

# The Early Career Gender Wage Gap among University Graduates

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## Abstract

A large literature has shown that the gender wage gap is small in the beginning of the career and increases gradually with age, mostly because of family decisions, i.e. a penalty caused by child birth. Using a unique dataset that links university graduates with detailed employment records from the German social security register, we find that a significant gender wage gap already exists in the first job after graduation. Interestingly, the gender wage gap decreases in the first year after graduation before slowly increasing over time. As an explanation for the decrease of the gender wage gap, we find that female graduates have higher returns to firm and occupation changes than their male counterparts. Specifically, women may use firm and occupation changes to correct for a skill mismatch, which is more common for women than men in the first job.

**JEL Classification:** I23, J16, J31, J71

**Keywords:** Gender Wage Gap, University Graduates, Early Career

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# 1 Introduction

Even though women's educational and career opportunities have increased in recent decades, there is still a persistent gender wage gap in economically advanced countries (Goldin, 2014; Olivetti and Petrongolo, 2016), which is even larger among individuals with higher levels of education (Blau and Kahn, 2017; OECD, 2019). Many studies have examined the gender wage gap among the highly educated and found that women's lower labor supply and more frequent career interruptions (mainly due to children) compared to men are the main reasons for this gender wage gap.<sup>1</sup>

Less is known about the existence and development of a gender wage gap at the beginning of a career. This lack is surprising given that starting wages and growth in early career wages have long-lasting effects on the labor market careers of university graduates and potentially on the gender wage gap. For example, Oreopoulos et al. (2012); Kahn (2010); Oyer (2006) show that labor market conditions, such as recessions, can also have an impact on entry wages and consequently on wages in the long run. Moreover, prior wages usually determine wage increases due to promotions within the same firm (Graham et al., 2000) and even wage rises as a result of a job change are usually based on previous wages (Hansen and McNichols, 2020). These findings show that entry wages are important in determining future wages over the long run and are therefore important for the emergence of a gender wage gap.

Whether a gender wage gap exists in the first years after graduation is theoretically ambiguous. Particularly in the first job, drivers of the gender wage gap, such as family-related decisions (e.g., childbirth or marriage), career-related developments (e.g., promotions), firm-specific or general work experience, and firm-specific networks are negligible. Therefore, we expect no or only a small gender wage gap in the first job.<sup>2</sup>

However, particularly in the first job, there is a great deal of uncertainty for both the applicants and the firms. As firms can only judge the labor market productivity of potential hires with no labor market experience on the basis of their university grades and the job interview, the GPA may be particularly important in the first job, because it serves as a crucial indicator of productivity. In this case, given that women tend to have higher GPAs than men nowadays (Becker et al., 2010; Francesconi and Parey, 2018), we might even expect the gender wage gap to be in favor of women in the first job.

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<sup>1</sup>For example, see Cortes and Pan (2020), Kleven et al. (2019a), Adda et al. (2017) and Kuziemko et al. (2018).

<sup>2</sup>The mean age of German mothers at first birth was 30.5 in 2021 (Destatis, 2022), while the average age of labor market entry for women in our sample is 27. Moreover, the average age of women at birth is expected to increase with the level of education. Thus, this issue is not expected to be of high magnitude in the case of women with a master's degree at labor market entry.

On the other hand, existing studies show that female applicants negotiate less in job interviews than male applicants (Babcock and Laschever, 2009; Bertrand, 2011). In addition, women might be more likely to accept a lower-paying job offers due to higher levels of risk aversion or because men are overly optimistic (Cortés et al., 2021). Furthermore, women prefer jobs that offer more non-wage amenities, such as work flexibility, rather than wages (Wiswall and Zafar, 2018). Finally, female applicants may face statistical discrimination at labor market entry before firms learn about their productivity over time (Altonji and Pierret, 2001; Pinkston, 2006). Therefore, the gender wage gap in the first job may be large and in favor of men.

This ambiguity about the gender wage gap may be even greater in the first few years after labor market entry, when firms have observed the productivity of their employees or when graduates change jobs to increase their wages. If women earn less than men in the first job because of discrimination, the gap may narrow over time as women move to less discriminatory firms or as employers learn about employees' true productivity over time (Altonji and Pierret, 2001; Farber and Gibbons, 1996). However, job changes in the early stages of a career may also lead to an increase in the gender wage gap over time, as the literature shows that women generally realize lower returns to job mobility compared to men (Albrecht et al., 2018; Topel and Ward, 1992). In addition, family decisions may become more and more important over time, which could also widen the gap. Overall, the gender wage gap at labor market entry and the dynamics of the gender wage gap in the first few career years remain unclear and important to study.

This paper examines the gender wage gap at the beginning of the career immediately after labor market entry and its evolution over five years after the first job among more than 5,000 university graduates with a master's degree or equivalent. We use unique administrative data on graduates of a large German university linked with detailed social security data from the Integrated Employment Biographies (IEB). The administrative dataset provides a wide range of information, including sociodemographic characteristics of the graduates, the attained university degree, field of study, the final high-school and university grades, the date of enrollment and the exact timing of graduation, labor market entry, and any occupation or firm changes.

Using these data we, first, estimate the gender wage gap at labor market entry among university graduates. Our findings show that males have significantly higher wages than females in their first full-time job immediately after graduation, despite our homogeneous and highly educated sample with high labor market attachment. The estimated unadjusted gender wage gap of about 12.5 log points corresponds to around 10 euros per day or 300 euros per month. The adjusted gender wage gap, conditional on a comprehensive set of personal and pre-graduation controls, is equal to 6.2 log points. Including occupation fixed effects reduces the gender wage gap to 4.7 log points. Other post-graduation characteristics, such as the timing of the first job, firm fixed effects, the share

of women in the firm, and the location of the firm do not alter the gender wage gap substantially.

Second, since both career paths and wages vary widely across fields of study (Altonji et al., 2016), we conduct a subgroup analysis for four broad groups of fields of study: economics and business; mathematics and natural sciences; humanities and social sciences; and medical studies. The results show that the unadjusted (raw) gender wage gap at the first job is prominent in almost all field groups except medical studies. For mathematics and natural sciences, the gender wage gap disappears when controlling for specific fields of study. The adjusted gender wage gap is the highest in the humanities and social sciences. This field group also has the lowest average daily wage in the first job and the highest share of females.

Third, as the dynamics are very important particularly in the early career years and have an impact on future wage growth, we examine the dynamics of the gender wage gap over five years after labor market entry. Our findings reveal a decrease in the estimated gender wage gap in the first three years after the labor market entry, followed by an increase in subsequent years. The largest reduction in the wage gap is observed one year after labor market entry. Moreover, we demonstrate that this decline is observed only among economics and business graduates and humanities and social sciences graduates who change both firms and occupations within one year of entering the labor market. However, this decline does not occur for graduates from other fields of study, nor for those who remain in the same firm or occupation.

Finally, our analysis focuses on these two field groups (economics and business; humanities and social sciences) shows that it is mainly women who change firms and occupations after their first job that drive the decline in the gender pay gap, as women benefit more from these changes than men. After rejecting several hypotheses as to why women benefit more from changing jobs and firms early in their careers, the most plausible explanation is the correction of qualification mismatch (or vertical mismatch) in the first job. Our data show that women are more likely than men to work in a mismatched occupation in the first job. By changing both firms and occupations, women move out of the lowest ranked occupations and are able to correct this mismatch, leading to a higher increase in wages compared to men.

Our study contributes to the existing literature in several important ways. Several studies examine the dynamics of the gender wage gap over the life cycle and find evidence that the gender wage gap is smaller at younger ages but increases over time, mostly due to family-related decisions (Bertrand et al., 2010; Albrecht et al., 2018; Manning and Swaffield, 2008)<sup>3</sup>. In contrast to this literature, we are the only study investigating the gender wage gap that uses administrative data to zoom in on the first job after graduation and start the analysis at this crucial point in the career.<sup>4</sup>

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<sup>3</sup>The effect of the child penalty on females' labor market outcomes is explored in several studies. For example, (Kleven et al., 2019b), (Dustmann et al., 2009)

<sup>4</sup>The study by Kunze (2005) uses administrative data, but focuses on younger graduates who have completed an

Similar to our findings among economics and business graduates of 7 percent, Cortés et al. (2021) find that women earn 10 percent less than men in their first job in a survey of about 1,350 business school graduates in the US. In a related German study, Francesconi and Parey (2018) find an unexplained gender wage gap of 20 log points and an adjusted gap of 5-10 log points among full-time German college graduates after 12-18 months. Although their adjusted gender wage gap is comparable to our findings, they find a higher raw gender wage gap. This can be explained by the fact that they cannot observe the first full-time job exactly.

In addition to correctly identifying the first job properly, these novel linked data have several other advantages. For example, because of the administrative nature of the data, we do not have problems with missing data, response rates, or measurement error due to retrospective questions. In addition, most other data used to study the gender wage gap either lack detailed information on graduates' pre-graduation characteristics (field of study, GPA) or are unable to track graduates into the labor market and lack information on graduates' occupation, industry and other important employment characteristics. In contrast, our data provide access to accurate and comprehensive measures of human capital that affect the productivity of individuals, such as academic grades and field of study as well as detailed information on employment, wages, and occupations.

Moreover, our study provides unique insights into the early career job dynamics and their impact on the gender wage gap. At the beginning of careers, high information frictions can lead to poor labor market job matches for recent graduates (Vesterlund, 1997). Fredriksson et al. (2018) highlights high separation rates among inexperienced employees due to limited information about the labor market. Consequently, graduates may correct these mismatches by changing jobs once they accumulate some experience. Topel and Ward (1992) further emphasize that job mobility is more prevalent during the early years of labor market entry, with young employees typically experiencing an average of seven full-time jobs within the first ten years after entering the labor market. The existing literature has shown that job changes are associated with wage growth (Albrecht et al., 2018; Manning and Swaffield, 2008; Del Bono and Vuri, 2011; Topel and Ward, 1992). It is also observed that men are more likely to change jobs<sup>5</sup> and tend to benefit more from job mobility than women, thereby exacerbating the gender wage gap over time (Albrecht et al., 2018; Manning and Swaffield, 2008; Del Bono and Vuri, 2011; Topel and Ward, 1992). However, these studies do not focus on the first years after labor market entry because it is difficult to observe this crucial early period without detailed administrative data. In contrast, we are able to follow all graduates over time, which allows us to observe the precise timing of any job changes and job search periods within the dynamic first years after labor market entry. This information allows us to observe the share of female and male graduates from each field of study who change their jobs and to ob-

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apprenticeship.

<sup>5</sup>Except for the study by Albrecht et al. (2018) finds similar probabilities of job change for men and women.

serve the returns to their mobility, which may have long-lasting effects on their future labor market careers. In addition, using information on firms, such as industry sector, firm size, and location, we are able to observe the influence of firm and occupation characteristics on the evolution of the wage gap for job changers.

The remainder of this paper is structured as follows. Section 2 describes the dataset, its advantages and shortcomings, characterizes the sample of university graduates used in the analysis, and presents some descriptive statistics. The results for the estimated gender wage gap at labor market entry and the dynamics of the gender wage gap over the first few years of a career are presented in Section 3 and Section 4 respectively. We examine gender differences in firm and occupational mobility in Section 5 and the underlying reasons behind this mobility in Section 6 before concluding in Section 7.

## 2 The Linked Administrative Dataset and University Graduates

### 2.1 Data

This study is based on a unique administrative dataset of graduates of the University of Regensburg linked with register data from the German Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). The linked dataset combines detailed study information on each graduate from the registry of the University of Regensburg with information on individual employment records covering the whole employment biography of jobs subject to social security contributions from the IEB dataset.

The University of Regensburg is a large university located in Bavaria, Germany.<sup>6</sup> It offered almost all fields of study except engineering degrees during the observed period. The available dataset from the University of Regensburg covers all its graduates from 1995 to 2016. The data are highly reliable as they are based on administrative records from the university registry. The dataset provides information on each graduate's personal characteristics, such as year of birth, gender, nationality, as well as the district and grade of the certificate of general qualification for university admission (*Abitur*), hereafter referred to as the final high-school grade point average (GPA). The dataset also includes study-related characteristics at the university, such as field of study, type of university degree attained, final GPA, and dates of enrollment and graduation.

The IEB is a large administrative dataset on individuals' employment biographies provided by the

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<sup>6</sup>In 2021, the University of Regensburg was ranked 44th out of approximately 400 universities in Germany (Times Higher Education, 2021). Liste der Hochschulen in Deutschland (2021) provides further details about the size of the University of Regensburg.

IAB for the period 1975-2019. The information provided by the dataset is highly reliable, as it is a legal requirement in Germany for all employers to provide information on their employees to the German Social Security Administration. The IEB dataset includes individuals in employment covered by social security, excluding the self-employed and civil servants. Thus, the IEB dataset covers about 80 percent of the total labor force in Germany. In addition to the precise timing of employment and out-of-employment spells, the dataset provides information on gross daily wages, industry, occupation, full-time status and other employment characteristics (Dorner et al., 2010).

The data from the University of Regensburg are merged with the IEB dataset using a linkage procedure established at the IAB based on an individual's full name, gender, and date of birth, with a 90 percent match rate (Möller and Rust, 2017).<sup>7</sup> The final dataset, covering graduation years 1995-2015, includes around 43,000 graduates (including bachelor's graduates) and 800,000 observations, as graduates are linked to multiple spells from the IEB data.<sup>8</sup>

## 2.2 Sample Choice

The focus of this study is on individuals with a master's degree or equivalent. This is because in Germany more than half (66 percent) of bachelor's graduates do not enter the labor market after graduation, but continue their studies with a master's degree (Destatis, 2023). We further restrict the sample and focus only on graduates working full-time in their first job<sup>9</sup>, with a graduation age between 24-35 and a daily wage of at least 10 Euros.<sup>10</sup> Since GPAs are not available for law graduates and grades are an important measure of human capital, we exclude law graduates from the sample to capture the effect of gender differences in GPAs on the gender wage gap.

We omit graduates who work in all types of employment other than full-time (part-time, mini-jobs, internships, as working students, etc.) in their first job after graduation, even if they switch to full-time employment afterwards, because we consider this the most policy-relevant group with a higher labor market attachment and the results are easier to interpret for a homogeneous group. If an individual has more than one wage spell at a given time, we choose the "main" employment spell as defined by the IAB. We also exclude graduates with a gap of more than 15 months between graduation and their first employment spell, as these individuals may have spent time abroad or

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<sup>7</sup>Please refer to the study by Möller and Rust (2017) for a more detailed explanation of the matching procedure.

<sup>8</sup>Appendix A provides more information about the linked dataset.

<sup>9</sup>Since information on working hours is not available in the linked dataset, we focus on full-time jobs in order to eliminate a potential bias in the gender wage gap induced by differences in working hours. Since we focus on full-time employees in our main analysis, men's and women's working hours should be reasonably comparable. However, even if employees are fairly homogeneous in terms of full-time employment, males may still work more hours than females, allowing them to earn higher wages (e.g., Goldin and Katz, 2016). The study by Francesconi and Parey (2018) documents that differences in hours worked among full-time employees do not significantly explain the gender wage gap among German graduates about 12 to 18 months after graduation. Therefore, we expect that our results are not driven by differences in working hours between full-time employed female and male graduates.

<sup>10</sup>Wages are deflated to 2010 euros using the consumer price index.

already worked on a self-employed basis (which is not captured by the data). Since our main analysis focuses on the first full-time job after graduation and the subsequent years, we keep graduates who have wage spells at the beginning of the first job and also one year after the first job. In addition, we restrict the graduation year cohorts to 1995-2010 in order to be able to analyze the dynamics of the gender wage gap for up to 5 years after labor market entry.<sup>11</sup> After these restrictions, the final sample for the main wage estimations consists of 5,212 individuals.

## 2.3 Descriptive Statistics

Table 1 presents descriptive statistics at labor market entry for our preferred sample of university graduates in full-time employment, which we use for the wage analysis in the following sections. While panel A of Table 1 documents pre-graduation characteristics, such as university and high-school GPA, duration of study, non-German citizenship, and others, panel B presents post-graduation characteristics, including characteristics of the first job.

Panel A of Table 1 shows that both men and women complete their degrees in about five and a half years on average, although women graduate at a younger age. The majority of graduates at the University of Regensburg (around 70 percent) acquire some form of work experience before graduation, with females more likely to work during their studies than males. In addition, consistent with the literature, the share of female graduates increases over graduation cohorts, with the male-female ratio even reversing in the most recent cohort group (2007-2010). This is also in line with the overall population of German graduates.<sup>12</sup> Consistent with the literature (see e.g., Becker et al., 2010), female graduates enroll at the University of Regensburg with better final high-school grades and leave the university with slightly better university grades (by around 11 percent of the sample standard deviation) than males.<sup>13</sup> Females are also more than twice as likely to graduate in humanities and social sciences. Mathematics and natural sciences graduates account for nearly a quarter of all male graduates, compared to only eight percent of all female graduates. Nevertheless, economics and business remain the dominant field of choice for both genders. Finally, the share of women studying medicine is around 10 percentage points higher than that of men. Table 1 also shows that female graduates are more likely than males to earn a

<sup>11</sup>For the analysis of the gender wage gap over the first 5 years after labor market entry, we keep individuals who have a wage spell in years 1-5 after their first job. With this balanced sample, we aim to focus on individuals with a stronger labor market attachment. For these estimations, the sample size is 3,585, with 1,205 females and 2,380 males.

<sup>12</sup>According to BMBF (2021), while the female-to-male ratio was around 0.8 in 1995, it increased to 1.1 in 2010. Appendix Figure B.1 shows the female-to-male ratio for the underlying sample of graduates of the University of Regensburg who work full-time in their first job after graduation. Among these graduates, the female-to-male ratio increases over time from around 0.3 to 1.1. Compared to the total population of German graduates, the share of females is lower in the first graduation cohorts and converges to the total population over time. Appendix Figure B.2 further illustrates that in our data the proportion of women is increasing for all fields of study except for mathematics and natural sciences.

<sup>13</sup>In our data, final high-school grades are only available in the data beginning with the 2001 graduation cohort.



Table 1: Descriptive Statistics

	Male		Female		Diff.
	Mean	(Std. dev.)	Mean	(Std. dev.)	
<b>Panel A: Pre-graduation and Personal Characteristics</b>					
Final High-School Grade (Abitur)	2.245	(0.616)	2.077	(0.594)	0.168***
Individuals	1,476		1,200		
Final University Grade	2.058	(0.604)	1.998	(0.568)	0.060***
Non-German Citizenship	0.015	(0.121)	0.033	(0.179)	-0.019***
Graduation Age	27.238	(1.864)	26.579	(1.906)	0.660***
Duration of Study	5.592	(1.308)	5.631	(1.372)	-0.039
Apprenticeship	0.065	(0.247)	0.061	(0.239)	0.004
Worked During Studies	0.673	(0.469)	0.742	(0.438)	-0.069***
Graduation Year					
- 1995 - 1998	0.283	(0.451)	0.156	(0.363)	0.127***
- 1999 - 2002	0.227	(0.419)	0.172	(0.377)	0.055***
- 2003 - 2006	0.227	(0.419)	0.269	(0.443)	-0.042***
- 2007 - 2010	0.263	(0.440)	0.403	(0.491)	-0.141***
Field of Study					
- Economics and Business	0.469	(0.499)	0.328	(0.469)	0.141***
- Mathematics and Natural Sciences	0.224	(0.417)	0.077	(0.267)	0.147***
- Humanities and Social Sciences	0.111	(0.314)	0.300	(0.458)	-0.189***
- Medical Studies	0.196	(0.397)	0.295	(0.456)	-0.099***
Type of Degree					
- Diploma	0.747	(0.435)	0.576	(0.494)	0.172***
- Magister	0.046	(0.210)	0.114	(0.317)	-0.068***
- Master	0.010	(0.102)	0.015	(0.123)	-0.005
- State Examination (Staatsexamen)	0.196	(0.397)	0.295	(0.456)	-0.099***
Individuals	3,258		1,954		
<b>Panel B: Post-graduation Characteristics</b>					
Left the Region	0.196	(0.397)	0.179	(0.383)	0.118
Left the City	0.683	(0.465)	0.655	(0.476)	0.028*
Mean of Job Search Duration	3.747	(3.128)	3.817	(3.039)	-0.070
Duration of Job Search					
- less than 1 Month	0.190	(0.392)	0.161	(0.368)	0.028***
- 1-3 Months	0.326	(0.469)	0.319	(0.466)	0.007
- 3-5 Months	0.214	(0.410)	0.247	(0.431)	-0.033***
- more than 5 Months	0.270	(0.444)	0.272	(0.445)	-0.002
Firm Size					
- less than 25 Employees	0.238	(0.426)	0.247	(0.432)	-0.009
- 25-250 Employees	0.273	(0.445)	0.266	(0.442)	0.007
- 250-2000 Employees	0.254	(0.436)	0.273	(0.446)	-0.018
- more than 2000 Employees	0.235	(0.424)	0.214	(0.411)	0.020*
Share of Women in Firm					
- less than 40%	0.356	(0.479)	0.201	(0.401)	0.155***
- 40%-70%	0.405	(0.491)	0.383	(0.486)	0.022
- more than 70%	0.239	(0.427)	0.417	(0.493)	-0.177***
Individuals	3,258		1,954		

Note: This table shows summary statistics of graduates' pre-graduation and post-graduation characteristics. The sample consists of graduates with a master's degree or equivalent who work in a full-time job in their first job after graduation. \*\*\*, \*\* and \* denote significance at the 1, 5, and 10% levels.

magister or state examination degree.<sup>14</sup> The vast majority of graduates have a diploma degree, with a higher proportion of men than women.

Panel B of Table 1 presents post-graduation and employment characteristics, such as mobility, time between graduation and the first full-time job,<sup>15</sup> establishment size, and the share of women in the establishment of the first job.<sup>16</sup> The table shows that about 70 percent of the graduates find their first full-time job outside of the city of Regensburg, with males being slightly more mobile. On average, female graduates take longer to find their first job than male graduates, around 3.7 and 3.8 months respectively. A breakdown of the job search duration into different categories shows that the share of male graduates with a job search duration of less than one month is higher. Finally, female and male graduates tend to work in establishments of similar size. However, in line with the literature, women are more likely to work in establishments with a higher proportion of female employees. A potential explanation for this might be the sorting of university graduates into specific industries by gender, resulting in female-dominated industries (Hellerstein et al., 2011).

### 3 Gender Wage Gap at Labor Market Entry

We begin our analysis by looking at gender wage differences at labor market entry.<sup>17</sup> Table 2 presents the first results of our empirical analysis<sup>18</sup> for the 1995 to 2010 graduation year cohorts. Column (1), controlling only for the year of graduation, shows a significant negative coefficient of 12.5 log points for the female dummy. This unadjusted (raw) gender wage gap indicates that female graduates earn 12.5 log points less in daily wages than their male counterparts in their first job after graduation. This gap is smaller than in the study by Francesconi and Parey (2018), who find a raw gender wage gap of around 20 log points based on survey data collected in a few selected years between 1988 and 2010 and conducted among graduates 12-18 months after graduation. This difference in the raw gender wage gap may reflect the timing of their data (they do not focus on the first job after graduation) as well as our conservative definition of the first job, i.e., we have a more homogeneous group of graduates with higher labor market attachment.

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<sup>14</sup>Because the Bologna reform was implemented in Germany between 2005 and 2010, only a small proportion of graduates in the sample have a master's degree.

<sup>15</sup>Hereafter referred to as "job search duration", even though this time is not necessarily spent searching for a job.

<sup>16</sup>In this paper, we use the terms "establishment" and "firm" interchangeably.

<sup>17</sup>By labor market entry, we refer to the first job after university graduation and use these terms interchangeably.

<sup>18</sup>For the wage regressions, we estimate the following equation:

$$\ln\_wage_i = \alpha + \gamma female_i + \beta X_i + \epsilon_i$$

$\ln\_wage_i$  is the log real daily wage at the first job. The analysis of the dynamics of the gender wage gap uses log daily wages 1-5 years after the initial job as the dependent variable.

Table 2: Gender Wage Gap at Labor Market Entry

Dependent Variable: Log Daily Wage							
	Personal and Pre-Graduation Characteristics					Additional Post-Graduation Characteristics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.125*** (0.012)	-0.130*** (0.012)	-0.068*** (0.012)	-0.064*** (0.012)	-0.062*** (0.012)	-0.045*** (0.011)	-0.047*** (0.011)
Graduation year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Field of study FE	No	No	Yes	Yes	Yes	Yes	Yes
Final university grade	No	No	No	Yes	Yes	Yes	Yes
Pre-graduation characteristics	No	No	No	No	Yes	Yes	Yes
Occupation FE	No	No	No	No	No	Yes	Yes
Post-graduation characteristics	No	No	No	No	No	No	Yes
R-squared	0.036	0.038	0.211	0.225	0.235	0.334	0.399
Individuals	5212	5212	5212	5212	5212	5212	5212

Note: This table shows the gender wage gap at labor market entry. The sample consists of individuals work in full-time job as their first job and also gave a wage spell 1 year after the first job. The dependent variable is the log gross daily wage at the first job. The controls variables are added gradually. Column (1) shows the results with only the graduation year as a control. Column (2) adds personal characteristics such as age and (not) having German citizenship and column (3) adds field of study (17 categories). Column (4) adds the final university grade and column (5) adds pre-graduation characteristics: duration of study, location of the final high-school examination, a dummy for apprenticeship and a dummy for working during studying. Column (6) adds occupation fixed effects (3 digits codes). Column (7) shows the results after adding post-graduation characteristics. These include job search time, job location, industry fixed effects (1-digit), firm size (7 categories), the share of women in firms (3 categories) and the beginning month of the first job. Robust standard errors in parentheses. \*\*\*, \*\* and \* denote significance at the 1, 5, and 10% levels.

While we add personal characteristics in column (2), in column (3) we additionally control for 17 fields of study (see Table C. 1 in the Appendix for a list of these 17 fields), which leads to a big decline in the gender wage gap to 6.8 log points in the first job after graduation. This striking decrease in the gender wage gap confirms the findings of existing studies (see, e.g., Machin and Puhani, 2003; Black et al., 2008) that female students sort into fields of study associated with lower wages.

Columns (4) and (5) show the extent to which the results change when we include the final university grades and other pre-graduation characteristics (duration of study, location of the high school, having completed an apprenticeship, and having worked while studying) in the regression. The estimated gender wage gap barely changes after controlling for these characteristics, suggesting that neither final university grades nor other characteristics explain a large part of the gender wage gap.<sup>19</sup> Table C. 2 in the Appendix presents additional results from an Oaxaca-Blinder decomposition. The decomposition also shows that the most important contributor to the gender wage gap among pre-graduation characteristics is the field of study, accounting for 40 percent of the total

<sup>19</sup>When we add final high school grades to the estimation, the gender wage gap decreases by only 0.003 log points.

gender wage gap at the first job. Since field of study explains the most important part of the gender wage gap, in the next section we examine the gender wage gap within a set of field of study categories.

Columns (6) and (7) additionally include occupation fixed effects (at the 3-digit level) and other post-graduation characteristics in the estimation. However, it is not clear whether these post-graduation variables should be included in the estimation, as they may themselves be outcomes of the variable of interest, such as choice of location or type of job (or occupation).<sup>20</sup> After adding occupation fixed effects to the estimation, the gender wage gap decreases to 4.5 log points, indicating that, similar to the field of study, the occupation of the first job after graduation explains a large part of the gender wage gap. Finally, column (7) adds all post-graduation controls, which does not further reduce the gender wage gap.

Overall, the gender pay gap remains significant at 6.2 log points for graduates in the same field of study, with similar grades and other pre-graduation and personal characteristics, and at 4.7 log points when we also condition on occupation and other post-graduation characteristics. These gaps are highly significant, as the unadjusted (raw) gender wage gap (12.5 log points) corresponds to 10 euros per day, or around 300 euro per month, less pay for women compared to men in their first job.

### *Field of Study*

Since earnings vary by field of study<sup>21</sup> and we have shown that field of study is the main contributor to the gender wage gap at labor market entry, we next examine the gender wage gap across fields of study.

The results show that the gender wage gap is high for all fields of study except medical studies. The raw gender wage gap (controlling only for year of graduation) is 8.6 log points for economics and business graduates. This gap is comparable to the study by Bertrand et al. (2010), which finds a raw gender wage gap of 8.9 log points at the time of graduation for MBA graduates, and to the study by Francesconi and Parey (2018), who find a raw gender wage gap of 10.3 log points for economics and business graduates.

For the remaining fields of mathematics and natural sciences, humanities and social sciences, and medical studies, the raw gender wage gap is 14.1 log points, 10.2 log points, and 1.5 log points, respectively. The raw gender wage gap for mathematics and natural sciences is comparable to the finding of Francesconi and Parey (2018) for the STEM field. The biggest difference with the study of Francesconi and Parey (2018) is the field of medical studies, where we find no gender wage

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<sup>20</sup> Angrist and Pischke (2009) define controls that can be dependent variables as "bad controls".

<sup>21</sup> Several studies demonstrate that different fields of study yield varying labor market returns. For example, Deming and Noray (2020); Kirkeboen et al. (2016); Kelly et al. (2010) and Altonji et al. (2012).

gap. This is to be expected since the wages of medical graduates (especially doctors) are set by collective bargaining agreements at the beginning of their careers, and therefore the gender wage gap is very small.

After controlling for detailed field of study categories, the gender wage gap becomes insignificant for the mathematics and natural sciences. This is because women in these fields tend to sort into lower-paid fields such as biology rather than physics. Interestingly, after adding controls, the largest and most significant gender wage gap is observed for the typically (compared to other field groups) female-dominated and lower-paid humanities and social sciences.

This finding aligns with the peer effect literature, which suggests that a higher proportion of females in the classroom may influence females to choose lower-paid occupations (Brenøe and Zölitz, 2020) and positions with a lower wage growth (Zölitz and Feld, 2018), ultimately exacerbating the gender wage gap over time. Another explanation may be that females value job flexibility or other non-wage amenities more (Wiswall and Zafar, 2018; Goldin, 2014; Goldin and Katz, 2011; Flabbi and Moro, 2012; Mas and Pallais, 2017), and Wiswall and Zafar (2018) show that these job characteristics have an impact on major choice. This evidence suggests that females prefer to work in more flexible jobs or jobs with high non-wage benefits and choose their majors accordingly, leading to lower wages for women in the future. Furthermore, (Adda et al., 2017) show that fertility decisions shape females' career choices long before they have children. Thus, fertility expectations may also lead women to sort into lower-paid fields at the stage of major decision making, and to work in more family-friendly jobs after graduation.

However, there may also be some unobserved labor market characteristics (such as labor demand, discrimination, etc.) that are more relevant for these field groups. For example, if women observe discrimination, they may not choose male-dominated fields Blau and Kahn (2017). To investigate this further, we employ the Oaxaca-Blinder decomposition by field and reveal that the unexplained component of the gender wage gap is most pronounced within the humanities and social sciences field. Specifically, the unexplained part constitutes 82 percent, 23 percent, and 86 percent of the gender wage gap for economics and business, mathematics and natural sciences, and humanities and social sciences, respectively. However, the unexplained part could also stem from other unobserved characteristics of the labor market that remain beyond the scope of our available data (Blau and Kahn, 2017).

Table 3: Gender Wage Gap at Labor Market Entry by Field of Study

Dependent Variable: Log Daily Wage				
	Economics and Business	Mathematics and Natural Sciences	Humanities and Social Sciences	Medical Studies
	(1)	(2)	(3)	(4)
<i>Add</i>				
Graduation Year	-0.086*** (0.018)	-0.141*** (0.032)	-0.102*** (0.030)	-0.015 (0.021)
Personal Characteristics	-0.091*** (0.018)	-0.142*** (0.032)	-0.102*** (0.032)	-0.010 (0.021)
Field of Study	-0.091*** (0.018)	-0.038 (0.031)	-0.124*** (0.032)	-0.030 (0.019)
Final University Grade	-0.086*** (0.018)	-0.029 (0.032)	-0.121*** (0.032)	-0.029 (0.019)
Pre-Graduation Characteristics	-0.085*** (0.018)	-0.000 (0.031)	-0.123*** (0.032)	-0.033* (0.019)
Occupation FE	-0.063*** (0.018)	-0.005 (0.030)	-0.097*** (0.032)	-0.029* (0.017)
Post-Graduation Characteristics	-0.060*** (0.017)	-0.018 (0.030)	-0.097*** (0.032)	-0.029* (0.015)
Share of Females	0.295	0.171	0.619	0.475
Average Daily Wage (Euro)	108.4	110.4	84.25	105.18
Individuals	2,167	882	947	1,216

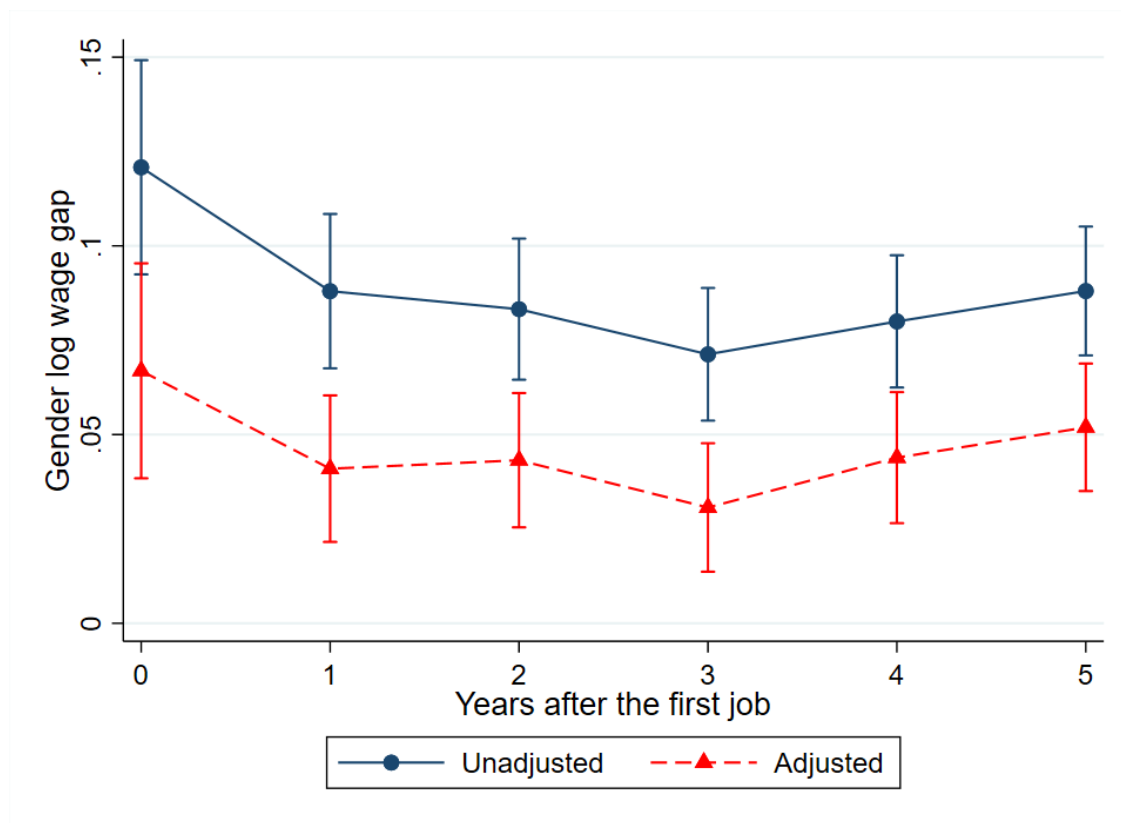
Note: This table shows the gender wage gap at labor market entry by field of study. The sample consists of individuals work in full-time job as their first job and also gave a wage spell 1 year after the first job. The dependent variable is the log gross daily wage at the first job. The controls variables are added gradually. Row (1) shows the results with only the graduation year as a control. Row (2) adds personal characteristics such as age and (not) having German citizenship and row (3) adds detailed field of study category. Row (4) adds the final university grade and Row (5) adds pre-graduation characteristics: duration of study, location of the final high-school examination, a dummy for apprenticeship and a dummy for working during studying. Row (6) adds occupation fixed effects (3 digits codes). Row (7) shows the results after adding post-graduation characteristics. These include job search time, job location, month of the first job, industry fixed effects (1-digit), firm size (7 categories), the share of women in firms (3 categories) and the beginning month of the first job. Robust standard errors in parentheses. \*\*\*, \*\* and \* denote significance at the 1, 5, and 10% levels.

## 4 Gender Wage Gap in the first Years after Labor Market Entry

After analyzing the gender wage gap at the first job, we now examine how the gender wage gap at the beginning of the career evolves during the first five years after labor market entry. In order to have a balanced sample, we only include individuals with high labor market attachment who are employed full-time for 5 years after their first job. This allows us to avoid human capital depreciation (Mincer and Polachek, 1974) due to career interruptions, such as maternity leave. As a robustness check, we also use an unbalanced sample focusing on individuals with full-time employment spells within 5 years of labor market entry.

This restriction results in a sample size of 2,280 male and 1,205 female graduates. With our

Figure 1: Dynamics of the Gender Wage Gap over Years After Labor Market Entry



Note: The sample size is 3,585 (2,280 male, 1,205 female). The sample consists of individuals who have wage spells in a full-time job over the first 5 years after labor market entry. The dependent variable is log gross daily wage. The unadjusted gender wage gap includes only graduation year as a control variable. The adjusted gender wage gap contains personal and pre-graduation characteristics and the beginning month of the first job. Additionally, we control for having a child between the years.

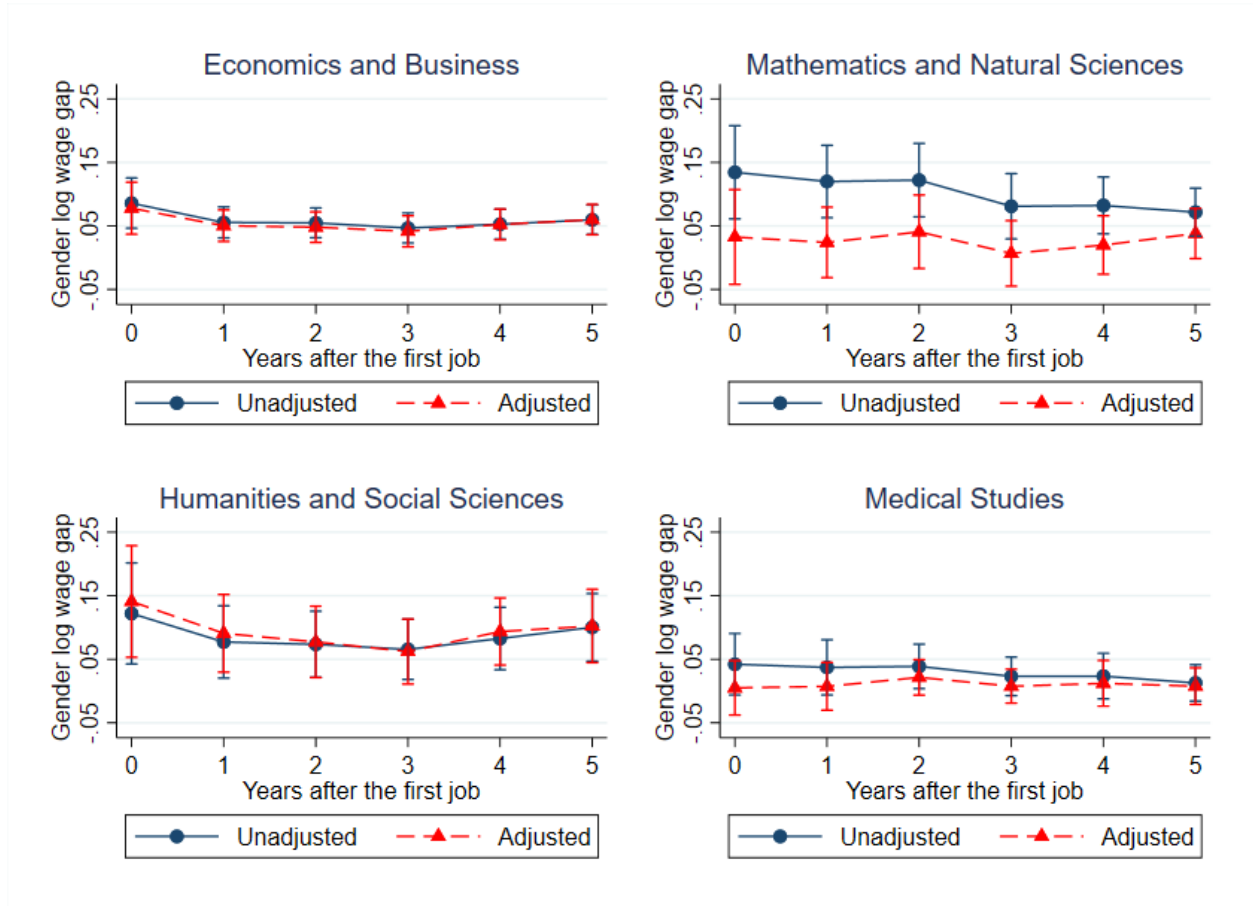
linked dataset, we can observe all employment and wages of graduates in this period, unless they become self-employed, civil servants, or move out of Germany. The blue line in Figure 1 shows the unadjusted gender wage gap for the new sample corresponding to the specification in column (1) of Table 2, with only the year of graduation added as a control. The red line shows the gender wage gap adjusted for pre-graduation and personal characteristics corresponding to the specification in column (5) of Table 2.

At the first job (0 years after labor market entry in Figure 1), the unadjusted gender wage gap is around 12 log points and drops to around 6.9 log points after including additional controls. Although the sample is somewhat more restricted and the adjusted wage gap is slightly higher, these gaps are consistent with the results presented in Table 2.

Looking at the evolution of the unadjusted gender wage gap over time, there is a sharp decrease of around 3 log points one year after labor market entry from 12 to 9 log points. After this initial drop, the gender wage gap remains relatively stable over the subsequent four years, with a slight increase after year 3. We also observe a similar pattern for the adjusted gender wage gap, which

falls by around 4 log points one year after the first job and remains relatively stable thereafter.

Figure 2: Dynamics of the Gender Wage Gap over Years After Labor Market Entry by Field of Study



Note: The sample sizes are 1,698, 677, 541 and 624 respectively. The dependent variable is the log gross daily wage. The sample consists of individuals who have wage spells over 5 years after labor market entry.

As we have shown that the gender wage gap in the first job varies considerably by field of study, Figure 2 examines whether the evolution of the gender wage gap in the first five years of employment also shows some variation across fields of study. The figure clearly shows that the phenomenon of the gender wage gap narrowing one year after the first job is concentrated among graduates in economics, business, humanities and social sciences, the fields with the largest gender wage gap at labor market entry. Among medical graduates, the gender wage gap is small and does not change significantly over time.



## 5 Firm and Occupation Mobility in the First Year After Labor Market Entry

After establishing that the gender wage gap narrows in the first 12 months after labor market entry, we want to examine this reduction in more detail. As a starting point, Table 4 analyzes the evolution of the gender wage gap one year after labor market entry for those fields of study with a decrease in the gender wage gap after one year: economics, business, humanities and social sciences (panel A) and those without a decrease: mathematics, natural sciences and medical studies (panel B).

The result in column (1) shows that, controlling for year of graduation and pre-graduation characteristics, women earn 9.8 log points less than men at labor market entry among economics and humanities graduates. Moreover, both female and male wages increase one year after the first job. However, female wages increase by 3.6 log points more on average than male wages. In line with Figure 2, we do not find a decrease in the gender wage gap one year after the first job for graduates in mathematics, natural sciences and medical studies (panel B).

Previous research shows that firm and/or occupational mobility affects wages and contributes to wage growth (Bartel et al., 2007; Topel and Ward, 1992). This is especially true when mobility occurs in the early stages of a career (Albrecht et al., 2018). For example, Topel and Ward (1992) find that job changes explain more than one-third of wage growth. Therefore, we continue our investigation by separating the sample into graduates who stay in the same firm and/or occupation (column 2 of Table 4), those who change occupation but remain in the same firm (column 3), those who change firm but remain in the same occupation (column 4), and those individuals who change firm and take up a new occupation (column 5).

Panel A of Table 4, which focuses on graduates in economics, business, humanities and social sciences, demonstrates that the gender wage gap does not decrease significantly for those individuals who either stay in the same firm and/or occupation one year after starting their first job (columns 2-4). In contrast, female firm and occupation changers increase their wages on average by around 19 log points more than their male counterparts (column 5). This increase has to be seen in the context that males who change either firm, occupation, or both benefit from these changes by around 25-27 log points, while the stayers increase their wages by only 10 log points. In addition, the initial gender wage gap is larger for individuals who change firms, occupations, or both than for individuals who remain in their position. The group that changes firm and occupation has the largest initial gap (almost 34 log points). Interestingly, the allocation of men and women to the four groups is relatively similar, so differences in shares do not seem to explain the different evolution of the gender wage gap after one year.

Table 4: Gender Wage Gap by Job Change Status

Dependent variables:					
	Pooled	Stayers	Only Firm Changers	Only Occupation Changers	Firm and Occupation Changers
	(1)	(2)	(3)	(4)	(5)
<b>Panel A: Economics, Business, Humanities and Social Sciences</b>					
1 Year After $\times$ Female	0.036*** (0.012)	-0.000 (0.008)	0.038 (0.063)	0.061 (0.083)	0.193*** (0.070)
1 Year After	0.130*** (0.007)	0.098*** (0.006)	0.252*** (0.042)	0.248*** (0.063)	0.271*** (0.039)
Female	-0.098*** (0.015)	-0.056*** (0.014)	-0.156** (0.068)	-0.139* (0.074)	-0.340*** (0.069)
Share of female	1	0.737	0.115	0.101	0.131
Share of male	1	0.796	0.091	0.058	0.105
R-squared	0.240	0.274	0.306	0.323	0.328
Individuals	3,114	2,407	267	194	312
<b>Panel B: Mathematics, Natural Sciences and Medical Studies</b>					
1 Year After $\times$ Female	-0.001 (0.011)	0.006 (0.009)	-0.010 (0.042)	-0.140 (0.132)	-0.088 (0.095)
1 Year After	0.150*** (0.008)	0.127*** (0.007)	0.182*** (0.031)	0.341*** (0.098)	0.386*** (0.054)
Female	-0.019 (0.016)	-0.024 (0.016)	0.008 (0.034)	0.074 (0.171)	0.049 (0.096)
Share of female	1	0.783	0.144	0.032	0.081
Share of male	1	0.838	0.086	0.037	0.070
R-squared	0.393	0.399	0.624	0.499	0.382
Individuals	2,098	1,718	204	60	137

For mathematics, natural sciences and medical studies, we find no reduction in the gender wage gap in the first 12 months after starting the first job, and we observe no initial gap for any of the changer groups (panel B of Table 4). However, even for these fields, the results show that movers have the highest wage growth, between 18 and 39 log points. Overall, the table shows that women benefit more from a complete new start after their first job, which includes a change of firm and occupation. This new start drives the observed reduction in the gender wage gap within one year after the first job.

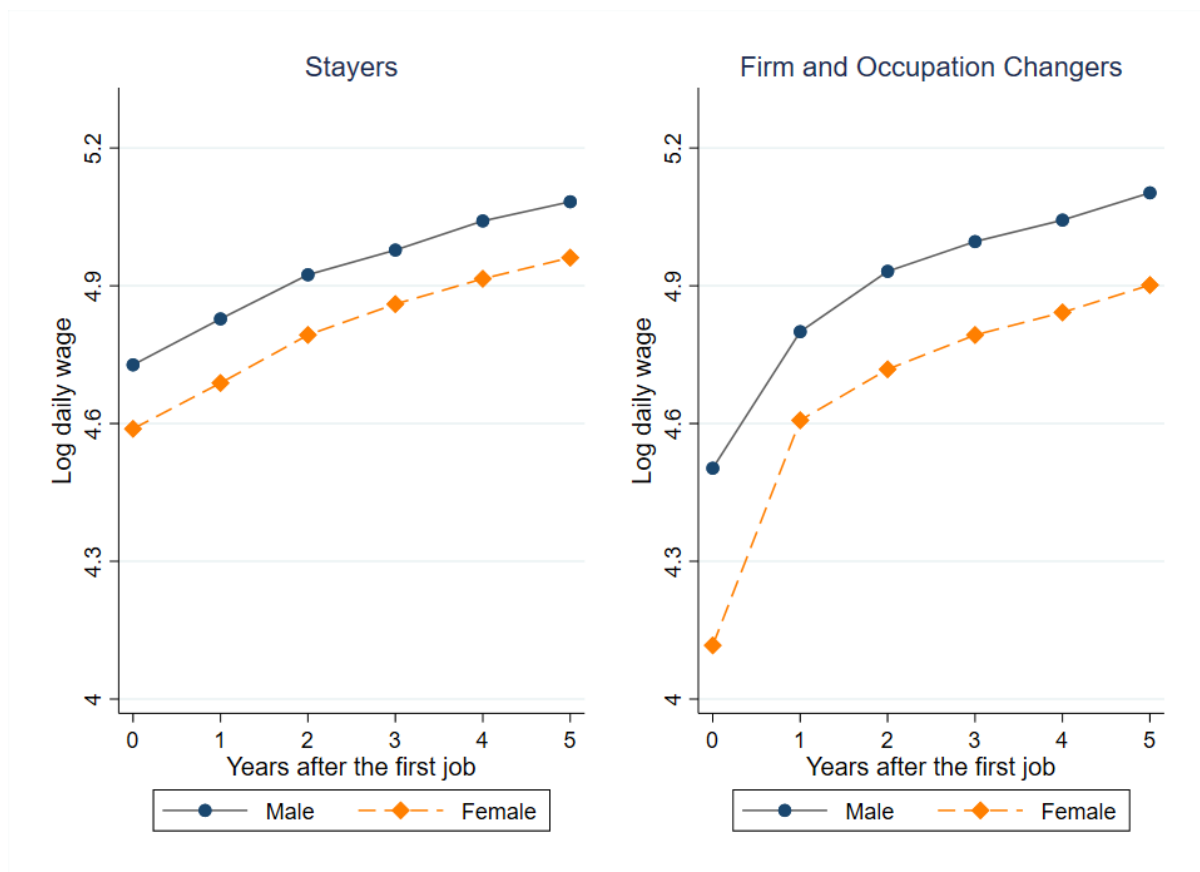


Figure 3: The Dynamic of Wages for Job Stayers and Job and Firm Changers by Gender

As a next step in our analysis, Figure 3 shows the dynamics of wages over 5 years after the first job for stayers and those graduates who change both occupation and firm. Confirming the result from Table 4, female and male movers initially earn lower wages on average than stayers. However, the wage difference between stayers and movers is higher for females than for males, due to the very low entry wages of those females who later change both occupation and firm. To summarize, women with low entry wages appear to correct their low wages by changing their firm and occupation within one year of entering the labor market.

## **6 Why is Switching Firm and Occupation in the Beginning of the Career more Beneficial for Females than Males**

In this section, we test several hypotheses to investigate why women benefit more than men from changing firms and occupations after their first job after graduation. We use two estimation approaches to test the hypotheses. First, we estimate whether women who change firms and occupations differ from men who change firms and occupations in terms of their personal characteristics, university outcomes, and characteristics of their first job, and whether these gender differences differ from those of stayers. Second, we estimate whether firm and occupation characteristics change differently for males and females after job transitions.

Table 5 presents gender differences in personal and pre-graduation characteristics (which do not change over time), between firm and occupation changers and stayers. In Table 6, panel A compares the gender differences in the first job characteristics for individuals who change firms and occupations with those who stay in the same position. Panel B of Table 6 examines gender differences in the characteristics of the first job and the subsequent job one year later for occupation and firm changers. Table C. 3 in the Appendix shows the mean differences in the full set of characteristics of female and male changers and stayers the characteristics of their first job.

A first potential explanation for the decline in the gender wage gap within 1 year after the first job is that firms discriminate against women at the hiring stage, when employers do not have sufficient information about the productivity of new hires (Altonji and Blank, 1999). As a first type of discrimination, "screening discrimination", Pinkston (2003) documents that the productivity signals that employers receive from females are noisier than males. Because of this, productivity signals at the hiring stage have a smaller or no effect on women's wages, while they have a larger effect on men's wages. In our case of university graduates, since the employer is able to observe the CVs of the applicants, the final university grades may be the only signal for the employer. We would expect that men with higher grades do not change jobs because they already earn high wages in their first job. On the contrary, women with higher grades may receive lower wages compared to their male counterparts at the beginning of their careers and thus change jobs in order to increase their wages. However, even though female movers and stayers have better grades on average than their male counterparts, both female and male movers have worse grades than stayers. Nevertheless, the difference in gender differences between movers and stayers is insignificant because the interaction term is insignificant (column (7), Table 5).

The literature also shows that there may be statistical discrimination in the labor market. In this case, employers would expect lower productivity from women and women would be paid lower wages accordingly. Thus, in the presence of statistical discrimination, we expect that, conditional

on hiring, employers will pay women lower wages at the beginning of their careers. However, once employers observe the real productivity of the women they hired ("employer learning"), women's wages would increase over time (Altonji and Blank, 1999; Altonji and Pierret, 2001; Pinkston, 2003). Therefore, we explore the hypothesis that discrimination against women explains the difference in female and male returns to firm and occupation switching. However, if there is statistical discrimination against women, the gender wage gap will narrow not only for those who switch firms and occupations, but also for those who stay, as employers should learn over time about the true productivity of each individual remaining in the firm. Since we do not observe a decrease in the gender wage gap for the stayers, statistical discrimination is unlikely to explain the differential returns to changing occupations and firms.

Another form of discrimination suggested by the literature is taste-based discrimination, where employers pay women lower wages to compensate for their (or co-workers') disutility.<sup>22</sup> The lower initial wage of female movers relative to male movers (Table 6) may indicate some form of taste-based discrimination (Becker, 1971). However, if firms discriminate against women, switching to non-discriminatory firms should be sufficient for women to improve their wages relative to men, while an additional change in occupation should not be necessary. As Table 4 shows, this is not the case, as the gender wage gap does not narrow significantly for those who only change firms. Furthermore, if taste-based discrimination explains the gender wage gap, we should observe that women who change firms will move to firms with more women, as these firms typically discriminate less. Contrary to this hypothesis, women who change their firm and occupation are more likely to work in firms with a higher share of women in their first job (panel A of Table 6 or panel A of Table C. 3 in the Appendix). Moreover, our estimation results show that women do not switch to firms with a higher female share compared to men (column (4), panel B of Table 6).

In addition, the literature suggests that women bargain for their wages less often, and when they do, they are less successful than men (Babcock and Laschever, 2009; Roussille, 2021; Bertrand, 2011). Therefore, we also test whether less frequent or less successful wage bargaining by females in their first job explains the decrease in the gender wage gap. Since re-bargaining within the firm is more difficult, females may change their jobs to increase their wages in the case of low wage bargaining outcomes (Caldwell and Harmon, 2019). Table C. 8 shows that the gender wage gap does not decrease for those who only change firms. If the explanation is solely based on the bargaining story, we should also observe a decrease in the gender wage gap for those who only switch firms and not only for those who change firms and occupations. This suggests that differences in bargaining behavior are unlikely to explain the decline in the wage gap.

The child penalty is another prominent explanation for the gender wage gap in the literature. How-

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<sup>22</sup>Becker (1964) shows in the model that firms that practice taste-based discrimination cannot survive in the competitive market in the long run.

ever, in our data on university graduates, females who change jobs rarely give birth after starting the first job or before changing jobs, suggesting that childbirth is not a primary reason for changing jobs. However, a woman may move to a more family-friendly job if she expects to have children in the future. In this case, females may move to more family-friendly firms with a higher share of part-time employees (Albrecht et al., 2018). Although it would not explain why female wages increase more than male wages as a result of moving, we test whether females switch to more family-friendly jobs more often than males. Panel A, column (2) of Table 6 shows that before the job change, female job changers on average work in firms with a slightly lower share of part-time employees than male job changers. However, they do not move to jobs with a higher share of part-time employees than males (column (2), Table 6).

Similar to the decision to move to family-friendly jobs, women may also change their jobs for other job attributes. A growing literature shows that women prefer non-wage job amenities such as flexibility while men value wages (Goldin and Katz, 2011; Goldin, 2014; Flabbi and Moro, 2012; Brenøe and Zölitz, 2020). Changing preferences for certain job attributes may also be a mechanism for job change. On the one hand, females may change to more flexible jobs in anticipation of having children in the future. However, it is not clear why this will lead to higher wage gains. On the other hand, at the beginning of their careers, women may prefer lower-paying jobs to compensate for some job amenities, but over time they change their preferences and switch to higher-paying and less flexible jobs. Assuming that larger firms have more flexible work arrangements (Albrecht et al., 2018), we test whether women switch to larger firms to enjoy more flexibility. However, we do not find that women are more likely than men to sort into larger or smaller firms compared to males as a result of a job change (column (5), Table 6). In addition, by following De Schouwer and Kesternich (2022), we also focus on other job amenities: schedule adaptability, telecommuting and part-time work, and categorize industry sectors accordingly. We find no evidence that women move to sectors with more or less non-wage benefits than men (Table C. 9).

The literature shows that risk aversion may be an important component of early career job search (Cortés et al., 2021) and job transitions, and that women are typically more risk averse than men (Niederle and Vesterlund, 2007). More risk-averse women may have lower reservation wages at the beginning of their careers (Pissarides, 1974; Feinberg, 1977; Acemoglu and Shimer, 1999; Cox and Oaxaca, 1992; Pannenberg, 2010) and consequently accept job offers relatively earlier, even if the job pays less (Cortés et al., 2021). However, these women may not be satisfied with the lower wages and change jobs when they find a higher-paid job. In this case, we would expect women to spend less time searching for a job after graduation than men, and women who find a job more quickly would be more likely to change jobs. Column (8) of Table 5 shows that although job changers find a job slightly earlier than stayers, there is no significant gender difference in

Table 5: Pre-Graduation and Personal Characteristics of Firm and Occupation Changers

Dependent variables:								
	Personal Characteristics		Pre-Graduation Characteristics				Finding First Job Characteristic	
	Age at the first job (1)	non-German (2)	Duration of Study (3)	Working During Studying (4)	Apprent. (5)	Origin is Bayern (6)	Final Uni. Grade (7)	Duration of Job Search (8)
Female × Firm and Occupation Changers	0.058 (0.269)	-0.021 (0.017)	0.226 (0.171)	-0.012 (0.053)	-0.019 (0.037)	-0.031 (0.041)	0.071 (0.073)	-0.342 (0.366)
Firm and Occupation Changers	0.444*** (0.156)	0.003 (0.010)	0.063 (0.096)	0.002 (0.037)	0.054** (0.026)	0.021 (0.027)	0.026 (0.045)	-0.035 (0.246)
Female	-0.803*** (0.082)	0.026*** (0.007)	-0.053 (0.053)	0.126*** (0.018)	-0.010 (0.010)	0.034** (0.014)	-0.206*** (0.023)	0.141 (0.131)
Means of dependent variable	27.309	0.023	5.515	0.719	0.074	0.858	2.115	3.859
R-squared	0.042	0.006	0.003	0.018	0.004	0.002	0.030	0.001
Individuals	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719

Note: Table documents gender differences in personal and pre-graduation characteristics among firm and occupation changers and stayers. Robust standard errors in parentheses. \*\*\*, \*\* and \* denote significance at the 1, 5, and 10% levels.

job search duration for stayers and job changers in the fields of economics, business, humanities and social sciences. In addition, wages do not decrease significantly with the duration of the job search.

Nevertheless, risk aversion may still lead women to choose jobs with lower match quality (Vesterlund, 1997). Thus, women may sort themselves into job mismatches at the beginning of their careers, and correct these occupation and firm mismatches by changing their occupation and firm. Here, we focus on two types of mismatch: horizontal and vertical mismatch. Horizontal mismatch is the field-occupation mismatch, where the employee's field of study does not match the field required for the job. A vertical mismatch is a skill mismatch where the skill level of the employee's qualification does not match the requirements of the job. Since our sample includes highly skilled university graduates, only jobs for which university graduates are underqualified are defined as vertical mismatches.<sup>23</sup>

Column (6), panel B of Table 6 shows that female job changers are more likely than male job changers to work in horizontally (by 12.7 percentage points) and vertically (by 13.9 percentage points) mismatched first jobs after graduation. However, female job changers reduce the frequency of vertical mismatch one year after the first job by 11.7 percentage points relative to men.

In this case, one might expect that women receive a higher wage as soon as they correct their mismatch. We also examine whether females move to higher-paid occupations. Column (9), panel B of Table 6 shows that female job changers work in lower-ranked occupations in their first job after graduation, but they do not move to (significantly) higher-paid occupations on average compared to men. However, Figure B.4 in the Appendix shows that the occupational rank distributions of

<sup>23</sup>There is a large body of literature showing that both vertical and horizontal mismatches have a negative effect on wages (Wolbers, 2003; Robst, 2007; Boudarbat and Montmarquette, 2009; Heijke et al., 2003).

male and female job changers are quite different at the first job, as females are less likely to work in higher-paid occupations and more likely to work in lower-paid occupations than males. After the job change, however, the distributions of males and females converge, especially in the lower tail, as females predominantly move from lower-paid occupations to higher-paid occupations. Panel B, column (10) of Table 6 shows that after a firm and occupation change, women reduce the probability of being in the bottom decile of ranked occupations relative to men by 11.5 percentage points.<sup>24</sup>

We have shown that females are more likely than males to start in the bottom tail of occupations ranked by pay and change to higher-paid occupations. Moreover, they start in occupations where they are overqualified and correct this vertical mismatch by changing jobs. If correcting the vertical mismatch explains the decrease in the gender pay gap, the question arises as to why women need to change firms as well as occupations within the same firm to correct the mismatch. Column (7) of Table C. 7 in the Appendix shows that females who change occupations within the same firm are also more likely to work in a vertically mismatched occupation prior to the change and to correct this mismatch after the change. Therefore, it appears that even if the mismatch is corrected, it is difficult to improve the wage within a firm, possibly because employees are on a certain wage track that is difficult to adjust only by changing occupation.

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<sup>24</sup>In addition, in occupations with a higher share of women, females value non-wage job attributes more and have higher job satisfaction (Lordan and Pischke, 2022) if these compensate for the lower wages of the occupation. To test this, we also check whether females switch to occupations with a higher female share compared to males. We also check whether females and males switch to female- or male-dominated occupations, but find no evidence of this.



Table 6: The Job Characteristics of Firm and Occupation Changers

Dependent variables:											
	Median Daily Log Wage of Full-time Employees (1)	Share of Part-time Employees (2)	Share of High Qualified Employees (3)	Share of Women in a Firm (4)	Log Firm Size (5)	Horizontal Mismatch (6)	Vertical Mismatch (7)	Horizontal or Vertical Mismatch (8)	Occupation Rank (9)	Occupation Rank < Quantile 10 (10)	Occupation Rank > Quantile 90 (11)
<b>Panel A: The Characteristics of the First Job of Firm and Occupation Changers</b>											
Female × Firm and Occupation Changers	-0.086* (0.049)	-0.007 (0.025)	-0.013 (0.032)	0.044 (0.027)	-0.204 (0.252)	0.008 (0.056)	0.117** (0.058)	0.070 (0.053)	-22.371* (11.815)	0.098** (0.044)	-0.025 (0.034)
Firm and Occupation Changers	-0.120*** (0.028)	0.018 (0.016)	-0.063*** (0.021)	-0.006 (0.017)	-0.341** (0.166)	0.119*** (0.035)	0.122*** (0.039)	0.150*** (0.037)	-7.680 (7.488)	0.017 (0.024)	-0.002 (0.026)
Female	-0.041*** (0.014)	-0.035*** (0.008)	-0.016 (0.011)	0.071*** (0.009)	-0.102 (0.090)	0.122*** (0.017)	0.005 (0.021)	0.051** (0.021)	-15.238*** (3.602)	0.013 (0.012)	-0.036*** (0.013)
Mean of Dependent Variables	4.617	0.781	0.372	0.482	5.099	0.219	0.506	0.594	226.031	0.104	0.104
R-squared	0.029	0.008	0.009	0.035	0.005	0.032	0.014	0.018	0.016	0.009	0.004
Individuals	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719
<b>Panel B: The Characteristics of Dynamic of Firm and Occupation Changers</b>											
Female × 1 year after	0.046 (0.053)	-0.016 (0.029)	0.011 (0.036)	-0.007 (0.032)	-20.260 (483.871)	-0.060 (0.048)	-0.131* (0.079)	-0.153** (0.071)	21.816 (14.263)	-0.115** (0.049)	-0.035 (0.049)
1 year after	0.123*** (0.031)	0.009 (0.018)	0.033 (0.024)	-0.022 (0.020)	377.790 (364.812)	-0.028 (0.034)	0.006 (0.055)	0.028 (0.049)	13.199 (9.661)	-0.040 (0.030)	0.057 (0.040)
Female	-0.161*** (0.047)	-0.018 (0.024)	-0.051* (0.030)	0.119*** (0.027)	-488.739** (235.755)	0.127** (0.055)	0.139** (0.055)	0.122** (0.050)	-38.079*** (11.476)	0.102** (0.044)	-0.061* (0.033)
Means of dependent	4.558	0.792	0.338	0.484	4.829	0.296	0.619	0.721	223.341	0.128	0.114
R-squared	0.113	0.093	0.059	0.085	0.035	0.065	0.060	0.044	0.054	0.047	0.053
Individuals	624	624	624	624	624	624	624	624	624	624	624

## 7 Conclusion

Although a large number of studies have investigated the gender wage gap, the existence and potential explanation behind early career gender wage differences remain unclear. This paper analyzes the gender wage gap among graduates of a German university with a master's degree or equivalent at the beginning of their career and over the first five years after labor market entry. We take advantage of a unique dataset linking administrative data on graduates from a German university with employment registers of the German social security system. This dataset includes extensive information on students' sociodemographic characteristics, their educational and labor market outcomes and the exact timing of graduation, labor market entry and any job change.

We find a significant gender wage gap among university graduates at the first job, which persists even after controlling for an extensive set of controls. The highest gender wage gap is observed among graduates in humanities and social sciences, where the share of females is highest and the average daily wage is lowest. We show no significant gender differences in wages of mathematics, natural sciences and medical graduates at the first job after graduation. In addition, in contrast to previous studies, we find an immediate decrease in the gender wage gap one year after labor market entry, which remains almost stable thereafter.

Further analysis shows that the decline in gender wage differences is concentrated on individuals who switch firm and occupation after their first job with a degree in economics, business, humanities and social sciences. As an explanation for the decrease in the gender wage gap, we further show that female graduates are more likely to start their careers in jobs they are overqualified for and correct this skill mismatch afterwards, leading to an increase in their wages. To avoid a potential skill mismatch in the future, universities can implement counseling interventions that provide information on job search and potential wage losses due to a skill mismatch. In addition, these counseling policies can inform students about the employment prospects associated with a degree in a particular field. The study also is particularly important showing the differences labor market outcomes, the labor market entrance, early career trajectories etc. are different among field of studies. as well as gender wage gap vary by field of study. It suggests that policy makers should take into account this differences and develop policies or counseling accordingly.

## References

- Acemoglu, D. and Shimer, R. (1999). Efficient unemployment insurance. *Journal of political Economy*, 107(5):893–928.
- Adda, J., Dustmann, C., and Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, 125(2):293–337.
- Albrecht, J., Bronson, M. A., Thoursie, P. S., and Vroman, S. (2018). The career dynamics of high-skilled women and men: Evidence from Sweden. *European Economic Review*, 105:83–102.
- Altonji, J. G., Arcidiacono, P., and Maurel, A. (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. In *Handbook of the Economics of Education*, volume 5, pages 305–396. Elsevier.
- Altonji, J. G. and Blank, R. M. (1999). Race and gender in the labor market. *Handbook of labor economics*, 3:3143–3259.
- Altonji, J. G., Blom, E., and Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annu. Rev. Econ.*, 4(1):185–223.
- Altonji, J. G. and Pierret, C. R. (2001). Employer learning and statistical discrimination. *The quarterly journal of economics*, 116(1):313–350.
- Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
- Antoni, M., Ganzer, A., Vom Berge, P., et al. (2016). Sample of integrated labour market biographies (siab) 1975-2014. *FDZ-Datenreport*, 4:2016.
- Babcock, L. and Laschever, S. (2009). *Women don't ask: Negotiation and the gender divide*. Princeton University Press, Princeton.
- Bartel, A. P., Borjas, G. J., and Rosen, S. (2007). *Wage Growth and Job Turnover: An Empirical Analysis*. University of Chicago Press.
- Becker, G. (1971). *The Economics of Discrimination*. University of Chicago Press, Chicago.
- Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Columbia University Press, New York.
- Becker, G. S., Hubbard, W. H., and Murphy, K. M. (2010). Explaining the worldwide boom in higher education of women. *Journal of Human Capital*, 4(3):203–241.

- Bertrand, M. (2011). New perspectives on gender. In *Handbook of labor economics*, volume 4, pages 1543–1590. Elsevier.
- Bertrand, M., Goldin, C., and Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, 2(3):228–55.
- Black, D. A., Haviland, A. M., Sanders, S. G., and Taylor, L. J. (2008). Gender wage disparities among the highly educated. *Journal of human resources*, 43(3):630–659.
- Blau, F. D. and Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865.
- BMBF (2021). Bundesministerium für bildung und forschung. <https://www.datenportal.bmbf.de/portal/de/K254.html>.
- Boudarbat, B. and Montmarquette, C. (2009). Choice of fields of study of university canadian graduates: the role of gender and their parents' education. *Education Economics*, 17(2):185–213.
- Brenøe, A. A. and Zölitz, U. (2020). Exposure to more female peers widens the gender gap in stem participation. *Journal of Labor Economics*, 38(4):1009–1054.
- Bruns, B. (2019). Changes in workplace heterogeneity and how they widen the gender wage gap. *American Economic Journal: Applied Economics*, 11(2):74–113.
- Caldwell, S. and Harmon, N. (2019). Outside options, bargaining, and wages: Evidence from coworker networks. *Unpublished manuscript, Univ. Copenhagen*, pages 203–207.
- Cortes, P. and Pan, J. (2020). Children and the remaining gender gaps in the labor market. Technical report, National Bureau of Economic Research.
- Cortés, P., Pan, J., Pilossoph, L., and Zafar, B. (2021). Gender differences in job search and the earnings gap: Evidence from business majors. Technical report, National Bureau of Economic Research.
- Cox, J. C. and Oaxaca, R. L. (1992). Direct tests of the reservation wage property. *The Economic Journal*, 102(415):1423–1432.
- De Schouwer, T. and Kesternich, I. (2022). It's all about the meaning: Work meaning, job flexibility, and the gender wage gap.
- Del Bono, E. and Vuri, D. (2011). Job mobility and the gender wage gap in Italy. *Labour Economics*, 18(1):130–142.

- Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and stem careers. *The Quarterly Journal of Economics*, 135(4):1965–2005.
- Destatis (2022). *Mothers at 1st birth and Länder*.
- Destatis (2023). *Bildung und Kultur*.
- Dorner, M., Heining, J. Jacobebbinghaus, P., and Seth, S. (2010). Stichprobe der integrierten arbeitsmarktbioografien (siab) 1975-2008. Technical report, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg.
- Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the german wage structure. *The Quarterly Journal of Economics*, 124(2):843–881.
- Farber, H. S. and Gibbons, R. (1996). Learning and wage dynamics. *The Quarterly Journal of Economics*, 111(4):1007–1047.
- Feinberg, R. M. (1977). Risk aversion, risk, and the duration of unemployment. *The Review of Economics and Statistics*, pages 264–271.
- Flabbi, L. and Moro, A. (2012). The effect of job flexibility on female labor market outcomes: Estimates from a search and bargaining model. *Journal of Econometrics*, 168(1):81–95.
- Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition methods in economics. In *Handbook of labor economics*, volume 4, pages 1–102. Elsevier.
- Francesconi, M. and Parey, M. (2018). Early gender gaps among university graduates. *European Economic Review*.
- Fredriksson, P., Hensvik, L., and Skans, O. N. (2018). Mismatch of talent: Evidence on match quality, entry wages, and job mobility. *American Economic Review*, 108(11):3303–3338.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119.
- Goldin, C. and Katz, L. F. (2011). The cost of workplace flexibility for high-powered professionals. *The Annals of the American Academy of Political and Social Science*, 638(1):45–67.
- Goldin, C. and Katz, L. F. (2016). A most egalitarian profession: Pharmacy and the evolution of a family-friendly occupation. *Journal of Labor Economics*, 34(3):705–746.
- Graham, M. E., Hotchkiss, J. L., and Gerhart, B. (2000). Discrimination by parts: A fixed-effects analysis of starting pay differences across gender. *Eastern Economic Journal*, 26(1):9–27.

- Hansen, B. and McNichols, D. (2020). Information and the persistence of the gender wage gap: Early evidence from california's salary history ban. Technical report, National Bureau of Economic Research.
- Heijke, H., Meng, C., and Ris, C. (2003). Fitting to the job: The role of generic and vocational competencies in adjustment and performance. *Labour Economics*, 10(2):215–229.
- Hellerstein, J. K., McInerney, M., and Neumark, D. (2011). Neighbors and coworkers: The importance of residential labor market networks. *Journal of Labor Economics*, 29(4):659–695.
- Jann, B. et al. (2008). The blinder-oaxaca decomposition for linear regression models. *The Stata Journal*, 8(4):453–479.
- Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour economics*, 17(2):303–316.
- Kelly, E., O'Connell, P. J., and Smyth, E. (2010). The economic returns to field of study and competencies among higher education graduates in ireland. *Economics of Education Review*, 29(4):650–657.
- Kirkeboen, L. J., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111.
- Kleven, H., Landais, C., Posch, J., Steinhauer, A., and Zweimüller, J. (2019a). Child penalties across countries: Evidence and explanations. In *AEA Papers and Proceedings*, volume 109, pages 122–26.
- 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.
- Kunze, A. (2005). The evolution of the gender wage gap. *Labour Economics*, 12(1):73–97.
- Kuziemko, I., Pan, J., Shen, J., and Washington, E. (2018). The mommy effect: Do women anticipate the employment effects of motherhood? Technical report, National Bureau of Economic Research.
- Liste der Hochschulen in Deutschland (2021). Liste der hochschulen in deutschland — Wikipedia, the free encyclopedia.
- Lordan, G. and Pischke, J.-S. (2022). Does rosie like riveting? male and female occupational choices. *Economica*, 89(353):110–130.
- Machin, S. and Puhani, P. A. (2003). Subject of degree and the gender wage differential: evidence from the uk and germany. *Economics Letters*, 79(3):393–400.

- Manning, A. and Swaffield, J. (2008). The gender gap in early-career wage growth. *The Economic Journal*, 118(530):983–1024.
- Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–3759.
- Mincer, J. and Polachek, S. (1974). Family investments in human capital: Earnings of women. *Journal of political Economy*, 82(2, Part 2):S76–S108.
- Möller, J. and Rust, C. (2017). The role of a local university for regional development - the case of Regensburg.
- Müller, D., Strauch, K., et al. (2017). Identifying mothers in administrative data. Technical Report 13, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg.
- Niederle, M. and Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much? *The quarterly journal of economics*, 122(3):1067–1101.
- OECD (2019). Education at a glance 2019. <https://www.oecd-ilibrary.org/content/publication/f8d7880d-en>.
- Olivetti, C. and Petrongolo, B. (2016). The evolution of gender gaps in industrialized countries. *Annual review of Economics*, 8:405–434.
- Oreopoulos, P., Von Wachter, T., and Heisz, A. (2012). The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1):1–29.
- Oyer, P. (2006). Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives*, 20(3):143–160.
- Pannenberg, M. (2010). Risk attitudes and reservation wages of unemployed workers: evidence from panel data. *Economics Letters*, 106(3):223–226.
- Pinkston, J. C. (2003). Screening discrimination and the determinants of wages. *Labour Economics*, 10(6):643–658.
- Pinkston, J. C. (2006). A test of screening discrimination with employer learning. *ILR Review*, 59(2):267–284.
- Pissarides, C. A. (1974). Risk, job search, and income distribution. *Journal of Political Economy*, 82(6):1255–1267.
- Robst, J. (2007). Education and Job Match: The Relatedness of College Major and Work. *Economics of Education Review*, 26(4):397–407.

- Roussille, N. (2021). The central role of the ask gap in gender pay inequality. *University of California, Berkeley*.
- Times Higher Education (2021). Best universities in germany 2022. <https://www.timeshighereducation.com/student/best-universities/best-universities-germany>.
- Topel, R. H. and Ward, M. P. (1992). Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics*, 107(2):439–479.
- Vesterlund, L. (1997). The effects of risk aversion on job matching: Can differences in risk aversion explain the wage gap? *Unpublished manuscript, Iowa State University*.
- Wiswall, M. and Zafar, B. (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics*, 133(1):457–507.
- Wolbers, M. H. J. (2003). Job Mismatches and Their Labour-Market Effects among School-Leavers in Europe. *European Sociological Review*, 19(3):249–266.
- Zölitz, U. and Feld, J. (2018). The effect of peer gender on major choice. *University of Zurich, Department of Economics, Working Paper*, (270).



## A Appendix: Data and Additional Descriptive Statistics

This section describes all data preparation steps before the main analysis. If there are multiple contemporaneous employment spells for an individual, we use the main employment spell and exclude the remaining employment spells. The main employment spell as defined by the IAB is the spell with the longest job duration and the highest daily wage. Furthermore, in order to eliminate errors in daily wages for full-time employees, we follow the literature and disregard daily wages below 10 Euro from the main sample (Dustmann et al., 2009; Bruns, 2019).

One issue to consider is that wages in the IEB dataset are only reported up to the social contribution threshold, as the information on wages is obtained from the German Social Security report. Thus, wages above the social contribution limit are right-censored. However, since we analyze the gender wage gap at the beginning of the career, there are not many censored wages in our restricted sample; censored wages account for only 1.3 percent for the first job and around 4.7 percent a year after the first job, with a small increase in subsequent years after graduation.

Moreover, working hours are not recorded in the IEB dataset, as only information is only available on whether a person works in a full-time or part-time job (working more or less than 30 hours per week). For this reason, we only focus on graduates who have a full-time job in their first job after graduation. An individual is considered a full-time employee if he or she works more than 35 hours per week.

We include occupational categories using 3-digit occupational codes (KldB 1988) in the estimations. Since the occupational structure has changed over time, the Federal Employment Agency introduced a new classification (KldB 2010) in 2011 that better fits the current German occupational structure. Since the new classification is more detailed (5-digit) than the old one, there is a significant increase in missing values in the occupation variable in 2011 (Antoni et al., 2016). To address this issue, we fill in the missing values in 2011 by keeping the last occupation spell before the change in occupational classification, and replacing it with latter missing spells, if the place of residence and work, industry code and establishment ID does not change. Following this procedure, the number of missing values in the occupation code reduces significantly for 2011.

Moreover, childbirths are not directly observed in our linked data. However, we can identify family-related interruptions in employment based on the IEB data by applying a reliable approach developed by Müller et al. (2017). This method allows us to identify the timing of employment interruptions and (approximately) the timing of childbirths.

## B Appendix: Figures

Figure B.1: Female Male Ratio across Graduation Years

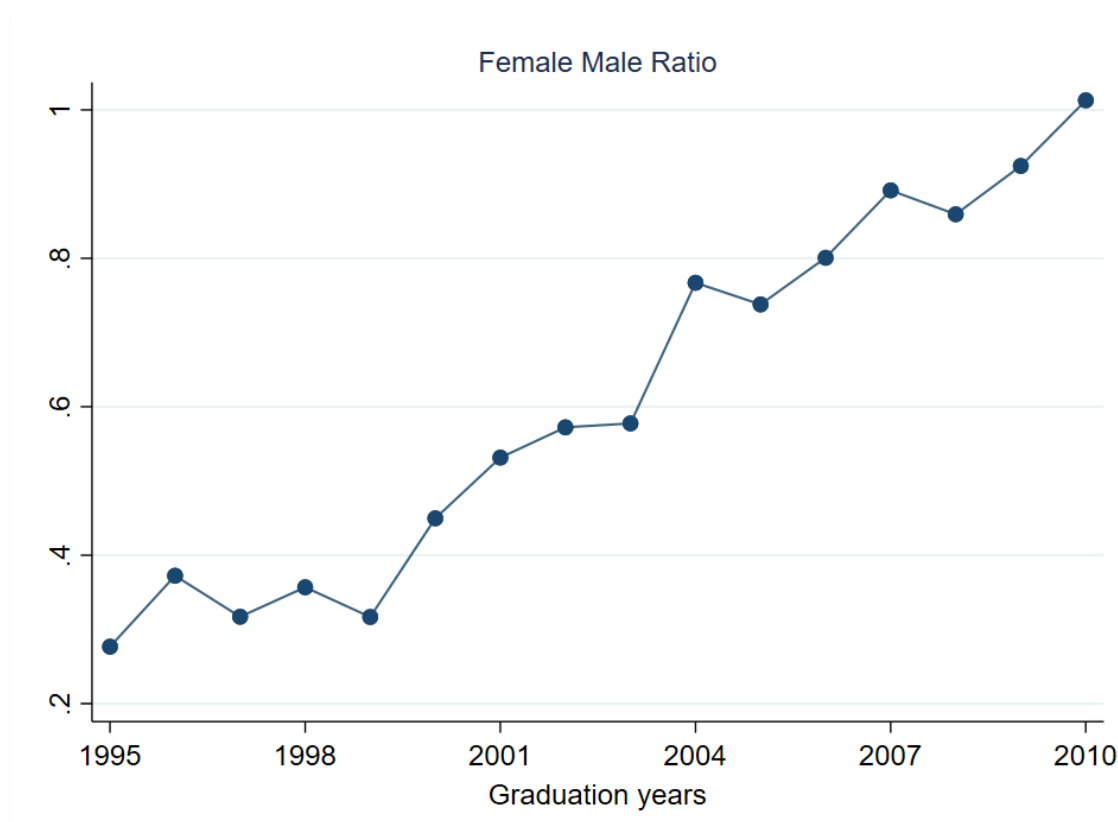


Figure B.2: Female Male Ratio across Graduation Years by Field of Study

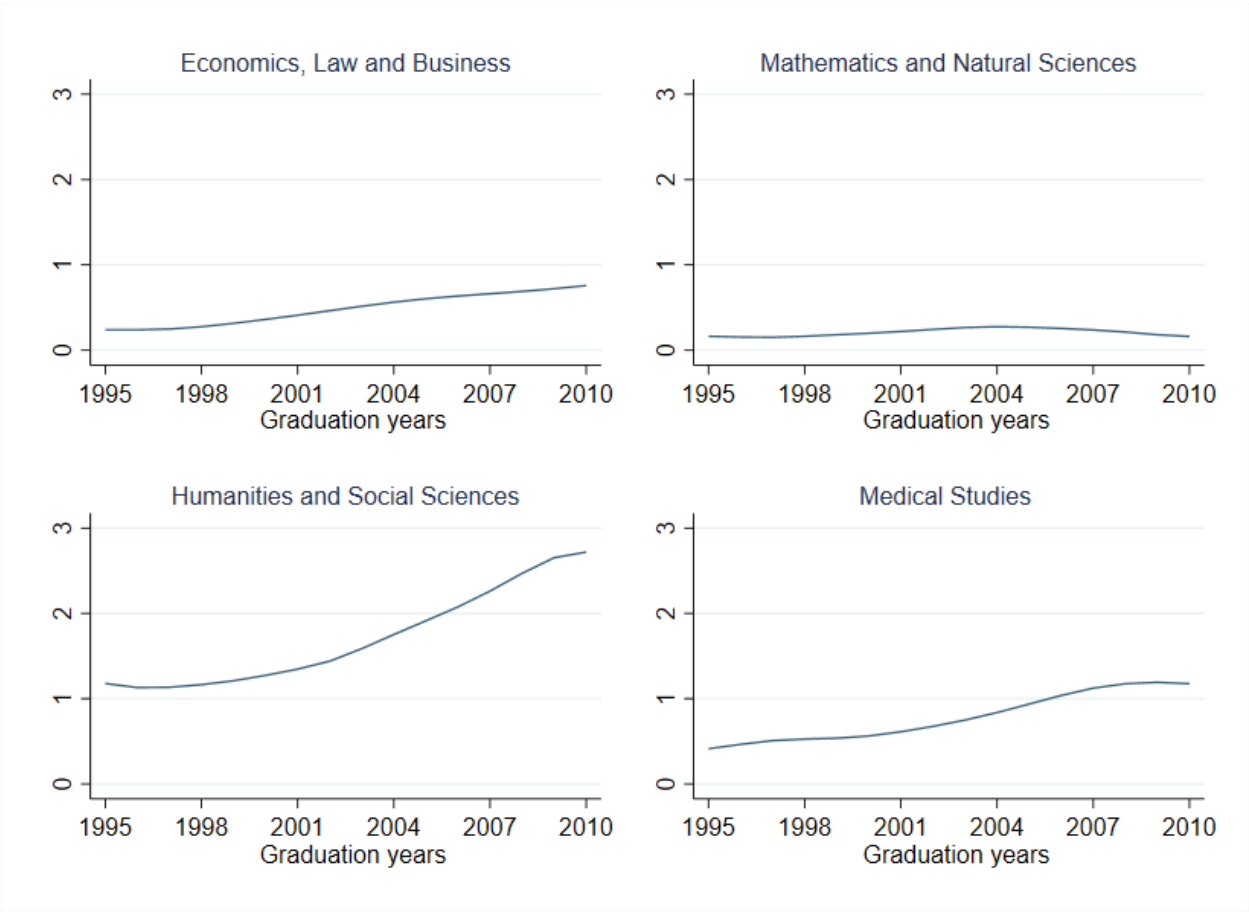


Figure B.3: Unbalanced Sample: Dynamics of the Gender Wage Gap over Years After Labor Market Entry

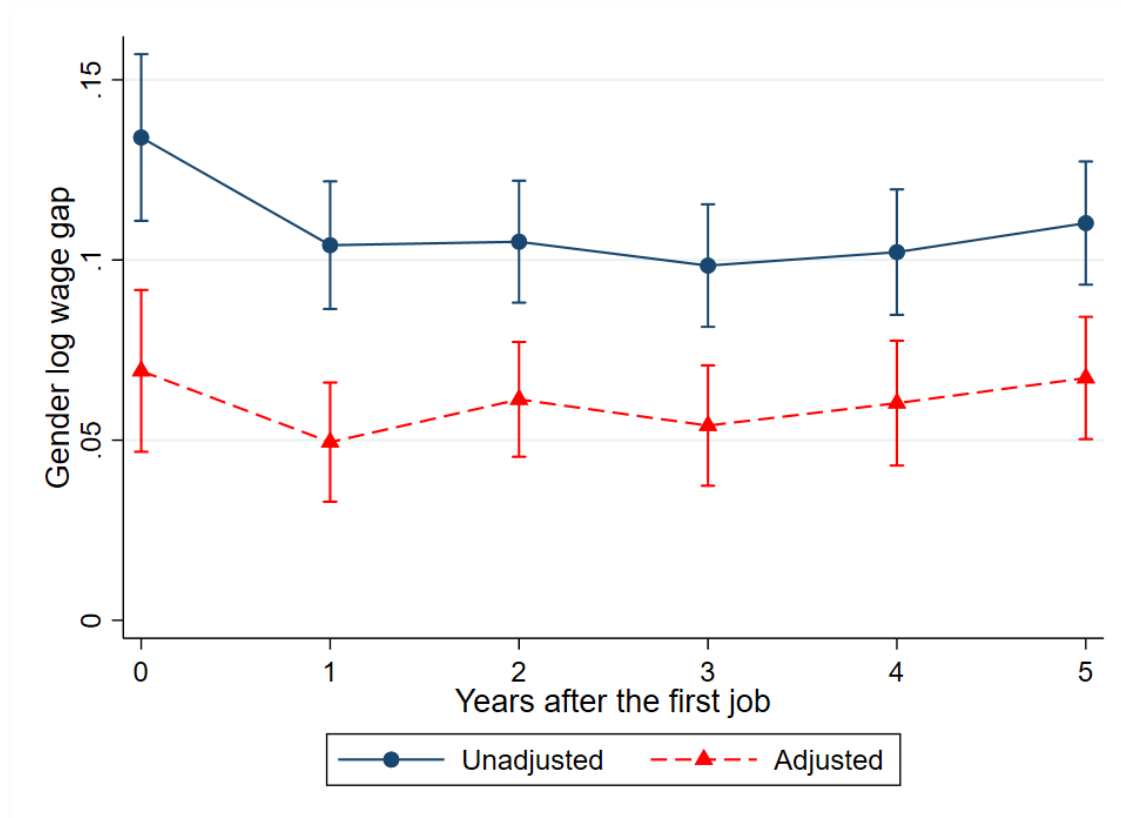
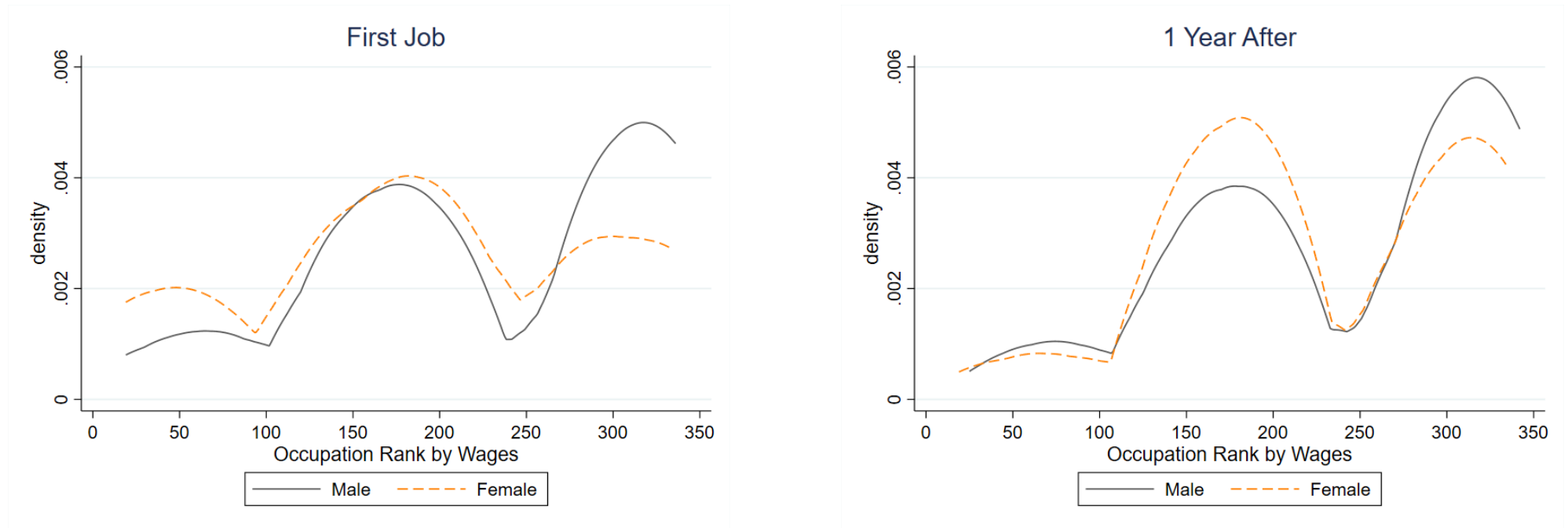


Figure B.4: Distribution of Occupations for Female and Male Job Changers



Note: The figure shows the distribution of male and female job changers across occupations. The plot on the left shows the distribution before the job change (at the first job) and the plot on the right after the job change (1 year after the first job) by gender. The x-axis plots occupations ranked by average earnings from the lowest paying occupation to the highest paying occupation. The ranking of occupations by average earnings is calculated from the SIAB dataset, a 2 percent sample of the entire IEB dataset.

## C Appendix:Tables

Table C. 1: Field of Study Categorization

Field of Study (Combined)	Field of Study (Detailed)
Economics and Business	Economics Business and Management
Mathematics and Natural Sciences	Information Systems Mathematics and Computer Science Physics Chemistry Biology
Humanities and Social Sciences	Geography Theology History, Archaeology and Humanities Languages, Literature and Culture Philosophy, Sociology and Political Psychology Education and Sport
Medical Studies	Medicine Dental Medicine Pharmacy

Table C. 2: Oaxaca-Blinder Decomposition

Dependent Variable: Log Daily Wage				
	First Job		1 Year After	
Mean of male daily wage	4.691		4.832	
Mean of female daily wage	4.570		4.733	
Raw gender wage gap	0.121***		0.099***	
	log points	Percent of gap explained	log points	Percent of gap explained
Total explained	0.052***	43	0.050***	50
Total unexplained	0.069***	57	0.049***	50
<i>Explained by:</i>				
Graduation year	0.005	4	0.006**	6
Age	0.005**	4	0.004**	4
Non-German	-0.002**	2	-0.002**	2
Field of study	0.048***	40	0.044***	44
Duration of study	-0.000	0	-0.000	0
Working during studying	-0.001	1	-0.001	1
Apprenticeship	-0.000	0	-0.000	0
Grade	-0.006**	5	-0.004***	4
Place of the final high-school examination	0.004*	3	0.004	4

Note: Decomposition methods allow to split the mean wage gap into an explained component (due to differences in characteristics) and an unexplained component (due to differences in returns to these characteristics). The decomposition model used in this table is the aggregate two-fold decomposition. See Fortin et al. (2011) for detailed information on the methodology, and Jann et al. (2008) for a STATA application.

Table C. 3: Descriptive Statistics - Stayers and Firm and Occupation Changers

Dependent variables:						
	Male	Stayers Female	Male-Female	Occupation and Firm Changers Male	Female	Male-Female
<b>Panel A: Economics, Business, Humanities and Social Sciences</b>						
Age at the First Job	27.467	26.674	0.793***	27.899	26.990	0.908***
non-German	0.014	0.038	-0.024***	0.017	0.015	0.003
Duration of Study	5.527	5.463	0.064	5.576	5.716	-0.140
Working During Studying	0.659	0.784	-0.124***	0.676	0.787	-0.110**
Apprenticeship	0.074	0.063	0.011	0.133	0.096	0.037
Origin is Bayern	0.843	0.876	-0.033**	0.867	0.875	-0.008
Final Uni. Grade	2.187	1.976	0.210***	2.223	2.082	0.140**
Duration of Job Search	3.388	3.518	-0.129	3.110	3.010	0.100
Median Daily Log Wage of Full-time Employees in a Firm	4.662	4.622	0.041***	4.543	4.416	0.126***
Share of Part-time Employees in a Firm	0.791	0.757	0.035***	0.809	0.767	0.042*
Share of High Qualified Employees in a Firm	0.395	0.379	0.016	0.332	0.302	0.030
Share of Women in a Firm	0.452	0.524	-0.071***	0.446	0.561	-0.115***
Log Firm Size	5.222	5.119	0.102	4.881	4.575	0.306
Horizontal Mismatch Occupation	0.148	0.270	-0.122***	0.267	0.397	-0.130**
Vertical Mismatch	0.469	0.475	-0.005	0.591	0.713	-0.122**
Horizontal or Vertical Mismatch	0.538	0.588	-0.051**	0.688	0.809	-0.121**
Occupation Rank	236.061	220.823	15.238***	228.381	190.772	37.609***
Occupation Rank < Quantile 10	0.090	0.118	-0.029**	0.102	0.213	-0.111***
Occupation Rank > Quantile 90	0.121	0.085	0.036***	0.119	0.059	0.060*
Observations	1503	904		176	136	
<b>Panel B: Mathematics, Natural Sciences and Medical Studies</b>						
Age at the First Job	27.476	26.993	0.482***	28.120	27.027	1.093***
non-German	0.014	0.018	-0.004	0.024	0.060	-0.036
Duration of Study	5.692	5.870	-0.178**	5.938	6.008	-0.070
Working During Studying	0.660	0.661	-0.002	0.747	0.720	0.027
Apprenticeship	0.043	0.041	0.001	0.133	0.120	0.013
Origin is Bayern	0.914	0.855	0.059***	0.880	0.820	0.060
Final Uni. Grade	1.858	2.007	-0.149***	1.835	1.845	-0.010
Duration of Job Search	3.330	3.671	-0.341**	2.748	3.462	-0.714
Median Daily Log Wage of Full-time Employees in a Firm	4.576	4.499	0.077***	4.306	4.236	0.070
Share of Part-time Employees in a Firm	0.689	0.609	0.080***	0.677	0.625	0.053
Share of High Qualified Employees in a Firm	0.317	0.242	0.075***	0.219	0.198	0.021
Share of Women in a Firm	0.552	0.714	-0.162***	0.522	0.755	-0.233***
Log Firm Size	5.594	5.690	-0.095	3.934	4.046	-0.111
Horizontal Mismatch Occupation	0.196	0.084	0.112***	0.425	0.260	0.165*
Vertical Mismatch	0.121	0.100	0.021	0.402	0.460	-0.058
Horizontal or Vertical Mismatch	0.263	0.139	0.124***	0.575	0.500	0.075
Occupation Rank	285.685	290.981	-5.296	227.080	199.800	27.280
Occupation Rank < Quantile 10	0.116	0.098	0.018	0.172	0.180	-0.008
Occupation Rank > Quantile 90	0.372	0.584	-0.212***	0.172	0.160	0.012
Observations	1148	570		87	50	



Table C. 4: Descriptive Statistics - Only Firm Changers and Only Occupation Changers

Dependent variables:						
	Only Firm Changers			Only Occupation Changers		
	Male	Female	Male-Female	Male	Female	Male-Female
<b>Panel A: Economics, Business, Humanities and Social Sciences</b>						
Age at the First Job	27.899	26.990	0.908***	27.536	27.125	0.411
non-German	0.017	0.015	0.003	0.027	0.044	-0.018
Duration of Study	5.576	5.716	-0.140	5.444	5.535	-0.092
Working During Studying	0.676	0.787	-0.110**	0.726	0.752	-0.027
Apprenticeship	0.133	0.096	0.037	0.097	0.088	0.009
Origin is Bayern	0.867	0.875	-0.008	0.876	0.814	0.062
Final Uni. Grade	2.223	2.082	0.140**	2.267	1.981	0.286***
Duration of Job Search	3.110	3.010	0.100	3.133	3.954	-0.820
Median Daily Log Wage of Full-time Employees in a Firm	4.647	4.503	0.144***	4.489	4.417	0.073
Share of Part-time Employees in a Firm	0.822	0.803	0.019	0.778	0.749	-0.020
Share of High Qualified Employees in a Firm	0.335	0.323	0.012	0.269	0.289	-0.024
Share of Women in a Firm	0.439	0.538	-0.099***	0.433	0.545	-0.112***
Log Firm Size	4.829	4.874	-0.044	5.016	4.705	0.311
Horizontal Mismatch Occupation	0.180	0.274	-0.094*	0.430	0.426	0.004
Vertical Mismatch	0.567	0.581	-0.015	0.656	0.723	-0.067
Horizontal or Vertical Mismatch	0.647	0.667	-0.020	0.828	0.842	-0.014
Occupation Rank	245.127	222.197	22.930**	171.000	178.396	-7.396
Occupation Rank < Quantile 10	0.293	0.427	-0.134**	0.161	0.208	-0.047
Occupation Rank > Quantile 90	0.140	0.043	0.097	0.075	0.089	-0.014
Observations	150	117		93	101	
<b>Panel B: Mathematics, Natural Sciences and Medical Studies</b>						
Age at the First Job	27.868	27.186	0.682	27.890	27.767	0.123
non-German	0.042	0.056	-0.014	0.000	0.000	0.000
Duration of Study	5.646	5.723	-0.077	5.764	5.772	-0.008
Working During Studying	0.677	0.622	0.055	0.686	0.654	0.032
Apprenticeship	0.052	0.033	0.019	0.078	0.154	-0.075
Origin is Bayern	0.885	0.800	0.085	0.941	0.769	0.172**
Final Uni. Grade	2.011	2.145	-0.135	1.908	1.809	0.099
Duration of Job Search	3.860	3.193	0.667	3.568	3.270	0.297
Median Daily Log Wage of Full-time Employees in a Firm	4.440	4.445	-0.005	4.386	4.384	0.002
Share of Part-time Employees in a Firm	0.665	0.596	0.069**	0.747	0.697	0.049
Share of High Qualified Employees in a Firm	0.234	0.205	0.029	0.236	0.213	0.023
Share of Women in a Firm	0.645	0.781	-0.136***	0.523	0.694	-0.171**
Log Firm Size	4.764	5.186	-0.421	4.834	4.827	0.007
Horizontal Mismatch Occupation	0.167	0.063	0.104**	0.526	0.364	0.163
Vertical Mismatch	0.157	0.063	0.095**	0.500	0.455	0.045
Horizontal or Vertical Mismatch	0.241	0.083	0.157***	0.658	0.545	0.112
Occupation Rank	285.074	303.615	-18.541	227.053	221.136	5.916
Occupation Rank < Quantile 10	0.380	0.271	0.109	0.132	0.136	-0.005
Occupation Rank > Quantile 90	0.454	0.688	-0.234***	0.211	0.227	-0.017
Observations	108	96		38	22	

Table C. 5: The First Job Characteristics of Stayers, Only Firm Changers, Only Occupation Changers

Dependent variables:								
	Personal Characteristics		Pre-Graduation Characteristics				Finding First Job Characteristic	
	Age at the first job (1)	non-German (2)	Duration of Study (3)	Working During Studying (4)	Apprent. (5)	Origin is Bayern (6)	Final Uni. Grade (7)	Duration of Job Search (8)
<b>Panel A: Stayers</b>								
Female × Stayers	-0.148 (0.182)	0.008 (0.013)	-0.100 (0.116)	0.039 (0.038)	0.005 (0.025)	0.062** (0.030)	0.009 (0.051)	0.199 (0.284)
Stayers	-0.235** (0.111)	0.001 (0.006)	-0.091 (0.071)	-0.005 (0.027)	-0.039** (0.017)	-0.032* (0.019)	-0.052 (0.033)	-0.158 (0.183)
Female	-0.654*** (0.162)	0.018 (0.011)	0.047 (0.104)	0.088*** (0.034)	-0.016 (0.023)	-0.028 (0.026)	-0.215*** (0.045)	-0.058 (0.252)
R-squared Individuals	0.038 3,114	0.006 3,114	0.002 3,114	0.016 3,114	0.004 3,114	0.002 3,114	0.033 3,114	0.000 3,114
<b>Panel B: Only Firm Changers</b>								
Female × Only Firm Changers	0.163 (0.244)	-0.000 (0.016)	-0.058 (0.144)	-0.018 (0.056)	-0.016 (0.039)	-0.044 (0.044)	-0.049 (0.077)	-0.375 (0.440)
Only Firm Changers	-0.036 (0.159)	-0.014*** (0.003)	0.138 (0.096)	0.014 (0.040)	0.050* (0.027)	0.029 (0.029)	0.053 (0.049)	0.282 (0.284)
Female	-0.803*** (0.082)	0.026*** (0.007)	-0.053 (0.053)	0.126*** (0.018)	-0.010 (0.010)	0.034** (0.014)	-0.206*** (0.023)	0.141 (0.131)
Means of dependent variable	27.216	0.023	5.516	0.711	0.078	0.856	2.115	3.412
R-squared Individuals	0.039 2,671	0.008 2,671	0.001 2,671	0.018 2,671	0.003 2,671	0.002 2,671	0.034 2,671	0.001 2,671
<b>Panel C: Only Occupation Changers</b>								
Female × Only Occupation Changers	0.140 (0.345)	-0.009 (0.029)	0.111 (0.235)	-0.092 (0.068)	0.045 (0.041)	-0.115** (0.052)	-0.068 (0.091)	-0.113 (0.540)
Only Occupation Changers	0.434** (0.219)	0.018 (0.019)	0.096 (0.158)	0.016 (0.050)	-0.005 (0.026)	0.048 (0.033)	0.131* (0.067)	0.276 (0.364)
Female	-0.803*** (0.082)	0.026*** (0.007)	-0.053 (0.053)	0.126*** (0.018)	-0.010 (0.010)	0.034** (0.014)	-0.206*** (0.023)	0.141 (0.131)
R-squared Individuals	0.040 2,598	0.007 2,598	0.001 2,598	0.017 2,598	0.001 2,598	0.003 2,598	0.035 2,598	0.001 2,598

Table C. 6: The Job Characteristics of Stayers

Dependent variables:											
	Median Daily Log Wage of Full-time Employees (1)	Share of Part-time Employees (2)	Share of High Qualified Employees (3)	Share of Women in a Firm (4)	Log Firm Size (5)	Horizontal Mismatch (6)	Vertical Mismatch (7)	Horizontal or Vertical Mismatch (8)	Occupation Rank (9)	Occupation Rank < Quantile 10 (10)	Occupation Rank > Quantile 90 (11)
<b>Panel A: The Characteristics of the First Job of Stayers</b>											
Female × Stayers	0.087*** (0.033)	-0.007 (0.017)	-0.005 (0.022)	-0.037* (0.019)	0.103 (0.183)	0.018 (0.039)	-0.064 (0.042)	-0.013 (0.039)	9.596 (8.154)	-0.042 (0.030)	0.022 (0.024)
Stayers	0.087*** (0.020)	-0.011 (0.011)	0.074*** (0.015)	0.010 (0.012)	0.316*** (0.118)	-0.109*** (0.024)	-0.123*** (0.028)	-0.156*** (0.027)	13.383** (5.336)	-0.040** (0.018)	0.004 (0.018)
Female	-0.127*** (0.030)	-0.028* (0.015)	-0.011 (0.019)	0.108*** (0.017)	-0.205 (0.160)	0.103*** (0.035)	0.069* (0.036)	0.064* (0.034)	-24.833*** (7.316)	0.055** (0.027)	-0.058*** (0.021)
Mean of Dependent Variables	4.617	0.781	0.372	0.482	5.099	0.219	0.506	0.594	226.031	0.104	0.104
R-squared	0.034	0.007	0.015	0.038	0.006	0.032	0.017	0.023	0.018	0.009	0.005
Individuals	3,114	3,114	3,114	3,114	3,114	3,114	3,114	3,114	3,114	3,114	3,114
<b>Panel B: The Characteristics of Dynamic of Firm and Occupation Changers</b>											
Female × 1 year after	-0.007 (0.005)	0.002 (0.003)	-0.004 (0.003)	0.011*** (0.003)	42.325 (37.631)	0.000 (0.000)	-0.008 (0.005)	-0.003 (0.004)	-0.000 (.)	0.000 (.)	0.000 (0.000)
1 year after	0.027*** (0.003)	-0.006*** (0.002)	0.010*** (0.002)	-0.003** (0.002)	17.426 (14.082)	-0.000 (.)	-0.002 (0.003)	-0.000 (0.002)	0.000*** (0.000)	-0.000 (0.000)	-0.000 (0.000)
Female	-0.075*** (0.014)	-0.016* (0.008)	-0.024** (0.011)	0.068*** (0.009)	-75.816 (149.017)	0.103*** (0.018)	-0.002 (0.022)	0.035 (0.021)	-12.180*** (3.687)	0.016 (0.013)	-0.038*** (0.013)
Mean of Dependent Variables	4.659	0.776	0.393	0.479	5.219	0.194	0.469	0.556	230.338	0.095	0.108
R-squared	0.080	0.059	0.018	0.046	0.009	0.038	0.009	0.014	0.022	0.010	0.013
Individuals	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814	4,814

Table C. 7: The Job Characteristics of Only Occupation Changers

Dependent variables:											
	Median Daily Log Wage of Full-time Employees (1)	Share of Part-time Employees (2)	Share of High Qualified Employees (3)	Share of Women in a Firm (4)	Log Firm Size (5)	Horizontal Mismatch (6)	Vertical Mismatch (7)	Horizontal or Vertical Mismatch (8)	Occupation Rank (9)	Occupation Rank < Quantile 10 (10)	Occupation Rank > Quantile 90 (11)
<b>Panel A: The Characteristics of the First Job of Only Occupation Changers</b>											
Female × Only Occupation Changers	-0.032 (0.061)	0.006 (0.033)	0.036 (0.037)	0.041 (0.035)	-0.209 (0.339)	-0.126* (0.073)	0.061 (0.070)	-0.037 (0.057)	22.634 (15.457)	-0.016 (0.066)	0.051 (0.039)
Only Occupation Changers	-0.173*** (0.040)	-0.013 (0.023)	-0.126*** (0.025)	-0.020 (0.023)	-0.205 (0.221)	0.282*** (0.052)	0.187*** (0.051)	0.290*** (0.041)	-65.061*** (10.759)	0.194*** (0.047)	-0.057** (0.027)
Female	-0.041*** (0.014)	-0.035*** (0.008)	-0.016 (0.011)	0.071*** (0.009)	-0.102 (0.090)	0.122*** (0.017)	0.005 (0.021)	0.051** (0.021)	-15.238*** (3.602)	0.013 (0.012)	-0.036*** (0.013)
Mean of Dependent Variables	4.617	0.781	0.372	0.482	5.099	0.219	0.506	0.594	226.031	0.104	0.104
R-squared	0.027	0.008	0.014	0.033	0.003	0.042	0.014	0.024	0.034	0.027	0.004
Individuals	2,601	2,601	2,601	2,601	2,601	2,601	2,601	2,601	2,601	2,601	2,601
<b>Panel B: The Characteristics of Dynamic of Only Occupation Changers</b>											
1 year after × Female	0.066 (0.061)	-0.029 (0.035)	-0.023 (0.044)	0.058 (0.037)	-624.132 (386.118)	0.134* (0.069)	-0.063 (0.085)	0.042 (0.079)	-23.973 (18.620)	0.108 (0.075)	-0.075 (0.057)
1 year after	0.039 (0.042)	0.049** (0.023)	0.060** (0.030)	-0.054** (0.021)	395.419 (353.225)	-0.194*** (0.050)	-0.075 (0.063)	-0.151*** (0.056)	63.280*** (12.952)	-0.237*** (0.055)	0.075* (0.045)
Female	-0.111* (0.059)	-0.013 (0.033)	0.012 (0.035)	0.098*** (0.035)	210.898 (693.816)	-0.022 (0.072)	0.078 (0.068)	0.011 (0.055)	1.021 (15.190)	-0.018 (0.065)	0.009 (0.037)
Mean of Dependent Variables	4.528	0.199	0.310	0.466	4.993	0.354	0.613	0.759	200.250	0.209	0.090
R-squared	0.072	0.091	0.069	0.165	0.094	0.090	0.063	0.063	0.121	0.116	0.034
Individuals	388	388	388	388	388	388	388	388	388	388	388

Table C. 8: The Job Characteristics of Only Firm Changers

Dependent variables:											
	Median Daily Log Wage of Full-time Employees (1)	Share of Part-time Employees (2)	Share of High Qualified Employees (3)	Share of Women in a Firm (4)	Log Firm Size (5)	Horizontal Mismatch (6)	Vertical Mismatch (7)	Horizontal or Vertical Mismatch (8)	Occupation Rank (9)	Occupation Rank < Quantile 10 (10)	Occupation Rank > Quantile 90 (11)
<b>Panel A: The Characteristics of the First Job of Only Firm Changers</b>											
Female × Only Firm Changers	-0.103** (0.048)	0.016 (0.023)	0.004 (0.033)	0.028 (0.027)	0.146 (0.259)	-0.028 (0.055)	0.009 (0.065)	-0.031 (0.062)	-7.693 (10.474)	-0.007 (0.031)	-0.061* (0.036)
Firm Changers	-0.015 (0.026)	0.030** (0.015)	-0.060*** (0.022)	-0.013 (0.017)	-0.392** (0.169)	0.032 (0.033)	0.098** (0.042)	0.109*** (0.041)	9.066 (7.005)	-0.032 (0.020)	0.019 (0.030)
Female	-0.041*** (0.014)	-0.035*** (0.008)	-0.016 (0.011)	0.071*** (0.009)	-0.102 (0.090)	0.122*** (0.017)	0.005 (0.021)	0.051** (0.021)	-15.238*** (3.602)	0.013 (0.012)	-0.036*** (0.013)
Mean of Dependent Variables	4.617	0.781	0.372	0.482	5.099	0.219	0.506	0.594	226.031	0.104	0.104
R-squared	0.011	0.010	0.006	0.033	0.003	0.022	0.004	0.006	0.009	0.002	0.005
Individuals	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674
<b>Panel B: The Characteristics of Dynamic of Only Firm Changers</b>											
1 year after × Female	0.119** (0.046)	-0.008 (0.023)	0.008 (0.028)	-0.047* (0.025)	20.356 (411.579)	-0.024 (0.017)	-0.010 (0.032)	-0.032 (0.029)	1.703 (4.971)	-0.002 (0.015)	-0.020 (0.024)
1 year after	0.056** (0.024)	-0.022 (0.015)	0.051*** (0.019)	0.028* (0.016)	72.473 (357.704)	0.007 (0.012)	-0.007 (0.020)	0.007 (0.018)	3.673 (3.327)	-0.007 (0.012)	0.020 (0.020)
Female	-0.174*** (0.047)	-0.009 (0.023)	-0.008 (0.033)	0.103*** (0.026)	-216.014 (317.327)	0.129** (0.056)	-0.007 (0.062)	0.025 (0.060)	-22.953** (10.857)	0.003 (0.034)	-0.110*** (0.035)
Mean of Dependent Variables	4.638	0.801	0.357	0.486	4.896	0.219	0.567	0.652	237.288	0.052	0.103
R-squared	0.107	0.079	0.063	0.071	0.033	0.054	0.078	0.069	0.087	0.026	0.101
Individuals	534	534	534	534	534	534	534	534	534	534	534

Table C. 9: The Additional Job Characteristics of Firm and Occupation Changers

Dependent variables:				
	Meaning (1)	Schedule Adaptability (2)	Telecommuting (3)	Parttime Work (4)
Female × 1 Year After	-0.010 (0.020)	0.025* (0.015)	0.037 (0.032)	-0.034 (0.022)
1 Year After	-0.005 (0.013)	-0.004 (0.010)	-0.027 (0.022)	0.001 (0.014)
Female	0.024 (0.016)	-0.021* (0.012)	-0.017 (0.025)	0.041** (0.018)
R-squared Individuals	0.048 312	0.034 312	0.026 312	0.043 312