Identifying Age Penalty in Women's Wages: New Method and Evidence from Germany 1984-2014

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Abstract

Given theoretical premises, gender wage gap adjusted for individual characteristics is likely to vary over age. We adapt DiNardo, Fortin and Lemieux (1996) semi-parametric technique to disentangle year, cohort and age effects in adjusted gender wage gaps. We rely on a long panel of data from the German Socio-Economic Panel covering the 1984-2015 period. Our results indicate that the gender wage gap increases over the lifetime, for some birth cohorts also in the post-reproductive age.

1 Introduction

Although the age dimension is often absent from the economic analyses of the gender wage gap, there are reasons why it could matter for the gender disparity in earnings.[1] Policy reports – such as OECD (2012) – show that raw differences in earnings tend to increase as men and women grow older. With aging, that should imply increasing raw gaps in aggregate terms due to a greater share of older workers in the population. Meanwhile, the aggregate *raw* gender wage gap remained fairly constant over time in most OECD countries, which hints at considerable changes in the *adjusted* gender wage gaps in the life cycle.

While looking deeper into the age and cohort differences in adjusted wage gaps seems particularly relevant, this dimension is nearly absent in the literature. Perhaps the most advanced attempts are the ones linking time trends to institutions, see Blau and Kahn (2003); Weichselbaumer and Winter-Ebmer (2007). Yet, the time span under these analyses combines a wide variety of changes, including declines in fertility, absolute and relative increases in women's educational attainment, changes in occupational and industrial structure as well as a number of societal and life-style changes. With gradually closing gaps in education between young men and women as well as near to par participation in the labor market for entry cohorts, one should expect considerable changes in the *adjusted* gender wage gap for the consecutive cohorts and in their life cycle patterns.

One of the reasons for the absence of age patterns in the analyses of gender wage disparity may be the technical challenge associated with the fact that age and cohort effects are at play jointly, together with period effects. Separating them statistically poses a difficulty, given that these variables are perfectly collinear: age equals year minus birth cohort. Our objective in this paper is to fill this gap in the literature, disentangling age and cohort effects and thus, providing new insights into the age patterns in unexplained women's penalty in wages. We propose to address the identification problem by a novel extension to the semi-parametric decomposition developed by DiNardo et al. (1996). This decomposition allows flexibility in defining the counterfactual structure of wages. To identify the effects of aging on the adjusted gender wage gap, we propose to utilize the most reliable counterfactual of all: one's past and / or future earnings. Our approach consists of providing a <u>double</u> decomposition of the changes in the gender wage gap: *against the same birth cohort* at different points in time and *against a different birth cohort* at the same point in time. We estimate this for both men and women, thus our estimates are, in fact, differences-in-counterfactuals.

To apply the proposed empirical strategy, one needs a relatively long panel, ideally observing the entire professional path, which is rare to find. Perhaps the one with highest quality is the German Socio-Economic Panel (GSOEP), spanning years from 1984 onwards for West Germany. In addition to offering high quality data, Germany itself is a particularly relevant case. The increase in educational attainment among women, the drop in fertility rates and the postponement in child bearing in Germany were among the most pronounced of all advanced economies (OECD, 2012). At the same time, Germany remains characterized by relatively high gender inequality. It has the highest raw gender wage gap in the EU (OECD, 2012) with estimates of 22% relative to men's wages at the median. Not only the pay gap is well above the OECD average (15%), it is also the only country where the difference has effectively grown over the last decade. Raw gaps actually understate the scope of gender inequality. Machin and Puhani (2003) show that the unexplained component was twice as large in Germany as it was in the UK in 1996, see also Arulampalam et al. (2007). Using high quality

matched employee-employer data, Hinz and Gartner (2005) as well as Heinze (2006) provide estimates of the adjusted gap that amount to as much as 20% of women's wages.

Although our paper is not the first to study the gender wage gap in Germany, to the best of our knowledge, it is the first to focus on wage patterns over the life cycle. Figure 1 is indicative of why this perspective is particularly relevant. The left panel displays the raw gender wage gap for a few selected cohorts, whereas the right panel does the same for the estimates of the adjusted gender wage gap. Both raw and adjusted gender gaps appear to vary with age. Naturally, Figure 1 confounds year effects with age effects. For example, a hike in both raw and adjusted gap experienced by cohorts born between 1950 and 1954 is reflected in a similar hike in ten years older age brackets for the cohorts born between 1940 and 1944. This tentative evidence demonstrates an important role for cohort, age and year effects in determining the adjusted gender wage gaps.

Figure 1: Gender wage gaps in Germany, evolution for selected cohorts.
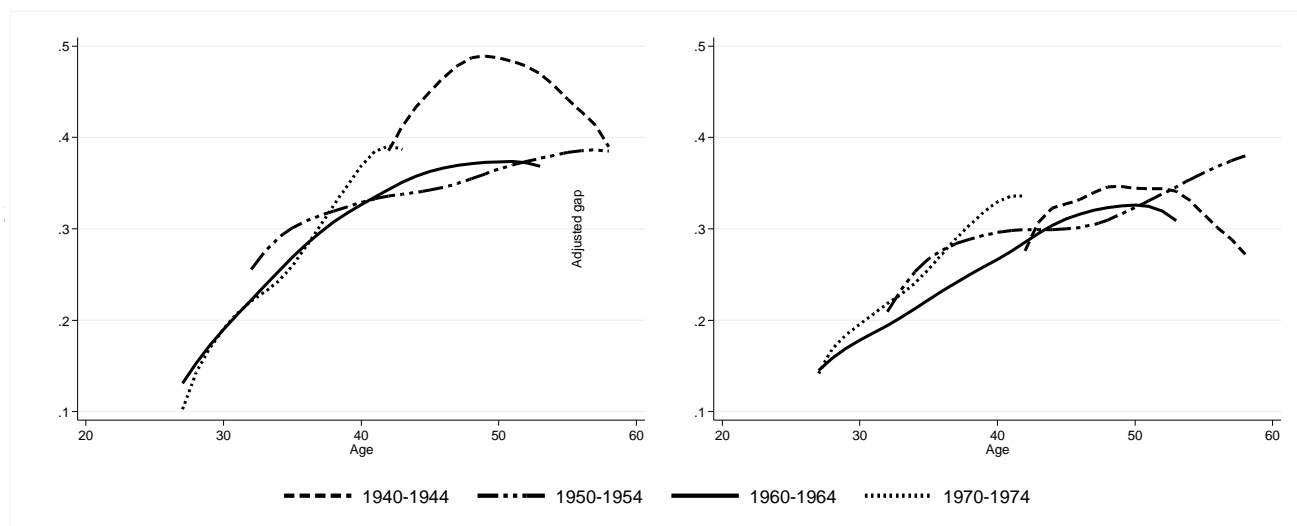
Notes: Figure shows values of the raw and adjusted gap for four selected cohorts. Adjusted gaps estimated using DFL decomposition. Controls include marital status, age, education level, tenure, and experience. Source: GSOEP, 1984-2015.

Also, subsequent cohorts appear to display different age patterns: the oldest cohort displayed in Figure 1 is characterized by an inverted U-shape pattern in both the raw and the adjusted gender wage gap, whereas the subsequent cohorts display a less curved inverted U-shape for the raw and an increasing pattern for the adjusted gap. Cohort effects might stem from societal changes, such as a revision of gender roles inside the household; the surge in most countries' female university enrollment rate, as well as postponed child bearing. They may also be driven by institutional changes, such as those in pension systems, maternity leave, access to child care facilities, etc. Year effects may reflect business cycle effects, tax and other welfare reforms, as well as other sources of changes in labor demand and labor supply, e.g. adoption of new technologies that reduce the effort demanded by household activities. Finally, age effects, being entirely individual, reflect changes in human capital as well as social norms related to employability and expected productivity of workers.

Our results suggest the existence of a strong age-related pattern, i.e. the adjusted gender wage gap increases with age, even at later stages in life. The rate of growth at various stages throughout the life cycle differs across the birth cohorts. Such patterns suggest that main explanations of the adjusted gender wage gap – i.e. career interruptions, effort at home, returns to investment – may be

interacting with societal explanations, such as the doubling of age and gender penalties in wages of women aged above the prime age.

The paper is structured as follows. First, we provide a review of the theoretical foundations. Furthermore, we sketch the empirical evidence on gender wage gaps in Germany, to show the potential for interaction between age and gender in determining wages. We then move to describing the details of the novel methodology developed in this study to dissect cohort, age and year effects. Finally, the results are reported in Section 4, complemented with the summary and recommendations in the concluding section.

2 Theory and context

A raw difference in wages across genders may be uninformative of the scope of the actual gender wage inequality. Imagine a scenario where men and women receive on average the same wages, but women are better educated. In this case, the raw difference in wages suggests no inequality, yet behind this apparent equality, we observe different rewards to the human capital embodied in men and women. Consequently, in order to obtain reliable measures of inequality, empirical studies strive to adjust the gender wage gap for observable, and thus explained, differences between men and women. In this framework, the part of the gap that is not attributed to characteristics (called the adjusted gender wage gap) is a proxy for discrimination. Because of its residual nature, the adjusted gender wage gap lumps together both *true* gender discrimination and unobserved gender differences in productivity. These unobserved differences are attributable to, among others, women's reproductive role, which tends to interrupt women's careers, limit their occupational choices and decrease their efforts and energy devoted to paid work, all of which are only poorly captured by surveys. These departures of empirical observations from theoretical concepts (in other words mismeasurement) depend on a variety of factors that might be intertwined with other labor market processes, including occupation (and occupation sorting), industry (and industry sorting) and time (i.e. due to technology adoption).

In the next section we discuss the theoretical mechanisms that give rise to gender wage gaps and their potential effect on the age shape of the adjusted gender wage gaps in more detail. When appropriate, we also discuss how potential mismeasurement affects the estimated adjusted gender wage gap.

2.1 Insights from the theory

Ever since the human capital theory of Becker, investment in human capital throughout the entire life span has become a central topic of economic analyses. Viewed through this lens, child bearing and child rearing induce career interruptions (Mincer and Polachek, 1974; Iversen and Rosenbluth, 2006), which are treated as human capital depreciation. Moreover, these expected interruptions may even discourage investment in human capital by primary care givers, typically women (Polachek et al., 2014). Caring obligations may limit women's occupational choice to jobs that allow to accommodate for non-market work, which are also characterized by fewer opportunities to accumulate human capital and yield lower rewards to seniority.[2] If human capital investment is cumulative in nature, motherhood wage penalty could continue beyond reproductive age. These differences in human capital investment and accumulation should be reflected in raw wage gaps. Properly accounting for differences in human capital investment should eliminate these differences from the observed wage gaps. Yet, experience and years of formal education are highly imperfect proxies of human capital, the more imperfect, the longer the labor market tenure of an individual.

In addition, time endowments available for market work differ between primary care givers and other household members, even many years after the career interruption, due to specialization within the household. Nested in a standard framework, specialization of household members in market and non-market work is rational, as it allows exploiting the comparative advantage that one member has in the labor market. As household activities demand more effort than leisure, those who engage in them, usually women, have less energy to devote to work and thus become less productive, even if they spend the same number of hours at work (Becker, 1985). Different levels of engagement in household activities could yield raw gaps increasing with age until the caring activities are completed.

The division of tasks in the household serves to perpetuate and magnify even small gender differences in the labor market. Notice that the prior existence of labor market gender discrimination is not necessary for this channel to operate; some policies to facilitate female participation could have similar unintended consequences, such as maternity leaves. Schober (2013) estimates that women who take longer maternity leaves tend to carry a larger share of household duties even upon their return to the labor market. While Schober (2013) interprets her finding in terms of habit formation, it could also result from the development of a comparative advantage in household tasks. In this setup, raw gender wage gaps should widen with age. However, the implications of this mechanism are somewhat less clear for the relation between adjusted gender wage gaps and age. The level effect of career interruptions is typically accounted for by including the years of experience in the adjustment process. Once adjusted for level effects, the adjusted gaps would widen with age if returns to experience accumulation were somehow nonlinear. Women who suspend careers to engage in domestic activities might not accumulate experience at the same pace as men do and lag behind in terms of productivity and thus seniority premiums. If that is the case, econometric models would yield uneven estimates of gender wage gaps across age as a mismeasurement of the actual differences in experience rather than returns to experience.

Although theories related to the supply side – based on human capital and career interruptions – suggest that gender wage gaps might increase with age, it remains unclear whether this increase should continue in the post-reproductive years of career. Indeed, child rearing eventually ends, which implies that whatever gap was accumulated up until that stage in life may remain fairly constant in subsequent years. Given that the motherhood wage penalty cannot be fully accounted for by the observed individual characteristics, its effect on the adjusted gender wage gap could in principle go beyond the reproductive age. Arguably, the gap may continue to widen if returns to earlier investment in human capital are non-linear. They might give rise to a difference in productivity between men and women, including the post-reproductive stage of life, which is hardly captured by commonly available proxies of human capital. By compounding, a small difference in productivity between men and women in the early stages of their careers could grow larger with time. However, stylized facts appear to be at odds with this proposition, as it would require ever-growing wages for men and women, while empirical studies suggest that hourly wages for both genders stagnate at ages above 50 years old and might even decline later on (e.g. Smyk et al., 2014; Rupert and Zianella, 2015; Bhuller et al., 2017; Hanushek et al., 2017). If wages decline at a different rate for men and women, the gender wage gap may continue to grow in age groups of 50 years and older, but the mismeasurement of human capital is not likely to be a mechanism behind these patterns.

On the labor demand side, rational employers – expecting women to give birth and subsequently carry a larger share of household chores – will discount that productivity shortfall in wages. In turn, rational workers of both genders will incorporate this insight in formulating the reservation wages

(see Arrow, 1973; Spence, 1974; Dahlby, 1983). This explanation, sometimes referred to as statistical discrimination, provides no insights into the age pattern of the adjusted gender wage gap. However, one may expect that with gradually declining fertility and delayed child bearing that discount should also decline gradually.[3]

Furthermore, if taste-based discrimination and/or statistical discrimination transform the labor market into an occupationally segregated market, where women are concentrated in occupations that reward seniority less than occupations held by men, then one can expect the raw gender wage gaps to grow with age. Naturally, after proper accounting for occupations held, the adjusted gender wage gap need not display any specific age pattern. Especially if occupational mobility declines with age, then the differences accumulated up to the career height should continue as men and women age, but it is not obvious that they would widen any further.

Another group of demand side reasons for why the adjusted wage gaps should *continue to increase* in the post-reproductive age resorts to the institutional theories for the prevalence of gender inequality in the labor market (Ferber and Nelson, 1993; Kabeer, 1994; Bergmann, 1996; Agarwal, 1997). One of those is the hypothesis that relates age and gender issues directly, which is referred to as "double standard of aging" hypothesis (Bergman, 1981; Sontag, 1982). Wilcox formulates the double standard of ageing as a "differential treatment of aging, in which women lose value and see themselves more negatively with increasing age, whereas men maintain or gain value" (Wilcox, 1997: 550).[4]

2.2 The case of Germany

Social norms tend to be strongly biased against working mothers in Germany. In a comparative study, Treas and Widmer (2000) found that women were expected not to work full-time between the time of giving birth and the time of school enrollment of their children, in fact only one percent of the respondents declared otherwise. Only after all children leave for education, it becomes socially acceptable for women to re-enter the labor market full-time (above 50% of the respondents supported this option).

These social norms are reinforced by a mixture of welfare policies. The "tax splitting" system lowers the average tax rate for the household, but imposes a high shadow tax rate for the second earner.[56]

In addition, childcare facilities are rare in Germany, with only 3% of the children aged below three having attended these institutions in the late '80s. Despite the subsequent increased availability, in the early 2000s, the percentage still hovered around 12%, which implies a high shadow price of professional work. The duration of the parental leave, which can only be utilized by the mother, increased from 4 months in 1984 to up to 34 months in 2006, which provides incentives for women to specialize in home production (during the leave period there is only a limited number of hours that a woman might work for pay, albeit also having been gradually raised from 15 hours in 1986 to 30 hours in 2001). Moreover, childcare benefits to be paid to the mother during the leave are fixed and do not depend on previous earnings, while childrearing benefits are means-tested and dual earner families are typically ineligible.[7] This legislation has been proven to adversely affect women's labor supply, see Merz (2004) and Schober (2012), further reinforcing the existing prejudices delineated by Treas and Widmer (2000).

On top of the gender-related concerns, participation of workers above 55 generally represents an important policy concern in Germany, even though the *de iure* minimum eligibility retirement age is

set at 65. Although the use of early retirement schemes is voluntary, labor contracts could include an additional provision whereby the workers committed to retiring early. Such provisions were abolished as of 1992. A correspondence study run by Bürsch et al. (2009) shows that older workers are 22% less likely to be called for an interview than younger workers. In addition, workers aged above 55 years are allowed to unilaterally reduce workload from full-time to part-time. Overall, the effective age of leaving the labor market and claiming pension benefits is around 60 (or even 58 if workers decide to retire and claim the unemployment benefit for two years, which yields a replacement rate of roughly 60%).

3. Methods and data

In this paper we contribute to the literature by delineating a life cycle and a cohort perspective on the adjusted gender wage gaps. Despite the richness of the parametric and non-parametric methods developed to estimate the gender wage gaps – see a recent review by Fortin et al. (2011) – no method has disentangled age, time and cohort effects with respect to the gender wage gaps so far. However, DiNardo et al. (1996), henceforth DFL, proposed a versatile semi-parametric approach for the decomposition of the entire wage distribution. As the estimation of the differences is based on a non-parametric kernel, it avoids the perils of specifying a functional form for wages.[8]

We propose a novel application of DFL, utilizing one's wages from the past/future to provide a "first counter-factual", i.e. isolating the age effects. We then exploit differences between men and women to provide an estimator based on "difference – in – counter-factuals", i.e. how the gender gaps change as men and women both age. Below, we discuss the proposed methodology and subsequently, the data properties.

3.1. Methodology

The DFL decomposition is based on the idea that average wages represent an integral over density function of individual characteristics. To build a counter-factual distribution, one modifies the density function, adapting it to the group of interest. Thus, to obtain women's distribution of wages if they were paid as if they were men, it is sufficient to reweight the density function of men according to women's distribution of characteristics. Whatever difference remains between the actual and counter-factual female wage distribution, it cannot be explained by the differences in characteristics and thus is analogous to the traditional understanding of the adjusted gender wage gap.

Even though it is possible to discretize the distribution of characteristics and reweight each resulting bin using the relative probabilities of belonging to each group, such approach would be inefficient: the number of bins grows and the statistical power declines with the number of characteristics to be included. To circumvent this issue, DFL introduce a weighting function $\Psi(x)$, to 'weight' all men observations by the probability of being a woman, given their characteristics. The procedure consists of estimating a probit model, where the dependent variable is the membership in a group of interest (men or women, young or old, etc.), e.g. weighting function of women's wages for the year t would be given by:

$$\Psi(x) = \frac{P(s = men\,|X = x, j = t)}{P(s = women|X = x, j = t)} * \frac{P(s = women|j = t)}{P(s = men|j = t)}$$

By changing the definition of $\Psi(x)$, one defines the specific counterfactual, which allows a comparison of the distribution of wages of female workers in two periods, and even to compare between men and women in different periods.

We exploit this feature of the methodology to produce a <u>double decomposition</u> across time and gender (see also Cho and Cho, 2011). Let Δ_t be the raw gender wage gap in year t. It represents a sum of the explained (by differences in endowments) and the unexplained (due to differences in rewards, also known as adjusted wage gap) components:

$$\Delta_t = \underbrace{\int f_{men,j}(w|x)h(x|s=men,t=t)dx - \int f_{women,j}(w|x)\Psi(x)h(x|s=women,t=t)dx}_{\textit{Unexplained component}}$$

$$+ \underbrace{\int f_{women,j}(w|x)\Psi(x)h(x|s=women,t=t)dx - \int f_{women,j}(w|x)h(x|s=women,t=t)dx}_{\textit{Explained component}}$$

The interest lies in estimating the changes across time, in short $\Delta_t - \Delta_{t-1}$. This difference consists of four components. The first one is the measure of changes in the characteristics of men and women, keeping the rewards to the characteristics constant at a given base (e.g. men in period t). A positive sign indicates that the change in endowments was larger for men than for women. The second is the change in the unexplained components, keeping the characteristics fixed at the level of women from period t. A positive change indicates that the adjusted wage gap grew over the period under analysis. The remaining components correspond to interactions between changes in endowments and changes in rewards. Since these interactions lack a clear interpretation, they are grouped under the term residuals. Clearly, the equation could also be employed to study the changes over time for a particular cohort. The full derivation of the decomposition is presented in the Appendix.

The decomposition proposed above offers a straightforward analysis of the changes in the wage gap over time for the entire population. For example, we can decompose the changes in the wage structure for women aged 30 to 34 in 1989, with respect to their situation in 1984, when they were 25-29. At this point, the advantage of using GSOEP becomes evident: by following individuals through the life cycle, we may repeat the procedure to obtain the estimates of changes in adjusted gender wage gaps as individuals age, controlling for individual and cohort specific effects.

3.2. Data

We work with the German Socio-Economic Panel (GSOEP) for West Germany for the period 1984-2015. GSOEP is a longitudinal survey conducted in annual face-to-face interviews (see Pannenberg 2000).[9] We follow each individual for as many years as (s)he is available in the sample, with over 1 810 individuals observed over the entire span of 30 years and over 360 000 individual-year observations in total.[10]

Individuals report family situation, which includes marital status and household composition. Along these household variables, GSOEP also provides valuable data on the labor market status of the individuals: it contains information on net wages, working hours, type of employment (whether part-time or full-time), experience (also split for part and full time), positions held and tenure, as well as firm industry and size. We construct (log) hourly wages by dividing the regular gross wage by the usual working hours reported in each period, wage data were deflated using GSOEP-provided inflation and converted to euros at the official conversion rate.

The sample comprises all West German nationals aged 25 to 59 who were wage employed in at least one period.[11] The double decomposition requires that each individual is observed at least twice. Since GSOEP is a panel, this requirement is not particularly binding. In total, GSOEP contains 208 589 observations for West Germany nationals with non-missing data for relevant characteristics (age,

education, household structure, etc.). Out of this sample, 201 846 observations reflect year-persons observed at least twice.

While thanks to the novel adaptation of the DFL our decomposition unveils the role of aging in determining women's wage penalty, it has a rather non-standard way to account for selection effects. Namely, the nature of this decomposition is to reweight the distribution of wages for a given group by the distribution of characteristics pertaining to a counter-factual group. We utilize one's past/future as the counter-factual, observing the differences between men and women. Thus, potential bias in estimating the age pattern of the adjusted gender wage gap could arise if the event of observing only once women's wages in the sample was substantially more frequent than for men. After testing this explicitly, we found that, indeed, women have more interruptions, but the differences between men and women concern never-workers rather than single-year workers. In fact, the share of observations dropped to 4.9% for men and 3.8% for women because an individual worked only once in the sample amounts. By contrast, the share of observations dropped because the share of respondents who never worked in the sample is 14.9% for men and 25.6% for women.

Clearly, as our decomposition cannot account for selection into never-working, this topic remains beyond the scope of our analysis. Child bearing is an individual characteristic utilized to obtain counter-factual distributions (changing with age in the majority of cases). Since for each ever-worker we utilize all available observations, our estimates are not troubled by the bias from potential unobserved heterogeneity in preferences for temporary inactivity (e.g. preference to stay away from the labor market longer after child bearing). Naturally, the conclusions apply to the 85.1% of men and 74.4% of women – ever working in GSOEP.

It may occur that an individual works in one period and does not work in the subsequent one. Given that working decisions are not random, this could lead to well-known selection bias problems. Moreover, the selection bias need not be constant over the life cycle: one could expect it to be particularly acute among workers close to the retirement age: individuals who value careers more are potentially more likely to work for the entire period between 45 and 59 years of age, hence ushering an additional reason for employment selection, which could be related to the experienced degree of labor market fairness. Simultaneously, age- and gender-specific selection may emerge if, for example, only more capable women stay in the market. From descriptive statistics reported in Table B.1, labor market exit is indeed early in Germany and it is likely to be selective in a sense that women with relatively higher wages are more likely to remain active in the labor market than those with relatively lower wages, ceteris paribus. The German system provided relatively low incentives to postpone the retirement and the eligibility age for women has been low for most of the analyzed period.

In order to mitigate selection bias[12], we assign, in separate estimations, the temporarily non-working respondents (i) the previous non-missing wage; or (ii) zero wages when they do not work.[13] To account for the fact that assigning wages may be more probable for some workers than for others, we introduce a specification where we include employment status in the estimation of the reweighting function. Since our estimates utilize wage distribution from previous age as a counterfactual, this source of potentially unobserved heterogeneity will affect results only if it is not constant across time. If, as hinted above, selection into employment is adversely and jointly age and gender specific, the true age effects would be larger than those estimated in our model.[14]

Figure B1 as well as Tables B1 in the Appendix portray the changes in individual characteristics and gender wage gaps over the age groups for selected periods. The data reveal a clear time pattern towards postponing marriage and forming a family in favor of tertiary education and working.

Between 1984 and 2009, the proportion of women living with at least one child in their household fell significantly.[15] The incidence of marriage has also decreased, though to a lesser extent. Men experienced comparable trends towards postponing the family formation, but at a lower rate. These changes in household composition and formation were accompanied by an almost twofold increase in the proportion of young women with tertiary degrees. As a result, towards the end of the sample the proportion of women with tertiary education among the youngest age group exceeded that of men of the same age.

Table B2 reports raw and adjusted gender wage gaps for selected birth cohorts in selected years. Estimated adjusted gender wage gaps are high, indicating a large extent of the unexplained gender inequality in the German labor market. We proceed to identification of the age pattern when controlling for cohort and year effects in the subsequent section.

4. Results

The first stage in the DFL decomposition is the estimation of a probit model, where the dependent variable is gender (it takes the value of 1 if the respondent is a man).We include three sets of controls: household characteristics, human capital and employment variables. Variables describing household characteristics are marital status of an individual (married or cohabiting) and a dummy for the presence of children younger than five years old in the household. Variables describing human capital are: educational attainment, tenure with the current employer and the number of years of experience. In order to accommodate for interruption in the career, experience is obtained as the difference between the actual experience and the average experience for workers of the same gender of a similar age. Finally, the employment is a dummy to distinguish employed respondents from non-employed respondents. We want to utilize the full extent of the available data, i.e. including the data points for the non-working periods of the individuals in the survey. Information is missing on occupation and industry at periods of non-working. We update this information in coherence with wages: previous occupation/industry if previous wages are used or zeroes in the specification where missing wages are treated as zeroes.

After the estimation of probit, we recover counterfactual distributions of wages for individuals. These are obtained for each birth cohort for each available age group. To assure a sufficient sample size, we define birth cohort as individuals born within a five-year span. Birth cohorts are not overlapping. Following a similar logic, we also pull together individuals of a similar age, forming five-year age groups. Thus, when we refer to a subsequent period, we mean a period when a given individual is 5 years older, whereas a subsequent cohort signifies an individual born in the five-year period following the five-year period relevant for a given woman. Hence, this second step of the analysis yields a matrix of relevant counterfactual wage distributions, i.e. distributions that are relevant for a given woman as she ages, relative to a man of the same birth cohort as he ages.

The final step of our analysis is the double decomposition, which identifies – in relative terms – the contribution of each age group to the pattern of the adjusted gender wage gap.

4.1. Quality of the estimates

The semi-parametric DFL decomposition relies on the quality of the first stage probit, thus it is useful to analyze the results of the first stage. Figure C.1 in the Appendix plots the value under the

ROC (Receiver Operating Characteristic) curve for each year and age group: the number of correct predictions varies for subsequent models, but is satisfactory.[16] Our model performs especially well in the case of older workers. Among the youth, the predictive ability of the model also varies across time: in the early years of the sample, probit models distinguish between men and women more accurately than in the last years of the sample. This suggests that the differences in observable characteristics between men and women are closing, especially after 1994.

4.2 Identifying age pattern in adjusted gender wage gaps

Table 1 below focuses on age patterns in the adjusted gender wage gaps. Rows indicate the initial age, whereas columns display the initial period. For example, the first row in the first column indicates the change in the adjusted gender wage gap experienced by women aged 25-29 in 1984 over the upcoming five years, when they eventually turn 30-34. The last row in the first column concerns individuals aged 50-54 as they become 55-59 (i.e. our last age group of observation). To better identify the role of changing age, the sample of respondents is kept constant in each adjacent two periods.[17] These estimates are additive, i.e. for each birth cohort, as they age, one should follow the diagonal to observe the changes in the adjusted gender wage gap. Positive values along diagonals signify that the adjusted gender wage gap widens as a given cohort ages. The last column summarizes the average – over the birth cohorts/periods – increase in the adjusted gender wage gap for given age brackets.

Estimates from Table 1 suggest that the adjusted gender wage gap increases as women age. The age profile that emerges from Table 1 indicates a steep increase from the beginning of the career that lasts beyond the reproductive age. Estimates presented in the middle and bottom panel of Table 1 reveal the importance of controlling for selection bias. In a majority of cases, the introduction of corrections for selection results in higher estimates of changes in the adjusted gender wage gap, which is consistent with the insights of Schober (2013). With the employment dummy in ψ function, women aged 40-44 experienced on average a 7-8 pp increase in the adjusted gender wage gap over the following five years. In the subsequent age brackets, the increase of the adjusted gender wage gap is slower and the actual size of the increment depends on the specification: if wages missing due to non-employment are anchored to the last observed wage, they tend to grow somewhat slower than if wages missing due to non-employment are replaced by zeros. Indeed, that may be related to the fact that pre-retirement or early retirement benefits could be superior outside option relative to e.g. unemployment benefits or social assistance, albeit this is not directly observed in our data. As revealed by Table B1 in the Appendix, over most of the analyzed periods, women catch up with men in terms of observable characteristics. Indeed, the opposite adjustment in rewards stands behind relatively stable raw wage gaps in Germany.

Cohort and year effects also appear to play a substantial role. The increases in the adjusted gender wage gap are non-monotonic, which points to the role of year effects, such as changes of legislation, but also the overall economic landscape. However, given how data intensive our methodology is, the GSOEP sample size is too small to quantify such effects.

The size of the increase in the adjusted gender wage gaps in post-reproductive age differs between cohorts. In general, the adjusted gaps increase in the 45-49 age group (with the exception of one or two birth cohorts, depending on specification) and continue to increase in the 50-54 age group (with the exception of one or two birth cohorts, depending on specification). Low incentives to

postpone retirement should imply that higher earning women are more likely to be observed among the working population. Although we are not able to fully disentangle the selection effect from the age patterns in the adjusted gender wage gaps (larger data sets, possibly administrative data would be needed), the estimated patterns increase in age on average. If adjusted gaps are lower among low earners, our estimates could be overstated. Conversely, if those with more unequal wages are more likely to leave early, our estimates would be understated.

Table 1: Changes in the adjusted gender wage gap

Age		Initial year						Average change
t	t+1	1984	1989	1994	1999	2004	2009	in AGWG
Missing wages replaced with previous wage, w/o employment dummy in ψ function								
25-29	30-34	-0.02	0.01	0.07	0.02	0.07	0.04	**0.03**
30-34	35-39	-0.06	0.06	0.00	-0.01	0.01	0.20	**0.03**
35-39	40-44	0.05	0.04	0.01	0.08	0.06	0.05	**0.05**
40-44	45-49	0.25	0.02	0.07	-0.01	0.02	0.03	**0.06**
45-49	50-54	-0.08	-0.02	0.08	0.09	0.00	0.01	**0.01**
50-54	55-59	0.02	-0.16	-0.01	0.16	0.06	0.08	**0.02**
Missing wages replaced with previous wage, w/ employment dummy in ψ function								
25-29	30-34	-0.08	0.02	0.07	0.02	0.03	0.06	**0.02**
30-34	35-39	-0.09	0.09	-0.01	-0.01	0.02	0.25	**0.04**
35-39	40-44	0.06	0.05	0.03	0.08	0.07	0.07	**0.06**
40-44	45-49	0.23	0.05	0.05	0.00	0.02	0.03	**0.07**
45-49	50-54	-0.06	0.02	0.04	0.10	0.00	0.02	**0.02**
50-54	55-59	0.14	-0.14	0.06	0.13	0.06	0.09	**0.06**
Missing wages replaced with zeroes, w/o employment dummy in ψ function								
25-29	30-34	0.12	0.16	0.00	0.19	0.05	0.25	**0.13**
30-34	35-39	-0.11	-0.13	0.13	0.17	0.10	0.62	**0.13**
35-39	40-44	-0.05	0.07	0.16	-0.02	0.06	0.09	**0.05**
40-44	45-49	0.25	0.04	0.10	-0.06	0.05	0.03	**0.07**
45-49	50-54	0.05	-0.24	0.03	0.18	0.03	0.10	**0.03**
50-54	55-59	0.23	0.15	0.01	0.09	0.03	0.14	**0.11**
Missing wages replaced with zeroes, w/ employment dummy in ψ function								
25-29	30-34	0.11	0.14	-0.01	0.17	0.04	0.18	**0.10**
30-34	35-39	-0.18	-0.10	0.15	0.20	0.07	0.61	**0.12**
35-39	40-44	-0.06	0.10	0.14	-0.02	0.08	0.12	**0.06**
40-44	45-49	0.22	0.03	0.07	-0.01	0.06	0.09	**0.08**
45-49	50-54	0.10	-0.17	0.01	0.15	-0.01	0.13	**0.04**
50-54	55-59	0.33	0.16	0.09	0.10	0.00	0.21	**0.15**

Notes: GSOEP 1984-2014. Adjusted gender wage gaps (AGWG) estimated using double DFL decomposition. Zero wage specification takes effectively 0.1€/CPI, i.e. the real value in 2005 euros of 10 euro cents. Changes in the adjusted gender wage gap decomposed by age, reweighed by the distribution of men's characteristics. Controls include marital status, age, education level, tenure, years of work experience (difference with respect to reference group mean), a dummy for workers in high skilled occupations (ISCO code smaller than three) and industry dummies. Sample in the upper panel includes only individuals who worked in the t and t +1. In the middle and bottom panels, sample includes individuals who worked for at least one period in our sample. Estimates in the bottom panel include an employment dummy in recovering the ψ function.

For numerous cohorts, the unexplained component continues to increase after the 40-44 age brackets, despite adjusting for the years of experience and tenure with the current employer (among other controls). This is equivalent to stating that as a man ages beyond 45 years old, his wage grows by more (or declines by less) than that of an observationally equivalent woman, as she ages beyond the post-reproductive age, despite accounting for the changing individual characteristics. One of the potential explanations for our findings may be dynamic mismeasurement of human capital. For example, some investment in human capital, made at the age of 30, may be reflected in productivity and thus, in wages only at the age of 50. Then, women with a career gap, due to child bearing and rearing, may be less likely to have made those investments. If this investment remains unobservable and if, at the same time, its relationship with experience is nonlinear, the omitted variable bias would exhibit as an increasing adjusted gender wage gap in the post-reproductive age. While theoretically possible, the effects of these investments would need to be, indeed, large, to widen the gap by an additional 7-8 percentage points twenty years later. More research would be needed on details of investment in human capital to identify if such gender differences exist and if their bearing on individual productivity could plausibly be as high as 7-8 percentage points.

An alternative explanation for increasing adjusted gender wage gaps after women have reached the reproductive age is the "double standard of aging" hypothesis. If age and gender are both considered handicaps in the labor market – see Deuisch et al. (1986); Wilcox (1997); England and McClintock (2009) – the overlap of both may explain the persistence of adjusted gender wage gaps in the post-reproductive period. Woman's age may be a more salient characteristic in labor demand than man's age, especially in the case of leadership roles, i.e. for the upper quartile in the income distribution (Nelson, 1996). In some professions, for example, aging women are regarded as less valuable than young women (e.g. the movie industry, Lauzen and Dozier, 2005; tv anchors and reporters, Saner 2010). The evidence is scarcer on more common occupations, but the "double standard of ageing" hypothesis could contribute to explain a widening gender wage gap with age.

5 Conclusions

Raw gender wage gaps prove to be remarkably persistent over time. Referring to differences in the accumulation of human capital for both genders, some theories predict an inverted U -shaped pattern of the adjusted wage gap with respect to age, whereas some of those theories, particularly social theories, can be interpreted to suggest an ever increasing age pattern. With aging, composition effects should imply gradually increasing aggregate estimates of the gender wage gap. However, subsequent cohorts of women are gradually better educated than men, their fertility decreases, childbearing is delayed and access to care facilities increases with an apparent trend towards an equalization of the division of labor within households. These trends imply smaller grounds for the statistical discrimination for the youngest age groups in subsequent birth cohorts. Theoretical implications for the cohort effects and for the age effects work in the opposite direction, blurring the analysis of changes in the aggregate inequality of men and women in the labor market.

Extending the DFL decomposition – a key methodological innovation of our study – helps to disentangle age and cohort effects. We construct estimates for the age patterns in gender wage gaps as differences-in-counterfactuals: differences between men and women, as both men and women age. As the first counterfactual we use the opposite gender, but as a second counterfactual, we use

one's own wage at earlier/later stages of the life cycle. This method requires panel data, for which we utilize the German Socio-Economic Panel for 1984-2015.

We find that women's unexplained penalty in wages is increasing with age, and continues to increase for many cohorts including during the post-reproductive age as well. Some of the earlier literature has suggested gender inequality prevails among older workers. This study shows that the scope of that inequality is actually increasing with age also among older workers. This suggests that age and gender are overlapping handicaps in the labor market, which calls for a policy intervention.

An obvious caveat of our study is that it only concerns one country – Germany. While it is an interesting case for a number of policy-related reasons, it may also prove singular, as the secular trends in education and fertility experienced in Germany were particularly strong. A second caveat concerns the data. Although GSOEP contains very high quality data, in cohort and age specific analyses, like ours, the sample size proves to be a constraint. Research with the use of large administrative data could corroborate the findings with more precise estimates, also over finer defined age groups and birth cohorts. Moreover, with such a large sample size one could enrich the analysis by looking into occupational specificity, thus providing additional answers about the universality of the identified age and birth cohort patterns.

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Appendix A Double decomposition method – adapting DiNardo et al. (1996)

Distribution of wages can be written in the following form:

$$f(w) = \int f(w|x)f(x)dx$$

which indicates that the distribution of wages (w) equals the integral of the conditional distribution of wages on the set of characteristics multiplied by the distribution of these characteristics. The set of x can include variables of different types: those related to the personal or job characteristics attributes. We can also write a gender-time specific formula is given by:

$$f(w|g = i, t = j) = \int f_{i,j}(w|x)f(x|g = i, t = j)dx$$

where *g* refers to gender, *t* to the time period and $f_{ij}(w|x)$ is the conditional distribution of wages on the characteristics, the gender and the period. Given the previous equation, we can write male's wage distribution if they had female characteristics as follows:

$$f(w|g = m, t = j) = \int f_{m,j}(w|x)f(x|g = f, t = j)dx$$

which can be rewritten as:

$$f(w|g = m, t = j) = \int f_{m,j}(w|x)\Psi(x)f(x|g = m, t = j)dx$$

where *Ψ(x)* is a reweighting factor defined as:

$$\Psi(x) = \frac{f(x|g = f, t = j)}{f(x|g = m, t = j)} = \frac{Pr(g = f|x, t = j)}{Pr(g = m|x, t = j)} \frac{Pr(g = m|t = j)}{Pr(g = f|t = j)} \qquad \text{(A.1)}$$

Although we do not observe the counterfactual distribution of wages, they can be estimated. This formula allows reweighting male distribution in order to obtain the distribution that would have prevailed if male workers had the same characteristics as their female counterparts. The explained component equals the difference between the actual male distribution and the counterfactual; while the unexplained component equals the difference between the counterfactual and the female distribution.

Notice that we could derive an expression similar to equation A.1 to estimate the counterfactual distribution of wages that would prevail in 1989 if the distribution of characteristics was the same as 1984 under the assumption that the distribution of characteristics does not affect the rewards (DiNardo et al., 1996), using the characteristics of the disadvantaged group from the initial period (Black et al., 2006). Adapting equation (5) from Yun (2009), define the wage gap in period j as

$$\Delta_j = \int f_{m,j}(w|x)f(x_{m,j})dx - \int f_{f,j}(w|x)f(x_{f,j})dx \qquad \text{(A.2)}$$

where, $f(x_{i,j}) = f(x|g = i, t = j)$ for $i = m, f$. Consequently, one can define the difference between two periods as follows,

$$\Delta_{89} - \Delta_{84} \quad = \int f_{m,89}(w|x)(f(x_{m,84}) - f(x_{m,89}) - f(x_{f,89}) - f(x_{f,84}) dx$$

$$+ \int f_{m,84}(w|x) \left(f(x_{m,84}) - f(x_{m,89}) \right) dx - \int f_{m,89}(w|x)(f(x_{m,84}) - f(x_{f,84}) dx$$

$$+ \int f_{m,89}(w|x) \left(f(x_{f,84}) - f(x_{f,89}) \right) dx - \int f_{f,89}(w|x)(f(x_{f,84}) - f(x_{f,89}) dx$$

$$+ \int \left(f_{m,84}(w|x) - f_{m,89}(w|x) - f_{f,84}(w|x) - f_{f,89}(w|x) \right) f(x_{f,84}) dx$$

$$(A.3)$$

Hence, we propose to decompose the change in the raw gaps into four different components:

　　a) the convergence in characteristics between men and women (first line);
　　b) the differences remaining in the last period (second line);
　　c) the differences in wage structure in the final period (third line); and
　　d) the convergence in wage structure between periods (last line).

The first component presents changes in characteristics, and thus it roughly corresponds to changes in the explained component. The last term of equation A.3. provides a clean overview of the changes in wage structure by maintaining the same characteristics as the basis for the calculations. Because the remaining terms, second and third, lack a clear interpretation, we merge them into a single category ("residuals") when reporting the results. We assume that period specific effects are independent of age, i.e. we use relative changes to determine which groups experienced larger increases in the adjusted wage gap.

Appendix B Descriptive statistics

Table B.1: Main descriptive statistics for men and women in four selected years.

	1984 Female	1984 Male		1994 Female	1994 Male		2004 Female	2004 Male		2014 Female	2014 Male	
							Real hourly wage					
25-29	12.33	13.38		12.28	15.09	***	13.16	13.83		10.85	12.02	***
30-34	14.50	17.22		13.09	17.33	***	14.31	17.35	***	12.92	16.11	***
35-39	13.40	20.50	**	14.88	18.21	***	15.70	20.44	***	13.88	18.52	***
40-44	16.26	18.91		15.17	19.20	***	15.87	22.04	***	14.72	22.18	***
45-49	11.52	17.41	***	15.02	19.78	***	17.30	25.57	***	15.54	21.92	***
50-54	14.96	17.51		13.46	21.38	***	16.91	24.36	***	14.66	21.89	***
55-59	10.70	18.13	***	12.84	21.25	***	16.37	26.11	***	16.33	28.54	***
							Hours usually worked					
25-29	36.15	43.71	***	35.93	41.68	***	36.04	40.59	***	34.94	38.03	***
30-34	31.03	44.06	***	30.50	43.40	***	31.49	44.08	***	30.72	44.09	***
35-39	30.42	45.64	***	30.09	44.42	***	28.42	45.01	***	27.56	43.21	***
40-44	30.23	45.53	***	27.54	42.81	***	28.60	44.97	***	27.72	43.81	***
45-49	31.78	44.71	***	30.72	45.54	***	29.90	45.61	***	29.47	44.03	***
50-54	32.34	44.73	***	30.23	43.92	***	30.08	44.90	***	30.56	43.61	***
55-59	33.07	42.76	***	30.83	43.00	***	30.41	44.66	***	30.14	43.43	***
							Working share					
25-29	0.59	0.80	***	0.65	0.75	***	0.67	0.73	**	0.69	0.78	***
30-34	0.52	0.95	***	0.59	0.91	***	0.68	0.91	***	0.67	0.89	***
35-39	0.56	0.93	***	0.63	0.94	***	0.73	0.93	***	0.73	0.93	***
40-44	0.51	0.97	***	0.69	0.94	***	0.76	0.94	***	0.81	0.94	***
45-49	0.58	0.96	***	0.71	0.92	***	0.77	0.94	***	0.83	0.93	***
50-54	0.44	0.91	***	0.62	0.92	***	0.73	0.89	***	0.84	0.93	***
55-59	0.34	0.81	***	0.46	0.79	***	0.63	0.79	***	0.78	0.85	***
							Tenure					
25-29	5.31	5.53		3.92	4.00		3.60	3.61		2.75	3.21	**
30-34	6.88	7.64		4.95	5.90	**	5.41	5.83		5.07	5.12	
35-39	7.90	9.97	***	6.79	9.32	***	7.03	8.21	***	6.79	8.15	***
40-44	9.29	13.72	***	8.94	14.52	***	8.67	11.63	***	8.66	11.06	***
45-49	10.75	16.49	***	10.71	15.49	***	11.51	15.23	***	11.02	13.96	***
50-54	13.95	19.75	***	12.49	20.01	***	15.55	19.26	***	12.33	16.29	***
55-59	16.75	23.81	***	16.76	23.50	***	17.06	22.04	***	16.61	22.32	***
							Experience					
25-29	6.96	6.64		5.80	5.59		5.11	5.01		3.98	4.31	***
30-34	10.59	10.66		9.82	9.75		9.26	9.46	***	7.70	8.73	***
35-39	13.69	15.13	***	13.36	14.87	***	12.86	14.04	***	11.14	13.29	***
40-44	17.18	20.81	***	16.38	20.42	***	16.57	19.22	***	14.88	18.05	***
45-49	21.30	26.80	***	20.91	24.55	***	20.56	24.13	***	19.89	22.75	***
50-54	24.78	31.73	***	23.29	30.31	***	25.18	29.18	***	23.74	27.97	***
55-59	27.63	34.87	***	29.49	35.90	***	28.75	33.91	***	28.58	33.37	***
							High skill occupation (ISCO codes 1-3 , proportion)					
25-29	0.25	0.31		0.17	0.18		0.10	0.13		0.18	0.15	
30-34	0.26	0.45	***	0.25	0.42	***	0.28	0.30	***	0.39	0.39	***
35-39	0.10	0.34	***	0.17	0.33	***	0.21	0.35	***	0.43	0.53	***
40-44	0.04	0.13	***	0.05	0.16	***	0.07	0.17	***	0.19	0.40	***
45-49	0.01	0.05	**	0.01	0.06	***	0.00	0.07	**	0.05	0.15	***
50-54	0.00	0.01		0.01	0.02		0.00	0.02		0.01	0.04	**
55-59	0.02	0.00	**	0.01	0.01		0.00	0.01		0.00	0.02	***
							Tertiary educated (proportion)					
25-29	0.11	0.10		0.09	0.11		0.18	0.13	*	0.30	0.20	***
30-34	0.16	0.18		0.14	0.20	**	0.22	0.27	*	0.28	0.34	**
35-39	0.12	0.18	*	0.17	0.22		0.18	0.28	***	0.27	0.33	**
40-44	0.08	0.20	***	0.16	0.21		0.19	0.27	***	0.28	0.32	*
45-49	0.04	0.13	***	0.13	0.19		0.24	0.34	***	0.24	0.33	***
50-54	0.06	0.11	*	0.09	0.25	***	0.25	0.33	***	0.24	0.29	**
55-59	0.08	0.13	*	0.04	0.17	***	0.23	0.33	***	0.26	0.33	**
							Married (proportion)					
25-29	0.58	0.54		0.44	0.35	**	0.23	0.18		0.26	0.19	
30-34	0.70	0.75		0.67	0.66		0.49	0.47		0.57	0.56	**
35-39	0.81	0.85		0.79	0.79		0.69	0.67		0.70	0.76	***
40-44	0.80	0.88	***	0.83	0.84		0.77	0.79		0.71	0.82	***
45-49	0.79	0.90	***	0.79	0.87	**	0.81	0.82		0.60	0.79	***
50-54	0.76	0.89	***	0.77	0.88	***	0.83	0.87	*	0.61	0.80	***

55-59	0.68	0.93	***	0.68	0.88	***	0.82	0.87		0.69	0.78
Children younger than 5 in the household (proportion)											
25-29	0.25	0.31		0.17	0.18		0.10	0.13		0.18	0.15
30-34	0.26	0.45	***	0.25	0.42	***	0.28	0.30		0.39	0.39
35-39	0.10	0.34	***	0.17	0.33	***	0.21	0.35	***	0.43	0.53 ***
40-44	0.04	0.13	***	0.05	0.16	***	0.07	0.17	***	0.19	0.40 ***
45-49	0.01	0.05	**	0.01	0.06	***	0.00	0.07	***	0.05	0.15 ***
50-54	0.00	0.01		0.01	0.02		0.00	0.02	**	0.01	0.04 ***
55-59	0.02	0.00	**	0.01	0.01		0.00	0.01		0.00	0.02 **

Notes: GSOEP 1984-2014. Real hourly wages are measured in euros, data for years 1984-2001 converted at an official conversion rate. Working share indicates the proportion of workers in the sample, including self-employed individuals. Married refers to individuals that are either married (irrespective of whether they live together or apart) or cohabiting. ***, ** and * indicate that the difference in sample means (proportions) between men and women is significant at the 1 %, 5% and 10%, respectively.

Table B.2: Raw and adjusted gender wage gaps for four selected years

	1984		1994		2004		2014	
	Raw gap	Adj. gap	Raw gap	Adj. gap	Raw gap	Adj. gap	Raw Gap	Adj. gap
25-29	0.17	0.17	0.15	0.15	0.05	0.08	0.12	0.14
30-34	0.25	0.22	0.29	0.26	0.18	0.17	0.25	0.22
35-39	0.42	0.39	0.21	0.16	0.29	0.22	0.32	0.27
40-44	0.42	0.34	0.36	0.31	0.36	0.29	0.41	0.35
45-49	0.46	0.36	0.34	0.24	0.40	0.30	0.35	0.24
50-54	0.41	0.31	0.51	0.37	0.40	0.34	0.39	0.27
55-59	0.48	0.48	0.46	0.28	0.48	0.39	0.37	0.28

Notes: GSOEP 1984-2014. Estimates of the adjusted gender wage gaps for several age groups obtained from 4 selected years. The gender wage gap is obtained taking female wages as a reference. All estimations include controls for age (within each age group), marital status, education level, tenure with current employer, years of work experience (full time equivalent), and industry (1 digit NACE codes).

Appendix C. Statistical properties of the estimates

Figure C.1: Area under the ROC curve for different years and age groups.
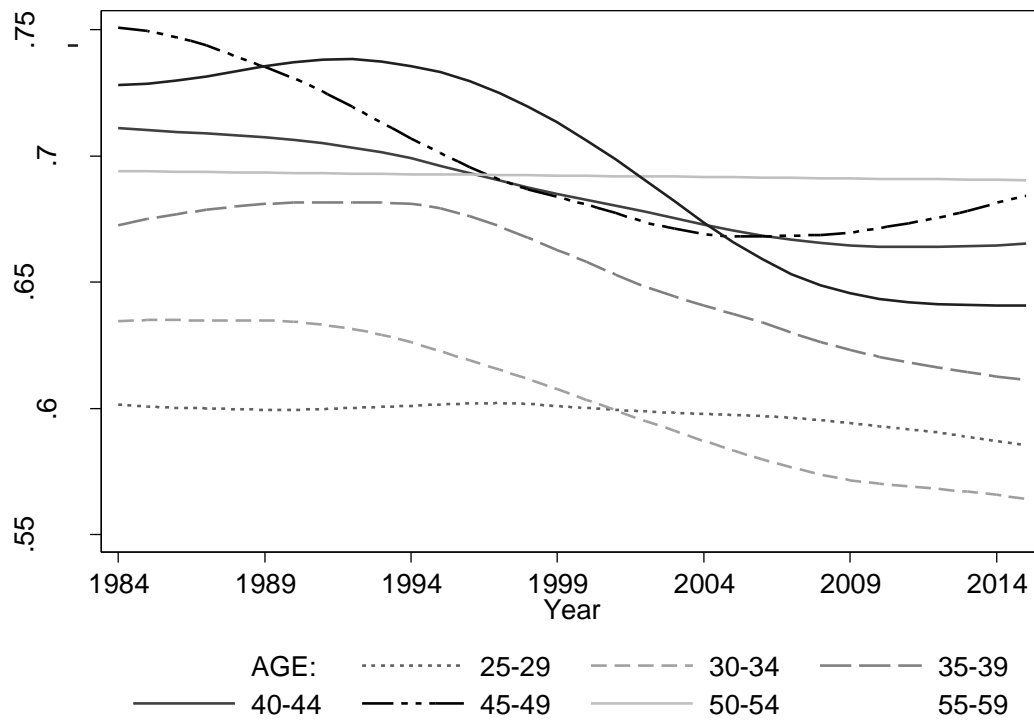
Source: own computation based on GSOEP 1984-2015. A larger area below ROC curve implies better fit of the probit and hence of the parametric estimates used to obtain the reweighting matrix.

Appendix D. Results

Table D.1: Decomposition of the raw gender wage gaps for selected birth cohorts.

	Time t		Components of change			Time t+1		
	Raw	Adjusted	Explained	Unexplained	Residuals	Raw	Adjusted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7) - (2)
Cohort 1945-1949								
35-39	0.29	0.06	-0.02	0.20	-0.15	0.32	0.31	0.25
40-44	0.32	0.31	0.13	-0.17	0.15	0.43	0.34	0.03
45-49	0.43	0.34	0.02	-0.11	0.05	0.39	0.29	-0.05
50-54	0.39	0.29	-0.04	-0.05	0.33	0.63	0.47	0.19
Cohort 1950-1954								
30-34	0.39	0.28	-0.02	-0.22	0.21	0.36	0.18	-0.10
35-39	0.36	0.18	-0.20	-0.16	0.50	0.51	0.42	0.24
40-44	0.51	0.42	0.05	-0.15	0.08	0.48	0.34	-0.08
45-49	0.48	0.34	0.00	-0.12	0.16	0.52	0.35	0.01
50-54	0.52	0.35	-0.13	-0.01	0.04	0.42	0.29	-0.06
Cohort 1955-1959								
25-29	0.15	0.16	-0.26	-0.28	0.53	0.14	0.10	-0.06
30-34	0.14	0.10	0.01	-0.15	0.21	0.21	0.27	0.17
35-39	0.21	0.27	0.08	-0.03	-0.11	0.16	0.20	-0.07
40-44	0.16	0.20	-0.08	-0.06	0.16	0.18	0.19	-0.01
45-49	0.18	0.19	0.11	0.10	-0.19	0.20	0.08	-0.11
50-54	0.20	0.08	-0.14	0.01	0.21	0.29	0.20	0.12
Cohort 1960-1965								
25-29	0.10	0.01	-0.07	-0.10	0.39	0.31	0.25	0.24
30-34	0.31	0.25	-0.08	-0.13	0.19	0.29	0.15	-0.10
35-39	0.29	0.15	0.01	-0.04	0.11	0.37	0.29	0.14
40-44	0.37	0.29	-0.03	-0.07	0.15	0.42	0.30	0.01
45-49	0.42	0.30	0.01	-0.08	0.09	0.45	0.29	-0.01
Cohort 1965-1970								
25-29	0.11	0.07	0.33	0.21	-0.37	0.27	0.02	-0.05
30-34	0.27	0.02	0.01	0.01	-0.04	0.26	0.12	0.10
35-39	0.26	0.12	0.18	0.28	-0.45	0.27	0.00	-0.12
40-44	0.27	0.00	-0.20	0.09	0.04	0.19	0.23	0.23

Notes: GSOEP 1984-2014. Raw and adjusted gender wage gaps for selected age brackets. Estimates are restricted to the population observed in every sample year, hence the sample is constant. Gaps are expressed as percentage of women's wage. Adjusted gaps estimated using double DFL decomposition. In the case of missing wages, we use the latest observed wage as a proxy, also among non-employed individuals. Changes in the raw gender wage gap are decomposed to three components: changes in characteristics, changes in returns to characteristics, and residuals. The values in the column 3, indicates the changes in the characteristics of men and women: a positive/negative sign indicates that men acquired more/less of the rewarded characteristics than women between t and t+1. Similarly, a positive sign in the column 4 indicates that adjusted wage gap of women increased over the period between t and t+1. Controls include marital status, age, education level, presence of small children in the household, an employment dummy, experience (deviation from mean in the age group), a dummy for whether individual works in a high skilled occupation, and three industry dummies.

Endnotes

[1] In the remainder of this paper, unless stated otherwise, by the term 'gender wage gap' or 'gender differences in earnings' we refer to the differential adjusted for individual characteristics. The unadjusted gap is identified by the term 'raw'.

[2] A similar argument applies to women's decision on which career to follow: anticipating interruptions, women might select the careers that impose a lower penalty on interruptions. E.g. Goldin and Katz (2008) show that women with more children tend to work in careers with lower wage penalties on interruptions.

[3] Importantly, alternative individualist explanations for the persistent gender wage gap even after accounting for individual characteristics – such as lower wage expectations of women (Blau and Ferber, 2011; Reuben et al., 2013), taste-based discrimination (Becker, 1971; Lang, 1986; Duncan and Loretto, 2004) – have no clear time/age related patterns. These explanations are also weakly founded in feminist theories.

[4] This approach finds some empirical support: Kuhn and Shen (2013) analyze job-ads from China and find that some job openings are subjected to strong bias towards young and attractive women. Moreover, firms tend to have a higher preference to hire men when looking for older workers than when looking for workers in other age groups (Lincoln and Allen, 2004; Duncan and Loretto, 2004; Lauzen and Dozier, 2005; Neumark et al., 2015).

[5] Lauer (2000) and Holst and Busch (2009) explore the glass ceiling in wages, by studying individuals in managerial positions, suggesting that the unexplained component within the top occupation is approximately 40% of males wages, once selection bias is taken into account. Reimer and Schröder (2006) also explore the relation between the adjusted wage gap and the field of education, but do so in a much homogeneous population (university students). Their results indicate that the adjusted gap among former students was between 4.3% and 7.6 % of female's wages. Though the value is much lower than in the previous case, it must be reminded that the sample covers only individuals at the beginning of their career.

[6] Triebe (2013) finds, that while an increase in salaries of women leads to reduced labor supply of men due to this mechanism, the reverse does not hold for women. Namely, married women do reduce working hours, because of the "tax splitting", but cohabiting women do not.

[7] This legislation was changed in 2007: benefits are not means-tested and they are proportional to previous earnings. Yet, the effects of this reform are to be observed only in the cohorts eligible between 2008 and 2015.

[8] Though originally intended to measure the consequences of the changes in the unionization rate, it was adopted to measure the impacts of other variables as well, among them gender. Warman et al. (2010) use the DFL decomposition to measure the differences in earnings between university professors in different periods, from the early 70's to the early 00's. Their analysis bears some similarities with ours, as we also consider a time dimension. However, the most important difference is that in our paper we focus on the gender wage gap at different ages. Sierminska et al. (2010) also employ the DFL decomposition for Germany, using data from the GSOEP as well to study the wealth gap, of which the salary is just one of the components.

[9] While data from East Germany are also available, the longitudinal dimension is substantially shorter. Moreover, the communist legacy and the process of economic transition suggest that trends in the gender wage gap in East Germany might be driven by different factors.

[10] Data correspond to the German national sample. Immigrants are not included in the analysis.

[11] Although in Germany the minimum legal working age is 15, in the most recent year, only 30% of young people entered the labor market before their 25th birthday. In 1984, however, this percentage was twice as high. Thus, analyzing the individuals under the age of 25 would have involved additional selection issues and educational choices. The employment ratio among individuals above the age of 60 remained below 10% during the entire sample period.

[12] The literature typically relies on cross-sectional data and hence frequently utilizes parenthood or age of children as an exclusion restriction in estimating the selection bias. However, most of men and women in our sample eventually have at least one child. Clearly, never-parents are not directly comparable ever-parents.

[13] Wages are taken in logarithms, hence we take 0.1€/CPI, i.e. the real value in 2005 euros of 10 euro cents.

[14] Another source of bias, particularly towards the upper tail of the age distribution, stems from the fact that if motivation to work is age dependent and heterogeneous across individuals and genders – the preference argument – our estimates would be biased upwards, because only individuals motivated enough to work will be observed in the working sample past certain age thresholds. Thus, our estimate of the age pattern in gender wage gap may partially confuse pure age effects and – should they indeed be heterogeneous across age and genders – preferences.

[15] The 2010 wave of the SOEP introduced a new wave of respondents to the panel. As the wave focused on families, this raised the average of couples living with children in the following years.

[16] A full results output from each of the numerous probit models is available upon request.

[17] The sample of respondents used to compare 1994 to 1989 is the same for both years, it might differ from the sample used to compare 1989 to 1984. This choice is motivated by panel attrition. If we require individuals to stay longer in the panel, up to 32 years, the sample size often drops below 150 observations. Estimates for those small groups are reported as a robustness check in Table D1.