42.46% lower than the observed rise for men, and 78.39% lower for women (compare tables 9 and 10, as well as figures 13 to 16) Which means that the effects of characteristics on inequality to baseyear 2010 are slightly weaker for men and stronger for women, compared to the results for baseyear 1985 (compare tables 7 and 8). The relative contribution of different characteristics, and the distribution of explanatory effects between the upper and lower half of the wage distribution varies with the baseyear. If changes in inequality due to changes in characteristics were symmetric for both baseyears, given that characteristics in 2010 are more heterogeneous (compare figures 5 to 4), this would imply that returns to characteristics which are comparatively rare in 1985 do not differ from the returns to relatively common characteristics. Such a wage structure is highly unlikely, considering, for example, the relative rarity and wage returns of individuals with university degrees. If we compare the results for male workers with those from baseyear 1985, we notice that changes in education explain substantially more of the 85/50 gap and, as a consequence, also of the 85/15 gap. 31.87% of the rise in the overall spread of wages can be attributed to changes in education, compared to 18.06% to baseyear 1985. A workforce with education of 2010, i.e. higher share of college degrees and only a small fraction of untrained workers, would already have had high inequality in 2010. This means that individuals with educational characteristics which are more prevalent in 2010 had very heterogeneous returns in 1985. With respect to the 85/15 gap, experience and labor market history can be attributed to fairly similar shares of the rise in inequality for both baseyear 1985 and 2010, although there is a shift in explanatory share from the lower to the upper half of the wage distribution. In contrast to the results for education, we see a lower explanatory effect of occupation and industry characteristics for the recent baseyear. The counterfactual rise in inequality, when adding occupation and industry to the specification for baseyear 2010, is actually higher than without those characteristics. Which means that inequality in 1985 would have been lower if the composition of occupation and industry characteristics had always been at the level of 2010. This implies that those industry and occupation combinations, which are more frequent in 2010, had a more compressed wage structure back in 1985. This result is consistent with the fact that the 85/15 gap in the non-manufacturing sectors, which have grown in share, has increased between 1985 and 2010. However, such a reversal of effects is not present for within-group inequality, as measured by residual inequality, which implies that within-group inequality has risen due to changes in occupation and industry, while between-group inequality has declined as a consequence of this characteristics change. The positive additional effect of occupation and industry on inequality is entirely driven by developments in the upper half of the wage distribution. In the lower half of the distribution, we do not observe any changes in wage quantiles due to the addition of occupation and industry characteristics.[7]

For female workers, table 10 shows that for every step of the sequential reweighting, reweighted quantile gaps are lower and therefore explained shares are higher than for baseyear 1985. However, this increased effect is not evenly distributed across the different characteristics. We see a more pronounced inequality effect of education for baseyear 2010, both above and below the median. This implies more heterogeneous returns to the educational degrees which are more frequent among women in 2010 than they were in 1985. Since highly educated women are more frequent, and medium educated female workers have largely replaced untrained female workers in 2010, the counterfactual inequality development reflects increasing spreads in returns to increasing levels of education. Labor market history also shows very strong inequality effects, with the cumulative explained inequality share of education, experience and history at 71.79% of the total rise in the 85/15 gap. Occupation and Industry characteristics contribute somewhat to the rise in inequality, as seen in columns eight and nine of table 10. By holding them fixed at the level of 2010, the rise in the counterfactual 85/15 gap is reduced to 0.047 log points, down from 0.062. There are, however, shifts within the counterfactual wage distribution when adding occupation and industry characteristics to the specification, in that the explanatory effect of characteristics is concentrated in the lower half of the wage distribution. The median shifts downwards, which entirely eliminates the rise in the 50/15 gap in the counterfactual wage distribution, but widens the remaining 85/50 gap. This indicates that the distribution of occupation and industry shares for women in 2010 primarily affects the center of the wage distribution, while low and high earnings do not depend heavily on those characteristics.

4.2 Counterfactual total employment sample

In the previous section we have analyzed composition effects due to changes in the selection into full-time work. These movements in or out of full-time work can either be caused by individuals entering full-time work from outside the labor force, or by shifting from part time work to full-time work within the labor force. To which degree composition changes of full-time workers are the result of switching between types of work is of importance for understanding wage inequality. It tells us if movement between types of work has positive or negative effects on wage inequality for the respective part of the labor market. It also shows to which extent composition changes in the population translate into labor force characteristics for the full-time and part-time section of the labor market, respectively. When attributing large fractions of the increase in wage inequality of the

[7] In the third row of table 9 , quantile gaps are unchanging up to the third digit for the addition of occupation and industry characteristics. This is caused by the fact that our daily wage data is rounded to full euros, therefore quantiles will only change in discrete steps.

full-time workforce to changes in composition, it is important to know to what extent the explanatory effects of composition changes of full-time workers are representative of the effects of composition on inequality in the entire labor force. In order to shed more light on the selection process, we use the two-step reweighting approach, described in section 3.2. By holding characteristics fixed at the level of the entire labor force in the baseyear, we can control for movement between part-time and full-time work, and therefore quantify the effect of selection into all forms of employment on wage inequality.

4.2.1 Comparison of total employment with observed full-time sample

In Figure 17, we show how wage inequality would have progressed if full-time employees had the skill distribution of the entire labor force. The counterfactual quantiles in Figure 17 can be interpreted as the wage distribution quantiles if no selective movement between full-time and part-time work had taken place. For male workers, differences between both distributions with respect to inequality are 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 development implies a degree of negative selection into part-time work. However, the part-time share of male workers has already started rising in the early nineties, while we only observe negative effects of selection into part-time a decade later. Which means that the initial expansion of part-time work among male workers was not accompanied by negative selection.

For women, at the start of our observation period, the full-time and total employment distributions are quite similar, especially at 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 which are prevalent among part-time workers collect lower returns than those of full-time workers, implying negative selection into part-time work with respect to characteristics. Since 1990, the distributional gap between full-time and counterfactual total employment samples has been almost constant, which means that the degree of positive selection into full-time work has not changed substantially over time.

4.2.2 Inequality development in total employment

In this section we study differences in the effects of composition changes between the counterfactual total employment labor force and the full-time worker sample. In analogy to section 4.1.1, we calculate the inequality measures which would have prevailed if workers had the same skill distribution as the total employment sample in baseyears 1985 and 2010. We plot this inequality development relative to the increase in inequality measures of the within-year counterfactual total employment sample. Therefore treating the counterfactual total employment inequality measures as "observed", which are then reweighted to reflect the characteristics distribution of the labor force in the baseyear. The results of this comparison are summarized in tables 11, 12 and figure 18. By contrasting the results in this table with those in tables 7 and 8, we can determine if the high share of inequality which can be attributed to characteristics changes is a phenomenon of the full-time workforce, or if we can see similar effects for the entire labor force. For male employees, the shares of the rise in inequality measures in total employment, associated with characteristics, are very similar to those of the full-time workforce. Which is expected, since the additional part-time workers are a relatively small fraction of the male workforce. The log differences are generally slightly larger, since the rise in inequality measures for the total employment distribution has been stronger as well. Notable differences are the following: Education and experience are associated with only 1.51% of the change in lower tail inequality, in contrast to 9.02% in the full-time sample, showing that at the lower end of the wage spectrum, selective changes in terms of education are more relevant between full-time and part-time work, than they are between working and non-working individuals. Also in the lower half of the wage distribution, composition effects of labor market history are stronger for the total employment sample, than they are for full-time working men. This indicates that interruptions and changes between type of work have stronger effects on wages at the lower margins of the labor market. If we reweight with the entire characteristics vector, composition changes explain 55.79% of the increase in inequality, compared to 52.97% in the full-time sample. This is largely due to a comparatively stronger effect of labor market history characteristics. For 2010 as the baseyear, the results are collected in table 9 and in figure 20. They show stronger effects of education and positive effects of occupation and industry characteristics on inequality, compared to the baseyear 1985. This pattern is extremely similar to what we observe for the full-time sample, which is discussed in section 4.1.3.

For men, we can conclude that effects of composition on inequality between full-time work and the total labor force differ primarily with respect to labor market history. Here we observe somewhat stronger effects for the total labor force, particularyl with baseyear 2010. Considering all characteristics, changes in selection in the total male labor force translate to a major degree into changes in the full-time labor force, which also means that selection dynamics have not lead to a systematic divergence in characteristics between full-time and part-time male workers over time.

For female workers, we expect more substantial differences between the effect of selection into full-time and total employment, compared to their male counterparts, due to the larger part-time share among female workers during all time periods. Results are summarized in tables 12 and 14 as well as figures 18 and 20. In all steps of the decomposition the effects on inequality associated with worker characteristics are weaker than those for the full-time sample. Which indicates that a substantial part of the increase in wage inequality for women is due to selective sorting between full-time and part-time work. This is most clearly visible through the effects of education and experience, especially concerning the upper part of the wage distribution. The composition of education and experience is associated with 45,05% of the increase in inequality in the 85/15 gap for the full-time sample, but only with 35,72% of the increase for the total employment sample. Sizable differences are also present for the 85/50 gap, where education and experience contribute 46,3% of the rise for full-time workers, and 23.16% for total employment. The pattern of a lower accumulated share of the rise in inequality to be attributed to characteristics of women in total employment continues through all specifications of baseyear 1985. Results to baseyear 2010 reinforce our conclusions from section 4.1.3, that, had all working women always had the characteristics of 2010, wage inequality would already have been higher in 1985. With respect to their characteristics, women who select into full-time work have become more heterogeneous than those who select into part-time. Therefore the changes in characteristics which have led to an increase in inequality, have affected those women working full-time to a larger degree than those working part-time.

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 statuatory minimum wage. Even though a large literature exists on the topic, no consensus has be reached regarding the driving forces behind the rise in wage inequality. This paper focuses an the time period 1985 to 2010 and we scrutinize the contribution of changes in the compositon of educational degrees, potential 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 baseyear. Our major contribution is that we account explicitly for the increasing heterogeneity of labor market experience regarding part-time work and employment interruptions. Furthermore, we extend the analysis to estimate the counterfactual full-time wage distributions for the entire labor force including both full-time and part-time workers.

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. Our decomposition analysis suggest that changes in observables explain a large part of the increase in wage inequality and the increasing heterogeneity of labor market experience plays a particular strong role. After controlling for education, potential experience, and employment histories, changes in industry and occupation explain very little. The composition effects are larger for females compared to males and for most characteristics when counterfactual wage distributions are estimated for the sample of employees in 2010. Therefore, workers in 2010 would already have experienced noticeably higher levels of wage inequality in 1985 compared to the workforce in 1985. When decomposing the changes in the counterfactual full-time wage distribution over time, we find that changes in characteristics affect wage inequality among the fulltime workforce more strongly than they affect part-time workers. At the same time, this part of the analysis confirms the negative selection of part-time workers based on observable characteristics including their work history. This adds further plausibility to the importance of heterogeneous employment histories. The results regarding industry and occupation cast doubt on explanations for the rise in wage inequality regarding international trade or the task-based approach.

As a caveat for our analysis, we can not account for the effects of the decline in coverage by collective bargaining based on the version of the SIAB data we can use. However, based on the results in the literature (Antonczyk et al. 2010; Card et al. 2013; Fitzenberger 2012) and based on the finding in this paper that changes in the industry composition had comparatively small increasing effects on wage inequality, we think that the decline in coverage by collective bargaining is unlikely to be a major driving force for the increase in wage inequality among full-time workers. Our findings regarding the growing importance of the heterogeneity in individual work history is consistent with the finding in Card et al. (2013) that the variability of person fixed effects has increased over time. As a second caveat, we acknowledge that the rise in the heterogeneity across firms emphasized by Card et al. (2013) is not captured by our analysis. However, it should be emphasized at the same time that our decomposition analysis shows that a large share of the increase in wage inequality can be explained - in a statistical sense - by changes in composition effects.

Möller (2016) suggests that the increase in wage inequality stopped between 2010 and 2011. At the same time, the way part-time and full-time work is recorded in the SIAB data changes in 2011 and this resulted in a large number of missings regarding the working time variable. Using heuristic imputation procedures to account for this structural change, Möller's (2016) analysis confirms the rise in wage inequality among full-time workers until 2010. It is unlikely that the key results in our paper are affected by the measurement problems in the data. Future research should investigate the reasons for the apparent end of the continuous increase in wage inequality in West Germany in 2011. In light of the structural break in 2011, one would have to cross-check the results with different data sets.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4b of *Handbooks in Economics*, chapter 12, pages 1044–1166. North Holland, Amsterdam.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2010a). Polarization and rising wage inequality: Comparing the u.s. and germany. ZEW Discussion Paper No. 10-015, Mannheim.

Antonczyk, D., Fitzenberger, B., and Leuschner, U. (2009). Can a task-based approach explain the recent changes in the German wage structure? *Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik)*, 229(2-3):214–238.

Antonczyk, D., Fitzenberger, B., and Sommerfeld, K. (2010b). Rising wage inequality, the decline of collective bargaining, and the gender wage gap. *Labour Economics*, 17:835–847.

Autor, D., Levy, F., and Murnane, R. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in us wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2):300–323.

Beblo, M. and Wolf, E. (2004). How much does a year off cost?: Estimating the wage effects of employment breaks and part-time periods. *ZEW Discussion Paper*.

Blundell, R., Dias, M. C., Meghir, C., and Shaw, J. M. (2016). Female labour supply, human capital and welfare reform. Technical report, National Bureau of Economic Research, Working Paper No. 19007 (first version 2013, revised March 2016).

Bosch, G. and Weinkopf, C. (2014). *Zur Einführung des gesetzlichen Mindestlohns von 8,50 € in Deutschland*. Arbeitspapier 304, Hans-Böckler-Stiftung.

Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Connolly, S. and Gregory, M. (2009). The part-time pay penalty: earnings trajectories of british women. *Oxford Economic Papers*, 61:76–97.

David, H. (2013). The "task approach" to labor markets: an overview. *Journal for Labour Market Research*, 46(3):185–199.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages. *Econometrica*, 64(5):1001–1044.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the german wage structure. *The Quarterly Journal of Economics*, 124:843–881.

Felbermayr, G., Baumgarten, D., and Lehwald, S. (2014). Increasing wage inequality in germany: What role does global trade play? *Global Economic Dynamics, Bertelsmann Stiftung.*

Fitzenberger, B. (1999). *Wages and Employment Across Skill Groups: An Analysis for West Germany.* Physica/Springer, Heidelberg.

Fitzenberger, B. (2012). Expertise zur Entwicklung der Lohnungleichheit in Deutschland. Arbeitspapier, Sachverständigenrat zur Begutachtung der Gesamtwirtschaftlichen Entwicklung.

Fitzenberger, B., Osikominu, A., and Völter, R. (2006). Imputation rules to improve the education variable in the iab employment subsample. *Schmollers Jahrbuch*, 126(3):405–436.

Gartner, H. (2005). The imputation of wages above the contribution limit with the german iab employment sample. *FDZ Methodenreport*, 2.

Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *The American Economic Review*, 96(3):461–498.

Manning, A. and Petrongolo, B. (2008). The part-time pay penalty for women in britain. *The Economic Journal*, 118:28–51.

Möller, J. (2016). Lohnungleichheit - Gibt es eine Trendwende? *IAB-Discussion Paper*, 9.

Paul, M. (2016). Is there a causal effect of working part-time on current and future wages? *The Scandinavian Journal of Economics*, 118(3):494–523.

Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (German Council of Economic Experts) [SVR] (2014). Jahresgutachten 2014/15: Mehr Vertrauen in Marktprozesse. *Stuttgart: Metzler-Poeschel.*

6 Appendix

6.1 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 fit 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. Importantly for our analysis, however, it does not lead to bias in the trend of wage dispersion.[8] Since we have to take into account that the variance of wages is correlated with individual characteristics, we modify the procedure suggested by Gartner (2005) to explicitly model the heteroscedastic variance for the Tobit regression. Log wages imputed without this modification would be less variable than the true unobserved wages, because of the correlation between characteristics and wage variance. Therefore we 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 men, and 0.2% and 3.2% for women across all years.

6.2 Descriptive Findings

Figure 1: Wage quantiles relative to levels of 1985

Table 4: Descriptives of full-time samples

Male FT sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	70.06	47.53	82.48	48.34
Log real wage	4.16	0.39	4.28	0.51
No/other degree indicator	0.19	0.40	0.08	0.28
Vocational degree indicator	0.71	0.46	0.71	0.45
University degree indicator	0.07	0.25	0.15	0.36
Work experience	27.34	11.19	28.98	10.13
No. of days in full time over 5 years	1546.04	487.51	1523.88	513.84
Fulltime spell in previous year?	0.96	0.19	0.96	0.20
No. of days in part time over 5 years	3.26	46.49	15.72	113.47
Part-time spell in previous year?	0.00	0.05	0.01	0.09
No. of days on UE benef. over 5 years	29.88	86.67	32.26	96.02
Unemployment spell in previous year?	0.07	0.25	0.06	0.23
Length of employment spells	337.19	67.87	319.33	84.99
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.03	0.17	0.02	0.13
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.03	0.17	0.03	0.17
Chemische Industrie	0.03	0.18	0.02	0.15
Metallerzeugung und bearbeitung, Maschinenbau	0.15	0.36	0.13	0.33
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.12	0.32	0.11	0.31
KonsumgÃ¼terindustrie	0.10	0.31	0.07	0.25
Gastgewerbe	0.01	0.11	0.02	0.13
Baugewerbe	0.12	0.32	0.08	0.28
Handel	0.12	0.33	0.14	0.35
Verkehr und NachrichtenÃ¼bermittlung	0.06	0.24	0.07	0.26
Kredit- und Versicherungsgewerbe	0.08	0.27	0.18	0.38
Ãffentliche und persÃ¶nliche Dienstleistungen	0.04	0.20	0.05	0.21
Erziehung, Soziale und Gesundheitseinrichtungen	0.03	0.18	0.05	0.23
Ãffentliche Verwaltung	0.06	0.24	0.04	0.20

Female FT sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	46.24	20.34	61.02	35.16
Log real wage	3.74	0.44	3.97	0.56
No/other degree indicator	0.27	0.45	0.08	0.27
Vocational degree indicator	0.66	0.47	0.73	0.44
University degree indicator	0.03	0.16	0.12	0.32
Work experience	24.03	11.90	27.39	11.14
No. of days in full time over 5 years	1356.01	598.16	1327.35	625.94
Fulltime spell in previous year?	0.93	0.26	0.93	0.26
No. of days in part time over 5 years	45.97	210.01	88.99	292.80
Part-time spell in previous year?	0.02	0.15	0.04	0.20
No. of days on UE benef. over 5 years	30.86	87.11	29.87	91.76
Unemployment spell in previous year?	0.06	0.24	0.05	0.22
Length of employment spells	335.87	69.68	313.68	89.55
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.01	0.08	0.01	0.08
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.02	0.14	0.01	0.11
Chemische Industrie	0.02	0.15	0.02	0.13
Metallerzeugung und bearbeitung, Maschinenbau	0.05	0.23	0.04	0.19
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.08	0.27	0.05	0.21
KonsumgÃ¼terindustrie	0.13	0.34	0.06	0.25
Gastgewerbe	0.03	0.18	0.03	0.18
Baugewerbe	0.02	0.14	0.02	0.13
Handel	0.18	0.38	0.16	0.36
Verkehr und NachrichtenÃ¼bermittlung	0.02	0.16	0.04	0.19
Kredit- und Versicherungsgewerbe	0.12	0.33	0.21	0.40
Ãffentliche und persÃ¶nliche Dienstleistungen	0.06	0.23	0.06	0.24
Erziehung, Soziale und Gesundheitseinrichtungen	0.17	0.38	0.24	0.42
Ãffentliche Verwaltung	0.08	0.27	0.06	0.24

Table 5: Descriptives of combined full-time and part-time samples

Male full sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	70.06	47.53	82.48	48.34
Log real wage	4.16	0.39	4.28	0.51
No/other degree indicator	0.19	0.40	0.08	0.28
Vocational degree indicator	0.71	0.46	0.71	0.45
University degree indicator	0.07	0.25	0.15	0.36
Work experience	27.34	11.19	28.98	10.13
No. of days in full time over 5 years	1546.04	487.51	1523.88	513.84
Fulltime spell in previous year?	0.96	0.19	0.96	0.20
No. of days in part time over 5 years	3.26	46.49	15.72	113.47
Part-time spell in previous year?	0.00	0.05	0.01	0.09
No. of days on UE benef. over 5 years	29.88	86.67	32.26	96.02
Unemployment spell in previous year?	0.07	0.25	0.06	0.23
Length of employment spells	337.19	67.87	319.33	84.99
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.03	0.17	0.02	0.13
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.03	0.17	0.03	0.17
Chemische Industrie	0.03	0.18	0.02	0.15
Metallerzeugung und bearbeitung, Maschinenbau	0.15	0.36	0.13	0.33
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.12	0.32	0.11	0.31
KonsumgÃ¼terindustrie	0.10	0.31	0.07	0.25
Gastgewerbe	0.01	0.11	0.02	0.13
Baugewerbe	0.12	0.32	0.08	0.28
Handel	0.12	0.33	0.14	0.35
Verkehr und NachrichtenÃ¼bermittlung	0.06	0.24	0.07	0.26
Kredit- und Versicherungsgewerbe	0.08	0.27	0.18	0.38
Ãffentliche und persÃ¶nliche Dienstleistungen	0.04	0.20	0.05	0.21
Erziehung, Soziale und Gesundheitseinrichtungen	0.03	0.18	0.05	0.23
Ãffentliche Verwaltung	0.06	0.24	0.04	0.20

Female full sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	46.24	20.34	61.02	35.16
Log real wage	3.74	0.44	3.97	0.56
No/other degree indicator	0.27	0.45	0.08	0.27
Vocational degree indicator	0.66	0.47	0.73	0.44
University degree indicator	0.03	0.16	0.12	0.32
Work experience	24.03	11.90	27.39	11.14
No. of days in full time over 5 years	1356.01	598.16	1327.35	625.94
Fulltime spell in previous year?	0.93	0.26	0.93	0.26
No. of days in part time over 5 years	45.97	210.01	88.99	292.80
Part-time spell in previous year?	0.02	0.15	0.04	0.20
No. of days on UE benef. over 5 years	30.86	87.11	29.87	91.76
Unemployment spell in previous year?	0.06	0.24	0.05	0.22
Length of employment spells	335.87	69.68	313.68	89.55
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.01	0.08	0.01	0.08
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.02	0.14	0.01	0.11
Chemische Industrie	0.02	0.15	0.02	0.13
Metallerzeugung und bearbeitung, Maschinenbau	0.05	0.23	0.04	0.19
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.08	0.27	0.05	0.21
KonsumgÃ¼terindustrie	0.13	0.34	0.06	0.25
Gastgewerbe	0.03	0.18	0.03	0.18
Baugewerbe	0.02	0.14	0.02	0.13
Handel	0.18	0.38	0.16	0.36
Verkehr und NachrichtenÃ¼bermittlung	0.02	0.16	0.04	0.19
Kredit- und Versicherungsgewerbe	0.12	0.33	0.21	0.40
Ãffentliche und persÃ¶nliche Dienstleistungen	0.06	0.23	0.06	0.24
Erziehung, Soziale und Gesundheitseinrichtungen	0.17	0.38	0.24	0.42
Ãffentliche Verwaltung	0.08	0.27	0.06	0.24

Table 6: Descriptives of counterfactual total employment samples

Male TE sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	70.02	47.86	81.45	48.56
Log real wage	4.16	0.39	4.27	0.52
No/other degree indicator	0.19	0.40	0.09	0.28
Vocational degree indicator	0.70	0.46	0.70	0.46
University degree indicator	0.07	0.26	0.16	0.36
Work experience	27.29	11.20	28.91	10.27
No. of days in full time over 5 years	1536.51	498.85	1469.90	567.86
Fulltime spell in previous year?	0.96	0.20	0.93	0.26
No. of days in part time over 5 years	7.60	81.92	47.63	223.21
Part-time spell in previous year?	0.01	0.09	0.05	0.22
No. of days on UE benef. over 5 years	30.07	86.96	33.75	98.30
Unemployment spell in previous year?	0.07	0.25	0.06	0.24
Length of employment spells	336.73	68.45	316.54	87.31
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.03	0.17	0.02	0.13
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.03	0.17	0.03	0.17
Chemische Industrie	0.03	0.18	0.02	0.15
Metallerzeugung und bearbeitung, Maschinenbau	0.15	0.36	0.12	0.33
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.12	0.32	0.10	0.30
KonsumgÃ¼terindustrie	0.10	0.31	0.07	0.25
Gastgewerbe	0.01	0.11	0.02	0.14
Baugewerbe	0.12	0.32	0.08	0.27
Handel	0.12	0.33	0.14	0.34
Verkehr und NachrichtenÃ¼bermittlung	0.06	0.24	0.07	0.26
Kredit- und Versicherungsgewerbe	0.08	0.27	0.18	0.38
Ãffentliche und persÃ¶nliche Dienstleistungen	0.04	0.20	0.05	0.21
Erziehung, Soziale und Gesundheitseinrichtungen	0.04	0.19	0.06	0.24
Ãffentliche Verwaltung	0.06	0.24	0.04	0.20

Female TE sample

	1985		2010	
	mean	sd	mean	sd
Real wage in Euro	44.50	20.02	57.57	32.81
Log real wage	3.70	0.46	3.91	0.57
No/other degree indicator	0.28	0.45	0.08	0.27
Vocational degree indicator	0.65	0.48	0.73	0.44
University degree indicator	0.03	0.16	0.11	0.32
Work experience	24.96	11.74	28.01	10.87
No. of days in full time over 5 years	1142.26	707.00	958.24	760.91
Fulltime spell in previous year?	0.78	0.42	0.66	0.47
No. of days in part time over 5 years	254.37	536.21	424.09	649.93
Part-time spell in previous year?	0.20	0.40	0.33	0.47
No. of days on UE benef. over 5 years	35.10	93.31	35.32	100.21
Unemployment spell in previous year?	0.07	0.26	0.07	0.25
Length of employment spells	330.18	75.89	301.35	96.89
Landwirtschaft,Bergbau, Gewinnung von Steinen und Erden	0.01	0.08	0.01	0.07
Herstellung Gummi- und Kunststoffwaren; Mineralstoffverabeitung	0.02	0.14	0.01	0.10
Chemische Industrie	0.02	0.14	0.01	0.12
Metallerzeugung und bearbeitung, Maschinenbau	0.05	0.22	0.03	0.18
Fahrzeugbau; Elektrotechnik, Feinmechanik und Optik	0.08	0.27	0.04	0.20
KonsumgÃ¼terindustrie	0.13	0.33	0.05	0.23
Gastgewerbe	0.03	0.18	0.04	0.18
Baugewerbe	0.02	0.14	0.02	0.13
Handel	0.19	0.39	0.16	0.36
Verkehr und NachrichtenÃ¼bermittlung	0.03	0.16	0.04	0.19
Kredit- und Versicherungsgewerbe	0.12	0.32	0.20	0.40
Ãffentliche und persÃ¶nliche Dienstleistungen	0.06	0.23	0.06	0.25
Erziehung, Soziale und Gesundheitseinrichtungen	0.17	0.38	0.27	0.44
Ãffentliche Verwaltung	0.08	0.27	0.07	0.25

[8] Compare the discussion in Card et al. (2013).

6.3 Graphs for Section 2.2

Figure 2: Part-Time Share over Time

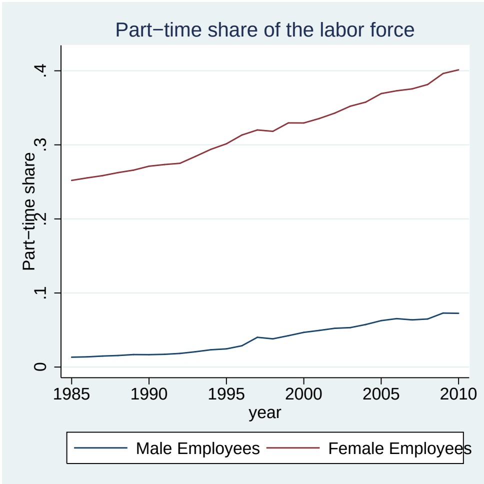
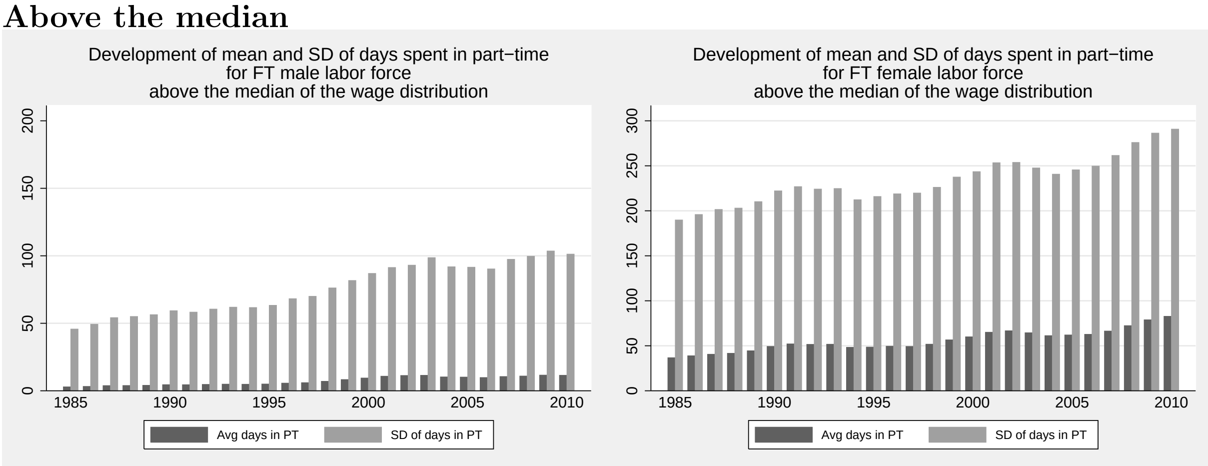
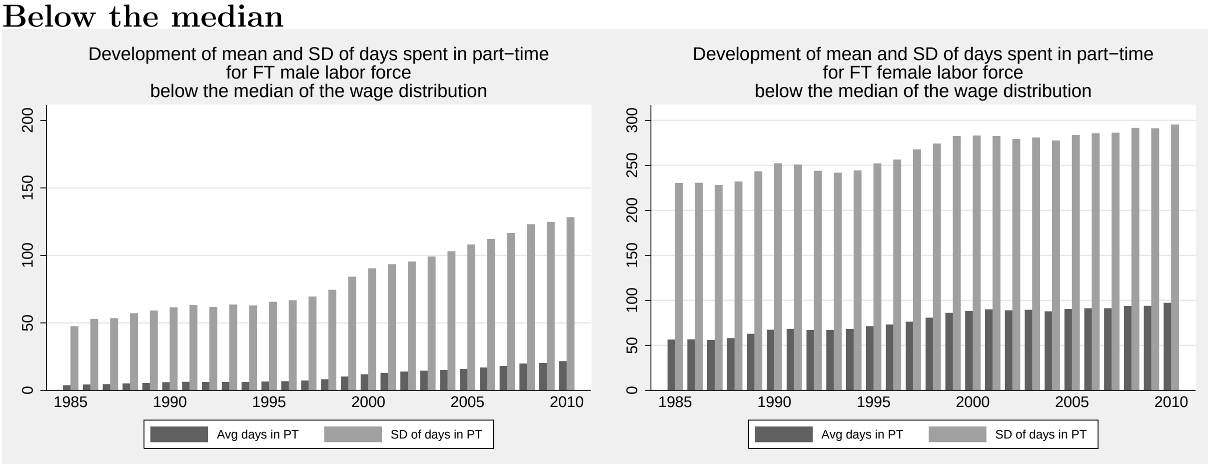


Figure 3: Time spent in part time work

Above the median



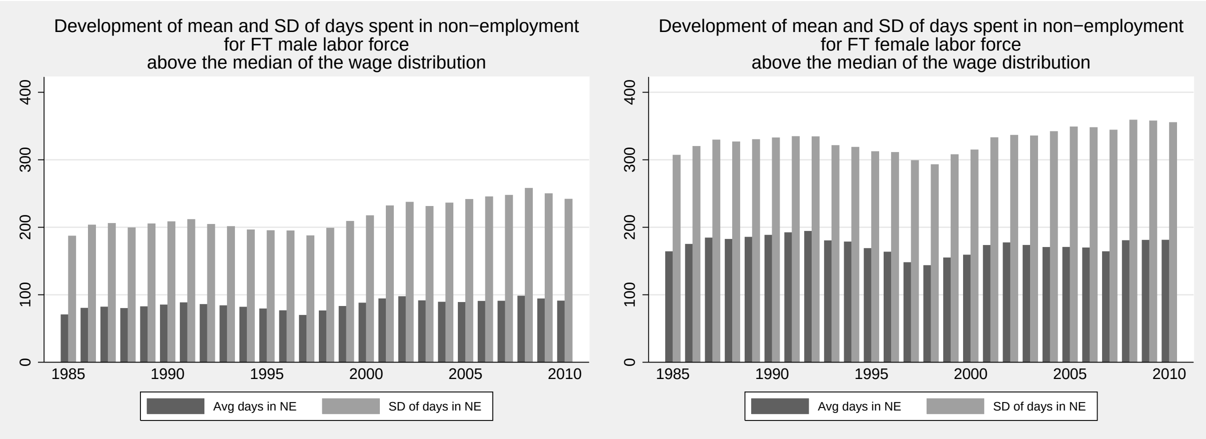
Below the median



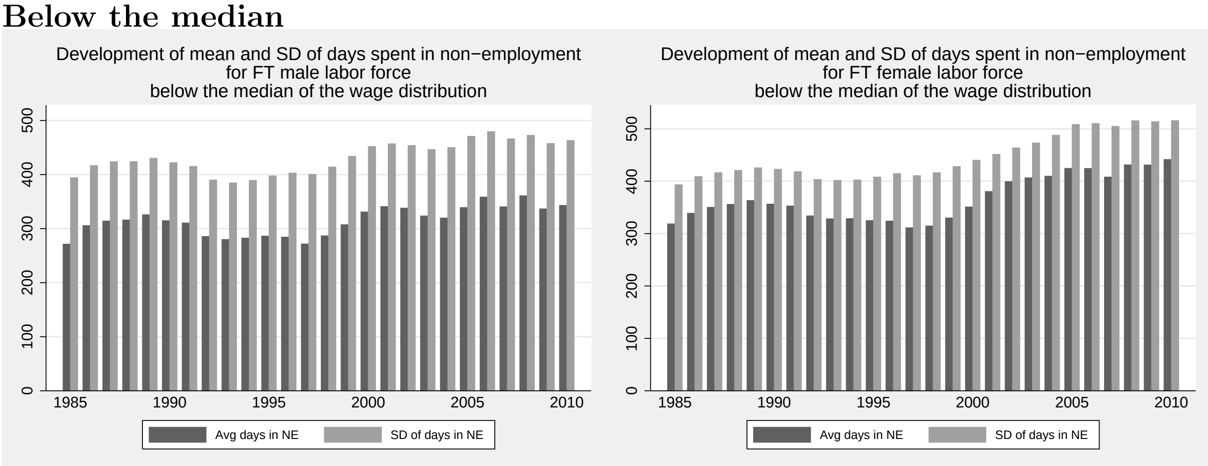
Note: The following graphs capture all kinds of non-employment starting at age 20, including education and sick-leave.

Figure 4: Time spent in non-employment

Above the median



Below the median



6.4 Graphs for Section 2.3

Figure 5: Share of education groups

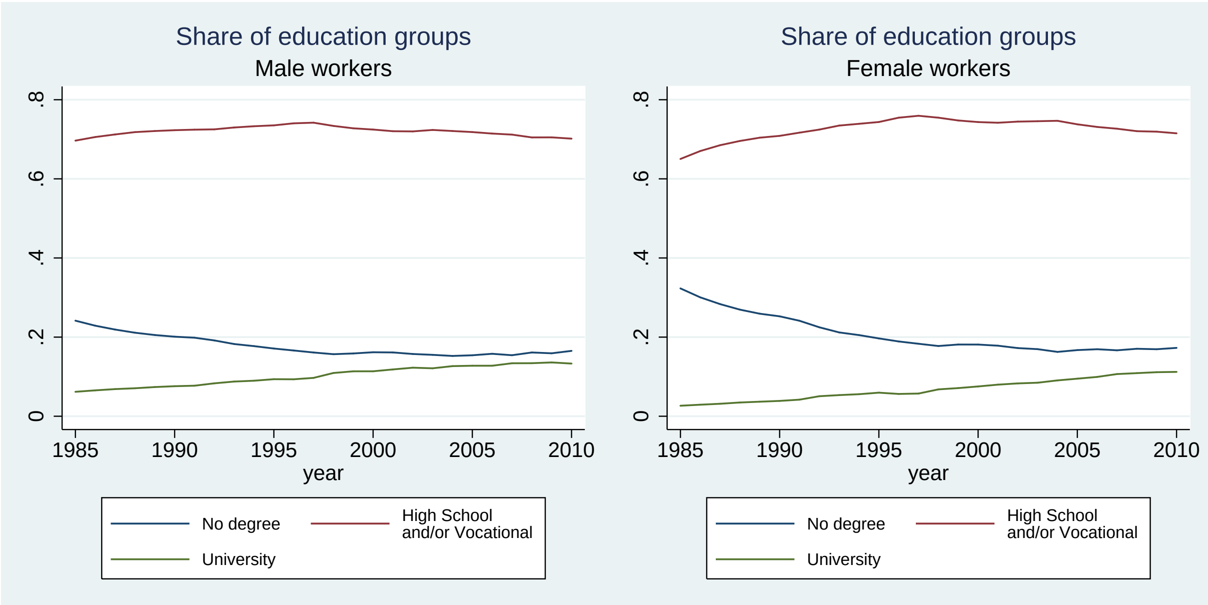


Figure 6: Share of experience groups

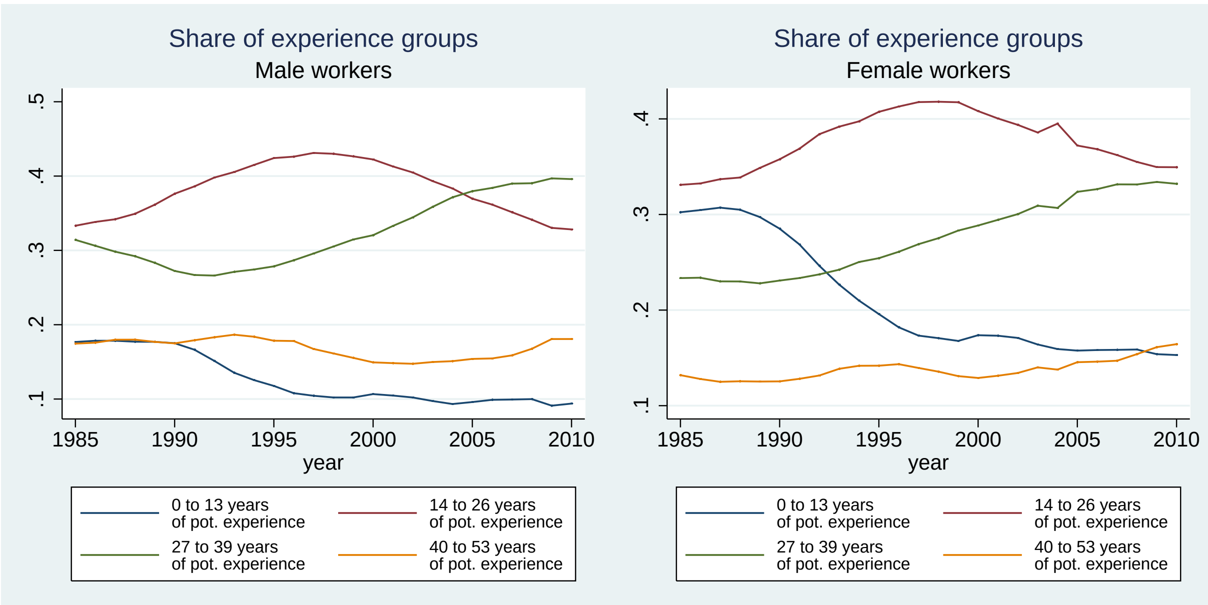
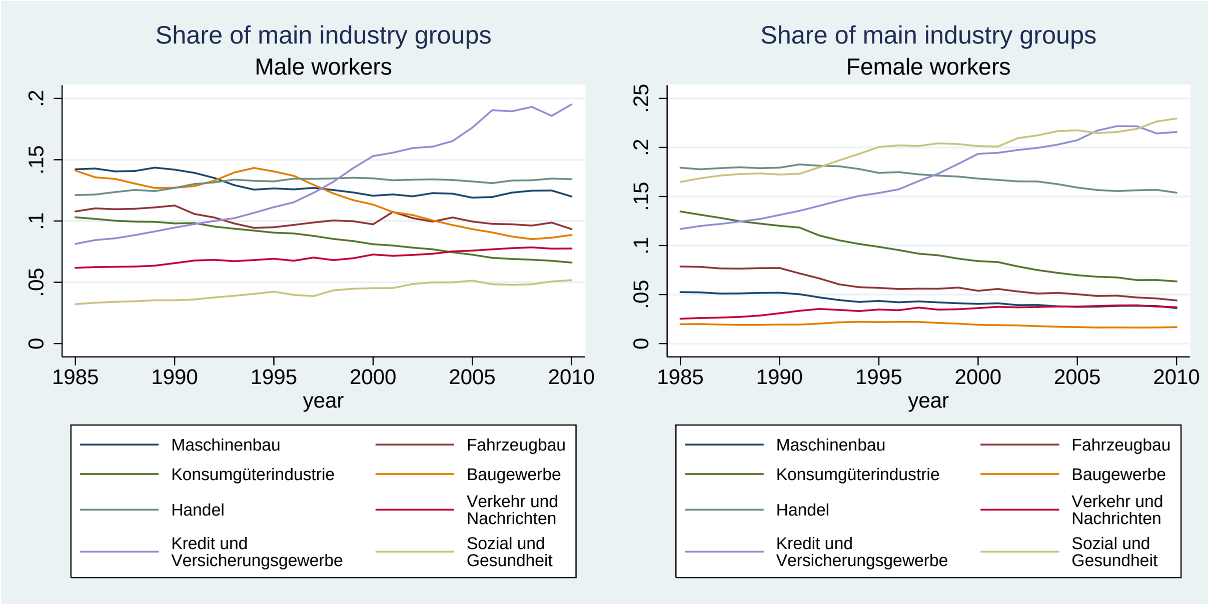


Figure 7: Share of industry sectors



6.5 Tables for Section 4

6.6 Graphs for Section 4.1.1

Figure 8: Inequality development baseyear 1985, specification E(ducation)

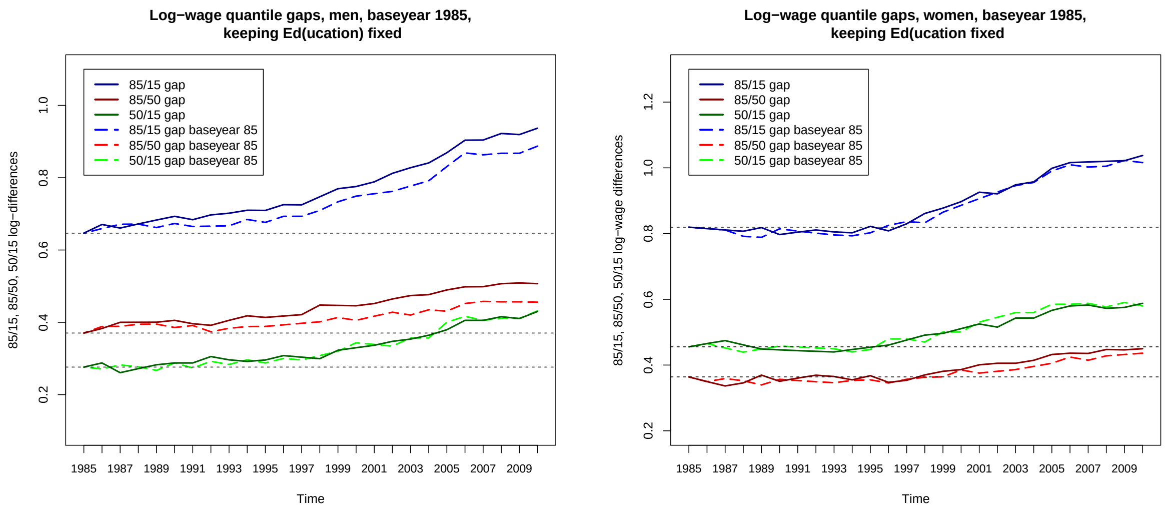


Table 7: Reweighted inequality increase, 1985-2010, men, compositions of baseyear 1985

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.290	0.241	17.11%	0.223	23.04%	0.174	39.95%	0.137	52.97%
85/50 gap	0.137	0.085	37.50%	0.084	38.82%	0.066	52.00%	0.062	54.64%
50/15 gap	0.154	0.155	-1.00%	0.140	9.02%	0.109	29.25%	0.075	51.49%
Residual 90/10 gap	0.183	0.170	7.07%	0.165	9.71%	0.146	20.37%	0.121	33.96%

Table 8: Reweighted inequality increase, 1985-2010, women, compositions of baseyear 1985

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.218	0.196	9.91%	0.120	45.05%	0.079	63.64%	0.079	63.64%
85/50 gap	0.086	0.072	15.90%	0.046	46.30%	0.033	61.89%	0.033	61.89%
50/15 gap	0.132	0.124	6.02%	0.074	44.23%	0.047	64.77%	0.047	64.77%
Residual 90/10 gap	0.185	0.193	-4.38%	0.132	28.77%	0.100	45.89%	0.090	51.56%

Table 9: Reweighted inequality increase 1985-2010, men, compositions of baseyear 2010

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.290	0.198	31.87%	0.192	33.87%	0.153	47.34%	0.167	42.46%
85/50 gap	0.137	0.055	59.40%	0.039	71.47%	0.027	80.17%	0.041	69.80%
50/15 gap	0.154	0.142	7.43%	0.153	0.48%	0.126	18.18%	0.126	18.18%
Residual 90/10 gap	0.183	0.149	18.64%	0.138	24.62%	0.107	41.36%	0.094	48.73%

Table 10: Reweighted inequality increase 1985-2010, women, compositions of baseyear 2010

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.218	0.159	27.10%	0.099	54.49%	0.062	71.79%	0.047	78.39%
85/50 gap	0.086	0.060	30.58%	0.044	48.38%	0.022	74.01%	0.051	40.09%
50/15 gap	0.132	0.099	24.85%	0.055	58.44%	0.039	70.36%	-0.004	103.22%
Residual 90/10 gap	0.185	0.180	2.55%	0.093	49.56%	0.061	66.94%	0.046	75.11%

Figure 9: Inequality development baseyear 1985, specification EE(xperience)

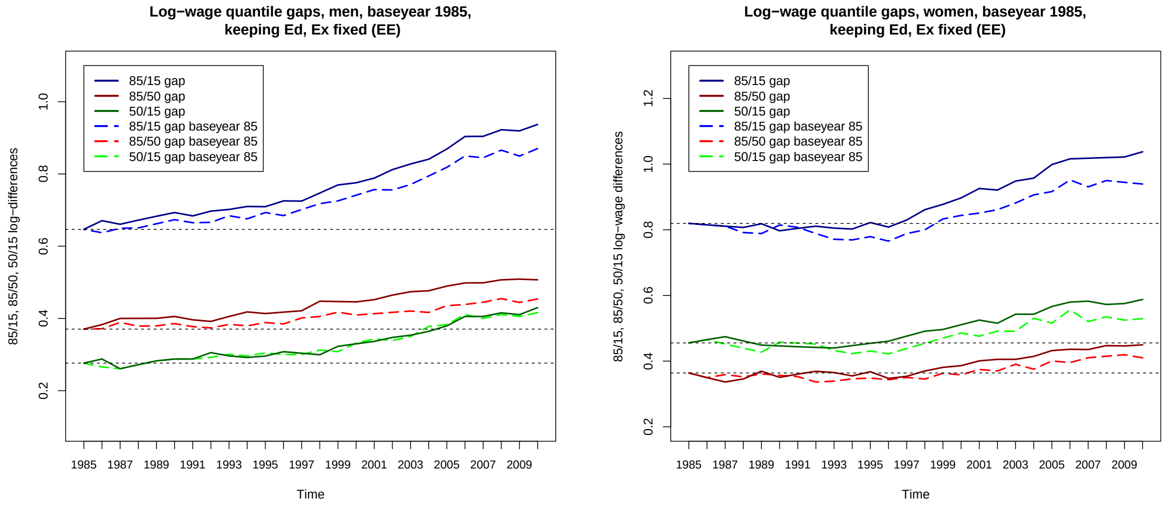


Figure 10: Inequality development baseyear 1985, specification EEH

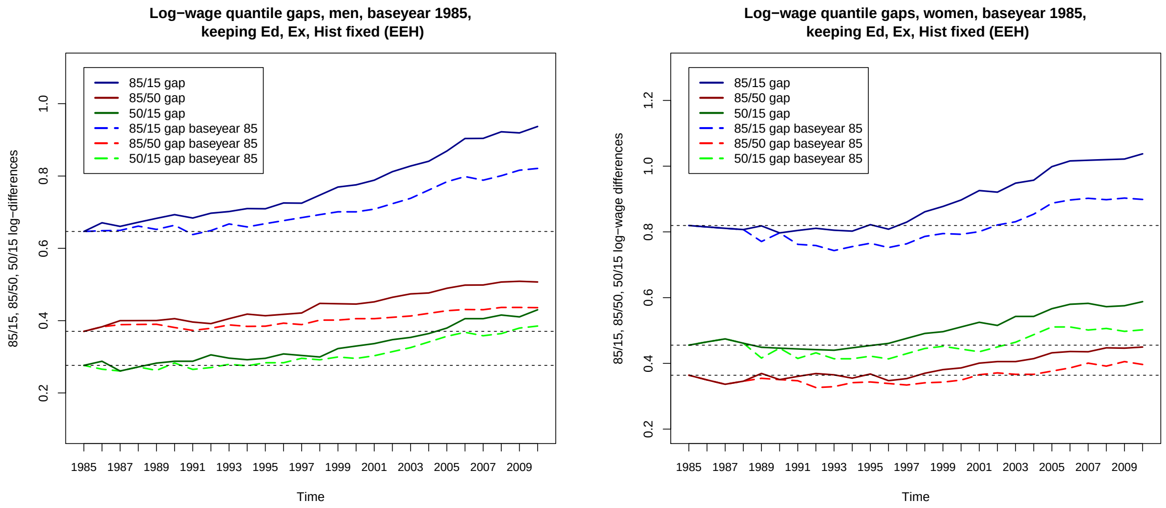


Figure 11: Inequality development baseyear 1985, specification EEHOI

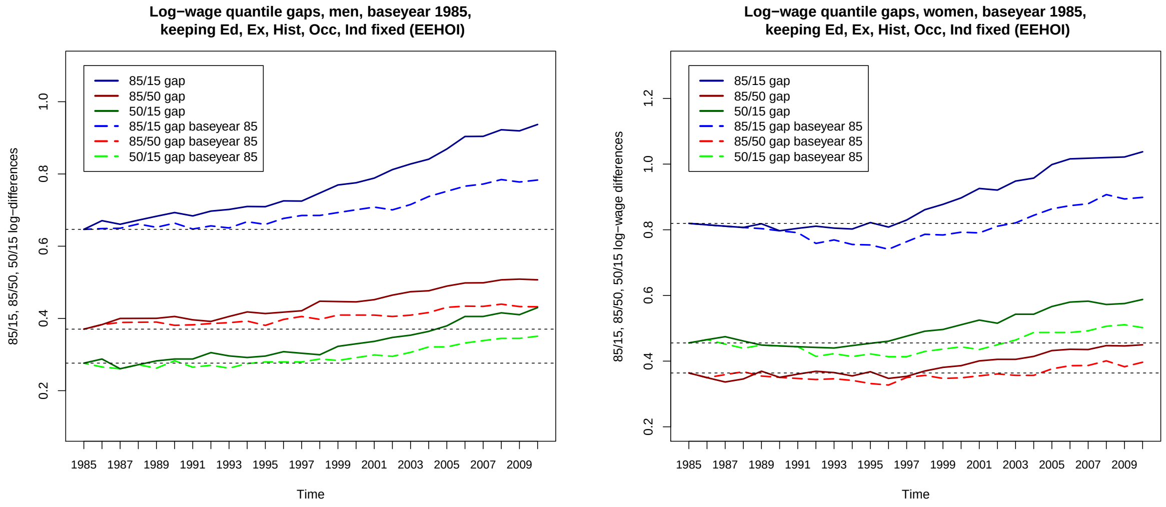
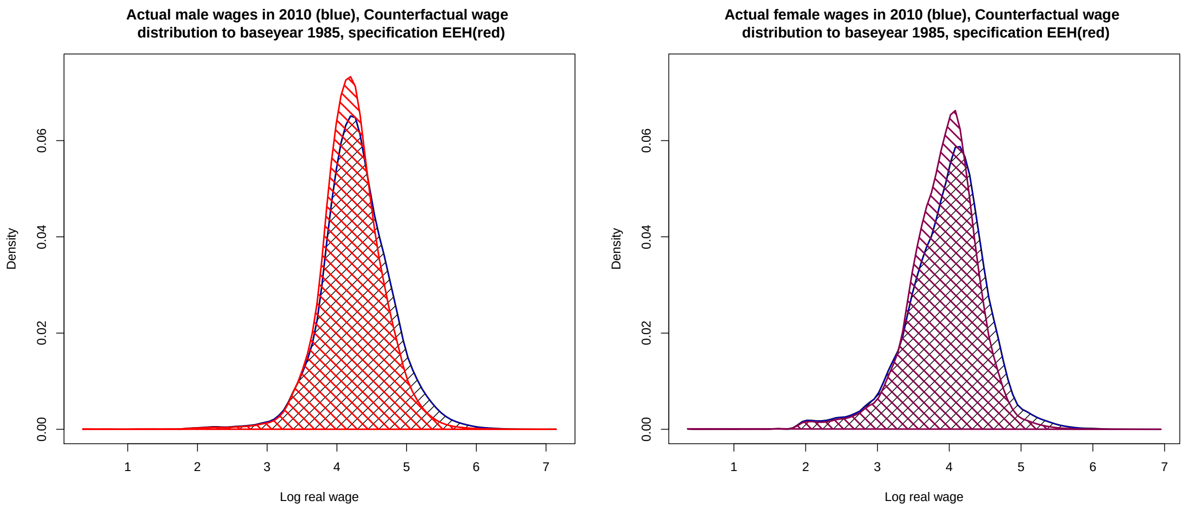


Figure 12: Comparison of observed and counterfactual wage distributions, specification EEH



6.7 Graphs for Section 4.1.2

Figure 13: Inequality development baseyear 2010, specification E

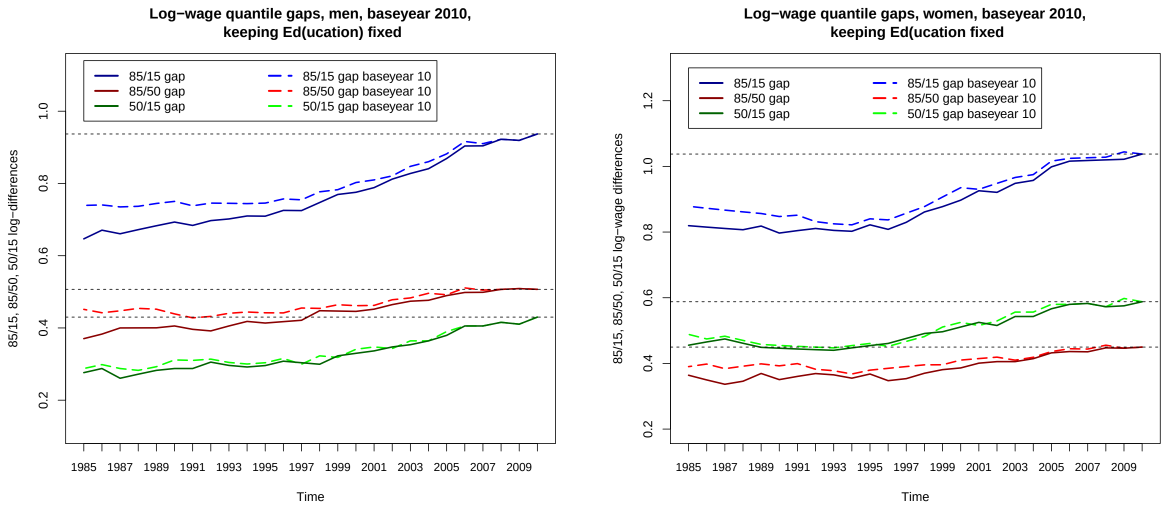


Figure 14: Inequality development baseyear 2010, specification EE

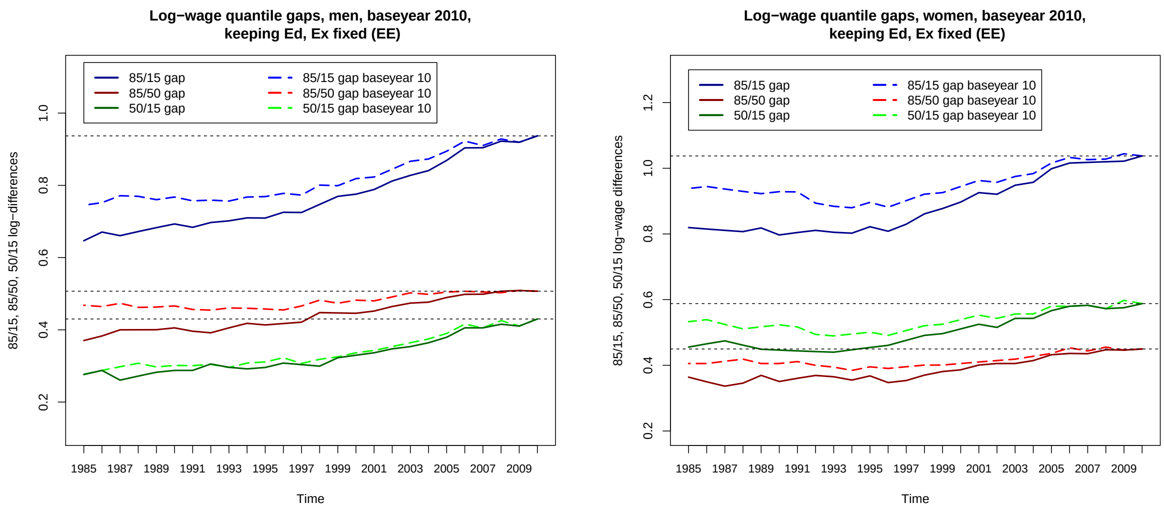


Figure 15: Inequality development baseyear 2010, specification EEH

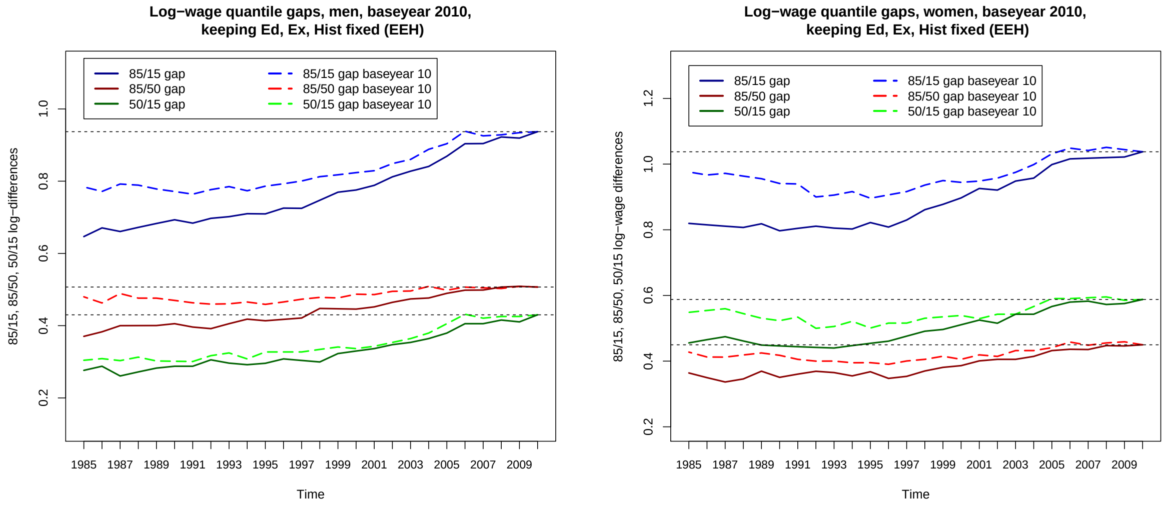


Figure 16: Inequality development baseyear 2010, specification EEHOI

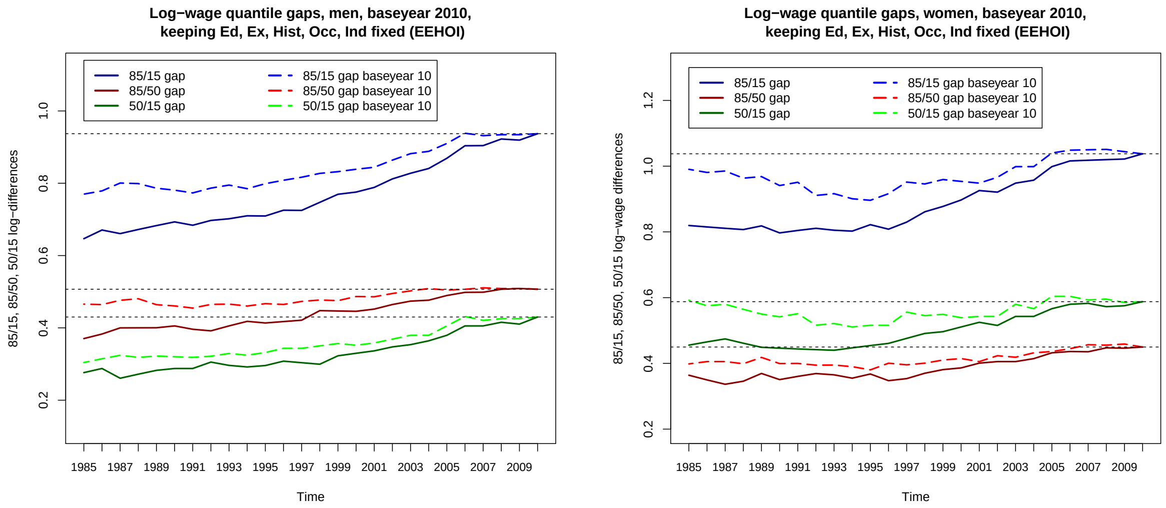


Table 11: Change in inequality measures since 1985, for men, composition adjusted to Total Employment in baseyear 1985

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.309	0.257	16.90%	0.249	19.24%	0.174	43.55%	0.137	55.79%
85/50 gap	0.144	0.096	33.72%	0.087	39.43%	0.076	47.43%	0.062	57.11%
50/15 gap	0.164	0.161	2.14%	0.162	1.51%	0.098	40.15%	0.075	54.64%
Residual 90/10 gap	0.195	0.183	6.23%	0.177	8.92%	0.143	26.75%	0.117	39.72%

Table 12: Change in inequality measures since 1985, for women, composition adjusted to Total Employment in baseyear 1985

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.234	0.222	5.19%	0.150	35.72%	0.101	56.76%	0.101	56.76%
85/50 gap	0.098	0.093	5.25%	0.075	23.16%	0.065	33.65%	0.051	47.56%
50/15 gap	0.136	0.129	5.15%	0.075	44.74%	0.036	73.36%	0.050	63.37%
Residual 90/10 gap	0.158	0.173	-9.09%	0.114	28.31%	0.078	50.44%	0.069	56.12%

Table 13: Change in inequality measures since 1985, for men, composition adjusted to Total Employment in baseyear 2010

	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.309	0.222	36.71%	0.215	39.24%	0.159	58.32%	0.166	55.96%
85/50 gap	0.144	0.069	60.46%	0.051	71.68%	0.045	75.67%	0.036	81.00%
50/15 gap	0.164	0.153	10.64%	0.164	0.71%	0.114	41.36%	0.131	29.29%
residual 90/10 gap	0.195	0.160	-4.04%	0.149	4.87%	0.056	68.78%	0.058	67.67%

Table 14: Change in inequality measures since 1985, for women, composition adjusted to Total Employment in baseyear 2010

	Observed increase in inequality	Increase reweightd with E 2010	Share associated with E	Increase reweightd with EE 2010	Share associated with EE	Increase reweightd with EEH 2010	Share associated with EEH	Increase reweightd with EEHOI 2010	Share associated with EEHOI
	Observed	Ed		Ed+Ex		Ed+Ex+Hist		Ed+Ex+Hist+Occ+Ind	
	Increase	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share	Remaining increase	Explained share
85/15 gap	0.234	0.173	31.10%	0.087	68.30%	0.035	88.04%	0.062	78.15%
85/50 gap	0.098	0.047	58.46%	0.047	58.46%	0.031	73.55%	0.039	66.00%
50/15 gap	0.136	0.127	8.88%	0.041	75.07%	0.004	97.73%	0.023	86.39%
mincer resid 90/10 gap	0.158	0.156	-15.97%	0.077	47.55%	0.036	76.60%	0.018	88.34%

6.8 Graphs for Section 4.2

Figure 17: Counterfactual wage distribution, if full-time workers had total employment characteristics

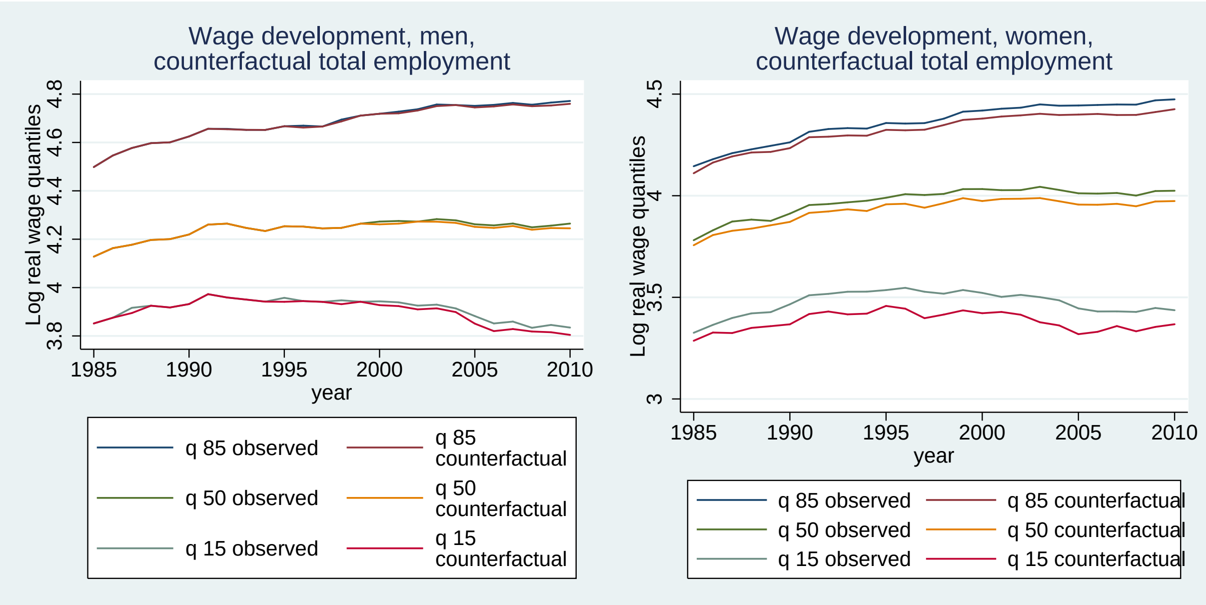


Figure 18: Inequality development baseyear 1985, specification EEHOI of Total Employment

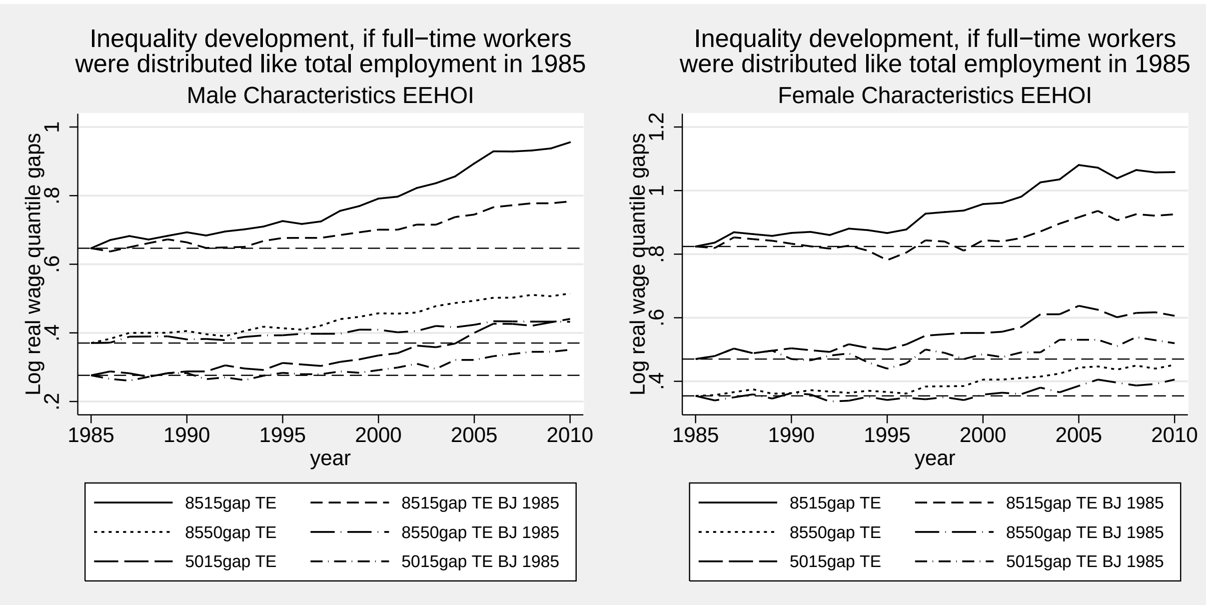


Figure 19: Comparison of observed, counterf. T.E. and reweighted counterf. T.E., specification EEHOI

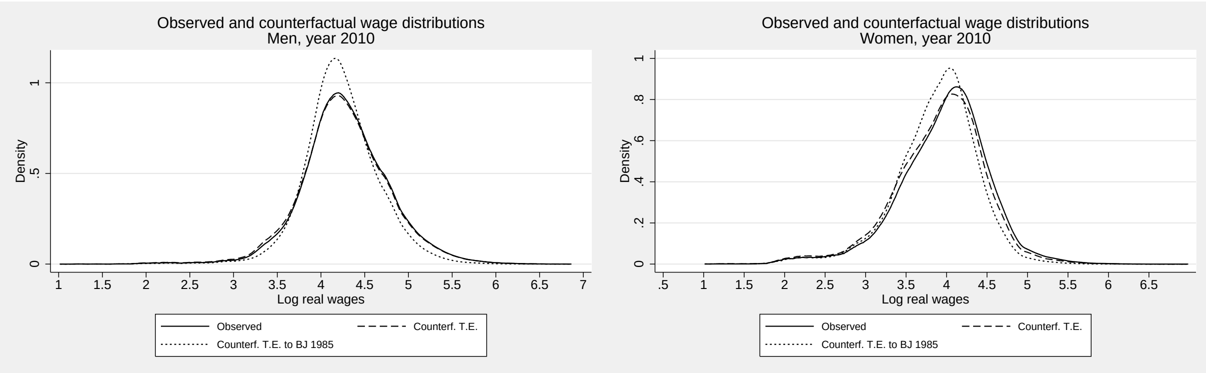


Figure 20: Inequality development baseyear 2010, specification EEHOI of Total Employment