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Selection into Employment and the Gender Wage Gap across the Distribution and Over Time

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Using quantile regression methods, this paper analyses the gender wage gap across the wage distribution and over time (1990-2014), while controlling for changing sample selection into full-time employment. Our findings show that the selection-corrected gender wage gap is much larger than the one observed in the data, which is mainly due to large positive selection of women into full-time employment. However, we show that selection-corrected wages of male and female workers at the lower half of the distribution have moderately converged over time. The reason for this development have been changes in the composition of the male full-time employment force over time, which in spite of the rather constant male full-time employment rate, have given place to a small but rising selection bias in male observed wages. In the upper half of the wage distribution, however, neither the observed nor the selection-corrected gender wage gap has narrowed over time.

Keywords: gender wage gap, quantile regression, selection into employment
JEL Classification: J31, J21

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1. Introduction

In all countries of the world, men earn - on average - higher wages than women. This differential, known as the gender wage gap, has been decreasing over the last decades, although recently at a lesser pace (e.g. Blau and Kahn 2017, OECD 2017). Many factors such as rising female educational attainment and labour market attachment have contributed to the decrease of the gender wage gap over the last decades, not least changing selection patterns into employment (e.g. Blau and Kahn 2006, Blundell et al. 2007, Mulligan and Rubinstein 2008). In addition, distributional studies about the gender wage gap have revealed a large variation over the distribution, particularly substantial glass ceilings and sticky floors in selected countries (Albrecht et al. 2003, Arulampalam et al. 2007, Rica et al. 2008). However, in the prevailing context of rising wage inequality as well as a general increase in female labour market participation, selection into employment is likely to differ along the distribution and also over time (e.g. Arellano and Bonhomme 2017). As a consequence, the effect that selection into employment has on the gender wage gap may also change across the distribution and over time. It is the aim of this paper to make use of recent developments in the econometrics literature to analyse selection-corrected gender wage gaps across the distribution and over time.

In particular, we follow Melly and Santangelo (2015)[1] and provide a distributional analysis of the gender wage gap for West Germany in the years 1990 to 2014. Importantly, the method controls for changing patterns of selection into employment across the distribution and over time. The goals of this paper are threefold: First, we provide a descriptive analysis of the evolution of the full-time employment rate and gender wage gap across the distribution and over time. Second, we show estimates of the selection-corrected wage gaps and explore the heterogeneity of the results along selected socio-economic dimensions. Third, we quantify the selection bias on observed male and female wages across the distribution and over time.

The empirical strategy used to take potential selection effects into account consists of imputing non-realised wages for those individuals who are not full-time employed in a given time period (see Neal 2004, Blau and Kahn 2006, Olivetti and Petrongolo 2008 for similar approaches). In particular, we use a new econometric method proposed by Melly and Santangelo (2014, 2015) that extends Athey and Imbens (2006)'s changes-in-changes model by accounting for covariates and adapts it to impute non-realized wages that account for both observable and unobservable characteristics of individuals. This method uses information from an individual's realized wage obtained from longitudinal data and assumes the time-invariance of the unobservables conditional on the observables to impute this individual's wage whenever he or she is out of work. This imputation-based approach allows us to characterize female and male selection-corrected wage distributions without having to rely on specific variables as exclusion restrictions.

Our analysis is based on the German Socio-Economic Panel (SOEP), a rich longitudinal

[1] Melly and Santangelo (2014) provide an analysis of the gender wage gap for the U.S. from 1968 to 2008.

dataset with detailed data on earnings, working hours and individual- and household-level characteristics. We restrict our analysis to full-time employees residing in West Germany over the time period 1990-2014. This is a time period in which Germany displayed a large gender wage gap, experienced a steep increase in female labour market participation, implemented numerous labour market, social- and family-policy reforms, and experienced large increases in wage inequality (see, e.g. Dustmann et al. 2009, Card et al. 2013, among others).

Our results show slight convergence of male and female observed full-time wages during the 1990s at selected points of the wage distribution - and stagnation at all points of the distribution thereafter. This is a phenomenon reported for several Western economies such as the U.S. (see Blau and Kahn 2017). Our findings also show that the selection-corrected gender wage gap is much larger than the one observed in the data, which is due to large positive selection of women into full-time employment. However, we show that selection-corrected female relative wages at the lower half of the distribution have moderately converged over time. The reason for this development have been changes in the composition of the male full-time employment force over time, which in spite of the rather constant male full-time employment rate, have given place to a small but rising selection bias in male observed wages.

A closer look at the results by selected socio-economic dimension reveals that the increasing male selection bias is driven by changing selection patterns among the youngest individuals (aged 20 to 29) in our sample. Furthermore, we find divergence in selection-corrected male and female wages from individuals with tertiary education over time. Finally, we find the observed convergence of median wages for parents to be solely the result of rising selection bias on mother wages over time - the selection-corrected gender wage gap for this group shows stagnation during the 25 years of our analysis.

This paper contributes to the large and growing literature examining differences in male and female wages. Whereas human capital levels (such as educational attainment) accounted for a large share of the gap in the 1980s and 1990s (Blau and Kahn 2017), women have caught up with men's educational achievement in virtually all high-income countries (see Goldin et al. 2006, Becker et al. 2010). However, the gender wage gap widens with age over the life cycle - both for older and younger cohorts - which researchers attribute to marriage and motherhood (see Anderson et al. 2002, Angelov et al. 2016, Juhn and McCue 2017, Kleven et al. 2019b or Kleven et al. 2019a among others). Other factors examined in the literature are occupational segregation (Groshen 1991, Fitzenberger and Kunze 2005, Ludsteck 2014), intra-firm gender wage gaps (Heinze and Wolf 2010, Card et al. 2016, Bruns 2019) as well as labour market institutions such as wage-setting mechanisms (Blau and Kahn 2003), unions (Blau and Kahn 1992, 1996; Booth and Francesconi 2003) and family policies (Christofides et al. 2013, Olivetti and Petrongolo 2017). Furthermore, the literature has also focused on estimating the extent and evolution of changing selection into employment (Dolado et al. 2019) as well as its effect on the gender wage gap (Blundell et al. 2007, Olivetti and Petrongolo 2008, Mulligan and Rubinstein 2008, Maasoumi and Wang 2019) and more generally on wage inequality (Arellano and Bonhomme 2017, Biewen et al. 2018). With regard to the impact of selection into employment on the gender wage gap, Olivetti and Petrongolo (2008) show that a large share of the cross-country differences in gender wage gaps can be explained by differences in female employment rates. Mulligan and Rubinstein (2008) present a theoretical framework that links increasing positive selection into employment to rising wage inequality and show that convergence of male and female wages in a context of rising wage inequality can be overestimated if increasing selection into employment is not taken into account. More recently, Maasoumi and Wang (2019) make use of Arellano and Bonhomme (2017)'s econometric model for controlling for selection into employment in the context of quantile regression and find that the relationship between employment rates and selection into employment varies across gender and over time. One last strand of literature relevant for this paper focuses on examining the large variation of the gender wage gap across the distribution as well as the different roots behind gender wage gaps among low- and high-earnings individuals (e.g. López-Nicolás et al. 2001, Albrecht et al. 2003, Gupta et al. 2006, Arulampalam et al. 2007, Kassenböhmer and Sinning 2014).

In the next two sections, we provide a detailed description of the empirical strategy and the data. Section 4 documents the evolution of full-time employment rates over time by gender and selected socio-economic characteristics. Sections 5 and 6 present our main results and explore the heterogeneity of those. Finally, Section 7 summarizes our findings and draws policy conclusions.

2. Empirical strategy

The aim of this paper is to identify the role of changing selection into employment for the evolution of the gender wage gap across the distribution and over time. To this end, we need a method to correct for selection into employment that is compatible with our distributional approach. In this paper we use a selection correction method proposed in Melly and Santangelo (2015), which consists of an imputation based approach[2].

Imputation-based approaches correcting for selection into employment have been widely used in the literature (Neal 2004, Blau and Kahn 2006, Olivetti and Petrongolo 2008 among others). Mostly, they rely on informed guesses of whether non-realized wages fall above or below observed median wages - mostly conditional on the education level of the individual. The imputation method proposed by Melly and Santangelo (2015) goes a step further and suggests imputing a point-identified wage for each individual out-of-work that takes into account both observable and unobservable characteristics of the individual. Once each individual in the sample gets assigned a wage, which can be either realized (i.e. observed) or non-realized (i.e. imputed), the resulting wage distribution is by definition selection-corrected.

[2] An alternative thereto would be the Arellano and Bonhomme (2017) model.

Throughout the paper, we denote the observed cumulative distributions of men and women's full-time log wages as $F_{W^M,t}$ and $F_{W^F,t}$, respectively, which are only defined for individuals pursuing full-time employment at time t. We refer to the selection-corrected counterparts as $\widehat{F}_{W^M,t}$ and $\widehat{F}_{W^F,t}$, which are defined for all individuals in the sample.

Thus, the observed gender wage gap at point $\tau \in (0,1)$ in the unconditional distribution is given by:

$$G_{obs}(\tau,t) = F^{-1}_{W^M,t}(\tau) - F^{-1}_{W^F,t}(\tau) \tag{1}$$

whereas the selection-corrected wage gap can be expressed as:

$$\widehat{G}_{corr}(\tau,t) = \widehat{F}^{-1}_{W^M,t}(\tau) - \widehat{F}^{-1}_{W^F,t}(\tau) \tag{2}$$

This is still quite a raw measure of the gender wage gap, as it does not control for differences in human capital between women and men, but it does control for differences of selection into full-time employment which is the focus of the paper. Next, by adding and subtracting expression (2) to (1), we can express the observed gender wage gap as:

$$G_{obs}(\tau,t) = \widehat{G}_{corr}(\tau,t) + \widehat{Sel}^{M}(\tau,t) - \widehat{Sel}^{F}(\tau,t) \tag{3}$$

where the two last terms capture the effect of selection into full-time employment on the male and female wage distribution, respectively[3]. These are measured by the distance between observed and selection-corrected wage distributions at different points of the distribution, which are allowed to differ by gender:

$$\widehat{Sel}^{M}(\tau,t) = F^{-1}_{W^M,t}(\tau) - \widehat{F}^{-1}_{W^M,t}(\tau) \tag{4}$$

$$\widehat{Sel}^{F}(\tau,t) = F^{-1}_{W^F,t}(\tau) - \widehat{F}^{-1}_{W^F,t}(\tau) \tag{5}$$

Confidence bands for estimates $\widehat{G}_{corr}(\tau,t)$, $\widehat{Sel}^{M}(\tau,t)$ and $\widehat{Sel}^{F}(\tau,t)$ throughout the paper are computed using a critical value obtained through an inversion of the Kolmogorov-Smirnov test.

The rest of this section is structured as follows. Next we present Melly and Santangelo (2015)'s imputation method of non-realised wages[4]. Later we discuss the specification of the conditional wage model.

2.1. Imputation of non-realized wages

At the core of Melly and Santangelo (2015)'s imputation procedure there is a wage model which states that individuals' wages W depend on a set of observable characteristics X and

[3] We also refer to these terms as selection bias throughout the paper

[4] See Melly and Santangelo (2015) for details. The aim of this subsection is merely to sketch the imputation method proposed by the authors so as to make it understandable - for a thorough explanation of the model it is advised to refer to the original sources.

on an unobservable component U. Given that vector X is observed for all individuals at all times in longitudinal data regardless of their employment status, the imputation procedure requires mostly assumptions on the distribution of the unobservable component U. In this setting, the person-specific unobservable component is captured by the conditional rank, i.e. the rank of an individual in the wage distribution of individuals with her same observable characteristics. The identifying assumption at the core of Melly and Santangelo (2015)'s model, and the main assumption in this paper, imposes the time-invariance of the unobservables conditional on the observables for a given group (G) of interest (e.g. full-time employed women or men). Formally:

$$A1: \quad f_{U|T,G,X} = f_{U|G,X}$$

A1 enables us to extract information on the person-specific unobservable from realised wages at any point in time and use it at a different point in time when we require an imputation. A1 can be understood as a fixed effect assumption, and rules out that individuals select into (full-time) employment whenever they would experience a positive wage shock and drop from (full-time) employment whenever they experience a negative one. This allows explicitly for individuals to experience growth in their wage level over the life-cycle but not to change relative position in the conditional wage distribution. Importantly, A1 needs to hold only in distribution, which allows for unsystematic slippages of the conditional ranks of particular individuals[5]

However, in this paper we require an auxiliary assumption which we use for individuals for whom we do not observe a full-time wage in the data. In this case, these individuals get allocated a random conditional rank:

$$A2: \quad U \sim U(0,1)$$

This assumption is justified by the fact that most reasons for us not observing a full-time wage for certain individuals relate to the design of the SOEP, which we argue is exogenous with respect to the unobservable wage component of these individuals (see Section 3 for a discussion on this). Furthermore, by allocating these individuals a random conditional rank, we do not modify the spread of the resulting wage distribution.

The imputation algorithm suggested by Melly and Santangelo (2015) starts by building subsamples with individuals that work in two given periods (group 0) and subsamples of individuals that only work in one of these two periods (group 1). The latter reveal information on their unobservables in the one period when they work, which is captured by their conditional rank in the wage distribution. The evolution of wages of group 0 allows imputing group 1 a conditional wage that responds to the wage structure of the time when the imputation is required and that accounts for both observable and unobservable characteristics of the individuals. This exercise is carried out separately for men and

[5] This is known in the literature as rank similarity and it is a weaker form than rank invariance (see, for instance, Chernozhukov and Hansen (2005) for a discussion of these terms).

women and for all possible combinations of two survey years in the data, which we refer to as $t \in \{k, l\}$. The assignment to a group according to the description above is captured by variables G_{kl}, each with realisation $g_{kl} \in \{0, 1\}$.

Formally, Melly and Santangelo (2015) show that the conditional wage distribution of those individuals not working in time period t=k but working in time period t=l can be derived as:

$$F^{-1}_{W|g=1,t=k,x}(\theta) = F^{-1}_{W|g=0,t=k,x}\left(F_{W|g=0,t=l,x}\left(F^{-1}_{W|g=1,t=l,x}(\theta)\right)\right) \tag{6}$$

and individual wages conforming $F^{-1}_{W|g=1,t=k,x}(\theta)$ can be imputed as:

$$\widetilde{w}_{ikl} = x_i\hat{\beta}_{g=0,t=k}\left(\int_0^1 \mathbb{1}\left(x_i\hat{\beta}_{g=0,t=l}(u) \leq x_i\hat{\beta}_{g=1,t=l}(\theta)\right)du\right) \tag{7}$$

where $\hat{\beta}_{g,t}(\theta)$ are the wage equation coefficients for quantile θ coming from the estimated conditional quantile regression processes. As each realised full-time wage provides enough information to impute all non-realised wages of an individual, expression 7 produces multiple available imputations for a single non-realized wage in most cases. We follow Melly and Santangelo (2015) and weigh all available imputations for an individual.

For those individuals for whom we require a random conditional rank, we predict a wage for them by using their observable characteristics for a given year and the coefficients from the wage process estimated on all imputed wages in a given year according to the main model (equation 7) - evaluated at their random conditional rank.

2.2. Conditional wage model

The wage process is estimated separately year-by-year for men and women in the subsamples defined by G_{kl} - kl being all possible two-year combination in the data - as a linear conditional quantile regression model (Koenker and Bassett, 1978):

$$Q_\theta(w_{it}|x_{it}) = x'_{it}\beta_t(\theta) \tag{8}$$

The dependent variable, w_{it}, is the natural logarithm of the hourly wage. The independent variables, x_{it}, consist of an intercept, age (polynomially), an indicator variable for an intermediate degree, an indicator variable for an advanced degree and a continuous variable capturing actual full-time working experience polynomially up to the power of three.

Ideally, we would like to include past part-time employment spells as a covariate in the wage model. However, we decided against given that in the data there is almost no variation for men and only little variation for women in the values of past part-time employment spells, a problem that accentuates in the presence of small subsamples conforming the two-year combinations required for the imputation procedure. Not including past part-time employment spells lets the model treat those qualitatively the same as non-employment spells and/or overlong education years conditional on achieved degree. The error incurred here should be moderate, as the literature has found that accumulation of human capital in part-time employment takes place very slowly if at all (Blundell et al., 2016, Paul, 2016). Furthermore, our wage model only includes covariates which we can observe regardless of the employment status of the individual - otherwise we could not use it to impute non-realised wages.

3. Data

Four our empirical analysis we use the German Socio-Economic Panel (SOEP) for years 1990 to 2014 (see Goebel et al. (2019) for a description of the dataset). The SOEP is a rich dataset for Germany that brings together a longitudinal dimension and detailed information on the number of working hours, which are both essential for the imputation of non-realised wages[6].

We restrict our estimation sample to those individuals aged 20 to 55 with residence in West Germany[7]. Furthermore, we exclude individuals in retirement, the military, disabled individuals, and the self-employed. Individuals who only appear once in the data are dropped, as the imputation procedure requires at least two observation per individual. Last, in order to minimize the number of individuals for whom we never observe a full-time wage, we restrict our analysis to Samples A to K - implying that we do not use any new sample joining the SOEP after 2009 - and adapt the weighting factors to keep the representativeness of our sample from 2010 onwards.

We focus only on the gender wage gap among full-time employees[8]. We define full-time employment based on whether individuals work at least 30 hours per week. Working hours are defined as actual working hours. The dependent variable is the natural logarithm of the hourly wage. The hourly wage variable has been constructed by diving gross monthly earnings over actual working hours. Hourly wages are inflated/deflated to 1995 prices based on CPI figures provided by the German Statistical Office. In order to minimize measurement error concerns, we drop each year the top and bottom 0.5% of wage observations in both the male and female wage distributions. For individuals who work in part-time employment or who are not employed, a wage is imputed. The same

[6] Using survey data often raises concerns about measurement error. Unfortunately, the administrative data set based on which the German Federal Statistical Office calculates the gender wage gap (Structure of Earnings Survey, SES), is not a longitudinal data set and does not include household characteristics. On the other hand, the administrative datasets from the Institute for Employment Research (IAB), which are based on social security records, do have the longitudinal dimension, however they lack detailed information on individuals' working hours.

[7] We restrict the analysis to West Germany because the labour market of East Germany during these years had very distinctive features that would require a separate estimation. Unfortunately, the number of observations for East Germany is too small for our data-intensive imputation method.

[8] Ideally we would like to analyse the gender wage gap for part-time employees as well. Unfortunately, this is not possible because of too few male part-time wage observations. We argue a joint analysis of the gender wage gap for full- and part-time employees would not be meaningful given the large expansion of part-time employment during the last decades, its strong gender dimension as well as growing part-time wage differentials.

applies for individuals that report being on full-time education (irrespectively of whether they have a side job) as well as for individuals with missing information on earnings but complete information on the covariates entering the wage equation.

The covariates entering the conditional wage model are age (measured in years), indicator variables for middle and advanced education degrees (built according to the CASMIN classification) and actual full-time working experience (also measured in years). We present our results aggregated in five-year periods covering the time span from 1990 to 2014. At the end, this leaves us with 76,927 male and 88,957 female person-year observations in our sample (see Table 1 below).

Table 1: Sample Size

	female proportion	female*working full-time	male*working full-time	person-year observations
1990-1994	.51	.39	.82	27545
1995-1999	.51	.38	.81	27501
2000-2004	.52	.38	.81	43599
2005-2009	.52	.40	.80	36320
2010-2014	.51	.45	.80	30919
Total	.51	.40	.81	165884

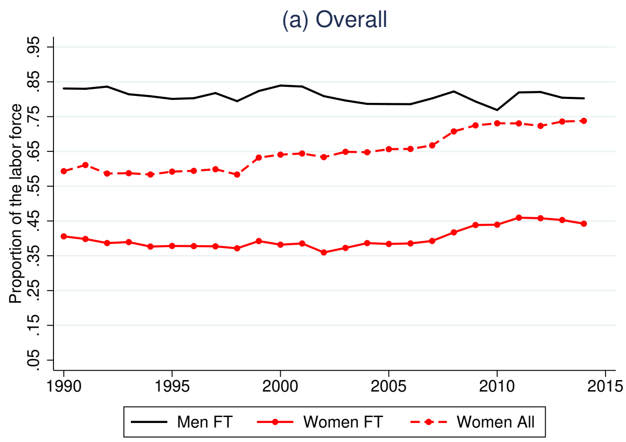
Source: SOEP.v34 Samples A-K, weighting factors used, own calculations.

The number of individuals for whom we never observe a full-time wage is of great relevant for the imputation procedure, as this is a group for which we use the auxiliary identifying assumption A2. Concretely, 3% to 10% of every year's male observations require random imputations, while only 1% to 6% never truly work full-time. For females, these figures go up to 24% to 33% of every year's, although only 7% to 10% of those truly never work full-time (see Tables A1 and A2 in the Appendix for year-by-year figures). We argue that use of assumption A2 is justified by the fact that this large discrepancy is due to the SOEP survey design (for instance, the age at which an individual is invited to participate in the SOEP for the first time), which should be exogenous to individuals' unobserved productivity U.

4. Full-Time Employment over Time

The evolution of male and female full-time employment rates is crucial to understanding the selection process which, in turn, affects the evolution of selection-corrected gender wage gaps over time. Thus, in this section we describe the development of full-time employment over the period of 1990-2014 for different socio-economic subgroups. As Figure 1 shows, the full-time employment rate of men has remained fairly constant at about 80 percent over the whole observation period. In contrast, the employment rate of women has been increasing by almost 20 percentage points. While an important part of this increase has been due to an increase in part-time employment, also full-time employment of women has been rising. The full-time employment rate of women stayed constant during the 1990s and started rising in the 2000s. By 2009 it has reached 45 percent of the labour force, which is 10 percentage points more than in 2000. The fact that the employment of women has risen substantially while the employment rate of men did not change most likely means that selection into employment, which affects the selection bias of observed wages, is likely to be different for men than for women, and to be changing over time.

Figure 1: Full-Time Employment Rates, by Gender



Source: SOEP.v34 Samples A-K, own calculations.

Looking at the evolution of full-time employment rates of men and women with different socio-economic characteristics gives some hints about how the selection into full-time employment might have changed over time. For example, Figure 2a shows that the full-time employment rate of men aged 20-29 has decreased by almost 20 percentage points. While this is also true of the full-time employment rate of women in this age group, women aged 30 to 39 and 40 to 49 have increased full-time employment by about 10 percentage points.

Differentiating by education levels, we find that the full-time employment rate of men with a basic degree has dropped by more than 10 percentage points until the mid of the 2000s. From then on, it has been increasing again and has reached a share of 85 percent at the end of the observation period. In contrast, the full-time employment rate of men with medium or advanced degree has remained fairly constant in the last 25 years. Likewise, the rate of full-time employment of men differentiated by number of children living in the household has remained constant in the same time period.

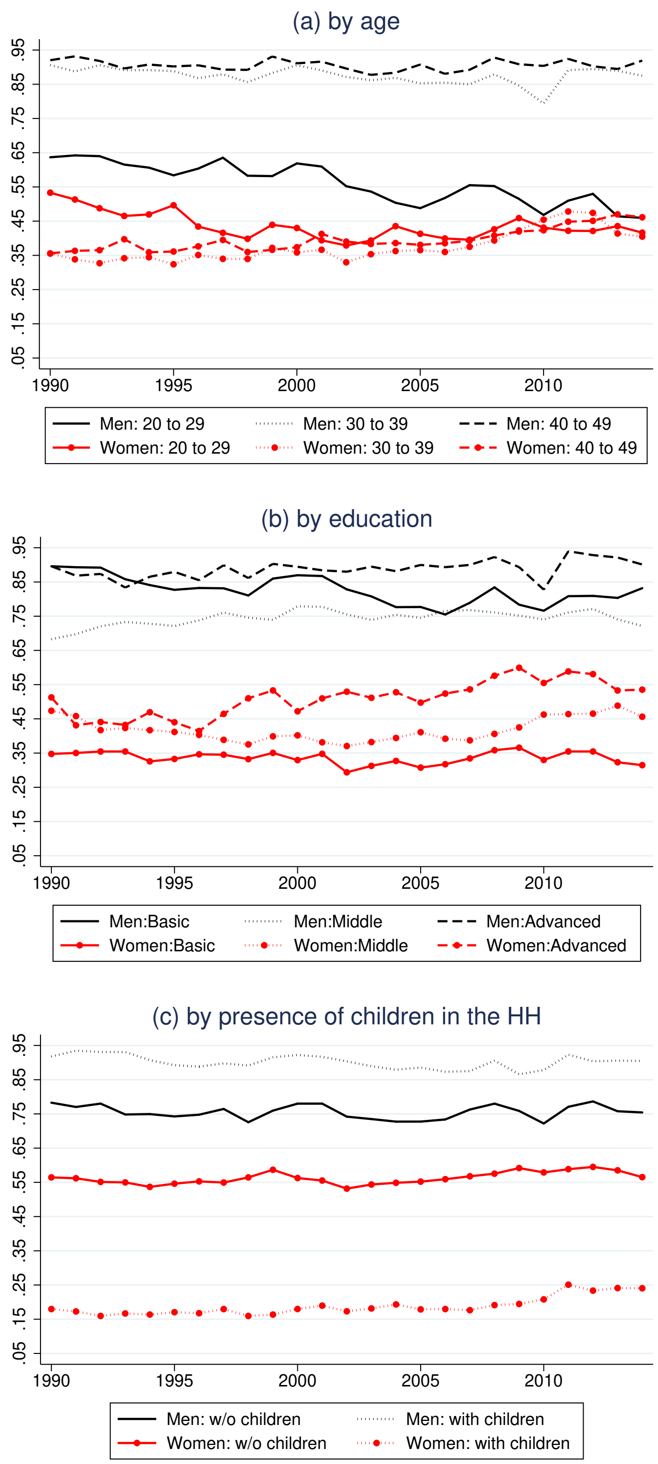
For women, we find very different evolutions of the full-time employment rates by socio-economic subgroups than for men. While – similar to men – the full-time employment rate of women aged 20-29 has dropped in the 1990s and early 2000s, it has increased since 2007 and has converged to the full-time employment rate of men by the end of the observation period. The full-time employment rates of women aged 30-39 and that of women aged 40-49 have been increasing steadily and amount to about 45 percent in 2014, which is 10 percentage points higher than in 1990.

While the full-time employment rate of women with a basic education degree has remained constant over the last 25 years, it has increased for women with intermediate and even more for women with advanced degrees. For the latter group, the full-time employment rate has increased by 10 percentage points and amounts to 55 percent in 2014.

As Panel c of Figure 2 shows, the full-time employment rate of men does not differ by the presence of children. This is very different for women. The full-time rate of women without children under 16 years in the household has been constant at about 55 percent over the whole observation period. In contrast, the full-time employment rate of women with children in this age group, used to be around 15 percent up until the mid 2000s and has risen since up to 25 percent by 2014.

To sum up, the key finding from this descriptive analysis is the fact that the full-time employment rate of men has remained rather stable over the past 25 years, while the full-time employment rate of women has been increasing by roughly 10 percentage points. Moreover, the development of the full-time employment rate has been different by age, education and presence of children. In particular, full-time employment has been increasing among women with medium and high education levels and among women with at least one child under 16 living in the household.

Figure 2: Full-Time Employment rates, by age, education and presence of children



Source: SOEP.v34 Samples A-K, own calculations.

5. Main Results

This section offers a descriptive analysis of the observed gender wage gap across the distribution and over time, and then moves to presenting our estimates of the selection-corrected gender wage gap.

Table 2: Observed Gender Wage Gap

	$\tau = .10$	$\tau = .25$	$\tau = .50$	$\tau = .75$	$\tau = .90$
(A) Levels at selected points in the distribution					
90-94	.322*	.260*	.239*	.261*	.274*
	[.259, .385]	[.220, .300]	[.210, .268]	[.218, .304]	[.217, .331]
00-04	.244*	.231*	.202*	.202*	.243*
	[.187, .300]	[.192, .269]	[.170, .234]	[.171, .232]	[.203, .283]
10-14	.239*	.190*	.182*	.206*	.238*
	[.156, .322]	[.125, .256]	[.142, .221]	[.153, .260]	[.172, .303]
(B) Changes over time					
Δ 90-94	.078*	.030	.037	.059*	.031
vs 00-04	[.004, .152]	[-.017, .077]	[-.002, .077]	[.013, .105]	[-.029, .092]
Δ 00-04	.005	.040	.020	-.005	.005
vs 10-14	[-.087, .096]	[-.030, .111]	[-.026, .065]	[-.063, .053]	[-.066, .076]
Δ 90-94	.083	.070	.057*	.054	.036
vs 10-14	[-.010, .176]	[-.001, .141]	[.013, .101]	[-.005, .114]	[-.047, .119]

Comments: Differences in log-points between the observed male and female wage distributions.

* Statistical significance at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34, own calculations.

Our analysis shows that the observed gender wage gap among full-time workers displays a slight u-shape over the wage distribution, as can be seen from Table 2. In the beginning of the 1990s, the observed gender wage gap was 32 log points at the bottom (10^{th} percentile), 24 log points at the median, and 28 log points at the very top (90^{th} percentile) of the wage distribution. The observed gender wage gap has decreased smoothly for all quantiles of the wage distribution over time[9], and the u-shape is still observed in the latest sub-period from 2010-2014. At the median, the observed gender wage gap among full-time workers has decreased by 6 log points between the two sub-periods of 1990-94 and 2010-14. The decrease has been even larger at the bottom of the wage distribution, where the gender wage gap has decreased by 8 log points over the same time period. In

[9]Complete results for all sub-periods are shown in Table A4 in the Appendix

contrast, we do not find a statistically significant convergence of the wages of male and female workers at the top of the wage distribution (see Table 2, Panel B).

Table 3: Selection-Corrected Gender Wage Gap

	$\tau = .10$	$\tau = .25$	$\tau = .50$	$\tau = .75$	$\tau = .90$
(A) Levels at selected points in the distribution					
90-94	.494*	.389*	.307*	.314*	.335*
	[.446, .543]	[.359, .420]	[.283, .331]	[.282, .345]	[.295, .375]
00-04	.430*	.336*	.294*	.281*	.305*
	[.370, .489]	[.302, .370]	[.269, .318]	[.255, .306]	[.275, .336]
10-14	.292*	.280 *	.246*	.267*	.313*
	[.217, .367]	[.233, .326]	[.211, .281]	[.226, .308]	[.268, .358]
(B) Changes over time					
Δ 90-94	.065*	.054*	.013	.033	.030
vs 00-04	[.001, .128]	[.013, .094]	[-.018, .045]	[-.003, .069]	[-.013, .073]
Δ 00-04	.138*	.056	.048*	.013	-.007
vs 10-14	[.038, .238]	[-.007, .120]	[.000, .096]	[-.041, .068]	[-.066, .051]
Δ 90-94	.203*	.110*	.061*	.046	.023
vs 10-14	[.108, .297]	[.048, .171]	[.012, .111]	[-.012, .104]	[-.042, .087]

Comments: Units are log-points differences between selection-corrected male and female wage distributions. In brackets 95% confidence bands (computed by bootstrap with 200 replications).
Source: SOEP.v34 Samples A-K, own calculations.

Table 2 summarizes the estimation results of the selection corrected gender wage gap for selected quantiles of the wage distributions and time periods. Comparing the selection-corrected to the observed gender wage gap summarized in Table 1, our main finding is that failing to account for selection into full-time employment leads to a strong underestimation of the gender wage gap. For example, the selection-corrected gender wage gap for the median of the wage distribution was 25 log points in the years 2010-14, which is 7 log points higher than the corresponding observed gender wage gap. As Table 2 shows, selection-corrected gender wage gaps are higher than observed gender wage gaps at all points in time and also across the whole wage distribution. The main reason for the selection corrected gender wage gap to be higher than the observed one is that positive selection into full-time employment is much larger for women than for men (see Tables 4 and 5 further below).

Similar to the development of the observed wages, we also observe a convergence of selection-corrected wages of male and female full-time workers over time. At the median, the selection-corrected gender wage gap has decreased by 5 log points between 1990-94 and 2010-14. Moreover, the convergence of the selection-corrected wages shows a similar pattern across the wage distribution as the convergence of the observed wages: At the bottom, we find a larger convergences, while there is no convergence at the top. As Panel B of Table 2 shows, the selection-corrected gender wage gap decreased by 15 log points between 1990-94 and 2010-14 at the 10^{th} percentile, by 9 log points at the 25^{th} percentile and by 5 and 4 log points at the 50^{th} and 75^{th} percentile, respectively. However, there is no statistically significant decrease of the selection-corrected gender wage gap for the 90^{th} percentile of the wage distribution. Therefore, the evolution of both, the observed and the selection-corrected gender wage gap over time and across the wage distributions shows that the so-called "sticky floors" have become less severe over time, while the "glass ceilings" still prevail.

The reason that the selection-corrected gender wage gap is higher than the observed one is obviously that selection into full-time employment is different for men and women. Throughout the whole period of observation, we find a statistically significant positive selection bias at all points in the wage distribution, both for men (Table 4) and women (Table 5). There is a small exception to this finding, which is the top of the male wage distribution in the periods 1990-94 and 2000-04. Positive selection implies that the observed wages are higher than if they were if the observed and unobserved characteristics of workers selecting into full-time employment were the same as of the whole population. In other words, a positive selection bias means that workers selecting into full-time employment have higher potential wages than those selecting in part-time or non employment. For both men and women we find that the magnitude of the selection bias is highest at the bottom of the wage distribution and then decreases with wages. For men, the selection bias has increased over time for the lower half of the wage distribution. For example, in the 25 years between 1990 and 2014, the selection bias at the 10^{th} percentile of the male wage distribution has increased by 15 log points. This decrease was less pronounced at the median (6 log points) and not statistically significant at higher quantiles of the wage distribution. These results are remarkable against the background of the relatively stable full-time employment rate of men over time. However, they are consistent with changes in the composition of the group of full-time working men as shown in section 4. In section 6, we further explore the evolution of the effect of selection on wages by age and education level.

The (positive) selection bias in the distribution of the wages of female full-time workers is much higher than for their male counterparts at all points of the wage distribution. Furthermore, the evolution of the effect of selection on wages over time is somewhat different for women than for men. In the first half of our observation period, we observe an increase in the effect of selection on female wages. Comparing the periods 1990-94 and 2000-04, we find that the selection bias in observed wages increases by 9 log points at the 10^{th} percentile and by 5 log points at the 50^{th} percentile of the female wage distribution. For the upper half of the wage distribution, we do not find any changes

Table 4: Effect of selection on the male wage distributions

	$\tau = .10$	$\tau = .25$	$\tau = .50$	$\tau = .75$	$\tau = .90$
(A) Levels at selected points in the distribution					
90-94	.061*	.043*	.035*	.039*	.030
	[.018, .104]	[.017, .068]	[.011, .059]	[.003, .075]	[-.012, .073]
00-04	.136*	.097*	.061*	.044*	.033
	[.096, .175]	[.068, .125]	[.038, .083]	[.021, .068]	[-.001, .068]
10-14	.214*	.131*	.092*	.071*	.049
	[.137, .291]	[.075, .187]	[.048, .136]	[.018, .125]	[-.002, .100]
(B) Changes over time					
Δ 90-94	-.074*	-.054*	-.026	-.005	-.003
vs 00-04	[-.128, -.021]	[-.092, -.017]	[-.057, .006]	[-.044, .033]	[-.054, .047]
Δ 00-04	-.078	-.034	-.031	-.027	-.016
vs 10-14	[-.157, .000]	[-.093, .025]	[-.078, .016]	[-.085, .031]	[-.072, .041]
Δ 90-94	-.153*	-.088*	-.057*	-.033	-.019
vs 10-14	[-.232, -.073]	[-.145, -.031]	[-.102, -.012]	[-.093, .028]	[-.077, .038]

Comments: Differences in log-points between the observed and the selection-corrected distributions.

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

in the effect of selection. Comparing the periods 2000-2004 and 2010-14, we do not find any statistically significant changes in the effect of selection at any point of the wage distribution. Against the background of increasing full-time employment rates of women, we would have expected a decrease in the selection bias on wages. However, we find the exact opposite, in particular in the first half of the observation period. This implies that the increase in full-time employment was not random but concentrated among women who have observed and unobserved characteristics that are highly rewarded in the labour market.

Table 5: Effect of selection on the female wage distributions

	$\tau = .10$	$\tau = .25$	$\tau = .50$	$\tau = .75$	$\tau = .90$
(A) Levels at selected points in the distribution					
90-94	.234*	.172*	.103*	.092*	.091*
	[.168, .299]	[.127, .216]	[.075, .131]	[.056, .127]	[.039, .144]
00-04	.322*	.202*	.153*	.123*	.096*
	[.267, .377]	[.166, .239]	[.124, .182]	[.095, .152]	[.062, .131]
10-14	.266*	.221*	.156*	.132*	.124*
	[.172, .361]	[.157, .284]	[.118, .193]	[.083, .182]	[.067, .182]
(B) Changes over time					
Δ 90-94	-.088*	-.030	-.050*	-.032	-.005
vs 00-04	[-.165, -.011]	[-.088, .027]	[-.087, -.012]	[-.071, .008]	[-.060, .050]
Δ 00-04	.055	-.018	-.003	-.009	-.028
vs 10-14	[-.067, .178]	[-.095, .058]	[-.057, .052]	[-.070, .052]	[-.100, .043]
Δ 90-94	-.033	-.049	-.053*	-.041	-.033
vs 10-14	[-.143, .077]	[-.126, .028]	[-.099, -.006]	[-.101, .020]	[-.112, .046]

Comments: Differences in log-points between the observed and the selection-corrected distributions.

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

6. Heterogeneity analysis

In this section we examine how our results differ by selected socio-economic dimensions. The first of these dimensions is age, as it is an established fact that in many economies gender wage gaps increase with age, often as a result of family formation and motherhood (see for instance Anderson et al. 2002, Angelov et al. 2016, Juhn and McCue 2017, Kleven et al. 2019b or Kleven et al. 2019a, among others). But also decisions regarding participation in the labour market and resulting patters of selection into full-time employment are much likely to differ by age segments. Therefore, we split our sample into three broad age categories (20 to 29 year olds, 30 to 39 year olds and 40 to 49 year olds) and examine whether there is heterogeneity in our results for these groups.

Table 6: Gender wage gap and selection bias, by age groups

	$G_{obs}\,(\tau=.5,t)$	$\widehat{G}_{corr}\,(\tau=.5,t)$	$\widehat{Sel}^{M}\,(\tau=.5,t)$	$\widehat{Sel}^{F}\,(\tau=.5,t)$
		(A) Age 20 to 29		
90-94	.132*	.189*	.031	.088*
	[.095, .169]	[.143, .234]	[-.003, .066]	[.048, .128]
00-04	.143*	.198*	.093*	.149*
	[.088, .199]	[.157, .240]	[.034, .153]	[.103, .194]
10-14	.048	.124*	.133*	.209*
	[-.065, .162]	[.051, .196]	[.046, .221]	[.108, .310]
		(B) Age 30 to 39		
90-94	.203*	.251*	.017	.065*
	[.145, .260]	[.207, .296]	[-.024, 0.057]	[.011, .119]
00-04	.155*	.260*	.027	.133*
	[.111, .198]	[.226, .294]	[-.005, 0.060]	[.082, .184]
10-14	.098	.207*	.053	.162*
	[-.006, .202]	[.117, .297]	[-.043, 0.149]	[.035, .290]
		(C) Age 40 to 49		
90-94	.231*	.382*	0.010	.161*
	[.165, .297]	[.331, .433]	[-0.041, .061]	[.091, .231]
00-04	.210*	.316*	0.026	.132*
	[.160, .260]	[.278, .355]	[-0.009, .060]	[.075, .190]
10-14	.213*	.295*	0.033	.115*
	[.147, .280]	[.240, .350]	[-0.018, .084]	[.055, .175]

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

In the raw data, the median gender wage gap increases with age[10]. However, for the two younger age categories it has decreased over time - even vanishing in the period 2010-2014. For the oldest category, the median gender wage gap displays a constant profile over time.

[10] In order to reduce the complexity of the results, Table 6 presents only results by age categories evaluated at the median. Results at other points in the distribution are available from the authors upon request.

Controlling for selection into employment does not alter the fact that the gender wage gap increases with age. Furthermore, selection-corrected wage gaps are higher than the observed ones for all age groups at all points in time. As with the aggregated gender wage gaps, the main reason behind this difference is that the female wage distribution is more strongly positively selected than the male one. Over time, the selected-corrected wage gap decreases for all age categories - although with different timings and magnitudes.

However, the key finding of exploring the heterogeneity of the results by age is the fact that the rise in male selection bias appears to be driven by men in the youngest age group. For this group, our results show an increase in the male selection bias of 10 log points over the entire period[11], while male selection bias has stayed constant and statistically insignificant for the other two age groups at all points in time. For women, we find positive selection into full-time employment for all age groups. The magnitude of the selection bias has increased over time for the two younger age groups, while it has stayed constant for the group aged 40 to 49[12].

Table 7 shows the heterogeneity of the results by education level. In terms of observed wage gaps, figures are relatively similar across groups and over time - with the exception of the rise in the observed median wage gap for the highly educated in 2010-14 (almost 9 log points with respect to the previous decade[13]).

The selection-corrected wage gap is much higher than the observed one for the group with basic education. Female selection bias reaches 14 to 19 log-points depending on the time period. However, observed and selection-corrected wage gaps are very similar for the groups with middle and high education. Given that the decomposition is an identity in the mathematical sense, this can only be true if the male and female selection bias are (statistically) the same. In the case of middle education, the selection bias in male wages is remarkably high (8 to 10 log points, large figures for male wages), which nonetheless is consistent with the lower full-time employment rates for this education group (see Figure 2). In the case of high education, we find zero selection bias for both the male and the female wage distribution up to the period 2000-04, which is a remarkably low figure for females. For the latest period, we observe an increase in female positive selection for the group with tertiary education, which results in statistically significant divergence of male and female selection-corrected wages for this group. For the other two groups, we do not find any time trend.

Table 8 shows heterogeneity by the presence of small children in the household[14]. As expected, raw gender wage gaps are much higher for parents than for childless people. While the gender wage gap for those without children has stayed quite constant over time, it has decreased by more than 12 log points for those with young children in the

[11] Table A5 in the Appendix reports confidence bands for changes over time

[12] The point-estimate for this group decreases over time but Table A5 shows that we reject an statistical significant change over time.

[13] Confidence bands for changes over time are reported in Table A6 in the Appendix

[14] Individuals are counted as parents if their children live the same household than they do. Parents whose children do not (any longer) live in their household are included in the childless category.

Table 7: Gender wage gap and selection bias, by education

	$G_{obs}\,(\tau=.5,t)$	$\widehat{G}_{corr}\,(\tau=.5,t)$	$\widehat{Sel}^{M}\,(\tau=.5,t)$	$\widehat{Sel}^{F}\,(\tau=.5,t)$
		(A) Basic or No Degree		
90-94	.264*	.382*	.022	.140*
	[.221, .306]	[.354, .410]	[-.001, .044]	[.098, .183]
00-04	.242*	.374*	.048*	.181*
	[.196, .288]	[.340, .408]	[.016, .080]	[.135, .226]
10-14	.214*	.327*	.079*	.192*
	[.121, .307]	[.269, .385]	[.029, .129]	[.104, .280]
		(B) Middle Degree		
90-94	.212*	.195*	.079*	.063*
	[.160, .264]	[.155, .236]	[.034, .124]	[.022, .104]
00-04	.188*	.222*	.080*	.113*
	[.146, .230]	[.189, .255]	[.040, .119]	[.076, .151]
10-14	.177*	.183*	.105*	.110*
	[.124, .230]	[.122, .243]	[.048, .161]	[.066, .154]
		(C) Advanced Degree		
90-94	.220*	.224*	.024	.028
	[.102, .339]	[.122, .326]	[-.038, .086]	[-.101, .157]
00-04	.202*	.215*	.024	.037
	[.143, .261]	[.161, .268]	[-.028, .06]	[-.028, .102]
10-14	.291*	.335*	.040	.083*
	[.206, .376]	[.249, .421]	[-.057, .136]	[.003, .164]

Notes: Education categories built according to CASMIN classification; Basic degree (=basic school degree without later vocational training); Middle degree (=intermediate school degree and/or vocational training); Advanced degree (=tertiary education)

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

Table 8: Gender wage gap and selection bias, by presence of children

	$G_{obs}\,(\tau = .5, t)$	$\widehat{G}_{corr}\,(\tau = .5, t)$	$\widehat{Sel}^{M}\,(\tau = .5, t)$	$\widehat{Sel}^{F}\,(\tau = .5, t)$
	(A) No children under 16 in the household			
90-94	.190*	.268*	.045*	.122*
	[.152, .228]	[.233, .302]	[.010 .080]	[.086 .159]
00-04	.157*	.216*	.084*	.143*
	[.124, .190]	[.184, .249]	[.047 .121]	[.112 .174]
10-14	.167*	.199*	.119*	.151*
	[.123, .210]	[.150, .247]	[.063 .176]	[.109 .193]
	(B) Children under 16 in the household			
90-94	.337*	.368*	.014	.045
	[.280, .393]	[.331, .405]	[-.018, .046]	[-.015, .105]
00-04	.251*	.393*	.029	.171*
	[.192, .309]	[.357, .428]	[-.004, .062]	[.110, .231]
10-14	.210*	.336*	.034	.161*
	[.105, .314]	[.270, .402]	[-.030, .098]	[.046, .275]

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

household.

However, the decrease of the observed gender wage gap for those with children is driven by changing (increasing) female selection bias. While male selection bias for this group is zero throughout the whole entire period under study, it has steeply increased for women (from 4 log points up to 17 log points)[15].

For the group without children, the selection-corrected wage gap displays a statistical significant decrease over time. Interestingly, female selection bias for this group has stayed fairly constant over time, while it has increased moderately for males (7 log points in the twenty years between 1990-94 and 2010-14).

7. Conclusion

Our analysis of the observed wages of male and female full-time workers in West Germany over the past 25 years (1990-2014) reveals a U-shaped curve of the gender wage gap across the wage distribution. Moreover, we find a moderate convergence of the observed wages of male and female workers, i.e. a decrease in the observed gender wage gap. This convergence of wages is more pronounced at the bottom of the wage distribution, moderate at the median, and, non-existent at the top of the wage distribution. In other words, while "sticky floors" seem to have become less severe over time, we do not find changes in the "glass ceilings". A closer look at the evolution of the wages of different socio-economic subgroups reveals that the observed decrease of the aggregate gender wage gap mostly comes from a strong convergence of male and female wages in the youngest age group of workers (aged 20 to 29 years) and for workers without children.

A meaningful interpretation of the development of the observed gender wage over time is not possible without an analysis of the evolution of the employment rates, and, more precisely, the evolution of selection into full-time employment. Our analysis shows the existence of a small but rising positive selection bias in male observed wages, implying that potential wages of men actually working full-time are somewhat higher than those of the entire male population. We find this development to be mostly driven by changing selection patterns of young men in their twenties. Our results also show a much larger and increasing selection bias in female observed full-time wages, a finding which is consistent with the results of Biewen et al. (2018) based on German administrative data.

Our measure of selection-corrected gender wage gap can be interpreted as the gender gap in potential wages of all individuals, both those employed and those non-employed. We find that the selection-corrected gender wage gap is larger than the observed one for all groups, which is due to the much larger positive selection into full-time employment for women than for men. Similar to the evolution of the observed gender wage gap, we find a moderate convergence of the selection-corrected gender wage gap over time for the lower half of the income distribution up to the median. However, our results reject any

[15]See Table A7 for confidence bands on changes over time.

convergence of male and female wages at the upper half of the distribution.

The separate analysis of different socio-economic sub-groups yields several interesting findings. First, in contrast to the observed gender wage gap, which decreased strongly for workers in their twenties and even turned insignificant in the latest sub-period (2010-2014), the selection-corrected gender wage gap decreased only slightly for this age group. Second, the difference between the observed and selection-corrected gender wage gap is largest for workers with only basic education level. For workers with intermediate or advanced education degree, the observed and the selection-corrected gender wage gaps are very similar in magnitude, at least for the median. Third, full-time workers with an advanced degree are the only group for whom we actually find an increase in the gender wage gap over time for both, observed and selection-corrected wages. Finally, splitting the sample by the presence of children shows that for workers without children, there is a convergence in observed and – even more pronounced – the selection-corrected wages of men and women working full time. This is consistent with our finding that wages of younger workers have converged over time, because these groups overlap to a large extent. In contrast, for workers with at least one child under 16 living in the household, the observed convergence is exclusively driven by changing mothers' selection patterns and vanish as soon as we control for those. As a result, the selection-corrected gender wage gap for workers with children stagnates at a very high level over the past 25 years.

The fact that the gender wage gap is (i) lower for young workers and (ii) higher for workers with children is well established in the literature and clearly reflected in the findings of the evolution of the gender wage gap over the life-cycle (see for instance Anderson et al. 2002, Angelov et al. 2016, Juhn and McCue 2017, Kleven et al. 2019b or Kleven et al. 2019a, among others). Our finding that the selection-corrected gender wage gap in particular for full-time workers with children does not change at all over time is bad news, because there have been several family policy reforms in Germany over the past 15 years (Geyer et al., 2015) aiming at facilitating work-family life balance in particular for women. The results of our analyses suggest that these policies might have been successful in terms of mothers' employment, in particular in terms of part-time employment, but have – at least not up to now – succeeded in increasing the wages of full-time working mothers. It remains an open question whether the increased part-time employment rates of women, in particular of mothers, can serve as a stepping-stone into full-time employment. This could potentially have positive effects on the wages of full-time working women in the longer run.

References

Albrecht, J., Björklund, A., and Vroman, S., 2003. Is there a glass ceiling in Sweden? *Journal of Labor Economics*, 21(1):145–177.

Anderson, D. J., Binder, M., and Krause, K., 2002. The motherhood wage penalty: Which mothers pay it and why? *The American Economic Review*, 92(2):pp. 354–358.

Angelov, N., Johansson, P., and Lindahl, E., 2016. Parenthood and the gender gap in pay. *Journal of Labor Economics*, 34(3):545–579.

Arellano, M. and Bonhomme, S., 2017. Quantile selection models with an application to understanding changes in wage inequality. *Econometrica*, 85(1):1–28.

Arulampalam, W., Booth, A. L., and Bryan, M. L., 2007. Is there a glass ceiling over Europe? Exploring the gender pay gap across the wage distribution. *Industrial and Labor Relations Review*, 60(2):pp. 163–186.

Athey, S. and Imbens, G. W., 2006. Identification and inference in nonlinear difference-in-differences models. *Econometrica*, 74(2):431–497.

Becker, G. S., Hubbard, W. H. J., and Murphy, K. M., 2010. Explaining the worldwide boom in higher education of women. *Journal of Human Capital*, 4(3):203–241.

Biewen, M., Fitzenberger, B., and de Lazzer, J., 2018. The role of employment interruptions and part-time work for the rise in wage inequality. IZA Journal of Labor Economics, forthcoming.

Blau, F. and Kahn, L., 2003. Understanding international differences in the gender pay gap. *Journal of Labor Economics*, 21(1):106–144.

Blau, F. D. and Kahn, L. M., 1992. The gender earnings gap: Learning from international comparisons. *The American Economic Review*, 82(2):533–538.

———, 1996. Wage structure and gender earnings differentials: An international comparison. *Economica*, 63(250):29–62.

———, 2006. The U.S. gender pay gap in the 1990s: Slowing convergence. *Industrial and Labor Relations Review*, 60(1):45–66.

———, 2017. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865.

Blundell, R., Costa Dias, M., Meghir, C., and Shaw, J., 2016. Female labor supply, human capital, and welfare reform. *Econometrica*, 84(5):1705–1753.

Blundell, R., Gosling, A., Ichimura, H., and Meghir, C., 2007. Changes in the distribution of male and female wages accounting for employment composition using bounds. *Econometrica*, 75(2):323–363.

Booth, A. and Francesconi, M., 2003. Union coverage and non-standard work in britain. *Oxford Economic Papers*, 55(3):383–416.

Bruns, B., 2019. Changes in workplace heterogeneity and how they widen the gender wage gap. *American Economic Journal: Applied Economics*, 11(2):74–113.

Card, D., Cardoso, A. R., and Kline, P., 2016. Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly Journal of Economics*, 131(2):633–686.

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.

Chernozhukov, V. and Hansen, C., 2005. An IV model of quantile treatment effects. *Econometrica*, 73(1):245–261.

Christofides, L. N., Polycarpou, A., and Vrachimis, K., 2013. Gender wage gaps, sticky floors and glass ceilings in Europe. *Labour Economics*, 21(C):86–102.

Dolado, J. J., Garcia-Peñalosa, C., and Tarasonis, L., 2019. The changing nature of gender selection into employment over the Great Recession. Bank of Lithuania Working Paper Series 58, Bank of Lithuania.

Dustmann, C., Ludsteck, J., and Schönberg, U., 2009. Revisiting the German wage structure. *The Quarterly Journal of Economics*, 124(2):843–881.

Fitzenberger, B. and Kunze, A., 2005. Vocational training and gender: Wages and occupational mobility among young workers. *Oxford Review of Economic Policy*, 21(3):392–415.

Geyer, J., Haan, P., and Wrohlich, K., 2015. The effects of family policy on maternal labor supply: Combining evidence from a structural model and a quasi-experimental approach. *Labour Economics*, 36(C):84–98.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., and Schupp, J., 2019. The german socio-economic panel study (soep). *Jahrbücher für Nationalökonomie und Statistik / Journal of Economics and Statistics*, 239(2):345–360.

Goldin, C., Katz, L. F., and Kuziemko, I., 2006. The homecoming of american college women: The reversal of the college gender gap. *The Journal of Economic Perspectives*, 20(4):133–156.

Groshen, E. L., 1991. The structure of the Female/Male wage differential: Is it who you are, what you do, or where you work? *Journal of Human Resources*, 26(3):457–472.

Gupta, N. D., Oaxaca, R., and Smith, N., 2006. Swimming upstream, floating downstream: Comparing women's relative wage progress in the united states and denmark. *ILR Review*, 59(2):243–266.

Heinze, A. and Wolf, E., 2010. The intra-firm gender wage gap: a new view on wage differentials based on linked employer-employee data. *Journal of Population Economics*, 23(3):851–879.

Juhn, C. and McCue, K., 2017. Specialization then and now: Marriage, children, and the gender earnings gap across cohorts. *Journal of Economic Perspectives*, 31(1):183–204.

Kassenböhmer, S. C. and Sinning, M., 2014. Distributional changes in the gender wage gap. *ILR Review*, 67(2).

Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimüller, J., 2019a. Child Penalties across Countries: Evidence and Explanations. *AEA Papers and Proceedings*, 109:122–126.

Kleven, H., Landais, C., and Søgaard, J. E., 2019b. Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics*, 11(4):181–209.

Koenker, R. and Bassett, G. J., 1978. Regression quantiles. *Econometrica*, 46(1):33–50.

López-Nicolás, A., Garcia Villar, J., and Hernandez, P., 2001. How wide is the gap? An investigation of gender wage differences using quantile regression. *Empirical Economics*, 26(1):149–167.

Ludsteck, J., 2014. The impact of segregation and sorting on the gender wage gap: Evidence from german linked longitudinal employer-employee data. *ILR Review*, 67(2):362–394.

Maasoumi, E. and Wang, L., 2019. The gender gap between earnings distributions. *Journal of Political Economy*, 127(5):2438–2504.

Melly, B. and Santangelo, G., 2014. The evolution of the gender wage gap: 1968-2008. Working Paper.

———, 2015. The changes-in-changes model with covariates. Working Paper.

Mulligan, C. B. and Rubinstein, Y., 2008. Selection, investment, and women's relative wages over time. *The Quarterly Journal of Economics*, 123(3):1061–1110.

Neal, D., 2004. The measured black-white wage gap among women is too small. *Journal of Political Economy*, 112(S1):S1–S28.

OECD, 2017. *The Pursuit of Gender Equality: An Uphill Battle*. OECD Publishing.

Olivetti, C. and Petrongolo, B., 2008. Unequal pay or unequal employment? A cross country analysis of gender gaps. *Journal of Labor Economics*, 26(4):621–654.

———, 2017. The economic consequences of family policies: Lessons from a century of legislation in high-income countries. *The Journal of Economic Perspectives*, 31(1):205–230.

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.

Rica, S. d. l., Dolado, J. J., and Llorens, V., 2008. Ceilings or floors? Gender wage gaps by education in Spain. *Journal of Population Economics*, 21(3):751–778.

A. Tables

Table A1: Male Person-Year Observations

	All	Work FT	Not Work FT	Ever Obs FT		Never Obs FT		Never Work FT	
	(1)	(2)	(3)	(4)	% of (3)	(5)	% of (1)	(6)	% of (1)
1990	2765	2296	469	387	83%	82	3%	42	1%
1991	2768	2263	505	419	83%	86	3%	47	1%
1992	2688	2204	484	418	86%	66	2%	28	1%
1993	2684	2141	543	475	87%	68	3%	30	1%
1994	2578	2036	542	463	85%	79	3%	35	2%
1995	2703	2119	584	495	85%	89	3%	40	2%
1996	2615	2060	555	463	83%	92	4%	41	2%
1997	2538	2045	493	408	83%	85	3%	37	2%
1998	2673	2144	529	423	80%	106	4%	44	2%
1999	2608	2170	438	337	77%	101	4%	42	2%
2000	4159	3479	680	505	74%	175	4%	81	2%
2001	4029	3391	638	457	72%	181	4%	78	3%
2002	4159	3403	756	556	74%	200	5%	87	3%
2003	4005	3229	776	570	73%	206	5%	86	3%
2004	3809	3051	758	567	75%	191	5%	77	3%
2005	3545	2835	710	552	78%	158	4%	56	3%
2006	3531	2846	685	524	76%	161	5%	60	3%
2007	3346	2757	589	436	74%	153	5%	59	3%
2008	3131	2598	533	396	74%	137	4%	43	3%
2009	2846	2316	530	394	74%	136	5%	36	4%
2010	2590	2076	514	380	74%	134	5%	34	4%
2011	2930	2375	555	358	65%	197	7%	65	5%
2012	2891	2323	568	341	60%	227	8%	76	5%
2013	2655	2126	529	318	60%	211	8%	65	5%
2014	2687	2183	504	271	54%	233	9%	75	6%
Total	101633	82304	19329	14524	75%	4805	5%	1938	3%

Source: SOEP.v34 Samples A to K, own calculations.

Table A2: Female Person-Year Observations

	All	Work FT	Not Work FT	Ever Obs FT		Never Obs FT		Never Work FT	
	(1)	(2)	(3)	(4)	% of (3)	(5)	% of (1)	(6)	% of (1)
1990	2843	1096	1747	840	48%	907	32%	658	9 %
1991	2840	1091	1749	875	50%	874	31%	629	9 %
1992	2821	1070	1751	933	53%	818	29%	590	8 %
1993	2794	1062	1732	945	55%	787	28%	566	8 %
1994	2743	999	1744	986	57%	758	28%	540	8 %
1995	2907	1065	1842	1058	57%	784	27%	554	8 %
1996	2843	1034	1809	1067	59%	742	26%	515	8 %
1997	2759	1004	1755	1063	61%	692	25%	469	8 %
1998	2962	1053	1909	1133	59%	776	26%	542	8 %
1999	2860	1080	1780	1062	60%	718	25%	493	8 %
2000	4735	1711	3024	1451	48%	1573	33%	1200	8 %
2001	4629	1693	2936	1404	48%	1532	33%	1158	8 %
2002	4837	1755	3082	1561	51%	1521	31%	1154	8 %
2003	4693	1744	2949	1534	52%	1415	30%	1060	8 %
2004	4476	1654	2822	1515	54%	1307	29%	966	8 %
2005	4227	1583	2644	1468	56%	1176	28%	847	8 %
2006	4340	1645	2695	1489	55%	1206	28%	888	7 %
2007	4087	1576	2511	1410	56%	1101	27%	796	7 %
2008	3773	1525	2248	1271	57%	977	26%	692	8 %
2009	3428	1422	2006	1174	59%	832	24%	585	7 %
2010	3122	1274	1848	1113	60%	735	24%	506	7 %
2011	3670	1553	2117	1110	52%	1007	27%	701	8 %
2012	3655	1555	2100	1079	51%	1021	28%	705	9 %
2013	3412	1483	1929	997	52%	932	27%	631	9 %
2014	3246	1461	1785	917	51%	868	27%	574	9 %
Total	115148	44327	70821	36443	51%	34378	30%	24788	8%

Source: SOEP.v34 Samples A-K, own calculations.

Table A3: Sample Means (Standard Deviations) and Sample Size

	intermediate degree (0/1)		advanced degree (0/1)		experience full-time		sample size
(A) Men working full-time							
1990-1994	0.27	(0.45)	0.16	(0.36)	16.6	(10.4)	10940
1995-1999	0.33	(0.47)	0.19	(0.39)	16.0	(9.7)	10538
2000-2004	0.36	(0.48)	0.20	(0.40)	16.5	(9.5)	16553
2005-2009	0.38	(0.49)	0.22	(0.42)	16.9	(9.5)	13352
2010-2014	0.40	(0.49)	0.27	(0.44)	17.1	(9.9)	11083
(B) Women working full-time							
1990-1994	0.45	(0.50)	0.09	(0.29)	11.2	(8.9)	5318
1995-1999	0.46	(0.50)	0.14	(0.35)	12.0	(9.0)	5236
2000-2004	0.49	(0.50)	0.18	(0.38)	12.4	(9.1)	8557
2005-2009	0.50	(0.50)	0.22	(0.41)	12.4	(9.4)	7751
2010-2014	0.52	(0.50)	0.27	(0.44)	11.5	(8.9)	7326
(C) Men not working full-time							
1990-1994	0.48	(0.50)	0.11	(0.31)	7.2	10.1)	2543
1995-1999	0.47	(0.50)	0.10	(0.30)	7.9	(10.1)	2599
2000-2004	0.49	(0.50)	0.10	(0.31)	7.4	(9.6)	3608
2005-2009	0.48	(0.50)	0.09	(0.29)	6.9	(9.4)	3047
2010-2014	0.55	(0.50)	0.11	(0.32)	5.6	(8.7)	2670
(D) Women not working full-time							
1990-1994	0.37	(0.48)	0.07	(0.26)	6.0	(5.8)	8723
1995-1999	0.42	(0.49)	0.09	(0.29)	6.3	(6.2)	9095
2000-2004	0.47	(0.50)	0.10	(0.30)	6.2	(6.2)	14813
2005-2009	0.50	(0.50)	0.12	(0.32)	6.1	(6.3)	12104
2010-2014	0.49	(0.50)	0.17	(0.38)	5.8	(6.3)	9779

Source: SOEP.v34 Samples A-K, weighting factors used, own calculations.

Table A4: Main Results for Inner Time Periods 95-99 and 05-09

	$\tau = .10$	$\tau = .25$	$\tau = .50$	$\tau = .75$	$\tau = .90$
	(A) Observed Gender Wage Gap				
95-99	.252*	.205*	.194*	.201*	.246*
	[.194, .309]	[.173, .238]	[.160, .228]	[.162 .240]	[.186, .305]
05-09	.214*	.231*	.185*	.184*	.202*
	[.148, .281]	[.191, .272]	[.141, .229]	[.144 .223]	[.160, .244]
	(B) Selection-Corrected Gender Wage Gap				
95-99	.399*	.312*	.257*	.263*	.298*
	[.343, .456]	[.275, .349]	[.235, .279]	[.234, .291]	[.260, .337]
05-09	.288*	.287*	.277*	.259*	.282*
	[.222, .354]	[.233, .341]	[.240, .315]	[.226, .292]	[.231, .333]
	(C) Effect of selection on the male wage distribution				
95-99	.106*	.064*	.057*	.044*	.037
	[.056, .156]	[.033, .095]	[.029, .086]	[.014, .075]	[-.007, .081]
05-09	.196*	.156*	.082*	.054*	.049*
	[.126, .267]	[.111, .201]	[.050, .114]	[.020, .088]	[.003, .095]
	(D) Effect of selection on the female wage distribution				
95-99	.254*	.171*	.120*	.106*	.090*
	[.196, .311]	[.135 .207]	[.090, .151]	[.071, .140]	[.040, .140]
05-09	.270*	.212*	.174*	.129*	.129*
	[.213, .327]	[.167 .257]	[.132, .216]	[.090, .169]	[.085, .172]

Comments: Units are log-points between wage distributions.

* Statistical significance at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

Table A5: Heterogeneity by age groups, changes over time

	$G_{obs}\,(\tau = .5, t)$	$\widehat{G}_{corr}\,(\tau = .5, t)$	$\widehat{Sel}^{M}\,(\tau = .5, t)$	$\widehat{Sel}^{F}\,(\tau = .5, t)$
(A) 20 to 29 years				
Δ 90-94	-.011	-.010	-.062	-.061*
vs 00-04	[-.077, .054]	[-.070, .050]	-.125, .001]	[-.121, -.001]
Δ 00-04	.095	.075	-.040	-.060
vs 10-14	[-.016, .207]	[-.009, .159]	[-.142, .062]	[-.156, .035]
Δ 90-94	.084	.065	-.102*	-.121*
vs 10-14	[-.025, .193]	[-.029, .159]	[-.193, -.011]	[-.224, -.017]
(B) 30 to 39 years				
Δ 90-94	.048	-.009	-.011	-.068
vs 00-04	[-.032, .129]	[-.071, .054]	[-.061, .039]	[-.151, .016]
Δ 00-04	.057	.052	-.026	-.030
vs 10-14	[-.051, .164]	[-.037, .141]	[-.125, .073]	[-.138, .078]
Δ 90-94	.105	.044	-.037	-.097
vs 10-14	[-.016, .225]	[-.054, .142]	[-.142, .069]	[-.234, .039]
(C) 40 to 49 years				
Δ 90-94	.021	.066*	-.016	.029
vs 00-04	[-.083, .125]	[.017, .114]	[-.071, .040]	[-.075, .132]
Δ 00-04	-.003	.021	-.007	.017
vs 10-14	[-.082, .075]	[-.045, .087]	[-.070, .056]	[-.055, .090]
Δ 90-94	.018	.087*	-.023	.046
vs 10-14	[-.063, .099]	[.017, .157]	[-.097, .050]	[-.050, .142]

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

Table A6: Heterogeneity by education groups, Changes over Time

	$G_{obs}\,(\tau = .5, t)$	$\widehat{G}_{corr}\,(\tau = .5, t)$	$\widehat{Sel}^{M}\,(\tau = .5, t)$	$\widehat{Sel}^{F}\,(\tau = .5, t)$
		(A) Basic or No Degree		
Δ 90-94	.022	.007	-.026	-.041
vs 00-04	[-.032, .076]	[-.041, .056]	[-.068, .015]	[-.097, .016]
Δ 00-04	.028	.048	-.031	-.011
vs 10-14	[-.070, .126]	[-.017, .112]	[-.096, .034]	[-.112, .090]
Δ 90-94	.050	.055	-.057	-.052
vs 10-14	[-.041, .140]	[-.009, .119]	[-.119, .005]	[-.148, .044]
		(B) Middle Degree		
Δ 90-94	.024	-.026	-.001	-.051
vs 00-04	[-.037, .084]	[-.082, .029]	[-.052, .051]	[-.106, .005]
Δ 00-04	.011	.039	-.025	.004
vs 10-14	[-.057, .079]	[-.012, .091]	[-.084, .034]	[-.050, .057]
Δ 90-94	.034	.013	-.026	-.047
vs 10-14	[-.037, .105]	[-.051, .076]	[-.107, .056]	[-.103, .008]
		(C) Advanced Degree		
Δ 90-94	.018	.009	.000	-.009
vs 00-04	[-.138, .175]	[-.087, .106]	[-.070, .071]	[-.156, .138]
Δ 00-04	-.089	-.120*	-.016	-.047
vs 10-14	[-.183, .005]	[-.211, -.029]	[-.115, .083]	[-.150, .057]
Δ 90-94	-.071	-.111*	-.015	-.056
vs 10-14	[-.229, .088]	[-.209, -.013]	[-.128, .097]	[-.193, .082]

Notes: Education categories built according to CASMIN classification; Basic degree (=basic school degree without later vocational training); Middle degree (=intermediate school degree and/or vocational training); Advanced degree (=tertiary education)

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.

Table A7: Heterogeneity by presence of children, changes over time

	$G_{obs}\,(\tau = .5, t)$	$\widehat{G}_{corr}\,(\tau = .5, t)$	$\widehat{Sel}^{M}\,(\tau = .5, t)$	$\widehat{Sel}^{F}\,(\tau = .5, t)$
	(A) Without children under 16 in the household			
Δ 90-94	.033	.051	-.039	-.021
vs 00-04	[-.020, .087]	[-.002, .104]	[-.085, .007]	[-.072, .030]
Δ 00-04	-.010	.018	-.035	-.008
vs 10-14	[-.076, .057]	[-.030, .066]	[-.099, .028]	[-.053, .037]
Δ 90-94	.023	.069*	-.074*	-.029
vs 10-14	[-.033, .080]	[.017, .121]	[-.140, -.008]	[-.093, .036]
	(B) With children under 16 in the household			
Δ 90-94	.086*	-.025	-.015	-.125*
vs 00-04	[.013, .160]	[-.077, .028]	[-.058, .029]	[-.209, -.041]
Δ 00-04	.041	.057	-.005	.010
vs 10-14	[-.084, .166]	[-.019, .132]	[-.088, .078]	[-.115, .135]
Δ 90-94	.127*	.032	-.020	-.116*
vs 10-14	[.021, .233]	[-.035, .099]	[-.093, .053]	[-.220, -.011]

* Uniform inference at the 5% level (computed by bootstrap with 200 replications).

Source: SOEP.v34 Samples A-K, own calculations.