The Transition from University to the Labor Market with a Focus on Gender

Inaugural Dissertation

zur Erlangung des akademischen Grades
"Dr. rer. pol."

eingereicht an der
Fakultät für Sozial-und Wirtschaftswissenschaften
Otto-Friedrich-Universität Bamberg

vorgelegt von
Ipek Yükselen, M.Sc.
2024

Bamberg

Kumulative Dissertation

Diese Arbeit wurde der Fakultät Sozial- und Wirtschaftswissenschaften der Otto-Friedrich-Universität Bamberg als Dissertation vorgelegen.

Mitglieder der Promotionskommission

Erstgutachterin:	Prof. Dr. Silke Anger Otto-Friedrich-Universität Bamberg
Zweitgutachterin:	Prof. Dr. Pia Pinger Universität zu Köln
Drittgutachter:	Prof. Dr. Guido Heineck Otto-Friedrich-Universität Bamberg

Tag der mündlichen Prüfung: 22.07.2024

URN: urn:nbn:de:bvb:473-irb-978816
DOI: https://doi.org/10.20378/irb-97881

Acknowledgements

First and foremost, I am extremely grateful to my first supervisor, Silke Anger, for her invaluable guidance, unwavering support, and encouragement throughout the journey of completing this dissertation. She helped me at every critical stage of my research and provided me with constructive and detailed feedback. Her commitment to her work and to the success of her students has kept me motivated and inspired.

I would also like to thank my second supervisor, Pia Pinger, for her generous time, insightful feedback, and support. I am also grateful to Nikki Shure for making my research stay at UCL a smooth, productive, and enlightening experience. My thanks also extend to Johanna Rickne and Ute Leber for their help, input, and guidance. I consider myself incredibly fortunate to have been guided along my academic journey by such intelligent, supportive, kind, and inspiring role models. I am also grateful to my dissertation committee member, Guido Heineck, and my mentor, Malte Sandner, both of whom have provided insightful feedback and support over the years.

Many of my colleagues and friends at the IAB have made the Ph.D. journey more fruitful and enjoyable. I would like to thank them all, especially Jacopo Bassetto, whom I have always admired both for his intellect and his kindness. Special thanks to Teresa Monteiro, Teresa Friedrich, Carina Toussaint, Anica Kramer, Judith Hild, and Max Kunaschk for their support and being a friendly ear during the ups and downs of the Ph.D. I would also like to thank the GradAB program of the IAB, which supported me both financially and otherwise.

I am also indebted to the IAB for the financial support of my online experiment, which played a crucial role in the progress of my research. Special thanks to Bernd Fitzenberger for his support of this experiment, and to the research assistants, especially Johanna Sauer, Derya Cevik, Regina Reck, and Paul Setzepfand for their excellent support throughout this study.

Outside of the IAB, I am immensely grateful to my friends, especially Deepita and her lovely family, for their constant presence and encouragement. I would also like to thank all my friends in Turkey, who are my extended family, for their incredible support and endless love. I would like to thank all my family members in Turkey, especially my mother, Gülay, for her love and constant support, and my dear sister, Irem, for her love, encouragement, and always sharing a laugh with me. This thesis would not have been possible without them. A special thank you to my partner, Salwan, who has been by my side throughout this challenging and rewarding journey. His patience, understanding, and love keep me strong and motivated.

This thesis is dedicated to the memory of my father, Vahit, and my grandmother, Necla, the most generous, kind, and selfless people I have ever known. Their love and support made it all possible.

Contents

List of Figures

List of Tables

List of Acronyms

ATE	Average Treatment Effect
EU	European Unions
FE	Fixed Effects
GPA	Grade Point Average
IAB	Institut für Arbeitsmarkt- und Berufsforschung (Institute for Employment Research)
IEB	Integrierte Erwerbsbiographien (Integrated Employment Biographies)
ITT	Intent-to-Treat
IV	Instrumental Variable
LATE	Local Average Treatment Effect
OECD	The Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
RCT	Randomized Controlled Trial
SD	Standard Deviation
STEM	Science, Technology, Engineering, and Mathematics
U.S.	United States
2SLS	Two Stage Least Squares Estimator

1 Introduction

The transition from university to the labor market is a crucial career stage for university graduates. Several studies show that lower entry wages have long-lasting effects on the careers of university graduates (e.g., Gerhart, 1990). In addition, negative experiences and unfavorable labor market conditions at labor market entry, such as unemployment and recessions, can negatively affect entry wages and thus wages in the long run (Oyer, 2006; Kahn, 2010; Oreopoulos et al., 2012). For example, Oreopoulos et al. (2012) find that graduates who enter the labor market during a recession have lower earnings on average compared to those who start their careers in better labor market conditions, and that this earnings penalty persists for 10 years. Moreover, initial wages play an important role in determining subsequent wage increases due to promotions within the same firm (Graham et al., 2000), while wage increases following a job change are also typically based on prior wages (Hansen and McNichols, 2020). These findings provide evidence that the transition period to the labor market plays an important role in determining both initial and future labor market outcomes of graduates in the long run and is therefore important to study.

However, at the beginning of a career, both workers and employers face information frictions and uncertainty (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Heller and Kessler, 2021). On the supply side, workers may face uncertainty regarding job opportunities and the identification of high-paying firms, while on the demand side, employers may be uncertain about the productivity of recent graduates, relying primarily on resumes for assessment (Holzer, 1988; Gonzalez and Shi, 2010). As a result, information frictions can lead to lower wages, unemployment, or skill mismatches at labor market entry (Heller and Kessler, 2021). The impact of information frictions may vary across different groups, for example, if females have less information about the labor market than males, or if employers discriminate against females as a result of information frictions (e.g., Blau and Kahn, 2017), which may translate into gender wage gaps in the labor market. For the stated reasons, active labor market policies have been implemented to reduce information frictions and asymmetries between groups and improve the labor market outcomes of employees (Card et al., 2010).

This dissertation analyzes key determinants of the transition from university to the labor market, with a particular focus on gender differences and the impact of information on labor market outcomes. The dissertation is structured in two parts. The first part focuses on gender differences during the transition from university to the labor market. In particular, in Chapter 2, I experimentally investigate the role of information in the gender negotiation gap, which may have implications for labor market outcomes such as wages. In Chapter 3, I empirically analyze the early career gender wage gap and the role of skill mismatch in narrowing the gender wage gap after labor market entry, which may be a result of information asymmetries. The second part of this dissertation (Chapter 4) focuses on graduates' networks from student jobs, which may improve entry wages by potentially reducing information frictions.

The chapters share three common themes. First, as noted above, all chapters cover the crucial transition period from university to the labor market. Second, the chapters focus on highly educated individuals, specifically master's graduates. Studying the labor market outcomes of master's graduates is important given the high returns to a postgraduate degree compared to vocational training, high school education, or only a bachelor's degree (Altonji et al., 2016). In addition, master's graduates have a higher degree of attachment to the labor market and form a relatively homogeneous group, making it easier to identify factors that impact entry-level wages. They are also an ideal group to study early career gender wage gaps, as child care, a key factor in the wage gap for highly educated individuals, has less of an impact at this stage.

Third, all chapters are based on data for Germany. Germany is an interesting case with a high employment rate of 94.4% for recent graduates (aged 20-34), which is higher than the EU average of 86.7% (Eurostat, 2023a). In addition, Germany has reliable and detailed administrative datasets that allow us to study student jobs, networks built from student jobs, and graduates' first wages after labor market entry. Furthermore, despite its strict anti-discrimination policies (e.g., Maier, 2007), Germany has a high gender wage gap of 17.6% , above the EU average, which is even higher for highly educated individuals (Kuziemko et al., 2018; Kleven et al., 2019b; Cortés et al., 2023). Finally, Germany has a comparatively high student employment rate of 60% (Staneva, 2015), which makes the analysis of potential networks acquired through student jobs in Chapter 4 more relevant.

The focus of the first part of this dissertation, gender inequality in the labor market, has been studied by a wide range of disciplines, including sociology, social psychology, psychology, business, and management. The prevailing argument for addressing this inequality is usually based on the fairness argument that women should have the same opportunities as men. However, why should economists in particular be interested in this phenomenon? Studies show that reducing gender inequality enhances economic growth by facilitating a more efficient allocation of human resources, in this case human talent, across various jobs and into high-paying occupations. The idea is based on the notion that men and women have a similar distribution of talent at birth. Nowadays, girls even outperform boys in school and invest more in education (Blau and Kahn, 2017). Thus, any barriers women face in the labor market not only limit their ability to fully utilize their skills, but also disincentivize further investment in human capital. This inefficient allocation of talent distorts economic outcomes (Bertrand, 2020; Sevilla, 2020). For example, Hsieh et al. (2019) show that from 1960 to 2008, approximately 15 to 20% of U.S. GDP growth can be attributed to the reduction of barriers for women and African Americans to enter occupations in which they were previously significantly underrepresented.

In the literature, the gender wage gap stands out as a prominent aspect of gender inequality in labor markets. This gap persists in advanced economies despite significant progress in women's educational attainment and increased labor force participation (Goldin, 2006; Bertrand, 2011; Blau and Kahn, 2017; Bertrand, 2020). In 2021, female workers in European countries earned on average 12.7% and in Germany 17.6% less than their male counterparts (Eurostat, 2023b). Previous research also documents both an unadjusted (raw) and an adjusted gender wage gap early in the career of university graduates (Francesconi and Parey, 2018; Cortés et al., 2023). In the literature, this unexplained part of the gender wage gap is typically attributed to gender differences in psychological traits and preferences, such as taste for competition and negotiation, as well as ability and wage discrimination (Blau and Kahn, 2017). Studies show that the gender negotiation gap accounts for a significant part of the unexplained part of the gender wage gap (Babcock and Laschever, 2003; Card et al., 2016), especially among university graduates (Säve-Söderbergh, 2019).

In Chapter 2, I focus on the gender negotiation gap, which is an important contributor to the gender wage gap, particularly for highly educated individuals. This chapter analyzes the causal effect of information on university graduates' negotiation intentions and actual negotiation behavior during their first job search after graduation, particularly for women. Many studies show that women are less likely to enter negotiations (Babcock and Laschever, 2003; Mazei et al., 2015; Stuhlmacher and Walters, 1999) and also gain less from negotiations than men (Säve-Söderbergh, 2019; Mazei et al., 2015; Stuhlmacher and Walters, 1999; Babcock and Laschever, 2003). This is particularly the case for highly skilled individuals (Brenzel et al., 2014). The recent personal experience of Claudia Goldin, a Nobel laureate for her work on women's labor market outcomes, is a good analogy for these findings. When evaluating a project, she did not feel compelled to ask for higher compensation, while two other male external consultants on the assignment negotiated the proposed pay. She later learned that the male consultants were paid about one and a half to two times more as a result of their negotiations (Levitt and Dubner, 2023).

In addition to the pronounced gender gap in negotiation, wage negotiation has also become more important over time. Many modern economies have moved towards more decentralized wage-setting practices, giving job seekers more room to negotiate. In EU countries, for example, the average coverage of collective bargaining fell from 66% in 2000 to around 56% in 2018 (Eurofound, 2022). Brenzel et al. (2014) document that 38% of German employees negotiate their wages during job interviews, and this figure is even higher for the highly educated. Taken together, the evidence suggests that understanding the gender gap in wage negotiations is becoming increasingly important.

There are several potential factors behind the gender negotiation gap. First, women expect lower wages than men at labor market entry (Filippin and Ichino, 2005; Wiswall and Zafar, 2018; Kiessling et al., 2024). If women expect lower wages than men, they are more likely than men to accept the offered wage rather than negotiate, and if they do negotiate, they are more likely to ask for a lower wage. Second, social roles may also play a role, as women's roles in society are associated with more communal characteristics, such as caring about the welfare of others and caring about their relationship with others. Meanwhile, men are generally perceived as more competitive and assertive. Therefore, women may be reluctant to negotiate as boldly as men in order to avoid being perceived as aggressive by deviating from social roles and consequently facing backlash (Mazei et al., 2015). In addition, there may be other personality traits or preferences that correlate with negotiation behavior, such as competitiveness, risk aversion, and altruism (Recalde and Vesterlund, 2023). Finally, information asymmetries between men and women about the range of attainable wages, the gains from negotiation, or how to negotiate can lead to a gender negotiation gap. Several laboratory experiments and a small number of empirical studies have shown that providing information about other people's gains and average requested wages can reduce or even eliminate the gender gap in negotiation (Rigdon, 2012;

Roussille, 2024).

Therefore, in Chapter 2, I focus specifically on asymmetric information between genders as a determinant of the gender negotiation gap and examine whether the provision of information can increase graduates' negotiation intentions or behavior. I investigate this question by conducting a large-scale online field experiment with around 6,000 final-year master's students from 108 German universities. As a primary channel for student recruitment, 400 German universities received personalized invitation letters informing them about the study. Subsequently, I sent follow-up emails to the same universities with a request to distribute a link to the online experiment to their students.

The experiment consists of three survey waves. In the baseline survey, I elicit students' negotiation intentions for their first job, their expected negotiation outcomes, and their beliefs about female and male negotiation behavior. Immediately after students answer these questions, I randomly assign them to one of two information treatments: the statistics treatment or the role-model treatment. The statistics treatment provides some statistics on the gender gap in the propensity to negotiate for base salary, the returns to wage negotiation, and the income losses over time for women relative to men due to a lower propensity to negotiate at the first job. The role-model treatment consists of short magazine-style interviews with successful role models in the labor market. The role models provide personalized information about the gains from negotiation, share their negotiation experiences, and give some negotiation advice. This intervention focuses not only on negotiating salary, but also on negotiating other monetary (e.g., bonuses) and non-monetary (e.g., working from home) benefits. The control group does not receive any information about negotiation. Finally, cross-randomized across all groups, half of the participants received an email invitation to a negotiation training intervention after completing the survey. This treatment consists of five short videos tailored specifically for women and prepared by an expert in the field.

Two to four months after the initial survey and intervention, I invited all participants to a first follow-up survey to briefly assess their negotiation intentions and expectations before entering the labor market. The second follow-up survey took place 6-8 months after the planned graduation date to ensure that participants had entered the labor market. The second follow-up collected information on graduates' wage negotiation behavior and the returns to these negotiations in their first job after graduation.

Focusing on the pre-treatment baseline results, I find that the intention to negotiate base salary and other monetary components for the first job after graduation is higher for males than for females. In terms of the treatment effect on negotiation intentions, I first find that the statistics treatment increases females' intention to negotiate base salary by 7.6 percentage points, with no significant effect on males or on the intention to negotiate other negotiation components 2-4 months after the interventions. This finding is in line with the aims of the statistics treatment, which targets females by providing information about gender differences and also focuses on negotiating base salary, i.e., it does not mention other monetary or non-monetary aspects. The role-model treatment increases base salary negotiation intentions by about 9 percentage points for both genders, but only increases women's intentions for other monetary components. Finally, the training treatment increases women's negotiation intentions for base salary and other monetary components, but the effects are not statistically significant.

Second, I find that women's expectations of a base salary increase through negotiation rise significantly by 5-7 percentage points following the statistics and role-model treatments. Third, to investigate the channel of the increase in base salary negotiation intentions and expected returns to negotiation, I examine the role of belief updating for men and women. I show that as a result of the statistics treatment, respondents perceive a larger gender gap than individuals in the control group. In addition, although women on average underestimate the wage increase as a result of negotiation, there are no treatment effects on beliefs about the returns to negotiation for base salary for either gender. These results suggest that the treatment effects are not a result of information updating, but rather an increase in information salience.

Finally, I examine how the increase in negotiation intention translates into actual negotiation behavior, particularly for females. I find that the treatments do not significantly affect women's and men's realized negotiation outcomes for base salary, other monetary, and non-monetary aspects. As reasons for not negotiating, treated women are more likely to report that they are unsure how to negotiate and that they are afraid of having their proposal rejected. This suggests that although the treatment was successful in increasing the intention to negotiate by increasing the salience of information, it was not sufficient to change women's actual negotiation behavior.

Therefore, the study demonstrates that even small amounts of information can impact females' intentions in high-stakes situations. This finding may encourage universities and other institutions to provide more information about negotiation, possibly through negotiation training, especially for women. This study highlights the need for further research to translate these intentions into actual behavior and to evaluate the impact of increased actual negotiation behavior on the early career gender wage gap.

While Chapter 2 analyzes factors influencing the gender pay gap at the beginning of a career that may exist prior to labor market entry, in particular gender differences in negotiation intentions, Chapter 3, co-authored with Malte Sandner, examines the early career gender wage gap among university graduates. Studying the gender wage gap at the beginning of a career is ideal because the most common reasons for wage differences between men and women, such as family-related decisions (e.g., childbirth or marriage), career-related developments (e.g., promotions), work experience, and firm-specific networks, may not be relevant in the early stages of a career.

However, other factors may be driving the early career gender wage gap. Particularly during the first job search, both job seekers and firms face considerable uncertainty. Firms can only assess the labor market productivity of candidates without prior work experience based on their university grades and interview performance. Considering that women now typically have a higher GPA than men, we might even expect women to earn more in their first job, conditional on differences in field of study choice and employer characteristics. On the other hand, as noted in Chapter 2, existing research indicates that female applicants negotiate less during job interviews than their male counterparts (Babcock and Laschever, 2003; Bertrand, 2011), and they may face statistical discrimination at labor market entry before their productivity is fully assessed by firms over time (Altonji and Pierret, 2001; Pinkston, 2006). Therefore, the gender wage gap, taking into account differences in field of study and employer characteristics in the first job, may in fact be large and in favor of men.

In Chapter 3, we specifically analyze the gender wage gap at the beginning of a career and how it evolves during the initial years of a career for more than 5,000 German university graduates with a master's degree or equivalent. We use unique administrative data on graduates of a large German university linked with rich social security data from the Integrated Employment Biographies (IEB). This linked dataset provides a wide range of information from the two data sources, including graduates' socio-demographic characteristics, attained university degree, field of study, final high-school and university grades, date of enrollment and exact timing of graduation, labor market entry, employment characteristics, and any occupation or firm changes. This linked administrative dataset also allows us to zoom in on the first job after graduation and avoid the reporting bias that can occur in survey-based studies at the beginning of a career due to frequent job changes.

First, our results reveal that a significant gender wage gap already exists at the onset of careers, before most young individuals make family-related decisions. The raw gender wage gap is about 12.5 log points, which decreases to 6.2 log points after controlling for a comprehensive set of personal and pre-graduation characteristics, such as field of study and grades. This finding is interesting given our homogeneous and highly educated sample of individuals with a strong attachment to the labor market.

Second, we conduct a subgroup analysis for four broad field of study groups: economics and business, mathematics and natural sciences, humanities and social sciences, and medical studies. The results show that the unadjusted (raw) gender wage gap in the first job is prominent in almost all field groups except medical studies. The adjusted gender wage gap is highest in humanities and social sciences. This field group also has the lowest average daily wage in the first job, the highest variation in wages, and the highest proportion of females.

Third, we find that the gender wage gap narrows in the first year after entering the labor market, before slowly widening over time. This reduction is primarily observed for graduates in economics and business, as well as humanities and social sciences 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 or for those who stay in the same firm or occupation. As an explanation for the narrowing of the gender wage gap, we find that female graduates have higher returns to changing firms and occupations than their male counterparts. In particular, women may use firm and occupation changes to correct a skill mismatch, which is more common for women than for men in the first job.

We have tested and rejected several hypotheses to explain why women change occupations and firms to correct skill mismatches after their first job. One plausible explanation is that women's preferences change over time. While non-wage job amenities are more important to them when they enter the labor market, this may change over time. Information frictions may also provide a possible explanation, i.e., women may be less informed about the labor market at the beginning of their job search and thus end up in mismatched jobs, but over time they gather more information and change their jobs. In this case, training students about the labor market prior to their job search may inform them and reduce this gap. Future research should focus on exploring the relationship between information asymmetries, skill mismatch, and early career job mobility.

Chapter 4 builds on the previous chapters' discussion of information frictions at labor market entry and their consequences for graduates' initial labor market outcomes by focusing on coworker networks which can reduce information frictions and improve graduates' labor market outcomes. Specifically, together with Gökay Demir, Friederike Hertweck, and Malte Sandner, we analyze to what extent university students' coworker networks from student jobs affect their starting wages after graduation. To the best of our knowledge, our study is the first to examine how peers from student jobs affect the labor market entry of university graduates.

The existing theoretical and empirical literature has highlighted the important role of social networks in accessing job opportunities and promoting career progression (e.g., Cingano and Rosolia, 2012; Glitz, 2017; Saygin et al., 2021). Studies analyzing the effects of networks on labor market success have focused on the role of family (Kramarz and Skans, 2014), neighborhood (Ioannides and Loury, 2004), student peers (Marmaros and Sacerdote, 2002), ethnic networks (Dustmann et al., 2016), close friends (Cappellari and Tatsiramos, 2015), or former coworkers in regular employment (e.g., Glitz, 2017; Saygin et al., 2021; Eliason et al., 2023). Among these, coworker networks stand out as particularly important due to their direct labor market relevance, access to job-related information (Cappellari and Tatsiramos, 2015), and sustained labor market attachment (Antoninis, 2006). There are several channels through which coworkers affect the labor market outcomes of individuals. Communication and interaction among coworkers can encourage employees to compare themselves to their coworkers and create peer pressure (Glitz, 2017). In addition, knowledge spillovers between coworkers can facilitate learning from each other (Cornelissen et al., 2017). These channels can help employees improve their productivity and consequently increase their wages.

Coworker networks not only improve workers' contemporaneous labor market outcomes, they can also help improve future outcomes, especially during the job search period, when information frictions are very high. First, employees can learn about job openings and better job opportunities from their coworkers (or former coworkers) and thus find superior, more compatible, or higher-paying jobs. In this case, better coworkers would have better information and be more helpful to the job seeker. When a job seeker applies for a job, former coworkers can act as referrals, and as a result, the employer may select that job seeker in an environment of high information uncertainty.[1] The empirical literature underscores the importance of coworker networks by showing that coworker productivity affects wages (Cornelissen et al., 2017; Battisti, 2017; Hong and Lattanzio, 2022) and that having higher-paid coworkers is associated with higher future wages (Jarosch et al., 2021).

Since most students have not worked full-time prior to entering the labor market, the only labor market-related networks that can be built are those from student jobs. However, it is unclear whether the effects of student job networks extend to individuals who are not yet attached to the labor market. This research gap is surprising given the increasing importance of work during studies in high-income countries, with student employment rates reaching 40% in the US (Irwin et al., 2022) and over 60% in Germany (Staneva, 2015). Moreover, information frictions between employers and employees may be particularly strong during the transition from university to employment and students' coworkers may help reduce these frictions. Finally, as noted before, the transition from graduation to employment is a crucial career stage with a lasting effect on later careers (e.g., Oyer, 2006; Oreopoulos et al., 2012; Wachter, 2020).

In this chapter, we go beyond the existing literature on coworker networks and analyze whether university students benefit from the quality of their coworker networks during their transition from university to the labor market. We use unique administrative university records of graduates from a large German university between 1995 and 2016

[1] The literature also shows that coworkers can help reduce information frictions (Caldwell and Harmon, 2019), and that reducing information frictions can induce workers to move to higher-paying jobs.

linked with their social security data. The data provide detailed information on university enrollment, field of study, grades, complete pre- and post-graduation employment histories, and the employment histories of all coworkers who work with the student in the same establishment. Our identification strategy overcomes potential bias due to non-random selection into networks by controlling for a wide range of individual, network, and establishment characteristics, as well as establishment fixed effects. The data also allow us to identify those coworkers who work in the same establishment and in the same (or a different) occupation as the student, allowing us to distinguish between close and less close coworkers. In the estimation, we focus on the close coworkers and control for the less close coworkers. Finally, the data provide the wages of former coworkers at the student's labor market entry, which we use for our measure of network quality.

Our results show that graduates benefit from the quality of their coworkers in student jobs in the form of higher wages after graduation. For example, a 10% increase in the average wage of former coworkers at the time of a student's graduation is associated with 0.76% higher wages in the graduate's first full-time job. To understand the underlying mechanisms, we examine several potential channels. First, we show that graduates benefit from having good coworkers particularly when they start their careers in the same establishment where they worked as a student or when they start working in an establishment that employs a former coworker. These findings suggest that direct support or information about a firm from a better network of former coworkers is an important channel explaining why the average wage of former student job coworkers has a positive effect on the future wages of graduates.

Second, we reject the channel that better coworkers lead to an increase in students' effort at university, which could potentially improve their transition to the labor market. Third, our results show that better coworkers shorten the time between students' graduation and their first job, leading them to enter the labor market faster. Fourth, we rule out the channel that the higher starting salary and faster labor market entry are due to a mismatch, which could lead to earlier layoffs in the years after graduation.

Moreover, we distinguish between jobs that students typically take for financial support (e.g., bartending or cashiering) and jobs that are more related to their studies, including paid internships. We show that coworkers from study-related jobs drive the wage effects. Finally, we examine potential heterogeneity by gender and student ability, as measured by university GPA. Our results show little difference between these groups. Information frictions about potential outside options remain a final explanation for why student co-workers may improve the labor market entry of recent graduates.

Taken together we shed light on the broader significance of student employment, which extends beyond simply providing financial support. The evidence suggests that high-quality networks of coworkers established during student jobs significantly improve the transition from university to the labor market. This benefit is most likely due to a reduction in information frictions at the beginning of the career. This research highlights the value of including coworker networks in policies aimed at smoothing the transition from university to the labor market. It also provides critical implications for future research on this topic.

Overall, this dissertation provides important insights into the crucial transition period from university to the labor market, a period that has a lasting impact on graduates' career trajectories. The chapters build on and aim to extend the existing literature along multiple dimensions, in particular with respect to the relationship between information frictions and labor market outcomes, gender inequalities among the highly educated, and the influence of student job networks. In addition, the experimental design used in this dissertation can be used in future research. The findings of this dissertation aim to improve the understanding of early career wages with a focus on gender and to identify key factors for a successful transition from university to the labor market. This understanding can help inform policies to ease this transition and reduce gender gaps in early careers.

Overview of Dissertation

	Chapter 2	Chapter 3	Chapter 4
Title	Gender Differences in Negotiation Behavior and the Role of Information: Evidence from a Randomized Field Experiment	Unraveling the Gender Wage Gap: Exploring Early Patterns Among University Graduates	Students' Coworker Networks and Labor Market Entry
Co-author(s)		Malte Sandner	Gökay Demir, Friederike Hertweck, Malte Sandner
Journal Submission	This paper has not been submitted to a journal or published anywhere.	This paper was submitted to the *Special Issue of the Scottish Journal of Political Economy on Gender Norms.**	This paper has not been submitted to a journal.**
Own Contribution	100%	80%	40%

*This paper is currently under review in the submitted journal. If published, the final version may differ slightly from the version in this dissertation.
**Versions of this paper are available as a conference paper and in Gökay Demir's dissertation via the following links, respectively: https://www.econstor.eu/handle/10419/277580 and https://docserv.uni-duesseldorf.de/servlets/DocumentServlet?id=65016.

Chapter 2

Gender Differences in Negotiation Behavior and the Role of Information: Evidence from a Randomized Field Experiment

I thank my supervisors Silke Anger and Pia Pinger for their support and encouragement. I am grateful to financial support from the Institute for Employment Research (IAB) of the German Federal Employment Agency. I also thank Bernd Fitzenberger, Nikki Shure, Johanna Rickne, Hedvig Horvat, Markus Nagler, Attila Lindner, Guido Heineck, Sydnee Caldwell, Daniel Kühnle, Simon Janssen, Adrian Lerche, Malte Sandner, Malte Reichelt, Anica Kramer, and seminar participants at UCL, LSE and IAB for their thoughtful discussions and valuable comments. Johanna Sauer, Derya Cevik, Regina Reck, Paul Setzepfand provided excellent research assistance. The experiment was approved by the Ethics Commission of the University of Bamberg and was registered on AEA RCT Registry (RCT ID: AEARCTR-0007257) before the end of data collection and the beginning of data analysis. All errors are my own.

2.1 Introduction

In recent decades, the gender wage gap has narrowed in economically advanced countries, largely driven by improvements in women's education, labor market attainment, and work experience (Goldin, 2014). However, even after accounting for a wide range of education and employment factors, an unexplained wage gap persists, which is even more pronounced among college graduates (Blau and Kahn, 2017; OECD, 2022). The literature points to gender differences in negotiation behavior as an explanation for an important part of the gender wage gap (Card et al., 2016), particularly among college graduates (Säve-Söderbergh, 2019).

In parallel, many countries have moved towards more decentralized wage-setting practices, leading to greater wage flexibility.[1] Therefore, understanding wage negotiation and the associated gender gap is becoming increasingly important. One potential reason for the gender gap in negotiation is that women may not be as informed as men about the benefits of negotiation, which leads to women having a lower propensity to negotiate and gaining less from negotiation than men (e.g., Rigdon, 2012).[2] However, how to close this gap is still not clear. Most studies examining the effect of information on negotiation behavior rely on non-causal surveys or lab experiments, which may not capture behavior in real-world, high-stakes negotiations.

This paper experimentally investigates the causal effect of information on negotiation intentions and actual negotiation behavior at the first job search, particularly for females. I focus on three components of negotiation; negotiation for base salary, for other monetary aspects such as bonuses, and for other non-monetary aspects. I conducted a randomized controlled trial (RCT) embedded in a survey of more than 6,000 final-year master's

[1] For example, in EU countries, the average coverage of collective bargaining decreased from 66% in 2000 to around 56% in 2018 (Eurofound, 2022).

[2] Other explanations for the gender gap in negotiation may include women's lower self-esteem or confidence (e.g., Barber and Odean, 2001), lower wage expectations (Filippin and Ichino, 2005; Reuben et al., 2017; Wiswall and Zafar, 2018; Kiessling et al., 2024), or fear of backlash (Babcock and Laschever, 2003).

students in Germany. Since the negotiation gap is more pronounced among highly skilled individuals and since master's graduates are more likely to enter the labor market after graduation, I provide interventions to final-year master students.

I first elicit students' intentions to negotiate for their first job after graduation and their expected returns from such negotiation, as well as their beliefs about female and male negotiation behavior, which I can use to measure beliefs about the gender negotiation gap. Immediately after answering these questions, I randomly assign the students to two information treatments that focus on both aspects of negotiation: the propensity to negotiate, i.e., whether women enter negotiations less often than men, and the returns to negotiation. Most studies show that women tend to negotiate less than men (Babcock and Laschever, 2003) and also gain less from negotiation than men (Säve-Söderbergh, 2019).

The first intervention, the statistics treatment, provides some statistics on the gender gap in the propensity to negotiate for base salary, the returns to wage negotiation, and women's income losses over time relative to men due to a lower propensity to negotiate at the first job. The second intervention, the role-model treatment, consists of short magazine-style interviews with successful role models in the labor market. The role models provide personalized information about the benefits of negotiation, share their negotiation experiences, and provide some negotiation advice. This treatment includes four female and one male role model to target primarily female students. It focuses not only on negotiating base salary, but also on negotiating other monetary (e.g., bonuses) and non-monetary (e.g., working from home) benefits. The aim of conveying information through role models is to increase the credibility of the information and make it more relatable by allowing participants to associate with role models. The control group does not receive any negotiation information. Finally, at the end of the first survey, half of the participants receive an email invitation to participate in a negotiation training treatment that is cross-randomized with the control, statistics, and role-model treatment groups. This treatment consists of five short videos (approximately 15 minutes in length) prepared by an expert in the field. The videos are tailored specifically for women and designed to train participants for future negotiations.[3]

At baseline, the results show that men are more likely to express an intention to negotiate base salary and other monetary components for the first job after graduation, while women are more likely than men to report that they have not thought about negotiating. Interestingly, there is no gender difference in the proportion of individuals who report that they do not intend to negotiate. Further analysis of intentions to negotiate base salary shows that the gender gap remains statistically and economically significant even after controlling for students' sociodemographic, educational, and psychological characteristics,

Concerning treatment effects on negotiation intentions, I first find that the statistics treatment increases females' intentions to negotiate base salary by 7.6 percentage points, with no significant effect on males or on intentions to negotiate other negotiation components for either gender 2-4 months after the interventions. This finding is in line with the aims of the statistics treatment, which targets females by providing information on gender differences and also focuses on negotiating base salary, i.e., it does not mention other monetary or non-monetary aspects. The role-model treatment increases base salary negotiation intentions by about 9 percentage points for both genders, but only increases women's intentions for other monetary components. Heterogeneity analyses show that the effect of the statistics treatment is stronger for women in STEM fields, women with lower grades, and women with lower risk preferences, whereas the role-model treatment has a stronger effect on women in non-STEM fields, women with lower grades, and women with higher risk preferences. The effect of the role-model treatment on base salary negotiation intentions is more pronounced for men in STEM fields, men with lower grades, and men with lower risk preferences. The training treatment increases women's negotiation intention for base salary and other-monetary components, however, the effects

[3] The statistics treatment is referred to as the "information treatment" in the pre-registration document.

are statistically insignificant. Second, I further examine the treatment effects on expected returns to negotiation. The statistics and role-model treatment significantly increase women's expectation of a base salary increase as a result of negotiation by 5-7 percentage points.

Third, to investigate the channel of the increase in base salary negotiation intentions and expected returns to negotiation, I examine the role of belief updating for men and women. I show that as a result of the statistics treatment, respondents perceive a larger gender gap than individuals in the control group.[4] In addition, graduates update their beliefs in the intended direction as a result of the treatments, but this does not explain the increase in the intention to negotiate base salary. I also elicit respondents' beliefs about the returns to negotiation for females and males. Although women underestimate the wage increase as a result of negotiation, there are no treatment effects on beliefs about the returns to negotiation for base salary for either gender. This suggests that the treatment effects are not driven by correcting misinformation, but rather by increasing the salience of information.

Finally, I examine how the increase in negotiation intention translates into actual negotiation behavior. I find that the treatments do not significantly alter the actual negotiation outcomes of women and men for base salary, other monetary, and non-monetary aspects, regardless of the examined subgroups. This intention-behavior gap is highlighted in the social psychology literature (e.g., Sheeran, 2002), which posits that even though people intend to behave in a certain way, it may not translate into actual behavior due to some external and internal difficulties. Because there may be multiple reasons for not negotiating, I examine these potential reasons by comparing the treatment and control groups by gender. I find that treated women are more likely to report that they are unsure of how to negotiate and that they are afraid of having their proposal rejected. This suggests that while the treatments were successful in increasing the salience of information,

[4] In this exercise, I focus only on the statistical treatment because only this treatment provides statistics on women's and men's propensity to negotiate.

they were not sufficient to make women feel more confident about entering negotiations. Another consideration is the possibility that the time gap between the intervention and the actual opportunity to negotiate may have diminished its impact. However, this finding is not consistently robust across different specifications.

This paper makes three key contributions to the existing literature. First, I contribute to the literature on the effects of information on negotiation intentions and behavior. The existing literature suggests that the gender gap in negotiation behavior can be reduced or eliminated through the provision of information. However, the existing evidence on the relationship between the gender gap in negotiation behavior and information is sparse and mainly based on laboratory experiments (Bowles et al., 2005; Small et al., 2007; Schwieren, 2012) or surveys (Babcock and Laschever, 2003; Säve-Söderbergh, 2019; Biasi and Sarsons, 2021).[5] The most relevant paper by Roussille (2024) shows that providing information about the median salary of a position on a job platform reduces the "ask gap", i.e., the gender gap in salary demands. However, this study is limited to a specific and highly skilled group of engineers, and because it uses a job platform, it cannot account for negotiations during job interviews. My paper contributes to this literature by exploring whether information interventions increase women's and men's intentions to negotiate 2-4 months after the interventions, as well as their actual negotiation behavior in a real-world setting. Furthermore, this paper also relates to the literature that examines the gender gap in negotiation. The literature typically shows that women are less likely to engage in negotiations than men (Babcock and Laschever, 2003; Card et al., 2016; Biasi and Sarsons, 2022)[6] and often achieve smaller gains (Stuhlmacher and Walters, 1999; Säve-Söderbergh, 2019; Dreber et al., 2022).[7] One exception is Exley et al. (2020), who conduct a lab

[5] A recent paper by Fröberg et al. (2023) conducts a survey experiment and shows that providing information about women's inferior status in salary negotiations increases women's negotiation intentions immediately after the intervention. However, this paper does not examine longer-term effects or actual negotiation behavior.

[6] One exception is Säve-Söderbergh (2019) who finds a small gender difference in the propensity to negotiate for Sweden.

[7] For a review of research on gender differences in negotiation behavior, see Stuhlmacher and Walters (1999), Bertrand (2011), Mazei et al. (2015), Kugler et al. (2018), Hernandez-Arenaz and Iriberri (2019) and Recalde and Vesterlund (2023).

experiment showing that women do not necessarily gain more when they are forced to negotiate compared to when they voluntarily enter a negotiation. I contribute to the literature by providing field evidence and highlighting a gender gap not only in base salary negotiations, but also in other monetary and non-monetary components. In addition, this study goes beyond actual negotiation behavior by showing that women intend to negotiate less than men and expect lower returns than men even before entering the labor market.

Second, this paper contributes to the literature on the effects of short and low-cost information interventions to study the gender negotiation gap.[8] The study by Settele (2022) provides a variety of statistics on the gender wage gap from different sources to examine how beliefs about the size of the gap influence policy preferences. The study finds that participants who are exposed to a more pronounced wage gap exhibit a stronger demand for specific policies aimed at mitigating it. In addition, Fröberg et al. (2023) find that a reminder of women's inferior position in negotiation outcomes increases women's negotiation intentions. However, as Fröberg et al. (2023) note, because negotiation intentions are elicited immediately after the interventions, the experimenter demand effect may play a role in the results. In this paper, the first information treatment highlights gender differences in wage negotiation behavior among university graduates and potential wage increases as a result of such negotiations.[9] By highlighting these differences, the aim is to inform and encourage women to engage in negotiation during their first job search after graduation. The findings show that exposure to gender differences in negotiation outcomes and potential gains from negotiation increases women's negotiation intentions even a considerable time (2-4 months) after the intervention, but does not affect men.

Finally, this paper adds to the growing literature examining the impact of role models. Most of the evidence on role-model interventions focuses on educational outcomes. For

[8] The literature examines the effects of information in many different domains, such as educational outcomes (Herber, 2018; Peter et al., 2021), job search (Altmann et al., 2018; Belot et al., 2022; Abebe et al., 2021) and policy preferences (Kuziemko et al., 2015; Settele, 2022; Haaland and Roth, 2023). See Haaland et al. (2023), for a review of the literature on information provision.

[9] The statistics used in this treatment are based on a survey by Babcock and Laschever (2003).

example, Herber (2018), using an approach similar to this paper, finds that providing information about the scholarship application process via role models significantly increases the likelihood of applying. Riley (2022) finds that showing students movies with potential role models significantly reduces the failure rate on math exams. Several other studies place role-model interventions in the context of gender. For example, female high school students exposed to role models working in scientific fields are more likely to pursue STEM fields (Breda et al., 2020). Similar results are observed in the choice of economics major (Porterfield and Winkler, 2007) and enrollment in software coding programs (Del Carpio and Guadalupe, 2022). A recent paper by Palffy et al. (2023) shows that exposure to role models in stereotypically male occupations increases female applications for STEM jobs. To the best of my knowledge, this paper is the first to focus on the effect of information conveyed by role models in the context of negotiation.[10] My findings suggest that personalized information provided by role models significantly increases negotiation intentions of both women and men, even 2-4 months after the interventions, but does not affect actual negotiation behavior.

The paper is organized as follows. Section 2.2 describes the surveys, interventions, and experimental design implemented in this study and presents descriptive analyses. Section 2.3 provides descriptive results on gender differences in negotiation intentions using pre-treatment data. Section 2.4 presents the methodology and the main results. Section 2.5 discusses the results and the underlying mechanisms. Section 2.6 concludes.

[10] Ashraf et al. (2020) study the effects of negotiation skills training by female coaches on the educational outcomes of female students in Zambia, which may capture the effect of role models.

2.2 Experimental Design and Interventions

2.2.1 Main Survey and Interventions

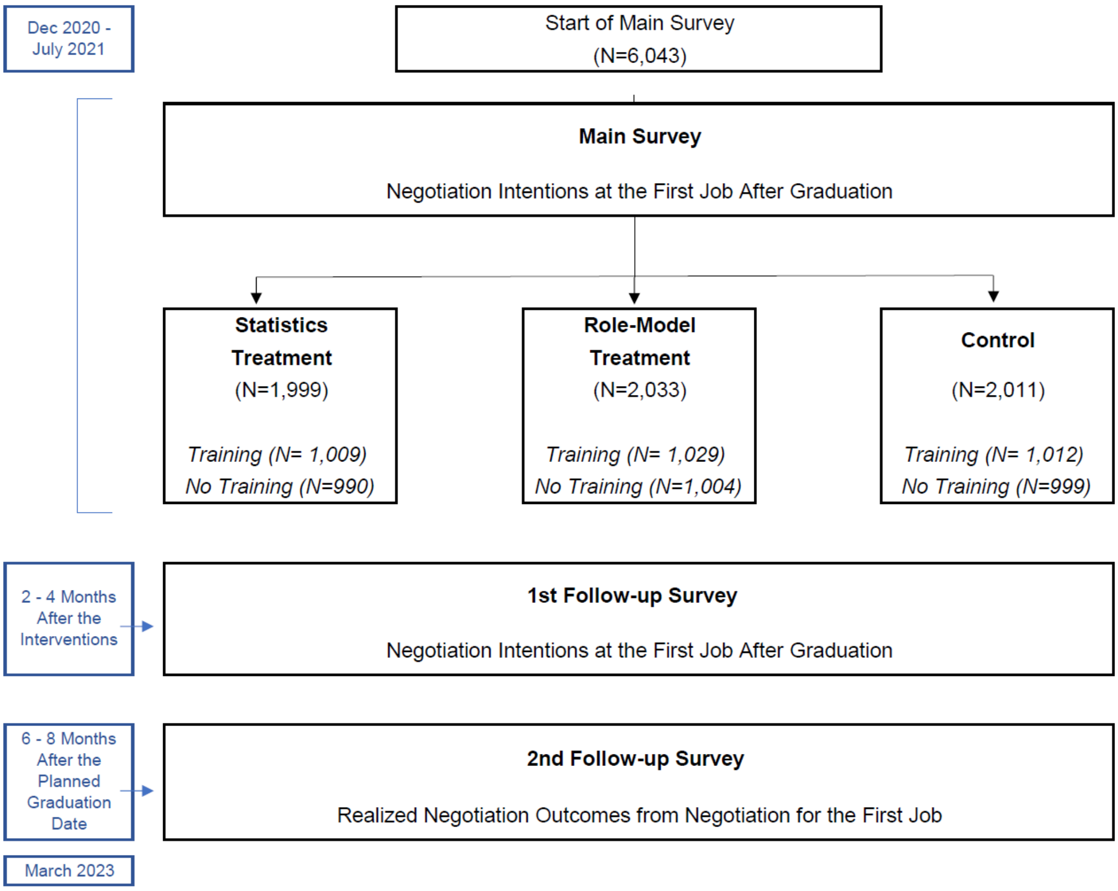
I conducted the first survey among final-year master's students between December 2020 and June 2021. Figure 2.1 illustrates the survey outline and the experimental design. As the primary channel for student recruitment, I first sent personalized invitation letters to the heads of approximately 400 German universities to inform them about the study. Subsequently, I sent follow-up emails to the same university heads and management offices with a request to distribute a link to the online experiment to their students. Most of the student respondents were recruited through this channel.[11] The experiment was also advertised on social media platforms, online forums, and select student magazines, with only 120 students participating in the study through these channels. The study does not include students studying to become teachers or medical students, as most of their wages are set by collective bargaining agreements at the start of their careers. A total of 6,043 students from 108 German universities and universities of applied sciences participated in the main survey.

The respondents answered sociodemographic, study-related, negotiation-related, and other pre-treatment questions, such as questions about the covid pandemic, regrets about their study, and personality traits. To mask the study's primary objective, some additional questions unrelated to the study were included. After completing the pre-treatment section, I randomly assigned individuals to the control, statistics, or role-model treatment groups. I utilized stratified randomization and defined strata based on field of study (5 categories), gender, grades (3 categories), and graduation date (2 categories). To incentivize participation in subsequent surveys, I provided a 5 Euro online gift voucher at the end of the survey. Cross-randomized across all groups, half of the participants received

[11] For the template of invitation letters, follow-up emails sent to university heads, and the data protection document and the flyer attached to the letters and e-mails see link https://doku.iab.de/grauepap/Supplementary_Materials.pdf. The flyer was designed by Christine Weidmann from the IAB.

an email invitation to a negotiation training intervention after completing the survey.

Figure 2.1: Survey Overview and Experimental Design



Note: This figure provides an overview of the main survey (first wave) and follow-up surveys, including the experimental design, the number of participants, and the timeline.

Statistics Treatment: The statistics treatment provides information on the gender gap in the incidence of wage negotiation, the percentage increase as a result of negotiation, and the starting salaries as a result of negotiation. This information is taken from a well-known study in the literature on the gender negotiation gap by Babcock and Laschever (2003). In addition, the treatment includes a hypothetical example of Felix and Anna, showing how much Anna will lose over time if Felix negotiates for the first wages, and Anna does not. This information is formulated similar to the study by Babcock and Laschever (2003), but adapted to the German context and wages. The treatment consists of five pages and includes intuitive graphs, images, short paragraphs of text, and a comprehension question.[12]

Providing information about other people's earnings or experiences may reduce the gender negotiation gap (Rigdon, 2012; Roussille, 2024). In addition, showing women's negotiation behavior relative to men may increase the salience of the information and encourage women to negotiate more. This treatment focuses only on base salary negotiation, does not provide information on other monetary or non-monetary aspects, and aims to increase female negotiation outcomes by demonstrating gender differences.

Role-Model Treatment: The role-model treatment also provides information about negotiation, but through successful role models in the labor market. I conducted short magazine-style interviews with one male and four female role models, supplemented by responses from other interviews.[13] The role models answer a series of questions about their negotiation experiences at labor market entry, potential gains as a result of negotiation, and also give some negotiation advice. The use of role models is intended to make the information more salient by increasing the students' sense of belonging. Because the participants in this study come from a variety of fields, including STEM and non-STEM, and the goal of the treatment is to increase women's negotiation outcomes, this treatment includes female role models from non-STEM and STEM fields and a male journalist role model.[14] Since the literature shows that forcing women to engage in negotiation may not always be beneficial (Exley et al., 2020), the role models in this intervention suggest that participants should do their research before entering negotiations and assess average wages in the labor market, as a signal to initiate negotiations only when it is deemed appropriate. Furthermore, the role models emphasize that even if the base salary is not negotiable, participants can negotiate other monetary aspects, such as bonuses, or non-monetary

[12] See Appendix Figure A.1 for example pages of the treatments, translated into English. For screenshots of all treatments, see link `https://doku.iab.de/grauepap/Supplementary_Materials.pdf`.

[13] See Appendix Figure A.2 for an example of an interview with one role-model, translated into English. Note that only selected questions are included in this example. For screenshots of all treatments, see link `https://doku.iab.de/grauepap/Supplementary_Materials.pdf`.

[14] Since around half of the participants are male students, I include one interview with a man, which is relatively shorter than the remaining interviews with successful women.

aspects, such as the option to work from home.

Training Treatment: One potential explanation for the gender gap in negotiation behavior is that women may lack knowledge about how or when to negotiate during job interviews (Babcock and Laschever, 2003). Ashraf et al. (2020) show that providing intensive negotiation training significantly improves educational outcomes for females in Zambia. Conversely, Chotiputsilp and Kim (2021) find that negotiation training for job seekers in Thailand increases the reported wages of men, but not women. The training intervention provides negotiation training videos prepared by a professional coach to improve students' negotiation skills and encourage them to negotiate more frequently. Students assigned to the training treatment receive an email invitation to the online negotiation training shortly after completing the first survey. The training consists of five negotiation training videos. The first four videos each cover a single topic (information, clarity, awareness, strategy) and last approximately 10-15 minutes. After watching each video, the participants are required to answer some control questions. The final video is a 5-minute summary by the instructor. The videos can only be viewed once and the link cannot be shared with others or third parties. The negotiation training was designed specifically for women (without mentioning women) and is similar to other workshops at universities in Germany that aim to improve women's negotiation skills.[15]

2.2.2 Follow-up Surveys

As presented in Figure 2.1, I invited all participants to a short follow-up survey 2-4 months after the main survey (wave 1) and the interventions. The participants did not receive any reminders about the treatments. The first follow-up survey (wave 2) collects initial results on students' negotiation intentions, their beliefs and expectations about negotiation, and their expected chances of gaining from negotiation. In cases where students had already

[15] The training videos are prepared by Susan J. Moldenhauer (STRATEGY PIRATES® GmbH & Co. KG).

found a regular job, they received questions about their realized negotiation outcomes from the second follow-up survey (wave 3).

The second follow-up survey took place 6-8 months after the planned graduation date. Since the planned graduation dates of the master's students varied over time, they received the second follow-up survey over a period of several months in 2022 and 2023. The survey collected information on the wage negotiation behavior of graduates in their first job after graduation. This survey includes questions about the occurrence of wage negotiations for the first job and the outcome of those negotiations. In cases where no negotiations took place, the reasons for non-negotiation were explored.

Both follow-up surveys took approximately 10-15 minutes to complete, and participants received a 5 Euro voucher after each survey. In addition, in order to increase the response rate, participants who did not participate in either of the follow-up surveys were invited to complete a very short survey (approximately 5 minutes) that included only the most relevant questions about their realized negotiation experiences.

2.2.3 Data and Summary Statistics

A total of 6,043 final-year master's students participated in the main survey, and the median time spent on the survey was around 22 minutes (including treatments). Table 2.1 shows the general characteristics of the students and the balance of covariates between the control and treatment groups for the main survey participants. The table shows that the randomization worked well, as the sample is balanced across covariates. Due to the low response rate to the negotiation training treatment (about 15%), I only include the statistics and role-model treatment groups in the table. The attrition rates in the first and second follow-up surveys are 35% and 52%, respectively. These rates are not significantly different between the treatment and control groups (see the last two rows of Table 2.1). Participants in non-master's programs or not in their final year of study were excluded at the beginning of the survey. The main outcomes are negotiation intentions (collected in wave 2) and actual negotiation outcomes (collected in waves 2 and 3, if participants found a job). Because some participants receive the realized negotiation questions directly and do not answer the negotiation intention questions, I create two different estimation sample groups. Participants who answered the negotiation intention questions belong to the first group, and those who answered the realized negotiation questions belong to the second group. Appendix Tables A.1 and Table A.2 show that there are no significant differences between the control and treatment groups for both sample groups.

Gender Differences: Appendix Table A.3 presents summary statistics for female and male participants in wave 1. Similar to previous studies, females on average achieve better grades than males (Becker et al., 2010; Francesconi and Parey, 2018)[16] and are much more likely to pursue studies in languages, humanities, and social sciences. Conversely, a higher proportion of males are enrolled in engineering fields, which is in line with overall population trends (Federal Statistical Office, 2023). In addition, women are younger at the time of the first survey and more likely to be born in Germany than men. There are no significant gender differences in terms of family educational background, having siblings, and starting to apply for a job. The monthly reservation wage (expected wage) of female students is around 2,836 Euros (3,359 Euros) compared to 3,387 Euros (3,973 Euros) for males. The gender gap in reservation and expected wages is approximately 16% . These findings are similar to the paper by Kiessling et al. (2024), which finds a 19% and 14% gender gap in reservation and expected wages, respectively. Finally, confirming the findings in the literature, women have lower risk preferences (i.e., are more risk averse) than men (Eckel and Grossman, 2002; Croson and Gneezy, 2009; Cortés et al., 2023).

[16] In the German education system, lower grades indicate better academic performance. They range from 1 (best) to 4 (passed).

Table 2.1: Summary Statistics: Balance in Covariates

	Pooled		Control (C)	Statistics Treatment (T1)	Role-Model Treatment (T2)	C - T1	C - T2	T1 - T2
	Mean	SD	Mean	Mean	Mean	*p*-value	*p*-value	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.552	0.497	0.553	0.552	0.551	0.955	0.908	0.953
Top Grade (<= 1.7)	0.554	0.497	0.553	0.554	0.553	0.970	0.991	0.979
Planned Graduation before May	0.243	0.429	0.245	0.237	0.246	0.537	0.976	0.516
Field of Study								
Languages, Humanities and Social Sciences	0.279	0.449	0.281	0.280	0.276	0.957	0.742	0.782
Economics, Business and Law	0.225	0.417	0.220	0.225	0.229	0.665	0.488	0.793
Mathematics and Natural Sciences	0.160	0.367	0.159	0.162	0.160	0.746	0.928	0.815
Engineering and IT	0.336	0.472	0.341	0.332	0.335	0.561	0.712	0.833
Age	27.044	2.966	26.984	27.136	27.015	0.131	0.758	0.243
Born in Germany	0.843	0.363	0.843	0.842	0.846	0.909	0.798	0.711
College Family Background	0.382	0.486	0.380	0.377	0.390	0.849	0.530	0.411
Having Siblings	0.837	0.369	0.841	0.833	0.838	0.483	0.827	0.629
University Type								
University	0.678	0.467	0.687	0.681	0.668	0.678	0.198	0.380
University of Applied Sciences	0.295	0.456	0.284	0.292	0.308	0.573	0.101	0.278
Worked During Studying								
No	0.083	0.276	0.089	0.086	0.075	0.697	0.106	0.218
Yes, Entirely	0.488	0.500	0.490	0.481	0.492	0.560	0.884	0.465
Yes, Occasionally	0.401	0.490	0.394	0.403	0.404	0.575	0.523	0.937
Risk Preferences	4.908	3.426	4.971	4.914	4.838	0.618	0.206	0.468
Started Applying For a Job	0.440	0.496	0.433	0.442	0.443	0.565	0.530	0.956
Reservation Wage	3068.858	899.879	3049.472	3081.697	3075.207	0.267	0.373	0.819
Expected Monthly Wage	3648.680	949.585	3628.860	3678.906	3637.843	0.103	0.768	0.170
Perceived Share of Women Who Negotiate the Wage of Their First Job	33.757	20.949	33.433	33.780	34.060	0.628	0.383	0.695
Perceived Share of Men Who Negotiate the Wage of Their First Job	59.342	20.888	58.863	59.103	60.061	0.736	0.090	0.175
Perceived Wage Increase after Women Negotiated Their Wage	10.348	11.885	10.279	10.257	10.508	0.959	0.615	0.575
Perceived Wage Increase after Men Negotiated Their Wage	15.169	14.301	15.030	15.298	15.177	0.614	0.784	0.821
Individuals	6,043		1,999	2,033	2,011			
Panel B. Attrition								
Not participated the follow-up 1	0.350	0.477	0.344	0.350	0.357	0.662	0.393	0.674
Not participated the follow-up 2	0.522	0.500	0.525	0.508	0.534	0.263	0.599	0.099

This table presents summary statistics for the sample of final-year master's students who participated in the main survey (wave 1). Column (1), and columns (2) to (5) present mean values for all individuals who participated in the first wave and the treatments, including the control group, statistics treatment group, and role-model treatment group, respectively. Columns (6) to (8) show the p-value for t-tests of the differences in means between the control and statistics treatment groups, the control and role-model treatment groups, and the statistics and role-model treatment groups. All variables are measured prior to treatment.

2.3 Gender Differences in Negotiation Intentions

This section presents gender differences in negotiation intentions along with a descriptive exploration of the potential underlying factors contributing to these differences. Figure 2.2 shows gender differences in (a) intentions to negotiate base salary, (b) other monetary salary components (e.g., bonuses), (c) and non-monetary aspects (e.g., flexible working hours) in the first regular job after graduation. Men are more likely to intend to negotiate base salary and other monetary aspects. While 42% (24%) of men intend to negotiate base salary (other monetary aspects), 32% (18%) of women express the same intention. However, this is not because women refuse to negotiate, but because they are more likely not to have thought about it. Although there is no significant gender gap in negotiation intentions for other non-monetary components, a higher share of women than men indicate that they have not thought about it.

To explore the sources of the gender gap in negotiation intention and other factors correlated with it, I create a dummy for negotiation intention that equals 1 if an individual intends to negotiate and 0 otherwise, and regress it on a female dummy and other control variables that are gradually added to the estimation. Table 2.2 shows that there is a raw gender gap of 9 percentage points in negotiation intentions for base salary. After all controls are added, the gender gap in negotiation intentions drops to 5.1 percentage points and remains statistically significant. The gender gap in negotiation intention is also economically significant. Given that the mean outcome is approximately 37%, the raw gender negotiation gap amounts to 25% of the mean intention to negotiate, while the adjusted gender difference is 10%.

By gradually adding controls, the table also shows which variables are correlated with negotiation intentions and which are relevant for reducing the gender gap in negotiation intentions. The largest reduction is observed when the field of study is included in the estimations. The inclusion of other variables does not substantially change the gender

Figure 2.2: Pre-Treatment Negotiation Intention

Note: The sample consists of final-year master's students who participated in the main survey (wave 1). The blue (green) bars represent the mean negotiation intentions of females (males) for the base salary (Panel A), other monetary aspects (Panel B), and other non-monetary aspects (Panel C). The outcomes are measured prior to the interventions. The point estimates indicate the difference between the mean responses of women and men. Controls are not included.

gap in negotiation intentions. The table also shows that the intention to negotiate is higher for people born in Germany and increases with age. In addition, students of economics, business and law as well as engineering and IT have a significantly higher intention to negotiate compared to students of languages, humanities and social sciences (base category), while there is no statistical difference between mathematics and natural sciences compared to the base category. Considering that negotiation experience may increase negotiation intentions, for example, people who had the opportunity to negotiate with their siblings or while working during their university studies, I show that having siblings does not affect the intention to negotiate for base salary, while working during studies increases negotiation intentions by about 11 percentage points (Column (4)). Interestingly, having good grades or having parents with a university degree does not affect the intention to negotiate the base salary. Finally, having a higher risk attitude is associated with a higher intention to negotiate.

Table 2.2: The Gender Differences in Intention to Negotiate for Base Salary

Dependent Variable: Intention to Negotiate for Base Salary							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.090***	-0.091***	-0.056***	-0.063***	-0.063***	-0.056***	-0.051***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Born in Germany		0.060***	0.070***	0.064***	0.068***	0.077***	0.075***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Age		0.007***	0.007***	0.006***	0.007***	0.006***	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
College Family Background		-0.022	-0.018	-0.011	-0.011	-0.010	-0.012
		(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Field: Economics, Business and Law			0.169***	0.176***	0.152***	0.147***	0.095***
			(0.019)	(0.019)	(0.019)	(0.019)	(0.021)
Field: Mathematics and Natural Sciences			-0.013	0.009	-0.003	-0.002	-0.004
			(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Field: Engineering			0.125***	0.138***	0.111***	0.108***	0.076***
			(0.018)	(0.018)	(0.018)	(0.018)	(0.020)
Top Grade				-0.009	-0.004	-0.001	-0.008
				(0.014)	(0.014)	(0.014)	(0.016)
Having Siblings				0.029	0.030*	0.032*	0.031*
				(0.018)	(0.018)	(0.018)	(0.018)
Worked During Studying				0.105***	0.110***	0.108***	0.097***
				(0.013)	(0.013)	(0.013)	(0.013)
Public Sector					-0.171***	-0.167***	-0.156***
					(0.017)	(0.017)	(0.018)
General Risk Attitude						0.012**	0.008**
						(0.005)	(0.004)
Other Controls	No	No	No	No	No	No	Yes
Mean of Dependent Variable	0.368	0.368	0.368	0.368	0.368	0.368	0.368
Adjusted R-squared	0.008	0.015	0.037	0.048	0.062	0.068	0.090
Individuals	5,168	5,168	5,168	5,168	5,168	5,168	5,168

Note: The sample consists of final-year master's students who participated in the main survey and answered the question on intentions to negotiate base salary in wave 1. This table reports gender differences in in intentions to negotiate base salary, based on OLS regressions. The outcome variable is binary, equal to 1 if the respondent intends to negotiate base salary and 0 otherwise. Other controls include a dummy for overconfidence, time preferences (7 categories), preferred sector to work in after graduation (private, public, indifferent, do not know), preferred number of working hours after graduation, and university fixed effects for universities with more than 50 students in the sample. *Mean of Dependent Variable* is the corresponding mean outcome (follow-up 1). Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

Even after adding a comprehensive set of controls, the gender gap in negotiation intention persists. Among other unobserved factors, a potential reason for this gap could be that women have not yet thought about negotiating compared to men, a lack of information about the importance of negotiation, or insufficient knowledge about how to negotiate during the job interview. In this case, the interventions could inform women and also encourage them to negotiate at a later point in time, potentially leading to a reduction in the observed gender gap in negotiation intentions in follow-up surveys.

2.4 Effects on Negotiation Intentions and on Realized Negotiation Outcomes

2.4.1 Main Empirical Specification

I estimate intention-to-treat (ITT) effects, since it is not certain that the students read all of the information on the page.[17] The main estimation equation for the statistics and role-model treatment effects is

$$y_{ij} = \beta_0 + \beta_1 Statistics_i + \beta_2 Rolemodel_i + \beta_3 X_i + \gamma_j + \epsilon_{ij} \tag{2.1}$$

where y_i is the outcome of interest for graduate i measured either in the first (2-4 months after the intervention) or in the second (6-8 months after the planned graduation date) follow-up survey. The main outcomes are binary indicators of negotiation intention and realized negotiation behavior. The negotiation intention dummy is equal to 1 if a student is planning to negotiate for their first regular job after graduation, and 0 if they are not planning to negotiate, if they have not decided yet, or if they have not thought

[17] Although I measure how long each participant stays on each page of the survey, I cannot be certain that they read the information.

about it.[18] The realized negotiation dummy is equal to 1 if a graduate has negotiated for their first regular job after graduation, and 0 otherwise. The negotiation outcomes include three elements; negotiation for base salary, negotiation for other monetary components (e.g., bonuses) and negotiation for other non-monetary components (e.g., flexible hours). The treatment indicators $Statistics_i$ and $Rolemodel_i$ are equal to 1 if a master student is assigned to statistics or role-model treatment, respectively. X_i includes strata fixed effects, a dummy variable for having ever participated in negotiation training,[19] and a set of baseline control variables such as being born in Germany, having parents with a college degree, having siblings, and days since the intervention. Strata variables are the field of study (5 categories), grades (3 categories) and planned graduation date (2 categories). γ_j is a university fixed effects for universities with more than 50 students in the sample. The remaining universities are grouped as "other".

2.4.2 Effects on Negotiation Intentions

Effects of the Statistics and the Role-Model Treatments

The first set of results, presented in Table 2.3, shows the effects of the interventions on the intention to negotiate for base salary (Columns (1) and (2)), other monetary aspects (Columns (3) and (4)) and other non-monetary aspects (Columns (5) and (6)) for female and male graduates 2-4 months after the interventions.[20]

Table 2.3 shows that the statistics treatment significantly increases females' intention to negotiate for base salary by 7.6 percentage points. The statistics treatment does not significantly affect men's negotiation intentions. This result is consistent with the aim of

[18] The exact negotiation intention questions are: Are you planning to negotiate for the base salary/other monetary components (e.g., bonuses)/other non-monetary components (e.g., flexible hours) of your first regular job after completing your master's degree?

[19] Half of the participants are invited to the negotiation training which, includes five short videos about negotiation. All videos are approximately 1 hour in length in total.

[20] The negotiation intention analysis includes only those individuals who responded to the negotiation intention questions in both the baseline and the first follow-up survey, as explained in Section 2.2.

the statistics treatment, which specifically targets female students by providing statistics on gender differences in negotiation behavior. The role-model treatment increases the intention of both female and male participants to negotiate their base salary by 9.2 and 9.1 percentage points, respectively. Compared to the mean of the control group, this corresponds to an increase of about 30% for women and 19% for men.

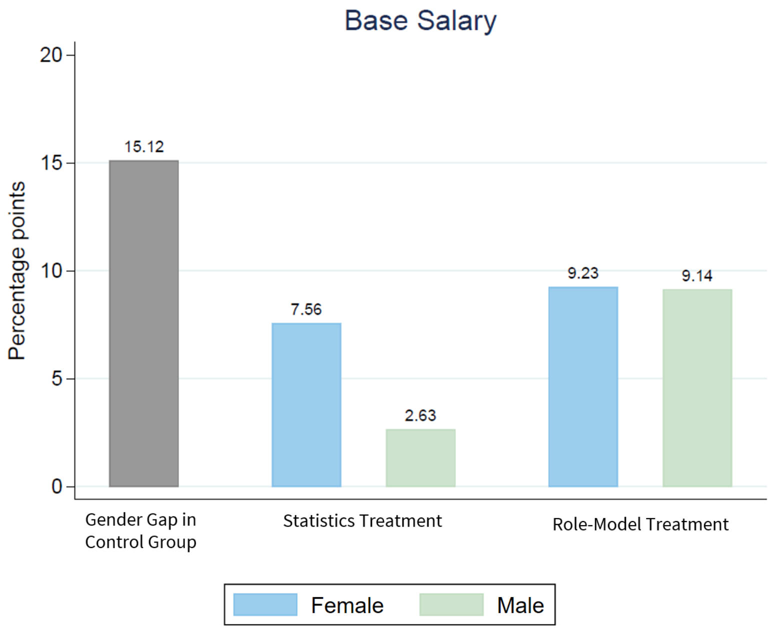
Table 2.3: The Treatment Effects on Negotiation Intentions

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Statistics Treatment	0.076**	0.026	0.047	0.051	0.037	0.006
	(0.031)	(0.038)	(0.029)	(0.036)	(0.032)	(0.038)
Role-Model Treatment	0.092***	0.091**	0.083***	0.060	0.051	-0.002
	(0.031)	(0.038)	(0.029)	(0.037)	(0.032)	(0.039)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.328	0.479	0.243	0.300	0.447	0.495
Individuals	1,468	1,024	1,468	1,024	1,468	1,024

Note: The table reports the effects of the treatments on the negotiation intention outcomes 2-4 months after the intervention, based on the estimation of Equation 2.1. The outcome variables are binary and equal to 1 if respondents intend to negotiate for base salary (Columns (1) and (2)), for other monetary aspects (Columns (3) and (4)), and other non-monetary aspects (Columns (5) and (6)), and equal to 0 otherwise. The statistics treatment and the role-model treatment are represented by dummy variables with a value of 1 if the respondent received the corresponding treatment and 0 for those in the control group. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and who responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. Strata fixed effects include field of study (4 categories), grades (2 categories), and planned graduation date (2 categories). Controls include being born in Germany, having parents with a college degree, having siblings, days since the intervention, ever participating in the negotiation training treatment, and university fixed effects for universities with more than 50 students in the sample. *Mean of Control Group* is the respective mean outcome in the control group at follow-up 1. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

The statistics treatment does not significantly increase negotiation intentions for other monetary or non-monetary aspects for either gender (Columns (3) to (6) of Table 2.3). This result is not surprising, given that the statistics treatment only provides information on the base salary. The role-model treatment significantly increases negotiation intentions for other monetary aspects, but only for women. It has no significant effect on non-monetary aspects where the gender gap is small.

Figure 2.3: The Treatment Effects on Negotiation Intention for Base Salary



Note: The figure shows the effects of the treatments on the intention to negotiate for base salary, based on the estimation of Equation 2.1. The coefficient estimates are taken from Columns (1) and (2) of Table 2.3. The gray bar represents the gender gap in the control group at follow-up 1. The blue (green) bars represent the treatment effect for females (males). Outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. Controls include strata fixed effects: the field of study (4 categories), grades (2 categories), and the planned graduation date (2 categories). Other controls include being born in Germany, having parents with a college degree, having siblings, days since the intervention, ever participating in the negotiation training treatment, and university fixed effects for universities with more than 50 students in the sample.

Figure 2.3 illustrates the effects of statistics and role-model treatments and plots the gender negotiation intention gap in the control group to benchmark the size of the treatment effects. The colored bars are based on Columns (1) and (2) of Table 2.3. The figure shows that providing information treatment to females closes about a half of the gender gap in the control group and the role-model treatment closes around two thirds of the gap. This result suggests that providing treatments exclusively to female students would eliminate an important part of the gender gap in negotiation intentions. The result is similar for other monetary aspects, but this time providing the role-model treatment only to women would even reverse the gap (Appendix Figure A.3 and Columns (3) to (6) of Table 2.3). Given that the treatment effects on males' negotiation intentions for other non-monetary aspects are so small, the treatments could be provided to both genders, which would almost entirely close the gap or even reverse it.

To understand which individuals are more affected by treatments, Appendix Table A.4 shows the main results separately for those who did not intend to negotiate in the baseline survey and those who did. As expected, the treatments significantly increase base salary negotiation intentions for individuals who had no prior intention of negotiating. The results are similar for other monetary aspects, except for women who intended to negotiate for other monetary aspects in the baseline.

I further examine the treatment effects on each category of responses to the negotiation intention questions. Appendix Figure A.4 shows that after the intervention, treated women are less likely to respond with *"undecided"* and *"haven't thought about it"* compared to women in the control group. The largest difference is observed in the *"haven't thought about it"* response, where the baseline gender differences are also the largest (see Figure 2.2). Therefore, females increase their negotiation intention for base salary primarily by thinking more about it than they would otherwise. Appendix Figure A.5 shows a similar pattern for other monetary aspects, while for other non-monetary aspects, the change in response is less distinct (Appendix Figure A.6).

Effects of the Negotiation Training Treatment

15% of all invited participants attended and 13% completed the training. The gender distribution of participants is balanced, with 14% of females and 16% of males participating, and 13% of females and 14% of males completing the training. Although individuals are randomly allocated to the training treatment, the decision to attend the training may be correlated with students' motivation or interest in ways that are not observable in our data, so OLS results may be biased. Therefore, in this analysis, I use the randomized invitation to the training treatment as an instrumental variable to determine the causal effect of the training program on negotiation intentions for base salary, and other monetary and non-monetary components.

The results of the first stage show that receiving an invitation significantly increases the probability of joining the treatment for both genders (Columns (1) and (2) of Table A.5).[21] The instrumental variable approach estimating the Local Average Treatment Effect (LATE) shows that participation in the training treatment positively increases both women's and men's intentions to negotiate base salary, with the effect being twice as pronounced for men (Columns (3) and (4) of Table A.5). However, the estimated coefficients are not statistically significant. The treatment coefficients indicate a pronounced and statistically significant effect for males for both monetary and non-monetary negotiation aspects (Columns (6) and (8)), in contrast to the smaller and statistically insignificant effects observed for females (Columns (5) and (7)). To sum up, the results suggest that the training treatment increases females' negotiation intention for base salary and other non-monetary aspects, however, the effects are statistically insignificant.

Heterogeneity of Treatment Effects

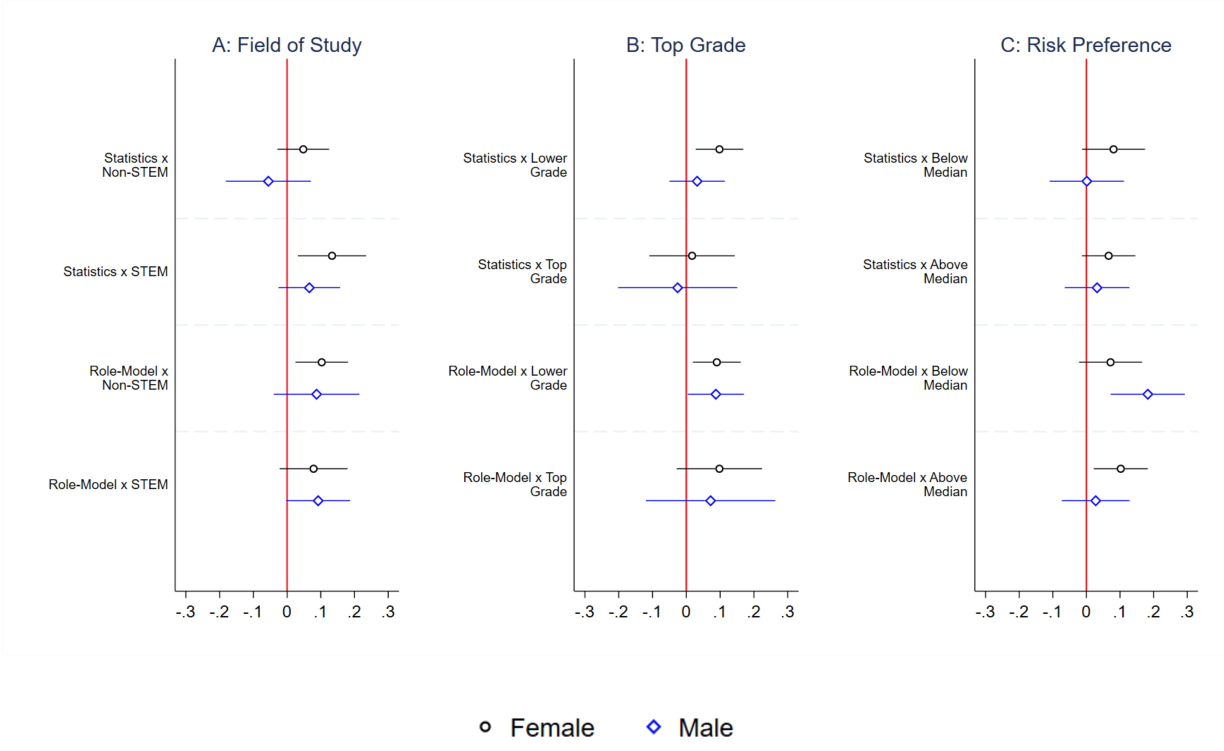
As graduates in various fields of study may have different labor market perspectives and outcomes (e.g., Altonji et al., 2016), they may also be affected by treatments differently. Therefore, I examine the treatment effects separately for STEM and non-STEM fields of study. Focusing on the primary outcome of negotiation intention for base salary, the left panel of Figure 2.4 reveals that the effects of treatment vary between study fields.[22] It is

[21] Participants received a code and a link to participate in the training treatment, so it is unlikely that people from the control group joined the treatment.

[22] All coefficient estimates are also presented in Appendix Table A.6.

notable that the statistics treatment has a positive and statistically significant effect on female STEM students, while the role-model treatment increases the intention to negotiate for base salary for female non-STEM students.

Figure 2.4: Heterogeneity in the Treatment Effect: Base Salary



Note: The figure shows heterogeneous treatment effects on the intention to negotiate for base salary. The coefficient estimates are taken from Columns (1) and (2) of Table A.6. The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. Controls include strata fixed effects: the field of study (4 categories), grades (2 categories), and the planned graduation date (2 categories). Other controls include being born in Germany, having parents with a college degree, having siblings, days since the intervention, ever participating in the negotiation training treatment, and university fixed effects for universities with more than 50 students in the sample.

The role-model treatment also has a significant effect on female non-STEM students regarding negotiation intentions for other monetary aspects (left panel of Appendix Figure A.7) and STEM students for other non-monetary aspects (left panel of Appendix Figure A.8). For males, both treatments have no significant effect on any outcome, regardless of the field of study. With the small exception of the role-model treatment, which increases (at the 10% level) base salary negotiation intentions for male STEM students.

Next, I examine the impact of the treatments based on different grades. I distinguish between high grades (1.3 and better) and lower grades (worse than 1.3). The central panel of Figure 2.4 shows that neither treatment produces significant effects on those with high grades. However, a different pattern emerges among students with lower grades. The statistics treatment solely increases negotiation intentions among females with lower grades with respect to base salary. In contrast, the role-model treatment enhances negotiation intentions for both male and female students, affecting not only the base salary but also other monetary components (central panel of Appendix Figure A.7). Moreover, for female students, this treatment increases negotiation intentions regarding non-monetary aspects as well (central panel of Appendix Figure A.8).

The effect of treatment might also be different for individuals with different levels of risk aversion. I explore whether treatments have different effects on individuals based on their levels of risk aversion. To conduct this analysis, I categorize individuals as either above or below the median level of risk aversion, which is calculated separately for men and women. The role-model treatment has a greater effect on base salary negotiation intentions for females with higher risk tolerance, while the statistics treatment has no significant effect (right panel of Figure 2.4). This suggests that risk-taking women who would not otherwise consider negotiating may be more willing to negotiate, especially after being exposed to the experiences of role models. Engaging risk-averse individuals in negotiation appears to be more complex and may require more intensive interventions.

Interestingly, role-model treatment has a significant and large effect (18 percentage points) on the intention to negotiate base salary for males who are risk averse (right panel of Figure 2.4). Finally, role-model treatment also has a significant effect on negotiation intentions for other monetary aspects for both genders with lower risk preferences (right panel of Appendix Figure A.7).

Expected Returns to Salary Negotiation

To investigate whether treatments influence the anticipated return of the negotiation, I examine the effects of the intervention on the expected percentage chance of a base salary increase conditional on a negotiation.[23] The results in Table 2.4 show that the effects of the treatments are significant for women, but only marginally significant for men. For women, the effect of role-model treatment is larger than the effect of statistics treatment. For example, statistics treatment increases the expected percentage chance of a base salary by 4.592 percentage points. Compared to the control group mean, this represents a large increase of around 24%. The distribution of the outcome variable by gender is presented in the Appendix Figure A.9.

Table 2.4: The Percentage Chance of Increase of Base Salary

	Female	Male
	(1)	(2)
Statistics Treatment	4.464***	3.661*
	(1.444)	(1.882)
Role-Model Treatment	6.750***	3.790*
	(1.468)	(1.957)
Strata FE	Yes	Yes
Controls	Yes	Yes
Mean of Control Group	28.637	35.040
Individuals	1,410	1,002

Note: This table reports the treatment effects on the expected percentage chance of a base salary increase as a result of negotiation. The outcome variable is continuous and is illustrated in Appendix Figure A.9. For explanations of the variables of interest and controls, refer to Table 2.3. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

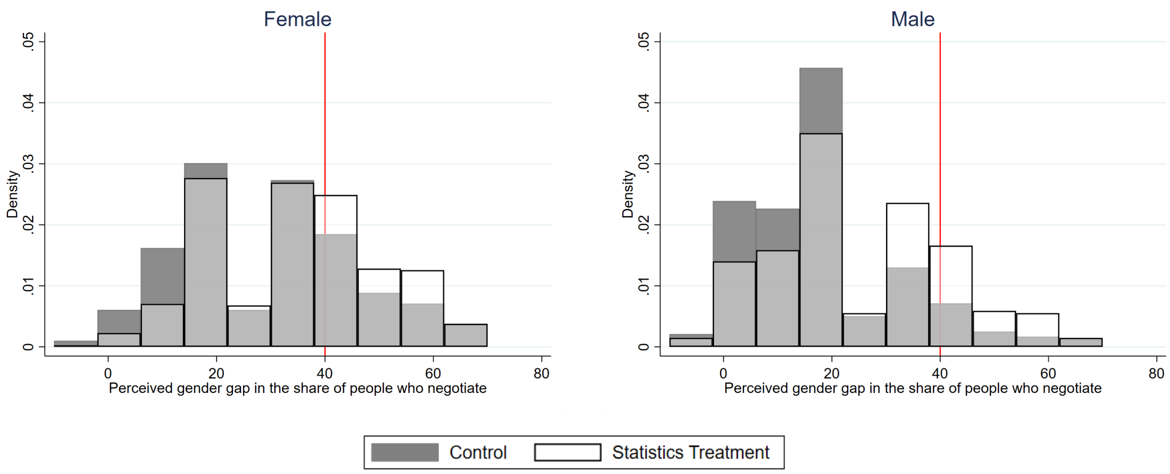
[23] The exact question is "If you were to negotiate with your future employer about the base salary of your first regular job after graduation, what do you think the percentage chance is that your base salary will increase?"

The Role of Belief Updating in Negotiation Intentions

The treatments may affect negotiation intentions and expected returns to negotiation via two channels. First, the treatments may increase participants' negotiation intentions by informing them about the percentage of women/men who negotiate their wages or about the potential returns to negotiation. This assumes that participants are misinformed ex-ante and adjust their beliefs after receiving the information (Rockoff et al., 2012; Bursztyn et al., 2020b). Second, assuming that respondents already have accurate information prior to the interventions, the treatments may increase the salience of the information (Bleemer and Zafar, 2018; Grewenig et al., 2020).

Figure 2.5: Perceived Gender Gap in Negotiation

(a) (b)



Note: The figure illustrates the post-treatment beliefs of females and males regarding the gender negotiation gap in the population. The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. The vertical red line represents the gender gap in salary negotiation intention, which is equal to 40% according to the statistics treatment. For explanations of the controls, refer to Table 2.3.

To examine these channels, I elicit participants' beliefs about the share of women and men who negotiate their first full-time wage both before and after the treatment. Figure 2.5 shows that 2-4 months after the statistics treatment, which highlights a 40% gender gap in wage negotiation, treated women perceive a larger gender gap compared to those in the control group. This difference is even more pronounced for men.[24]

Following Bleemer and Zafar (2018), I explore the mechanisms that facilitate belief updating in the following way:

$$\Delta Belief_{ij} = \beta_0 + \beta_1 Statistics_i + \beta_2 Error_i + \beta_3 (Statistics_i \times Error_i) + \beta_4 X_i + \gamma_j + \epsilon_{ij} \quad (2.2)$$

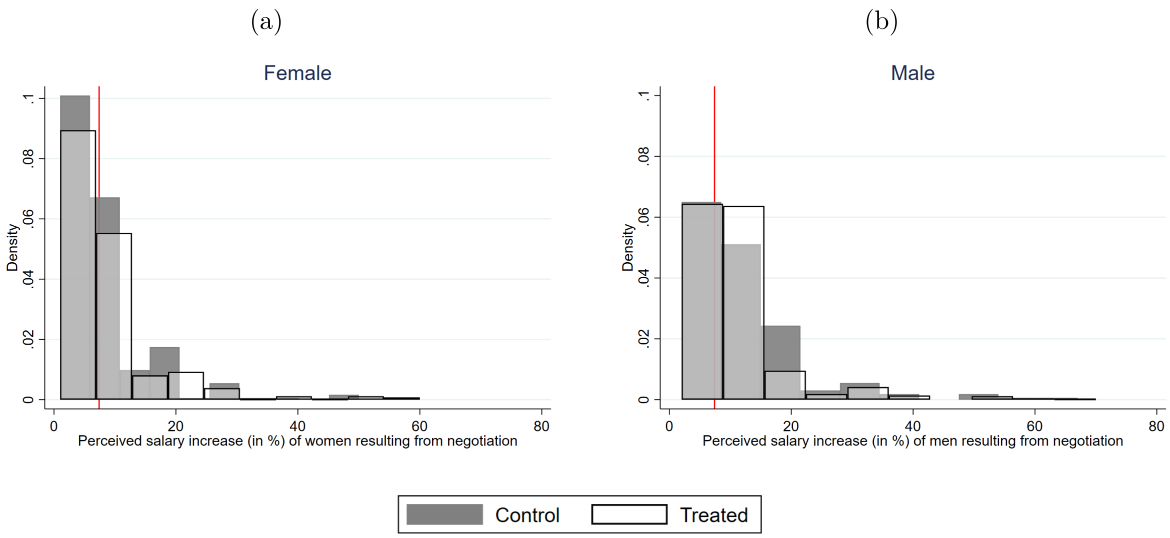
where the outcome variable $\Delta Belief_{ij}$ denotes the belief update of individual i 2-4 months after the intervention. Given the range of beliefs, from those far from the true value to those close to it, I compute an error variable to assess the role of belief accuracy. This error, denoted as $Error_i$, is calculated as the difference between the perceived gender gap in the proportion of people who negotiate their wages and the true value according to the statistics treatment (40%), so a positive (negative) error indicates an overestimation (underestimation). $Statistics_i$ is an indicator for participant i being assigned to the statistics treatment. For individuals whose error in the perceived gender negotiation gap is zero, β_0 reflects the average belief update in the control group, while β_1 denotes the average update for individuals assigned to the statistics treatment. β_2 is the average belief update related to the error for the control group. Finally, β_3 captures the mean update in beliefs associated with the error in the gender negotiation gap for treated individuals. When β_1 is non-zero, respondents update their beliefs due to an increase in the salience of information related to the gender negotiation gap. However, if respondents are updating their beliefs as a result of information updating, β_3 must be different from zero. In order to test whether belief updating has any effect on the intention to negotiate for base salary, I use a dummy for the intention to negotiate (see Section 2.4.1 for more details), which takes the value 1 if a graduate i intends to negotiate for their first job after graduation, and 0 otherwise.

The results derived from Equation 2.2 show that the statistics treatment leads to a 3.5

[24] Since only the statistics treatment includes information about the gender gap in wage negotiation, I exclude those who received the role-model treatment in the first estimation.

(5.7) percentage point increase in women's (men's) perceptions of the gender negotiation gap when there is no pre-treatment error (Columns (1) and (2) of Appendix Table A.7), implying an upward revision. The coefficient on the interaction term in Row (3) is negative and significant for women, indicating that women who overestimate (underestimate) the true population gender negotiation gap revise down (up) their beliefs. Overall, however, the relationship between revisions and errors is weak for women and absent for men.

Figure 2.6: Perceived Wage Increases as a Result of Negotiation



Note: The figure illustrates the post-treatment beliefs about negotiation success rates in the population, separately for women and men. he outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-Up 1 (wave 2) and responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. The vertical red line represents the the expected increase in the average salary as a result of negotiation, which is equal to 7.4%, according to the statistics treatment. For explanations of the controls, refer to Table 2.3.

In addition, when analyzing the intention to negotiate base salary as the outcome, it appears that the effect of the statistics treatment on negotiation intentions cannot be attributed to belief updating, as the interactions in Columns (3) and (4) (Appendix Table A.7) are statistically insignificant, indicating that the magnitude of the treatment effect is not related to information updating.

Furthermore, the results in Section 2.4.2 document that the treatments have an effect on anticipated wage increases as a result of negotiations. To examine whether information updating plays a role in this result, I focus on the question asking participants how much they expect the average female (male) salary to increase (in percent) after women (men) negotiate. In the statistics treatment, the reported true population value is 7.4%, while in the role-model treatment it ranges from 5 to 15%. For this exercise, I use the 7.4 threshold as the true value. The treatments focus on the overall success of wage negotiation rather than the gender gap. Therefore, in figures and estimates, I use the female (male) response as the corresponding reported belief for women (men). Figure 2.6 documents the distribution of perceived wage increases for women and men separately after treatment. On average, women underestimate the salary increase as a result of negotiations. However, the difference between the control and treatment groups is not very clear.

To explore this further, I examine the effect of the error in beliefs about the true value (7.4%) of returns to negotiation on post-treatment beliefs and negotiation intentions. I use an approach similar to Equation 2.2, but since participants' beliefs about their own gender's success would play a larger role, I run the analysis separately for women and men.[25]

Columns (5) and (6) in Appendix Table A.7 first show that the statistics and role-model treatments do not significantly change beliefs about the returns to negotiation for either men or women. The results also reveal that the effects of both treatments on negotiation intentions (Columns (7) and (8)) are unrelated to the size of the error in beliefs, as the coefficients on the interaction terms are insignificant for both genders. Thus, the error in beliefs about the returns to negotiation does not play a role in the estimated treatment effects. Overall, this section suggests that the increase in negotiation intention is not

[25] For example, the estimation equation for women is as follows:

$$\begin{aligned}\Delta Belief_{ij} = \beta_0 + \beta_1 Statistics_i + \beta_2 Rolemodel_i + \beta_3 Error - Female_i + \\ \beta_4 (Statistics_i \times Error - Female_i) + \beta_5 (Rolemodel_i \times Error - Female_i) + \beta_4 X_i + \gamma_j + \epsilon_{ij}\end{aligned} \tag{2.3}$$

explained by belief updates, but rather by an increase in the salience of information.

2.4.3 Effects on Realized Negotiation Behavior

The Treatments Effects

This section examines the effects of the treatments on the actual negotiation for the base salary, other monetary aspects, and other non-monetary aspects.[26] Table 2.5 documents that the effects of the statistics and role-model treatments are insignificant for all negotiation outcomes and for both genders. The insignificant effect on realized negotiation for base salary is surprising, given that the statistics treatment significantly increased women's negotiation intentions for base salary, and the role-model treatments increased the negotiation intentions of both women and men. Overall, the results suggest that although individuals increased their intention to negotiate, this did not translate into actual negotiation behavior.

In addition, I perform a heterogeneity analysis to assess whether the null effects of treatments might be masked by variations in the fields of study (Non-STEM vs. STEM), grades (better than or worse than 1.3), and risk preferences (below vs. above the median). Appendix Table A.9 shows that treatments do not significantly alter the actual negotiation behavior of these different groups.

Treatment Effect Channels

Reasons for not Negotiating for Base Salary

Conditional on not negotiating for their first job, participants were asked to provide reasons

[26] The outcome variables are measured in waves 2 and 3 and take the value 1 if an individual negotiates for their first job and 0 otherwise. Participants answer this question in wave 2 if they have started applying for a job, and also in wave 3. If an individual answers this question in both waves, I focus on the first answer from wave 2. As a robustness check, I re-estimate the treatment effects by dropping the individuals who answer this question in both waves and who give different answers and the result does not change (see Appendix Table A.8).

Table 2.5: The Treatment Effects on Realized Negotiation Outcomes

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Statistics Treatment	-0.006	0.001	0.029	-0.010	-0.031	-0.006
	(0.037)	(0.040)	(0.028)	(0.034)	(0.031)	(0.031)
Role-Model Treatment	-0.008	0.013	0.033	-0.022	0.004	0.032
	(0.037)	(0.041)	(0.027)	(0.033)	(0.031)	(0.033)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.403	0.470	0.147	0.192	0.236	0.176
Individuals	1,051	909	1,051	909	1,051	909

Note: This table reports the treatment effects on realized negotiation outcomes, based on the estimation of Equation 2.1. The outcome variables are binary and equal to 1 if respondents negotiated for base salary (Columns (1) and (2)), for other monetary aspects (Columns (3) and (4)), and for other non-monetary aspects (Columns (5) and (6)) for their first regular job after negotiation, and equal to 0 if they did not. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) or follow-up 2 (wave 3) and who responded to the realized negotiation outcomes (base salary, other monetary aspects, non-monetary aspects) in the first follow-up or second follow-up. If a participant answers this question in both waves, I focus on the first answer from follow-up 1 (wave 2). For explanations of the variables of interest and controls, refer to Table 2.3. *Mean of Control Group* is the respective mean outcome in the control group at follow-up 1. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

for not negotiating for their base salary. Table 2.6 compares the control and treated groups on the reasons for not negotiating, separately for men and women.[27] Treated women are more likely to report that they were *"unsure how to negotiate"*. They were also more likely than the control group to *"be afraid of having their proposal rejected"*, although the difference is only slightly significant. In contrast, females in the control group are more likely to report that they *"did not want to be perceived as too aggressive"*. Thus, the results suggest that the treatments make women consider negotiation by increasing

[27] Because of the small sample size of those who answered this question, I combine the reasons for not negotiating for their first regular job after graduation and for not negotiating during their first job search.

their intention to negotiate; however, they do not address the issue of how to conduct a negotiation intensively or how to get rid of fears.

Table 2.6: Reasons for Not Negotiating: A Comparison of Control and Treatment Groups

	Female			Male		
	Control	Treated	Control - Treated	Control	Treated	Control - Treated
	(1)	(2)	(3)	(4)	(5)	(6)
Base Salary Was Fixed	0.718	0.645	0.074	0.493	0.547	-0.054
Salary Did Not Matter	0.035	0.054	-0.019	0.071	0.076	-0.004
Fear of Not Getting the Job	0.158	0.221	-0.064	0.143	0.124	0.019
Fear of Having Proposal Rejected	0.035	0.114	-0.079*	0.086	0.034	0.051
Unsure What Amount to Propose	0.140	0.215	-0.074	0.114	0.090	0.025
Unsure How to Negotiate	0.105	0.228	-0.123**	0.129	0.110	0.018
Thought the Salary Was Fixed	0.053	0.047	0.006	0.086	0.007	0.079***
Salary Was Not Discussed	0.263	0.295	-0.032	0.214	0.276	-0.062
Would Not Want to Be Perceived as Too Aggressive	0.105	0.040	0.065*	0.057	0.041	0.016
Already Negotiated Other Aspects	0.035	0.027	0.008	0.071	0.048	0.023
Concern about Negative Relationship with Employer	0.053	0.107	-0.055	0.043	0.062	-0.019
Salary Offer Was Reasonable	0.439	0.369	0.069	0.514	0.476	0.038
I Don't Know	0.000	0.007	-0.007	0.029	0.041	-0.013
Other Reason	0.246	0.221	0.024	0.200	0.248	-0.048
Individuals	110		252	67	172	

Note: This table shows the distribution of responses to the question "What were the main reasons for not negotiating the base salary of your first regular job after your master's degree?", which was asked only of participants who reported not negotiating the salary of their first job. Columns (1) to (3) show female responses and Columns (4) to (6) show male responses. Columns (1) and (4) show the responses of the control group, Columns (2) and (5) show the responses of the treatment group, combination of statistics and role-model treatments, and Columns (3) and (6) compare the responses of the control and treatment groups. ***, ** and * denote significance at the 1, 5, and 10% levels.

Interestingly, for men, the only significant difference between the control and treatment groups lies in the perception that the *"base salary was fixed"*, and men in the control group report this more frequently than treated men. This difference could potentially arise from men in the control group do not really consider negotiating unless they receive the treatment.

Since we find that treatment and control groups differ in different ways for men than for women, Appendix Table A.10 additionally presents the reasons for not negotiating by gender by pooling control and treatment groups. As expected, females are more likely to work in more secure jobs with fixed salaries. In addition, women are significantly more likely to report concerns such as *"fear of not getting the job"*, *"unsure what amount to propose"*, or *"unsure how to negotiate"*. In contrast, men often justify their decision not to negotiate by asserting that *"the salary offer was reasonable"* or *"I don't know"*.

Timing of the Intervention

One potential reason for the observed null effect might be that graduates simply forgot about the intervention, since the negotiation takes place a considerable time after the intervention for some graduates. To address this concern, I separated the analysis into two groups: those who answered the negotiation questions during the second wave (2-4 months after the intervention), and those who answered during the third wave (6-8 months after the planned graduation date).

Appendix Table A.11 shows that role-model treatment significantly increases all realized negotiation outcomes for women who responded to the negotiation question during the second wave. The effect becomes insignificant and negative for those who answered in the third wave.

In addition, I examine the time between the intervention and the responses to the negotiation questions. Since the planned graduation dates vary, respondents faced the negotiation questions at different intervals after the interventions. Appendix Figure A.10 illustrates the density of the months between the intervention and the base salary negotiation question. To investigate the timing effect, I divided the individuals into two groups based on whether the time between the intervention and the question answered was less than 8 months or longer. Appendix Table A.12 indicates a positive and significant impact on those who received the negotiation question earlier after the intervention. However, when I limited the analysis to respondents who had non-missing responses for all negotiation outcomes, including negotiations for base salary and other monetary and non-monetary aspects, the significance of the coefficients disappeared. Therefore, the timing after the intervention seems to provide only a partial explanation for the null effects.

Robustness Checks

I conduct two robustness analyses that explore different negotiation contexts and expand the sample size by not dropping observations with missing values in other negotiation outcomes. First, the initial analysis concentrated on whether graduates negotiate for their first regular job after graduation. However, it is also possible that graduates do not negotiate for their first regular job, but negotiate during their first job search. Since the survey asks these two questions separately, I am also able to examine whether a negotiation occurs at any point during the job search process. The results, presented in Appendix Table A.13, are similar to the main analysis, showing no substantial treatment effects.

Second, the main sample of analysis for realized negotiation outcomes is limited to respondents who have a non-missing response to all negotiation outcome questions for base salary, other monetary aspects, and other non-monetary aspects. I repeat the analysis of treatment effects on the negotiation intention for base salary outcomes without excluding those with missing data on other monetary and non-monetary aspects. Even with the expanded sample for base salary negotiation (Columns (1) and (2)), the findings remain consistent and reveal no meaningful treatment effects (see Appendix Table A.14).

2.5 Discussion of Treatment Effect Channels

The results show that both the statistics and the role-model treatments substantially increase women's intention to negotiate, and the expected percentage increase in salary conditional on negotiation. Given that the interventions are cheap and short, the effect on negotiation intention is large and significant. As noted in Section 2.2, both treatments aim to provide master students with information about the importance and benefits of salary negotiation. In the role-model treatment, this information is conveyed by successful role models in the labor market.

Two main reasons could explain the increased intention to negotiate. First, the treatments might have corrected pre-existing misinformation, leading people to update their beliefs (Rockoff et al., 2012; Bursztyn et al., 2020a). Second, the treatments might have increased the salience of the information (Schwarz and Vaughn, 2002; Chetty et al., 2009; DellaVigna, 2009; Bleemer and Zafar, 2018; Grewenig et al., 2020). The statistics treatment aimed to increase the salience, particularly for women, by emphasizing gender differences in negotiation behavior. The role-model treatment, on the other hand, conveyed information via role models and aimed to make master's students, particularly females, relate and increase their attention to real-life examples of positive experiences. In addition, role-model treatment included some helpful tips about negotiation that might encourage students to learn more about it.

To investigate these channels, I tested in Section 2.4.2 whether the participants update their beliefs as a result of negotiation. I find that students update their beliefs about the proportion of people who negotiate according to the information provided in the statistics treatment. However, this updating of beliefs did not affect their negotiation intentions. In addition, the section showed that the treatments do not significantly change beliefs about the potential gains from negotiation. These findings suggest that the observed increase in negotiation intentions does not stem from information updating. Instead, it appears to be driven by an increase in the salience of the information provided.

Section 2.4.2 further illustrates that the effect of the treatments is particularly pronounced among women who *"hadn't thought about"* negotiating before the treatments.

This pattern also suggests that the treatments may encourage students to pay more attention to the topic of negotiation, to think about it, to seek out more information about it, and to reduce the likelihood of forgetting about negotiation during the job search period. This is particularly important for those who might not have thought about negotiation before the treatments were provided.

Although the treatments succeeded in increasing graduates' intentions to negotiate, they did not lead to a change in their actual negotiation behavior. This disconnect between intention and action is a well-documented phenomenon in the field of social psychology and psychology, often referred to as the "intention-behavior gap" or the "intention-action gap." The intention-behavior gap occurs primarily when an individual intends to achieve a goal but does not act accordingly. The meta-analysis conducted by Sheeran (2002) shows that the median proportion of people who intend to act but do not act is 47%. This gap can be attributed to various challenges and external factors that can complicate the transition from intention to action (Wiedemann et al., 2009; Moghavvemi et al., 2015; Hassan et al., 2016).

In the context of wage negotiations, there are several obstacles that can prevent a negotiation. For example, the salary might be fixed, leaving no room for negotiation. There may also be a fear of backlash or a lack of confidence in negotiating, especially among women. In such situations, a short intervention may not be sufficient to overcome these fears or increase confidence. To address this issue, Section 2.4.3 examined the reasons for not negotiating. It shows descriptively that women are more likely to express concerns such as being *"unsure how to negotiate"*, having *"fear of having a proposal rejected"*, and *"not wanting to be perceived as being too aggressive"*. This result shows that although the treatments increased individuals' intentions to negotiate by making the information given more salient, they were not intensive enough to overcome fears, encouraging enough to increase confidence or providing sufficient guidance on how to negotiate. They also did not encourage individuals to seek out this information on their own. The findings highlight the complexity of turning intention into action, especially in the context of wage negotiation.

It is also possible that the graduates, especially those who received the treatments a long time ago, may have forgotten about the treatments during their job search. In this case, the effect of the treatments would likely be more pronounced for those who found their first job shortly after the interventions. Section 2.4.3 provides some evidence in support of this hypothesis, showing that the effect of the role-model treatment was positive and significant for females who responded during the second wave, 2-4 months after the intervention. However, this significant effect was not observed in the third wave of responses. Further analysis indicates that the result is not robust when focusing on our main sample, which has no missing responses for all negotiation outcomes (base salary, other monetary and non-monetary aspects), suggesting only a partial explanation for the null effect of treatments on actual salary negotiation.

2.6 Conclusion

I conduct a randomized controlled trial to assess how providing information affects the negotiation intentions and outcomes of master's graduates, particularly for women. The first information intervention, the statistics treatment, provides students with information about the significance and potential benefits of negotiations, emphasizing the gender gap in negotiation behavior to increase the salience of the information. The second treatment, the role-model treatment, provides personalized information via role models, designed to both inform and motivate graduates, especially female graduates, to negotiate.

I first establish the existence of a gender gap in negotiation intention before the interventions take place. Furthermore, 2-4 months after the interventions, the statistics treatment increases negotiation intentions by 7.6 percentage points for women but has no effect on men. Conversely, the role-model treatment increased the negotiation intentions of both genders by roughly 9 percentage points. For women, these treatments also significantly affect the expected chance of a salary increase resulting from negotiation. The significant effect is primarily attributed to the salience of the information rather than mere information updates. Additionally, I demonstrate that the treatments do not significantly impact actual negotiation behavior. This implies that converting intentions into actions in high-stakes contexts, such as wage negotiations, is challenging. Consequently, more intensive interventions are necessary to alleviate the fear of negotiation and educate individuals on negotiation techniques.

The findings of this paper show that providing even a small amount of information can encourage graduates to consider participating in negotiations. While highlighting gender differences mainly affects females, using role models appeals to both men and women. However, to empower women to engage in negotiations, they may require more comprehensive and targeted training just before (or during) the job search period. These findings may encourage universities and other institutions to provide more negotiation training, especially for women. Universities could also consider adding negotiation courses into their curricula as a means of addressing the gender negotiation gap and, consequently, the gender wage gap among university students. However, given the findings of Exley et al. (2020) from a laboratory experiment, general "lean-in" advice to women may not necessarily be beneficial. Therefore, more research is needed to better understand which type of negotiation advice works best in which context.

Chapter 3

Unraveling the Gender Wage Gap: Exploring Early Career Patterns Among University Graduates

with Malte Sandner

We are thankful for valuable comments from Silke Anger, Alex Bryson, Astrid Kunze, Nikki Shure, Markus Nagler, Uta Schönberg, David Wilkinson, Bernd Fitzenberger and all participants at the Annual LERN Conference 2019, ESPE 2019, AASLE 2019, Workshop on Labour Economics 2021, Research Seminar at the TH Nürnberg, International Conference on The German Labor Market in a Globalized World (ZEW) 2022. Additionally, we are grateful to University of Regensburg for the data access and to Joachim Möller and Christopher Rust for their support.

3.1 Introduction

Despite advances in women's education and career opportunities in recent decades, a persistent gender wage gap remains prevalent in economically advanced nations (Goldin, 2014; Olivetti and Petrongolo, 2016), this gap is even larger among individuals with higher levels of education (Blau and Kahn, 2017; OECD, 2022). Many studies have examined the gender wage gap among highly educated individuals and found that women's lower labor supply and more frequent career interruptions (mainly due to child care) compared to those of men are the main reasons for this gender wage gap.[1]

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 future labor market outcomes of university graduates and potentially on the gender wage gap. For example, Oyer (2006), Kahn (2010) and Oreopoulos et al. (2012) show that labor market conditions at the beginning of the career, such as recessions, can 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); even wage increases 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 origin 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, some common reasons for pay differences between men and women, such as family-related decisions (e.g., childbirth or marriage), career-related developments (e.g., promotions), work experience, and firm-specific networks, may not yet be relevant.[2] Therefore, we expect no or only a small gender wage gap in the

[1] For example, see Adda et al. (2017), Kuziemko et al. (2018), Kleven et al. (2019a), and Cortés and Pan (2023).

[2] The mean age of German mothers at first birth was 30.5 in 2021 (Federal Statistical Office, 2022), while the average age of labor market entry for women in our sample is 27. Moreover, the average

initial job, especially when we account for gender differences in the field of study and the characteristics of the employer in the first job.

However, particularly in the first job, both the applicants and the firms face considerable uncertainty. Firms can assess only the labor market productivity of candidates without prior work experience based on their university grades and interview performance. Given that women currently tend to have higher GPAs than men (Becker et al., 2010; Francesconi and Parey, 2018), we may even expect the gender wage gap that is conditional on differences in field of study choice and employer characteristics to favor women in the first job. On the other hand, existing studies show that female applicants negotiate less in job interviews than male applicants do (Babcock and Laschever, 2003; Bertrand, 2011) and may face statistical discrimination at labor market entry (Altonji and Pierret, 2001; Pinkston, 2006). Furthermore, differences in preferences or personality traits, such as risk aversion or overconfidence, can be particularly important at the beginning of a career. Studies show that women are more risk-averse (e.g., Cortés et al., 2023) and less self-confident than men (e.g., Adamecz-Völgyi and Shure, 2022), which may lead them to accept lower-paying job offers. As a result, the gender wage gap could be substantial and in favor of men, given differences in field of study and employer characteristics in the first job.

This ambiguity about the gender wage gap may be even greater in the 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 their first job as a result 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 (Farber and Gibbons, 1996; Altonji and Pierret, 2001). However, the gender wage gap may also increase over time due to job changes in the early stages of a career, as the literature shows that women generally realize lower returns to job mobility than men (Topel and Ward, 1992; Albrecht et al., 2018). In addition, the gap may widen over time

age of women at birth is expected to increase with the level of education. Therefore, this issue is not expected to be of high magnitude in the case of women with a master's degree at labor market entry.

as family-related decisions become more important over time. Overall, the gender wage gap at labor market entry and the dynamics of the gender wage gap in the early years of a career remain unclear and thus require examination.

This study examines the gender wage gap immediately after entering the labor market and its evolution during the initial years of a career for 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). This linked administrative dataset provides a wide range of information from the two data sources, 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 in 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 approximately 12.5 log points corresponds to approximately 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 substantially alter the gender wage gap.

Second, since both career paths and wages vary widely across fields of study (Altonji et al., 2016), we conduct a subgroup analysis of 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 in 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 the major subject within the field 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, the highest variation in wages, and the highest share of females.

Third, as dynamics are very important, particularly in the early years of a career, and have an impact on future wage growth, we examine the dynamics of the gender wage gap over the first years after labor market entry. Our findings reveal a decrease in the estimated gender wage gap in the first three years after labor market entry, followed by an increase in subsequent years. The largest reduction in the wage gap occurs one year after labor market entry. Moreover, we demonstrate that this decrease 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 or for those who remain in the same firm and occupation.

Finally, our analysis focuses on two field groups: economics and business and humanities and social sciences. This analysis shows that women who change firms and occupations after their first job drive the decline in the gender wage gap, as women benefit more from these changes than men. Our data show that women are more likely than men to work in a mismatched occupation at the first job. By changing both firms and occupations, women move out of the lowest paid occupations and are able to correct this mismatch, leading to a greater increase in wages than men. After comparing these empirical findings with several theories in the gender wage gap literature, one explanation for our finding may be that women immediately after graduation have a high preference for certain job and firm amenities, such as job meaning and relevance, leading them to initially accept mismatched jobs. One year after labor market entry, individuals' preferences may change, and they may correct this mismatch by changing occupation and firm. However, our data do not allow for a definitive test of this hypothesis.

Our study contributes to the literature in three important ways. First, 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, mainly due to family-related decisions (Manning and Swaffield, 2008; Bertrand et al., 2010; Albrecht et al., 2018).[3] Although these studies provide valuable insight into the dynamics of the gender wage gap in general, they do not focus on the first job after graduation. The few papers that examine the gender wage gap at the beginning of a career rely primarily on survey data. For example, Cortés et al. (2023) find in a survey of approximately 1,350 business school graduates in the U.S. that women earn 10% less than men in their first job. In a related German study, Francesconi and Parey (2018) find an adjusted gap of 5-10 log points among full-time German college graduates 12-18 months after graduation. In contrast to this literature, we are the only study to investigate the gender wage gap among university graduates using administrative data, with a focus on the first job after graduation. Administrative data help to avoid reporting bias that can occur in survey-based studies at the beginning of a career due to frequent job changes. With our data, we are able to analyze the origins of the gender wage gap when university graduates earn wages for the first time in their careers.[4]

Second, in addition to accurately identifying the first job, this novel linked dataset offers several other advantages. For example, the administrative nature of the data overcomes concerns associated with missing data, response rates, or measurement error due to retrospective questions. In addition, most of the other data used to study the gender wage gap either lack comprehensive information on graduates' pre-graduation characteristics (field of study, GPA) or are unable to track graduates as they transition into the labor

[3] 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).

[4] The studies by Kunze (2003, 2005) use administrative data but focus on younger graduates who have completed an apprenticeship.

market and lack information on graduates' occupation, industry, and other important employment characteristics. In contrast, our linked data provide access to accurate and comprehensive measures of human capital determinants of productivity, including academic grades and field of study, as well as detailed information on employment, wages, and occupations.

Third, our study provides unique insights into early career job dynamics and their impact on the gender wage gap. At the beginning of careers, a high level of information friction can lead to poor job matches in the labor market for recent graduates (Vesterlund, 1997). Fredriksson et al. (2018) highlight 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 literature shows that job changes are associated with wage growth (Topel and Ward, 1992; Manning and Swaffield, 2008; Del Bono and Vuri, 2011; Albrecht et al., 2018). Several studies also observe that men are more likely to change jobs[5] and tend to benefit more from job mobility than women, thereby exacerbating the gender wage gap over time (Topel and Ward, 1992; Manning and Swaffield, 2008; Del Bono and Vuri, 2011; Albrecht et al., 2018). However, these studies do not focus on the first years after labor market entry because observing this crucial early period without detailed administrative data is difficult.

In contrast, we are able to follow all graduates without attrition over time, which allows us to observe the exact timing of any job changes or job search periods within the first few 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 jobs and to observe the

[5] Except for the study by Albrecht et al. (2018), who find similar probabilities of job change for men and women.

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 3.2 describes the data and its advantages and shortcomings, characterizes the sample of university graduates used in the analysis, and presents descriptive statistics. The results of 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 3.3 and Section 3.4, respectively. We examine gender differences in firm and occupational mobility in Section 3.5 and the underlying reasons for this mobility in Section 3.6 before concluding the paper in Section 3.7.

3.2 The Linked Administrative Dataset and University Graduates

3.2.1 Data

This study is based on a unique administrative dataset of graduates from the University of Regensburg linked with registry 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. During the observation period, almost all the fields of study are considered except for engineering degrees. The available dataset from the University of Regensburg covers all of 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 the personal characteristics of each graduate, such as year of birth, gender, nationality, and 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 the field of study, the type of university degree attained, the final GPA, and the dates of enrollment and graduation.

The IEB is a large administrative dataset of individuals' employment biographies provided by the 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 approximately 80% 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 (3-digit), 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, sex, and date of birth, with a 90% match rate (Möller and Rust, 2018).[6]

3.2.2 Sample Choice

The focus of this study is on individuals with a master's degree or equivalent with available university GPA data. We further focus on graduates who are working full-time in their first regular job with a daily wage of at least 10 Euros[7] and omit graduates who are not

[6] Please refer to the study by Möller and Rust (2018) for a more detailed explanation of the matching procedure.

[7] Wages are deflated to the year 2010 using the consumer price index.

full-time employed in their first job after graduation, i.e., part-time, mini-jobs, internships, working students, etc., even if they subsequently switch to full-time employment. We choose this approach to consider the most policy-relevant group with greater labor market attachment, and the results are easier to interpret for a more homogeneous group.[8] If an individual has more than one wage spell at a given time, we choose the "main" employment spell as defined by the IAB.

Furthermore, we exclude individuals who are older than 35 years (1.5% or 104 individuals). We also omit graduates with a gap of more than 15 months between graduation and their first employment spell (14% or 999 individuals), as these individuals may have spent time abroad or 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 subsequent years, we keep graduates with wage spells at the beginning of their first job and one year after their first job (8.6% or 478 individuals were dropped). Finally, after dropping observations with missing values, the final sample for the main wage estimations consists of 5,212 individuals.

3.2.3 Descriptive Statistics

Table 3.1 presents descriptive statistics on 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 3.1 documents pre-graduation characteristics, such as university and high school GPA, duration of study, non-German citizenship, and

[8] 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, the working hours of men and women 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 approximately 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.

others, Panel B presents post-graduation characteristics, including characteristics of the first job.

Panel A of Table 3.1 shows that both men and women complete their degrees in approximately 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%) acquire some form of work experience before graduation, with females being more likely to work during their studies than males. In addition, consistent with the literature, the share of female graduates increases with graduation cohort, with the male-female ratio reversing even in the most recent cohort group (2007-2010). This finding is also in line with the overall population of German graduates. 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% of the sample standard deviation) than males.[9] Females are also more than twice as likely to graduate in the humanities and social sciences. Mathematics and natural sciences graduates account for nearly a quarter of all male graduates, compared to only 8% of all female graduates. Nevertheless, economics and business remain the dominant fields of choice for both genders. Finally, the share of women studying medicine is approximately 10 percentage points greater than that of men. Table 3.1 also shows that female graduates are more likely than male graduates to earn a magister or state examination degree.[10] The vast majority of graduates have a diploma degree, with a greater proportion of men than women.

Table B.1 in the Appendix compares our estimation sample with official German register data and other representative studies. For 2010, our sample shows a slightly higher representation of women (50%) than the data from the Federal Statistical Office (46%). The share of females by field of study is also comparable. The largest difference

[9] In our data, final high school grades are only available in the data beginning with the 2001 graduation cohort.

[10] Because the Bologna Process reform was implemented in Germany no earlier than between 2005 and 2010, only a small proportion of graduates in the sample have a master's degree.

Table 3.1: Descriptive Statistics

	Male		Female		
	Mean	(Std. dev.)	Mean	(Std. dev.)	Diff.
Panel A: Pre-graduation and Personal Characteristics					
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***
Origin is Bavaria	0.876	(0.329)	0.861	(0.346)	0.016
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		
Panel B: Post-graduation Characteristics					
Left the State	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 as their first job after graduation and who have a wage spell 1 year after their first job. ***, ** and * denote significance at the 1, 5, and 10% levels.

is observed in mathematics and natural sciences. According to our data, the proportion of females in this field is 18%, while according to the register data it is 35%. In our sample, students have a slightly better final high school GPA than in the survey data taken from the study Simeaner et al. (2014) and university grades that are similar to those of the representative sample taken from the survey data used by Francesconi and Parey (2018). The graduates in our sample are, on average, about five months younger because we use examination rather than ex-matriculation dates. Notably, 11% of our students are non-German, compared to 22% in the survey data used by Francesconi and Parey (2018), as we cannot observe individuals in our data if they move to another country after graduation.

Panel B of Table 3.1 presents post-graduation and employment characteristics, such as mobility, the time between graduation and the first full-time job,[11] establishment size, and the share of women in the establishment of the first job.[12] The table shows that approximately 70% of the graduates find their first full-time job outside the city of Regensburg, with males being slightly more mobile than females. On average, female graduates take longer to find their first job than male graduates, i.e., approximately 3.7 and 3.8 months, respectively. A breakdown of the duration of job searches into different categories shows that the share of male graduates with a job search duration of less than a month is greater. 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).

[11] Hereafter referred to as "job search duration", even though this time is not necessarily spent searching for a job.

[12] The data only include information on establishments not on firms. However, in this paper, we use the terms "establishment" and "firm" interchangeably.

3.3 Gender Wage Gap at Labor Market Entry

We begin our analysis by examining gender wage differences at labor market entry.[13] To identify gender differences, we estimate the following regression equation:

$$Y_i = \alpha + \gamma Female_i + \beta X_i + \epsilon_i \tag{3.1}$$

where Y_i presents 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. $Female_i$ is a dummy equal to one if the graduate is female. X_i includes a set of control variables documented in Table 3.1.

Table 3.2 presents the first results of our empirical analysis for the 1995 to 2010 graduation year cohorts. Column (1), which controls for only 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 that in the study by Francesconi and Parey (2018), which finds a raw gender wage gap of approximately 20 log points based on survey data collected in a few selected years between 1988 and 2010, with the survey being 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.

While we add personal characteristics in Column (2) and Column (3), we additionally control for 17 fields of study (see Table B.2 in the Appendix for a list of these 17 fields),

[13] By labor market entry, we refer to the first job after university graduation and use these terms interchangeably.

Table 3.2: 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***	-0.130***	-0.068***	-0.064***	-0.062***	-0.045***	-0.047***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(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	5,212	5,212	5,212	5,212	5,212	5,212	5,212

Note: This table shows the gender wage gap at labor market entry, based on the OLS model specified in equation 3.1. The sample consists of graduates with a master's degree or equivalent who work full-time in their first job after graduation and have a wage spell 1 year after their first job. The dependent variable is the log gross daily wage in the first job. The control variables are added stepwise. Column (1) shows the results with only the year of graduation as a control. Column (2) adds personal characteristics such as age and (non)German citizenship status, and Column (3) adds field of study (17 categories). Column (4) adds the final university grades and Column (5) adds pre-graduation characteristics, i.e., duration of study, location of the final high school examination, a dummy for apprenticeship and a dummy for working while studying. Column (6) adds 3-digit occupation fixed effects. Column (7) shows the results after adding post-graduation characteristics, i.e., job search duration, job location, 1-digit industry fixed effects, firm size (7 categories), the share of women in the firm (3 categories) and the starting month of the first job. Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

which leads to a large 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 (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 final university grades and other pre-graduation characteristics (duration of study, location of high school, having completed an apprenticeship and having worked while studying) in the regression. The estimated gender wage gap barely changes after we control for these characteristics, suggesting that neither final university grades nor other pre-graduation characteristics explain a large part of the gender wage gap.[14] Table B.3 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% of the total gender wage gap at the first job. Since the field of study explains the largest part of the gender wage gap and, therefore, explanations for the pay gap may strongly vary between fields of study, in the next section, we examine the gender wage gap within a broader set of fields of study.

In addition, Columns (6) and (7) 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).[15] After adding occupation fixed effects to the estimation, the gender wage gap decreases to 4.5 log points, indicating that, similar to what is the case in 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 approximately 300 Euros per month, signifying less pay for women than for men in their first job.[16]

[14] When we add final high school grades to the estimation, the gender wage gap decreases by only 0.003 log points.

[15] Angrist and Pischke (2009) define controls that can be dependent variables as "bad controls".

[16] We also estimate the same equation including all types of first jobs and document the results in Table B.4 of the Appendix.

Field of Study

Since earnings vary by field of study,[17] 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 in Table 3.3 show that the gender wage gap is high for all fields of study, except medical studies. The raw gender wage gap (controlling only for the year of graduation) is 8.6 log points for economics and business graduates. This gap is comparable to the findings of Bertrand et al. (2010), who find a raw gender wage gap of 8.9 log points at the time of graduation for MBA graduates, and to those of 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 gaps are 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 similar to the finding of Francesconi and Parey (2018) for the STEM field. The greatest difference from the study of Francesconi and Parey (2018) is found in the field of medical studies, where we find no gender wage gap. This finding is not surprising since the wages of medical graduates (especially doctors) are set by collective bargaining agreements at the beginning of their careers; therefore, the gender wage gap is very small.

After we control for the specific field of study categories, the gender wage gap becomes insignificant for mathematics and the natural sciences. The gap is not significantly different from zero anymore because women in these fields tend to sort into lower-paid fields such as biology rather than physics. After adding controls, the largest and most significant gender wage gap is observed in those fields typically characterized by a higher female composition and lower earnings.

[17] Several studies demonstrate that different fields of study yield varying labor market returns, for example, Kelly et al. (2010), Altonji et al. (2012), Kirkeboen et al. (2016) and Deming and Noray (2020).

Table 3.3: Gender Wage Differences 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)
Add				
Graduation Year	-0.086***	-0.141***	-0.102***	-0.015
	(0.018)	(0.032)	(0.030)	(0.021)
Personal Characteristics	-0.091***	-0.142***	-0.102***	-0.010
	(0.018)	(0.032)	(0.032)	(0.021)
Field of Study	-0.091***	-0.038	-0.124***	-0.030
	(0.018)	(0.031)	(0.032)	(0.019)
Final University Grade	-0.086***	-0.029	-0.121***	-0.029
	(0.018)	(0.032)	(0.032)	(0.019)
Pre-Graduation Characteristics	-0.085***	-0.000	-0.123***	-0.033*
	(0.018)	(0.031)	(0.032)	(0.019)
Occupation FE	-0.063***	-0.005	-0.097***	-0.029*
	(0.018)	(0.030)	(0.032)	(0.017)
Post-Graduation Characteristics	-0.060***	-0.018	-0.097***	-0.029*
	(0.017)	(0.030)	(0.032)	(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 based on the OLS model specified in equation 3.1. The sample consists of graduates with a master's degree or equivalent who work in a full-time job as their first job after graduation and who have a wage spell 1 year after their first job. The control 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, i.e., duration of study, location of the final high-school examination, a dummy for apprenticeship and a dummy for working while studying. Row (6) adds 3-digit occupation fixed effects. Row (7) shows the results after adding post-graduation characteristics, i.e., job search time, job location, 1-digit industry fixed effects, firm size (7 categories), the share of women in firms (3 categories), and the beginning month of the first job. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

The finding that the gender wage gap is greater in fields with a greater share of females aligns with the literature on peer effects, which suggests that a greater proportion of females in the classroom may influence females to choose lower-paid occupations (Brenøe and Zölitz, 2020) and positions with lower wage growth (Zölitz and Feld, 2018), ultimately exacerbating the gender wage gap over time. In addition, there may also be some unobserved labor market characteristics (such as labor demand and discrimination) 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).

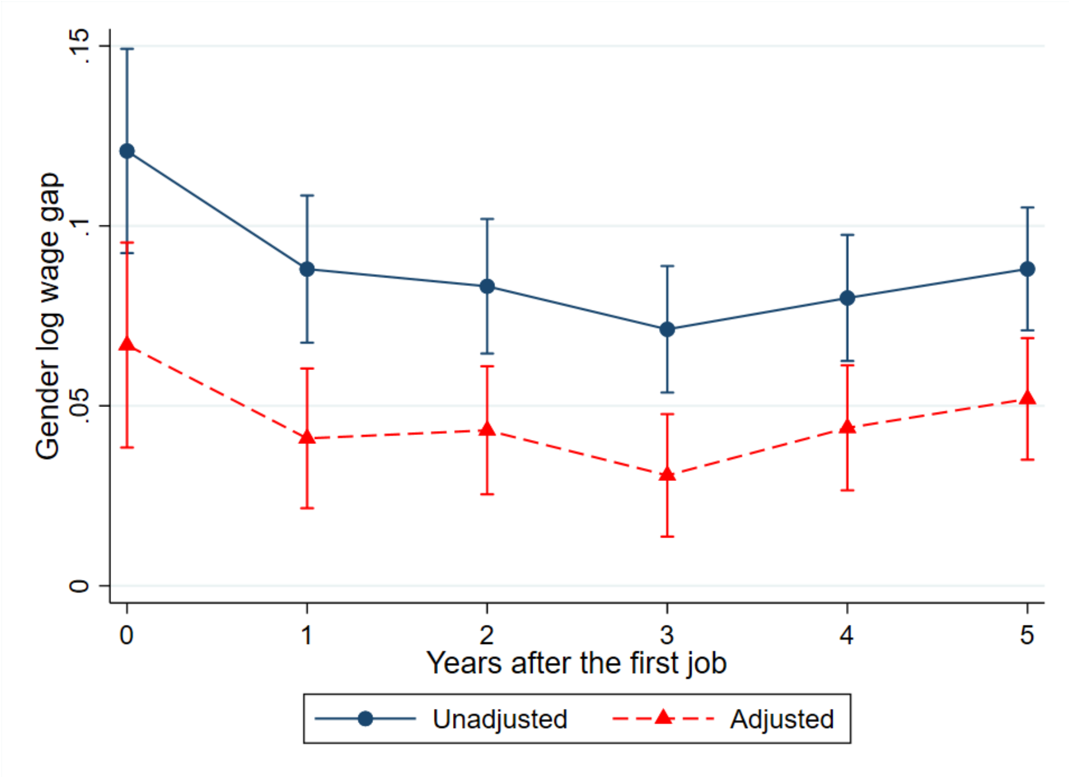
To investigate this explanation further, we employ Oaxaca-Blinder decomposition by field and find that the unexplained component of the gender wage gap is most pronounced within the humanities and social sciences field. Specifically, the unexplained part constitutes 82% and 86% of the gender wage gap for economics and business, and humanities and social sciences, respectively. The unexplained part is only 23% for mathematics and natural sciences. However, as we mentioned earlier, 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).

3.4 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. For the analysis, we include only individuals with high labor market attachment who are employed full-time more than 5 years after their first job. We decide to use a balanced sample to avoid individuals leaving the sample because of family decisions, which are likely to occur more often for females. We include only full-time employees because our data do not include the exact number of hours worked for part-time employees, which leads to bias in the hourly wage for part-time employees.

This restriction results in a sample size of 2,280 male and 1,205 female graduates, with approximately two-thirds of the graduates having high labor market attachment. The blue line in Figure 3.1 shows the unadjusted gender wage gap for the new sample corresponding to the specification in Column (1) of Table 3.2, 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 3.2.

Figure 3.1: Dynamics of the Gender Wage Gap in the First Years After Labor Market Entry

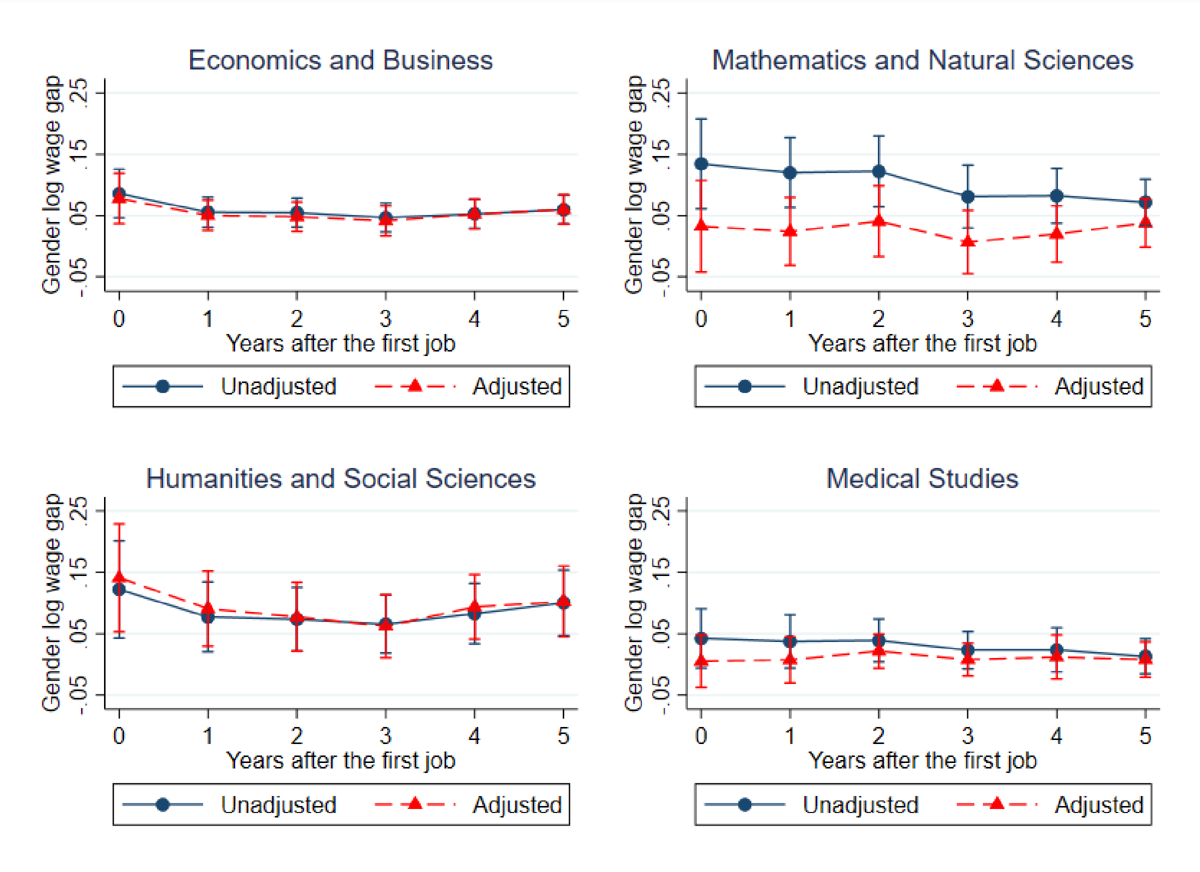


Note: This figure plots the gender wage gap over the first 5 years after the first job. Each year is estimated separately based on the OLS model specified in equation 3.1. The sample size is 3,585 (2,280 males, 1,205 females). The sample consists of individuals who have wage spells in a full-time job within the first 5 years after labor market entry. The dependent variable is the log gross daily wage. The unadjusted gender wage gap includes only the year of graduation as a control variable. The adjusted gender wage gap includes personal and pre-graduation characteristics as controls. The personal characteristics include age and German citizenship. The pre-graduation characteristics include duration of study, place of the final high school exam, and working while studying. All estimations include the starting month of the first job as a control.

In the first job (0 years after the first job on the X axis in Figure 3.1), the unadjusted gender wage gap is approximately 12 log points and drops to approximately 6.9 log points after additional controls are included. Although the sample is somewhat more restricted, and the adjusted wage gap is slightly greater, these gaps are consistent with the results presented in Table 3.2.

Looking at the evolution of the unadjusted gender wage gap over time, we find a sharp decrease of approximately 3 log points one year after labor market entry, i.e., 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 approximately 4 log points one year after the first job and remains relatively stable thereafter. These results are robust to focusing on an unbalanced sample of individuals with a first job spell, as documented in Figure B.1 of the Appendix.

Figure 3.2: Dynamics of the Gender Wage Gap in the First Years After the 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 unadjusted gender wage gap includes only graduation year as a control variable. The adjusted gender wage gap contains personal and pre-graduation characteristics as controls. The personal characteristics include age and having German citizenship. The pre-graduation characteristics include duration of study, place of high school final exam and working during study. All estimations include the beginning month of the first job as a control. Additionally, we control for having a child between the years.

As we have shown that the gender wage gap in the first job varies considerably by field of study, Figure 3.2 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 path of the graphs indicates that the phenomenon of the gender wage gap narrowing one year after the first job concentrates on 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.

3.5 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 3.4 analyses 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, namely, economics, business, humanities and social sciences (Panel A), and those without a decrease, namely, 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 their first job. However, female wages increase on average by 3.6 log points more than male wages. In line with Figure 3.2, we do not find a decrease in the gender wage gap one year after the first job for graduates in mathematics, natural sciences, or medical studies (Panel B).

Previous research shows that firm and/or occupational mobility affects wages and contributes to wage growth (Topel and Ward, 1992; Bartel and Borjas, 1981); mobility is especially important 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. To analyze whether job changes explain the drop in the gender wage gap, we continue our

Table 3.4: Gender Wage Gap by Job Change Status

Dependent Variable: Log Daily Wage					
	Pooled	Stayers	Only Firm Changers	Only Occupation Changers	Firm and Occupation Changers
	(1)	(2)	(3)	(4)	(5)
Panel A: Economics, Business, Humanities and Social Sciences					
1 Year After × Female	0.036***	-0.000	0.038	0.061	0.193***
	(0.012)	(0.008)	(0.063)	(0.083)	(0.070)
1 Year After	0.130***	0.098***	0.252***	0.248***	0.271***
	(0.007)	(0.006)	(0.042)	(0.063)	(0.039)
Female	-0.098***	-0.056***	-0.156**	-0.139*	-0.340***
	(0.015)	(0.014)	(0.068)	(0.074)	(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
Panel B: Mathematics, Natural Sciences and Medical Studies					
1 Year After × Female	-0.001	0.006	-0.010	-0.140	-0.088
	(0.011)	(0.009)	(0.042)	(0.132)	(0.095)
1 Year After	0.150***	0.127***	0.182***	0.341***	0.386***
	(0.008)	(0.007)	(0.031)	(0.098)	(0.054)
Female	-0.019	-0.024	0.008	0.074	0.049
	(0.016)	(0.016)	(0.034)	(0.171)	(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

Note: This table shows the gender wage gap at labor market entry by job change status based on the OLS model specified in equation 3.1. The sample consists of graduates with a master's degree or equivalent who work in a full-time job as their first job after graduation and who have a wage spell 1 year after their first job. The dependent variable is the log gross daily wage at the first job. The estimations include personal and pre-graduation characteristics as controls. The personal characteristics include age and having German citizenship. The pre-graduation characteristics include duration of study, place of high school final exam, and working during studying. All estimations include the beginning month of the first job as a control. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

investigation by separating the sample into graduates who stay in the same firm and/or occupation (Column 2 of Table 3.4), those who change firms but remain in the same occupations (Column 3), those who change occupations but remain in the same firms

(Column 4), and those who change firms and occupations (Column 5).[18]

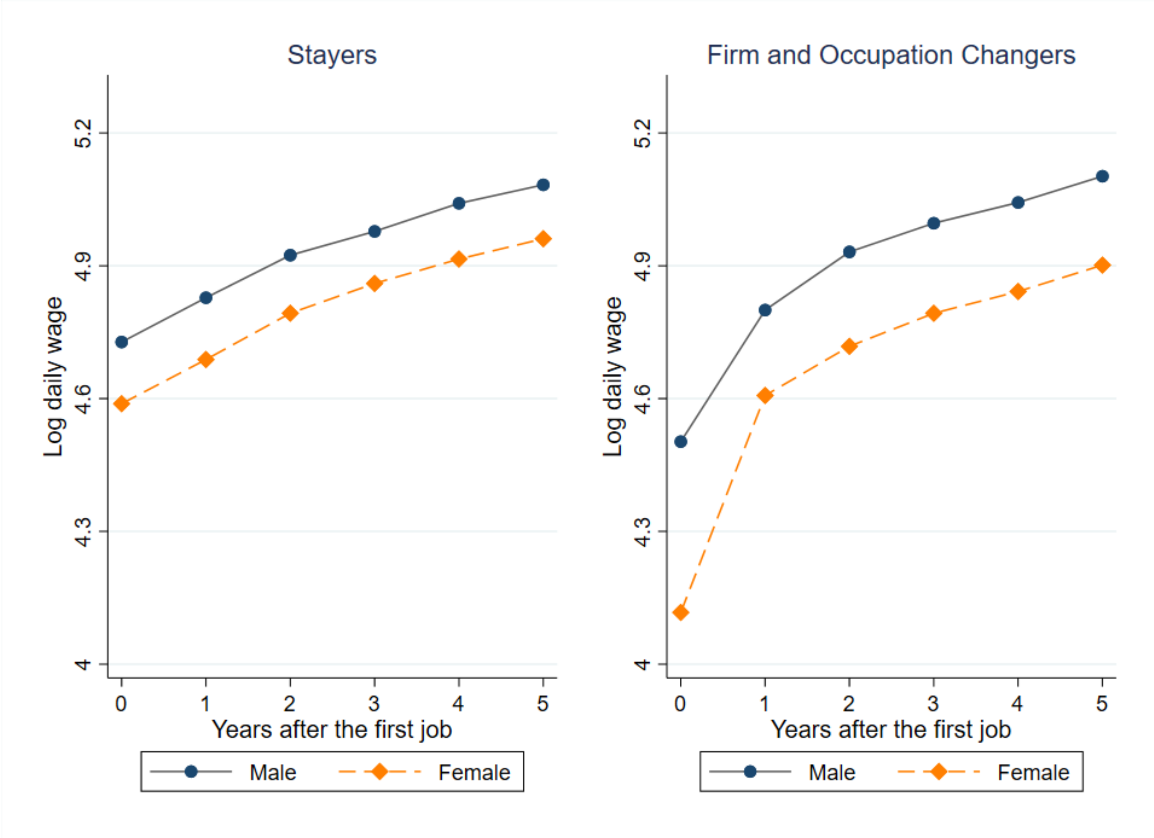
Panel A of Table 3.4, which focuses on graduates in economics, business, humanities and social sciences, demonstrates that the gender wage gap does not decrease significantly for those individuals who either stay in the same firm and/or occupation one year after starting their first job (Columns 2-4). In contrast, female firms and occupation changers increase their wages on average by approximately 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 approximately 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 occupation in the same firm. The group that changes firms and occupations has the largest initial gap (almost 34 log points). Interestingly, the allocation of men and women to the four groups is relatively similar; thus, differences in shares do not seem to explain the different evolutions of the gender wage gap after one year.

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 3.4). 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 in economics, business, humanities, and social science benefit more than men from a complete new start after their first job, which includes a change in firm and occupation. This new start drives the observed reduction in the gender wage gap within one year after the first job.

As a next step in our analysis, Figure 3.3 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 results shown in Table 3.4, female and male movers initially earn lower

[18] We define an occupation change as when the 3-digit occupation code changes.

Figure 3.3: Dynamics of Wages for Job Stayers and Occupation and Firm Changers by Gender



Note: The figures plot the dynamics of wages over 5 years after the first job for stayers (left panel) and for firm and occupation changers (right panel), and the sample sizes are 312, and 137 respectively. The dependent variable is the log gross daily wage. The graduation year, personal and pre-graduation characteristics are added as controls. The personal characteristics include age and having German citizenship. The pre-graduation characteristics include duration of study, place of high school final exam, and working during study. All estimations include the beginning month of the first job as a control. Additionally, we control for having a child between the years.

wages on average than stayers. However, the wage difference between stayers and movers is greater 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 more than men by changing their firm and occupation within one year of entering the labor market.

3.6 Why is Switching Firm and Occupation in the Beginning of the Career More Beneficial for Females than for Males?

In this section, we use our rich administrative data 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 conduct our analysis. First, we estimate whether women who change firms and occupations differ from men who change firms and occupations in terms of demographic 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. At the end of the section, the results of the two estimation approaches are discussed with respect to common theoretical explanations for the gender wage gap.

Table 3.5 compares gender differences in personal and pre-graduation characteristics (both of which are constant over time) between firms and occupation changers and stayers. In Table 3.6, Panel A compares gender differences in the characteristics of the first job for individuals who change firms and occupations with those who stay in the same position. Panel B of Table 3.6 examines gender differences in the characteristics of the first and subsequent jobs one year later for occupation and firm changers. Table B.5 in the Appendix shows the mean values of all variables from Tables 3.5 and 3.6 by gender and the corresponding mean gender differences for stayers and for firm and occupation changers.

Row (1) of Table 3.5 reports the interaction coefficients between the female variable and a dummy for firm and occupation change. The coefficients in Row (1) indicate that none of the personal characteristics, pre-graduation characteristics, or job search characteristics differ more between males and females who change firms and occupations than between

Table 3.5: Personal and Pre-Graduation Characteristics of Firm and Occupation Changers

Dependent variables:	Personal Characteristics		Pre-Graduation Characteristics					Finding First Job Characteristic
	Age at the first job	non-German	Duration of Study	Working During Studying	Apprent.	Origin is Bayern	Final Uni. Grade	Duration of Job Search
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female × Firm and Occupation Changers	0.058	-0.021	0.226	-0.012	-0.019	-0.031	0.071	-0.342
	(0.269)	(0.017)	(0.171)	(0.053)	(0.037)	(0.041)	(0.073)	(0.366)
Firm and Occupation Changers	0.444***	0.003	0.063	0.002	0.054**	0.021	0.026	-0.035
	(0.156)	(0.010)	(0.096)	(0.037)	(0.026)	(0.027)	(0.045)	(0.246)
Female	-0.803***	0.026***	-0.053	0.126***	-0.010	0.034**	-0.206***	0.141
	(0.082)	(0.007)	(0.053)	(0.018)	(0.010)	(0.014)	(0.023)	(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: The table documents gender differences in personal, pre-graduation, and first-job characteristics, between firms and occupation changers and stayers. The sample size is 2,719, including stayers (Column 2, Table 3.4) and firm and occupation changers (Column 5, Table 3.4). Each Column is a different estimation that is time invariant. The estimations include a female dummy, a dummy variable for firm and occupation changer dummy (= 1 if an individual changes her or his firm and occupation within 1 year after labor market entry, = 0 if an individual stays at the same firm and occupation), and an interaction of these dummies. All estimations include the beginning month of the first job as a control. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

males and females who stay in the same firm and occupation.

However, Table 3.6 demonstrates that out of several characteristics, job-education mismatch and occupational rank (Columns 6-11) are two characteristics that differ between males and females who switch occupations and firms in their first job and develop differently after the job change. We separate job-education mismatches into two types: horizontal and vertical mismatches. A horizontal mismatch is a field-occupation mismatch in which 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 overqualified are defined as vertical mismatches.[19] In addition, occupation rank is a measure that ranks occupations by their average wage (Columns 9-11 of Table 3.6).[20]

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

[20] Average wages within 3 digit occupation codes are calculated using the SIAB data, which represent 2% of the IEB data.

Specifically, Columns (6) and (7), Panel B of Table 3.6 show 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, compared with males, female job changers reduce the frequency of vertical mismatch one year after the first job by 13.1 percentage points.

After correcting the vertical mismatch, one might expect women to receive a higher wage as soon as they correct their mismatch. Although Column (9), Panel B of Table 3.6 shows that female job changers work in lower-ranked occupations in their first job after graduation, they do not move to (significantly) higher-paid occupations on average compared to men (Row 1, Column 9, Panel B).

However, Figure B.2 in the Appendix shows that the occupational rank distributions of 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 are. After the job change, the distributions of males and females converge, especially in the lower tail, as females predominantly move from lower-paid occupations to higher-paid occupations. In line with the convergence in the lower tail, Panel B, Column (10) of Table 3.6 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.

Table 3.6: Job Characteristics of Firm and Occupation Changers

Dependent variables:	Median Daily Log Wage of Full-time Employees	Share of Part-time Employees	Share of High Qualified Employees	Share of Women in a Firm	Log Firm Size	Horizontal Mismatch	Vertical Mismatch	Horizontal or Vertical Mismatch	Occupation Rank	Occupation Rank < Quantile 10	Occupation Rank > Quantile 90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: First Job Characteristics of Firm and Occupation Changers											
Female × Firm and	-0.086*	-0.059	-0.013	0.044	-0.204	0.008	0.117**	0.070	-22.371*	0.098**	-0.025
Occupation Changers	(0.049)	(0.041)	(0.032)	(0.027)	(0.252)	(0.056)	(0.058)	(0.053)	(11.815)	(0.044)	(0.034)
Firm and Occupation Changers	-0.120***	-0.007	-0.063***	-0.006	-0.341**	0.119***	0.122***	0.150***	-7.680	0.017	-0.002
	(0.028)	(0.032)	(0.021)	(0.017)	(0.166)	(0.035)	(0.039)	(0.037)	(7.488)	(0.024)	(0.026)
Female	-0.041***	-0.034**	-0.016	0.071***	-0.102	0.122***	0.005	0.051**	-15.238***	0.013	-0.036***
	(0.014)	(0.016)	(0.011)	(0.009)	(0.090)	(0.017)	(0.021)	(0.021)	(3.602)	(0.012)	(0.013)
Mean of Dependent Variables	4.617	0.220	0.372	0.482	5.099	0.219	0.506	0.594	226.031	0.104	0.104
R-squared	0.029	0.003	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
Panel B: Jobs Characteristics Before and After the Job Change within Firm and Occupation Changers											
Female ×	0.046	0.103*	0.011	-0.007	-20.260	-0.060	-0.131*	-0.153**	21.816	-0.115**	-0.035
1 year after	(0.053)	(0.054)	(0.036)	(0.032)	(483.871)	(0.048)	(0.079)	(0.071)	(14.263)	(0.049)	(0.049)
1 year after	0.123***	-0.030	0.033	-0.022	377.790	-0.028	0.006	0.028	13.199	-0.040	0.057
	(0.031)	(0.039)	(0.024)	(0.020)	(364.812)	(0.034)	(0.055)	(0.049)	(9.661)	(0.030)	(0.040)
Female	-0.161***	-0.048	-0.051*	0.119***	-488.739**	0.127**	0.139**	0.122**	-38.079***	0.102**	-0.061*
	(0.047)	(0.040)	(0.030)	(0.027)	(235.755)	(0.055)	(0.055)	(0.050)	(11.476)	(0.044)	(0.033)
Means of dependent	4.558	0.203	0.338	0.484	4.829	0.296	0.619	0.721	223.341	0.128	0.114
R-squared	0.113	0.039	0.059	0.085	0.035	0.065	0.060	0.044	0.054	0.047	0.053
Individuals	312	312	312	312	312	312	312	312	312	312	312

Note: Panel A documents the gender differences in the first job characteristics among firms and occupation changers and stayers. The sample size is 2,719, including stayers (Column 2, Table 3.4) and firm and occupation changers (Column 5, Table 3.4). Panel B uses firm and occupation characteristics as dependent variables (each column is a different estimation), which are time-variant; i.e., they may vary before and after the job change. The sample size is 312 and includes only firm and occupation changers (Column 5, Table 3.4). The estimations include a female dummy, a dummy variable for one year after the job change (=0 for the first job, =1 for the new job one year after the first job) and an interaction of these dummies. All estimations include the beginning month of the first job as a control. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

Overall, the results of Tables 3.5 and 3.6 demonstrate that females are more likely than males to start in an occupation that is in the bottom tail of the occupation rank distribution and change to higher-paid occupations if they switch both occupation and firm. Moreover, they start in occupations in which they are overqualified and correct this vertical mismatch by changing both occupation and firm. As our data show that correcting the vertical mismatch at the first job explains the decrease in the gender wage gap, the question arises as to why women need to change both firms and occupations to correct the mismatch. We now test common hypotheses in the gender wage gap literature that may explain our finding.

Different Types of Discrimination

A first potential explanation for the decline in vertical mismatch and 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, namely, "screening discrimination", Pinkston (2003) documents that the productivity signals that employers receive from females are noisier than from males. Therefore, 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 curricula vitae of the applicants, the final university grades may comprise the only signal for the employer. We would expect men with higher grades to not change jobs because they already have a good match in their first job. In contrast, women with higher grades may experience a mismatch compared to their male counterparts at the beginning of their careers and thus change jobs to correct the mismatch. However, our results show that female movers and stayers have better grades on average than their male counterparts do, and both female and male movers have worse grades than stayers. Nevertheless, the difference in the gender gap between movers and stayers is insignificant, as the interaction term is insignificant (Column 7, Table 3.5).

The literature on the gender wage gap suggests that females may face statistical discrimination in the labor market. This means that employers may expect lower productivity from females and hire them for less suitable jobs. Consequently, conditional on being hired, females work in more mismatched jobs and receive lower initial wages at the beginning of their careers. However, over time, as employers learn about the actual productivity of new hires ("employer learning"), such mismatches could be corrected, resulting in higher wages for women (Altonji and Blank, 1999; Altonji and Pierret, 2001; Pinkston, 2003). If females are statistically discriminated against, we would expect the gender wage gap to likely narrow not only for those who change firms and occupations but also for stayers. Since we do not find a significant reduction in the gender wage gap for 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 their coworkers') disutility.[21] The greater mismatch and lower initial wage of female movers relative to male movers (Table 3.6) may indicate some form of taste-based discrimination (Becker, 1971). However, if firms discriminate against women, switching to nondiscriminatory firms should be sufficient for women to improve their wages relative to those of men, while an additional change in occupation should not be necessary. As Table 3.4 shows, this is not the case, as the gender wage gap does not narrow significantly for those who change only 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 greater share of women in their first job (Panel A of Table 3.6). Moreover, our estimation results show that women do

[21] Becker (1964) shows in the model that firms practicing taste-based discrimination cannot survive in the competitive market in the long run.

not switch to firms with a greater female share than men (Column 4, Panel B of Table 3.6).

Risk Aversion, Confidence and Job Searching Time

The literature shows that risk aversion and (over)confidence may be an important component of early career job search, with women typically having higher levels of risk aversion (Niederle and Vesterlund, 2007; Cortés et al., 2023) and lower levels of (over)confidence compared to men (Adamecz-Völgyi and Shure, 2022). More risk-averse and less self-confident women may have lower reservation wages at the beginning of their careers (Pissarides, 1974; Feinberg, 1977; Cox and Oaxaca, 1992; Acemoglu and Shimer, 1999; Pannenberg, 2010) and thus accept job offers earlier, even if the job pays less and is not a good match (Cortés et al., 2023). However, these women may not be satisfied with lower wages and mismatches and change jobs when they find a higher-paid and better match job. In this case, we would expect women to spend less time searching for a job after graduation than men would, and women who find a job more quickly would be more likely to change jobs. Column (8) of Table 3.5 shows that although job changers find their first job slightly earlier than stayers, there is no significant gender difference in 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.

Job Amenities

As an alternative explanation, a growing body of literature shows that women prefer nonwage job amenities such as flexibility or meaning, relevance, or responsibility for the occupation more than men, who have a greater preference for wages (Goldin and Katz, 2011; Flabbi and Moro, 2012; Goldin, 2014; 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, these changes may not lead to higher wage gains. On the other hand, at the beginning of their careers, women may prefer lower-paying jobs with a vertical mismatch to compensate for some job amenities; however, over time, they change their preferences and switch to higher-paying and less flexible jobs.

Assuming that larger firms offer more flexible work arrangements (Albrecht et al., 2018), we test whether women switch to smaller firms. We do not find that females are more likely than men to sort into larger or smaller firms as a result of a job change (Column 5, Table 3.6). However, our data do not cover other proxies for job amenities, such as the meaning of jobs, schedule adaptability, or telecommuting (De Schouwer and Kesternich, 2022). Therefore, we believe that changing preferences for job amenities may still be an important explanations for why women reduce their vertical mismatch and increase their wages when they switch firms and occupations.

3.7 Conclusion

Although many studies have investigated the gender wage gap, the existence and potential explanations for early career gender wage differences remain unclear. This paper analyses the gender wage gap among graduates of a German university with a master's degree or equivalent at the beginning of their careers and over the first years after their labor market entry. We take advantage of a unique dataset that links administrative data on graduates of a German university with employment registers of the German social security system. This dataset includes extensive information on students' sociodemographic characteristics, educational and labor market outcomes, as well as the exact timing of graduation, labor market entry, and any job changes.

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

Further analysis shows that the decline in the gender wage gap is concentrated among individuals who change firms and occupations after their first job with a degree in economics, business, humanities, or social sciences. As an explanation for the decrease in the gender wage gap, we also show that female graduates are more likely to start their careers in jobs for which they are overqualified and subsequently correct this skill mismatch, leading to an increase in wages. Correcting the mismatch is costly for females, which may be an additional explanation for the wage gap later in their career.

Universities have an important opportunity to mitigate the risk of future skill mismatches by implementing counseling interventions. These interventions can provide valuable information on effective job search strategies and potential wage losses due to skill mismatches, particularly for female students. Our study also highlights significant differences in labor market entry and early career paths depending on the chosen field of study. For this reason, counseling programs that help students understand their career prospects should be tailored specifically to each field of study. By implementing such counseling, universities can provide graduates with the insight they need to successfully navigate the dynamic labor market.

Chapter 4

Students' Coworker Networks and Labor Market Entry

with Gökay Demir, Friederike Hertweck and Malte Sandner

We are grateful to David Card, Thomas Cornelissen, Simon Janssen, Philipp Lergetporer, and Cheti Nicoletti for their valuable feedback. We also thank participants of SEHO 2023, EALE 2023, VfS 2023, HELM Forum 2023, and research seminars at the University of Magdeburg, the University of York, RWI, IAB, and IZA for their helpful comments.

4.1 Introduction

A large body of theoretical and empirical research has emphasized that coworker networks play an important role in accessing job opportunities and enhancing career advancement. Studies analyzing the role of networks in labor market success have focused on the role of family (Kramarz and Skans, 2014), neighborhood (Ioannides and Loury, 2004), student peers (Marmaros and Sacerdote, 2002), ethnic networks (Dustmann et al., 2016), close friends (Cappellari and Tatsiramos, 2015), or former coworkers in regular employment (e.g., Cingano and Rosolia, 2012; Glitz, 2017; Saygin et al., 2021; Eliason et al., 2023).

However, to the best of our knowledge there is no evidence about the role of coworker networks from student jobs in accessing job opportunities and enhancing career advancement. This lack is surprising for at least three reasons. First, student employment is a common phenomenon that has increased in recent years, reaching 40% in the US (Irwin et al., 2022) and over 60% in Germany (Staneva, 2015). Second, information frictions between employers and employees may be particularly strong during the transition from higher education to employment – and students' coworkers may be helpful in reducing these frictions. Third, the transition from higher education to employment is a crucial career stage with lasting consequences for later careers (e.g., Oyer, 2006; Oreopoulos et al., 2012; Wachter, 2020).

In this paper, we go beyond the existing literature on coworker networks and analyze whether college students benefit from the quality of their coworker networks during their transition from college to the labor market. Conducting this research requires to solve major data and identification challenges. First, data must comprise information about a student's labor market history, including college and post-graduate employment, about all former coworkers, and about the student's university studies. Second, identification is challenging because students do not randomly sort into student jobs and thus into coworker networks.

We solve the data challenge by utilizing administrative university records of students from a large German university linked with their social security records. The data provide detailed information on university enrollment, fields of study, and grades, on student's college and graduate employment, and on the employment of all coworkers who work with the student in the same establishment. The data also allow us to identify those coworkers who work with the student in the same establishment and in the same (or another) occupation as the student, so that we can distinguish between close or more distant coworkers. Finally, the data provide the wages of the former coworkers at the student's labor market entry, which we use to operationalize our measure of network quality.

To solve the identification challenge, an ideal experiment would randomly assign employees as well as students to establishments. In the most simple setting, these people can interact and we could measure future labor market outcomes. Yet, while such a setting may be – if at all – feasible in a laboratory experiment, it is not possible to design a field experiment where people are randomly assigned to real jobs. The only exception we can think of are intermediaries that organize simple student jobs, and students are assigned jobs solely based on their pre-specified availability. Yet, using data from such an intermediary would not lead to generalizable results on student coworker networks for the variety of students and student jobs due to the fact that motivation for working differs among students: While some students solely work to sustain a living (and therefore may be interested in getting a job via the intermediary), others use the job to improve their human capital.

In our setting, we regress the characteristics of a graduate's job at labor market entry on the quality of the student's former coworkers from the student job. To get as close as possible to random assignment of student jobs, and to address the endogeneity issue that students with better coworkers also work in more productive establishments, we control for detailed student job characteristics, industry characteristics, and a proxy for establishment productivity proposed by Abowd et al. (1999). In addition, we focus on the close coworkers and control for the less close coworkers. If we expect unobserved establishment shocks or policies, such as establishment training policies, to positively bias our network quality indicator, we should expect the same bias for coworkers who work in the same establishment but not closely with the student. Finally, we run an estimation including establishment fixed effects, estimating the effect of coworker for students with different coworker networks within the same establishment, which prevents specific establishment characteristics from biasing our results. Another potential endogeneity issue is the sorting of high-ability students to better coworkers. To account for this issue, we control for a wide range of individual pre-college characteristics and a reliable measure of pre-college ability, which is students' high school GPA.

Our results show that graduates benefit from their embedded coworker networks by receiving higher wages after graduating from college. For instance, a 10% increase in the average wage of former coworkers at the time of a student's graduation is associated with a c.p. 0.76% higher entry wage at the graduate's first full-time job. The effect size does not change much when we include establishment fixed effects to the estimation. Furthermore, these results are robust to different model specifications and to different definitions of coworker quality and the coworker network.

To understand the underlying mechanisms, our rich data allow us to examine several potential channels. First, we show that graduates benefit from good coworkers particularly when they start their career in the same establishment where they worked as a student or when they start in an establishment where a former coworker works. These findings suggest that direct support from better coworkers or information about the establishment from better coworkers at the first job is an important channel explaining why the average wage of former coworkers in student jobs has a positive effect on future wages of graduates. Second, we reject the channel that better coworkers lead to an increase in students' effort at university, which in turn could have positive effects on the transition to the labor market.

Third, our results show that better coworkers speed up the labor market transition leading to a shorter time between students' graduation and their first job. Fourth, we reject the channel that the higher entry salary and earlier labor market entry are based on an unsustainable match, which could lead to earlier layoffs in the two years after graduation.

We also distinguish between jobs that students typically take to support themselves (e.g., bartending or cashiering) and jobs that are more related to their studies, including paid internships. We show that coworkers in more study-related jobs drive the effects on wages. Finally, we examine potential heterogeneity by gender and student ability, measured by college GPA. Our results do not show much difference between these groups. The gender result is surprising, as previous research shows that male college graduates benefit more from their employee networks than female graduates (Mengel, 2020). A likely remaining explanation for why student job coworkers may improve the labor market entry of graduates is information frictions on potential outside options, which are high during labor market entry: Jäger et al. (2022) show that these frictions partly explain wage differentials between similar workers, and Belot et al. (2019), Carranza et al. (2022), Demir (2023) provide evidence that reducing these frictions can induce workers to switch to better-paying jobs. A recent paper by Caldwell and Harmon (2019) shows that coworker networks can help reduce information frictions for individuals. However, we cannot state with certainty that information frictions are the underlying mechanism.

Because our study is the first to examine how peers from student jobs affect the labor market entry of college graduates, it makes several novel contributions to the literature. First, we add to the literature on peer effects in college that exploits random variation in the assignment of students to dormitories, classes, or introductory courses. However, this literature examines the effects of peers on student achievement or behavioral outcomes (e.g., Sacerdote, 2001; Feld and Zölitz, 2017) and does not examine whether networks support later career success. The small literature that has examined how networks during education relate to labor market entry has focused on classmate networks. For example, Zhu (2022) examines how classmate networks at community colleges in Arkansas affect job search. Zimmerman (2019) focuses on elite colleges in Chile and shows that peer ties formed between classmates at elite colleges can affect labor market outcomes later in life. Finally, Marmaros and Sacerdote (2002) examine how randomly assigned roommates at Darmouth College affect each other's labor market entry. However, this literature neglects peer effects from student employment networks, which are very likely to affect students given the high employment rates and many hours students spend working while studying.[1]

Second, we contribute to the growing literature on coworker networks. Using a linked employer-employee dataset for Germany, Cornelissen et al. (2017) show that the productivity of a coworker has a small but positive impact on employee's contemporaneous wages. In Italy, Battisti (2017) and Hong and Lattanzio (2022) reveal more pronounced effects of coworker productivity on both contemporaneous and future wages. Furthermore, Jarosch et al. (2021) present evidence that having higher paid coworkers is associated with higher future wages. However, while these previous studies present evidence that coworker quality is important for individuals who are already in the labor market, whether coworker networks from student jobs also have effects on individuals who are yet not attached to the labor market remains unclear.

Third, this paper also contributes to a growing literature that examines the determinants of the transition from college to employment. This literature has shown that lower early career wages have long-lasting effects on the careers of college graduates (e.g., Oyer, 2006; Oreopoulos et al., 2012; Wachter, 2020) and has identified factors that influence the transition from college to the labor market. For example, Oreopoulos et al. (2012) show that graduates who enter the labor market during a recession have lower earnings on average than graduates who start their careers in better labor market conditions and that this earnings decline persists for 10 years. Furthermore, Hensvik et al. (2023) identify referrals as an important factor for transition from school to work. Our findings add to

[1] For a literature review on these peer effects see Sacerdote (2014).

these findings that the network quality established during student jobs is also an important factor in the college to labor market transition.

Fourth, this paper contributes to the more general literature on the effect of working while studying. Although some studies show that working during studies can have positive effects on later wages (e.g., Hotz et al., 2002; Le Barbanchon et al., 2023), the existing studies often do not identify the mechanisms behind these positive effects. Our findings show that the quality of coworkers in student jobs is an important channel mediating the returns to working while studying.

The rest of the paper is organized as follows: Section 4.2 describes the data and our sample. Section 4.3 presents the empirical strategy and describes the large set of control variables we include to account for different endogeneity issues. Section 4.4 presents and discusses our results as well as possible underlying mechanisms. Finally, Section 4.5 concludes.

4.2 Data and Descriptive Statistics

The data include detailed labor market and college information for each student, social security records for their coworkers, and administrative records of the establishments in which the students worked during their studies. All datasets and merges are described in the following.

Student-Level Data

The core of our dataset consists of the administrative records of all students who graduated from a large German university between 1995 and 2016 linked with detailed social security records. These social security records come from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). The IEB cover the universe of employees in Germany[2] and contain detailed daily information on employment, benefit receipt, and job search. The university administrative records are matched to the IEB based on a student's name, date of birth, and gender (Möller and Rust, 2018). This matching allows us to uniquely identify students in the data who worked in student jobs while attending university.

For each student in the dataset, we have detailed information on individual characteristics (e.g., gender, year of birth), pre-college and college education (e.g., field of study, high school and college GPA, time of enrollment and graduation), and each student's entire labor market history, including their student and graduate employment (e.g., start and end dates, occupation, employment type, wage).

Coworker Networks

For each student job spell, we know the establishment and the exact start and end dates. Since we have access to the social security records of the entire workforce in Germany, we can then create a list of employees who worked in the same establishment at the same time as the student. We define the student coworker network as individuals who worked with student i in student job k. In the final stage of data preparation, we extract the socio-demographic characteristics (gender, age, nationality, educational attainment) and labor market history (employment status, occupation, deflated daily wage) of each potential coworker.

[2] The IEB can track an individual's employment status to the day. Individuals are included in the IEB if they have (or had) at least one of the following employment statuses: employment subject to social security contributions (in the data since 1975), marginal part-time employment (in the data since 1999), receipt of benefits according to SGB III or II (SGB III since 1975, SGB II since 2005), officially registered as job-seekers with the Federal Employment Agency, or (planned) participation in active labor market policy programs (in the data since 2000)

AKM Data

We also add AKM fixed effects to our data. These are provided by Bellmann et al. (2020). The establishment AKM fixed effect measures the proportional wage premium paid to all workers in an establishment, net of worker composition (Abowd et al., 1999; Card et al., 2013). Abowd et al. (1999) show that establishments with a high establishment fixed effect are more productive and profitable. In addition, Card et al. (2013) show systematic selection of highly skilled workers into establishments with a higher AKM fixed effect. We use the establishment AKM fixed effect as a proxy for the productivity of an establishment, thereby accounting for the non-random selection of workers into establishments.

4.2.1 Sample Selection

We are interested in whether students' coworker networks affect their labor market transitions after graduation. Therefore, we include in our sample only those students who are likely to work in the social security system after graduation and who had at least one student job while studying.[3] We consider all employment spells as student jobs if the spell occurred while the student was enrolled in college and if it occurred up to 5 years before graduation (Figure 4.1).

To ensure that students and their coworkers have sufficient contacts and interactions, we focus on student jobs (and thus coworker networks) that last longer than three months, as well as network sizes of less than 250 employees from each student job.[4] In addition, we distinguish between close coworkers, those coworkers in the same 3-digit occupation and in the same establishment, and less close coworkers, all other coworkers in the same

[3] This means that we exclude all students enrolled in teacher training programs, as they often become civil servants shortly after entering the labor market and thus do not work in the social security system. We also exclude bachelor's students because they may enroll in a master's program after completing their undergraduate studies and do not enter the labor market directly.

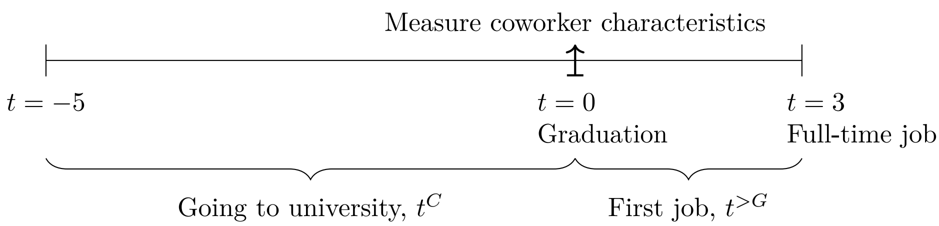
[4] Figures C.1 and C.2 show that students typically work in smaller establishments during their studies, hence their networks tend to be smaller than 250 employees in most cases.

establishment.

Our outcomes of interest relate to a graduate's transition to the labor market after graduation. We restrict our analysis to the first full-time job, dropping all graduates who do not find a full-time job within three years after graduation and some implausible cases (i.e., graduates who earn less than 10 Euros per day in a full-time job). Our main outcome variable is the deflated log daily wage of the graduate's first full-time job. We compute the deflated log daily wage of the graduate using the Consumer Price Index from the Federal Statistical Office.[5]

For coworkers and our key independent variables, we assign a missing value to observations with a wage below the first percentile of the wage distribution for coworkers. Again, we convert gross daily wages to real daily wages using the Consumer Price Index from the Federal Statistical Office. We measure coworker characteristics at the exact year the student graduates from college ($t = 0$ in Figure 4.1). If the coworkers have multiple employment spells at the time of graduation of the student, we keep the spell with the longest tenure to measure the characteristics.

Figure 4.1: Measurement of Coworker Characteristics



We then create a comprehensive set of variables that describe the quality of the network. These include the average daily wage, the employment rate, the network size, the average age (and its square), the share of coworkers with vocational training, the share of coworkers with a college degree, the share of female coworkers, and the share

[5] The daily wage variable is top-coded at the annually varying ceiling on social security contributions in the IEB data. Because we focus on the first job after graduation, only 1.20% of graduates' wages are censored. Thus, censored wages are unlikely to affect our results.

of non-German coworkers. In addition, we calculate the average AKM establishment fixed effects across student jobs, i.e., weighted by the duration of the student job in the establishment of interest.

4.2.2 Descriptive Statistics

Our sample restrictions leave us with 3,261 individual graduates who worked in student jobs and started their first full-time job within three years of graduation between 2000 and 2016. Table 4.1 presents descriptive statistics on the graduates, their coworker networks, and their first full-time job.

58% of the graduates are female and 2% have a non-German citizenship. The average age at first full-time employment is 28 and the average high school GPA is 2.33, with a range from 1 (best) to 4 (passed). Most graduates in our sample studied either humanities and social sciences (45%) or economics and business (28%). 17% of the graduates studied a medical subject and 10% studied mathematics and natural sciences. Table 4.1 also shows the top industries of their student jobs: "Accommodation and food service activities" and "Wholesale and retail trade; repair of motor vehicles and motorcycles" have the highest shares of graduates, with 23% and 19%, respectively. Table 4.1 also shows the top occupations of the students. Students in our sample are most likely to work as waiters or office specialists.

During their studies, students worked on average 3.7 different student jobs in rather small establishments with below-average productivity, as indicated by the negative AKM fixed effect. Figure C.3 in the Appendix shows the left-skewed distribution of the network size of graduates. The average coworker network can be described as predominantly female (64%), mostly employed (63%), composed of German citizens (94%), and with lower levels of education (72%).

The average daily wage of graduates in their first full-time job after graduation is about 76 Euros, which is about 2,280 Euros per month. Figure C.4 in the Appendix shows the distribution of daily wages of graduates in their first full-time job. The average time between graduation and the first full-time job is about 3.5 months. Because we focus on the first full-time job after graduation, other types of jobs (such as part-time employment) may increase the time until the first full-time job. Figure C.5 in the Appendix shows the distribution of days to first full-time job. The distribution is left skewed with a median of 112 days (about 3-4 months).

Table 4.1: Descriptive Statistics

	Mean	SD
First Job after Graduation Characteristics		
Log Daily Wage at the First Job After Graduation	4.33	0.63
Log Days to Start First Job After Graduation	4.66	1.36
Network Quality at Graduation		
Average Log Daily Wage of Close Coworkers	3.90	0.66
Graduate Characteristics		
Female	0.58	0.49
Non-German	0.02	0.13
Age at the First Job After Graduation	27.47	2.54
Final High School GPA	2.33	0.60
Number of Student Jobs	3.69	3.43
Log Average Wage in Student Jobs	2.40	0.77
Field of Study		
Economics and Business	0.28	0.45
Mathematics and Natural Sciences	0.10	0.30
Humanities and Social Sciences	0.45	0.50
Medical Studies	0.17	0.38
Student Jobs Characteristics		
Average AKM Establishment FE	-0.15	0.42
Industry of Student Jobs		
Acommodation and Food Service Activities	0.23	0.42
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcyle	0.19	0.39
Professional, Scientific and Technical Activities	0.14	0.35

Continued on next page

Table 4.1 – continued from previous page

	Mean	SD
Human Health and Social Work Activities	0.10	0.30
Information and Communication	0.08	0.27
Manufacturing	0.05	0.21
Administrative and Support Service Activities	0.05	0.21
Occupation in Student Job		
Waiters, Stewards	0.17	0.38
Office Specialists	0.15	0.35
Salespersons	0.10	0.30
Office Auxiliary Workers	0.07	0.26
Others Attending on Guests	0.05	0.21
Network Characteristics		
Log Network Size	3.16	1.33
Employment Rate of Coworkers	0.63	0.17
Share of Female	0.64	0.27
Share of Non-German	0.06	0.11
Mean Age of Employees	34.04	7.41
Share of Middle Educated	0.20	0.27
Share of Highly Educated	0.08	0.18
Individuals	3,261	

Notes: This table reports the means and standard deviations of the selected characteristics. Graduate characteristics include the individual characteristics of students who graduated between 2000 and 2016, as well as the characteristics of jobs where students worked for at least three months over five years prior to graduation (student jobs). We include the industry and occupation of the last student job. 12 industries are not displayed here because less than 5% of the students in the sample worked in these industries. Network characteristics include the characteristics of close coworkers (same establishment and occupation) of college students from their student jobs. We present descriptive statistics on the network characteristics of less close coworkers (same establishment but other occupation) in Table C.1. Network coworker characteristics are measured at the time of graduation. First job characteristics are based on the first full-time job after graduation.

4.3 Empirical Strategy

The relationship of interest is whether the network of coworkers a student builds in student jobs affects the student's labor market outcomes after graduation. Our empirical analysis must account for the non-random allocation of students to their student jobs and the underlying unobserved motivation for choosing one job over another.

We can exploit the variation in coworker networks induced by individual students having multiple student jobs, and by different students working in the same establishment but at different times (and thus having different coworkers).

We estimate the following baseline wage equation:

$$\begin{aligned} log\, w_{i,t^G} =& \beta_1 log\, \overline{w}_{\sim i,jot^G} + \beta_2 log\, \overline{w}_{\sim o,ijt^G} + \\ & \gamma \mathbf{x'}_{i,t^G} + \delta_1 \mathbf{p'}_{\sim i,jot^G} + \delta_2 \mathbf{p'}_{\sim o,ijt^G} + \\ & s_{jt^C} + \theta_{ot^C} + \mu_{jt^C} + \eta_{t^G} + \epsilon_{i,jot^C} \end{aligned} \tag{4.1}$$

Our main outcome is $log\, w_{i,t^G}$, the log wage of student i after graduation, i.e., at time t^G. We regress the log wage of the graduate on the average quality of all former coworkers from student jobs. Coworkers are defined as working in the same establishment j in the same (three-digit) occupation o at the same time t^C as the student. We proxy the quality of coworkers by their wages at the time of the student's graduation, i.e., $log\, \overline{w}_{\sim i,jot^G}$. While students sort themselves into occupations and establishments during their student jobs (i.e., at time t^C), we assume that the actual wage of the coworkers at the time the student graduates from college (i.e., at time t^G) is unrelated to the students' non-random allocation to student jobs. However, in alternate specifications, we relax this assumption and estimate the wage change among coworkers from t^C to t^G, subtracting the persistent time-constant part in wages linked to non-random allocation. The corresponding β_1 is our main coefficient of interest.

We also include the average wage at time t^G of all workers who worked in the same establishment at the same time as the student but in different occupations ($\sim o$) than the student: $log\, \overline{w}_{\sim o,ijt^G}$. We thereby control for shocks common to all workers who worked at the same time and in the same establishments as the student. An example of such a shock is a common training for all workers in the establishment.

To control for high ability students sorting into jobs with high quality coworkers, we include a large set of individual, establishment, occupation, and network characteristics. First, we include individual characteristics x'_{i,t^G} that include time-invariant characteristics (gender, nationality, high school GPA) as well as characteristics at the time of graduation (number of student jobs, log average wage in student jobs, field of study).

Second, we include characteristics of the student's job: We control for the industry of the establishment of the student job, s_{jt^C}, the occupation of the student, θ_{ot^C}, and the characteristics of the establishment, μ_{jt^C}. The establishment and occupation characteristics of the student's job were observable to the student. Students may have chosen certain establishments or occupations in order to build a network of high quality colleagues. By including θ_{ot^C} and μ_{jt^C}, we account for self-selection into student jobs. To reduce the dimensions in our estimation, we operationalize μ_{jt^C} with the AKM establishment effects developed by Abowd et al. (1999) and provided for the universe of German employees by Bellmann et al. (2020). In addition, we include s_{jt^C}, θ_{ot^C}, and μ_{jt^C} only for the last student job before graduation. While we include these restrictions for practical reasons, we believe that the last student job before graduation is the job with the highest degree of selection into favorable coworker networks.

Third, we include a comprehensive set of network characteristics. Again, we distinguish between networks of direct coworkers, i.e., employees working in the same occupation as the student, $p'_{\sim i,jot^G}$, and networks of other employees from the same establishment, $p'_{\sim o,ijt^G}$. These two vectors of network characteristics p' include the log network size of a student, the employment rate of the coworkers, the share of female and non-German coworkers, the average age of the coworkers, and their education. We measure these characteristics at the time of graduation t^G to account for possible changes in the network since the student left the student job.[6]

[6] This strategy accounts for the fact that former coworkers may have been promoted, taken parental leave, or changed employers since the student left the establishment. In an alternative specification, we could also include these network characteristics at the time of the student job. Including all $p'_{.,t^C}$ would then account for the fact that students have preferences regarding their network prior to starting

We also include fixed effects for graduation cohort η_{t^G}. This is relevant because of differences in the first wage after graduation caused by different labor market conditions at the time of graduation (e.g., Schwandt and Von Wachter, 2019; Wachter, 2020).

ϵ_{ijot^C} is the residual error term. After controlling for individual characteristics, student sorting, and labor market conditions at graduation, we argue that the error term is uncorrelated with both our dependent variable and all covariates. However, there are more hypothetical scenarios that could lead to bias: First, workers could choose a particular establishment and occupation after a student joins the establishment, leading to the reflection problem provided by Manski (1993). We believe that – if present at all – these cases are so rare that they hardly affect our results. Second, we cannot observe the occupation-specific knowledge of the student. For example, suppose a new technology is introduced in a number of establishments just before students graduate from college, and the network of coworkers is already benefiting from the new technology. If students lack knowledge about the technology, the higher quality of workers may not be reflected in the graduate's wages. This possibility would lead to a downward bias, underestimating the true effect of the network on the graduate's wage.

4.4 Results

4.4.1 Main Results

Table 4.2 shows our main results from estimating Equation 4.1. While Column (1) reports the results for our main outcome, the log of a graduate's wage in the first full-time job after graduation, Column (2) adds establishment fixed effects of the last

a student job. While in most cases the characteristics of future coworkers are unobserved, students may have some knowledge about potential coworkers from interviews for the student job, referrals from student peers who previously worked at the establishment, or career counselors who have close ties to some establishments. We believe that these cases are rare and are already captured by including occupation and establishment effects.

student job establishment. In this specification, the main sources of variation in average coworker quality come from the timing of the student job (students working in the same establishment but at different times), the date of graduation (students working in the same place at the same time but graduating at different times) students working in the same establishment but in different occupations, or from variation in coworker wages in previous student jobs. By isolating and exploiting only these sources of variation in coworker quality with the establishment fixed effects along with our control variables, we argue that our estimates come closer to random assignment of coworkers to students.

The results in Table 4.2 show a positive and statistically significant relationship between coworker quality and the log wage of the graduate's first full-time job. Former coworker quality positively affects the first wage after graduation (Column (1)). Specifically, we find that a 10% increase in the average wage of coworkers is associated with a 0.76% higher wage of the graduates' first full-time job. In addition, Column (2) indicates that the results are similar in magnitude and statistical significance when we compare only students who had their last student job before graduation in the same establishment. In contrast, the average wage of coworkers who work in the same establishment but in different occupations has no statistically significant effect on wages at labor market entry.

Table 4.2: Effects of Student Job Coworker Networks

	Log (Daily) Wage at the First Job	
	(1)	(2)
Log avg. coworker wage – Same occupation	0.076***	0.071**
	(0.022)	(0.028)
Log avg. coworker wage – Other occupation	0.030	0.038
	(0.024)	(0.033)
Adjusted R-squared	0.248	0.206
Individuals	3,261	3,261
Graduate controls	yes	yes
Coworker network controls	yes	yes
Other employee controls	yes	yes
Industry fixed effects	yes	yes
Establishment effects	yes	yes
Occupation fixed effects	yes	yes
Graduation cohort fixed effects	yes	yes
Establishment fixed effects (student job)	no	yes

Notes: Column (1) shows OLS estimation results from the regression specified in Equation 4.1. Column (2) adds establishment fixed effects and includes the same control variables as in our baseline specification. The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. Graduate characteristics include gender, nationality, high school GPA, number of student jobs, log average wage in student jobs, field of study, and age. Coworker network and other employee controls include student's log network size, the employment rate of coworkers, the share of female and non-German coworkers, the coworkers' mean age and their education. Establishment effects are the average AKM establishment effects across student jobs. Industry fixed effects and occupation fixed effects are included for the last student job prior to graduation. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.4.2 Robustness

Our main results in Section 4.4.1 use the average wage of coworkers at students' labor market entry as a proxy for coworker quality. One may argue that average wages are not an adequate proxy for quality, or that average wages tend to be correlated with unobserved student or establishment characteristics. Therefore, we specify our independent variable in two additional ways, assuming that the results are robust if all definitions of coworker quality generate similar results.

First, we use the person AKM effect provided by Bellmann et al. (2020) as the independent variable of interest. The person AKM effect is estimated by regressing wages on worker and establishment fixed effects for the universe of employment spells covered by social security contributions, and can be interpreted as a combination of skills and other factors that are valued equally across employers (Card et al., 2013). This eliminates the need for additional conditioning on other network control variables or the establishment AKM effect. The person AKM effect is estimated only for full-time workers aged 20 to 60 (Bellmann et al., 2020). The results using the average person AKM effect of a college graduate's coworkers are presented in Panel B of Table 4.3. Our findings indicate that the coefficient size for log wages as the outcome is comparable to our baseline estimate, although statistically insignificant. This statistical insignificance is likely due to the smaller number of observations and reduced variation as the person AKM is only computed for full-time workers.

Second, instead of using the average coworker wage as a proxy for network quality, we use the change in the average coworker wage between the time of the student job and the students' graduation. The change in network wage may be a particularly good proxy as students cannot observe the future wage trajectories of their coworkers, and therefore can hardly self-select to coworkers based on their future wage trajectories. Furthermore, by subtracting the average coworker wage at the time of the student job from the average coworker wage at the time of the student's graduation, we relax the assumption made in Section 4.3 that the coworker wage at the time of the student's graduation is unrelated to the non-random assignment of students to student jobs. In other words, we remove the persistent part of the wage that could be related to the selection of students into student jobs and instead exploit only the variation in the wage increase that is more likely due to coworker quality. The results using the change in coworker wages as the independent variable are presented in Panel C of Table 4.3. The change in the proxy has a similar effect on entry wages. As the wage results are robust to different definitions of network quality, we are confident that network quality is at least related to our wage outcomes and not to something unobserved.

Table 4.3: Wage Effects: Robustness to Different Proxies for Coworker Quality

	Log (Daily) Wage at the First Job
	(1)
Panel A: Baseline	
Log avg. coworker wage - Same occupation	0.076***
	(0.022)
Log avg. coworker wage - Other occupation	0.030
	(0.024)
Adjusted R-squared	0.248
Individuals	3,261
Panel B: Worker AKM Effects	
Avg. coworker AKM - Same occupation	0.064
	(0.050)
Avg. coworker AKM - Other occupation	0.041
	(0.046)
Adjusted R-squared	0.245
Individuals	3,026
Panel C: Change in Coworker Average Wages	
Δ Log avg. coworker wage - Same occupation	0.065***
	(0.018)
Δ Log avg. coworker wage - Other occupation	-0.019
	(0.027)
Adjusted R-squared	0.247
Individuals	3,261

Notes: The table shows robustness checks of our baseline estimation in Equation 4.1. In panel A, we present the baseline specification. In panel B, we use the average person AKM of coworkers in the same and other occupation instead of log average wages. Therefore, we exclude all network characteristics and establishment AKM effects from the estimation in panel B. In panel C, we use the change in log average wages of coworkers in the same and other occupation instead of log average wages. Specifically, we subtract the log average wage of coworkers at the time of graduation from the log average wage of coworkers at the time of the student job. The unit of observation is an individual university graduate. We consider only the first full-time job after graduation as the first job. We include all other control variables, besides the network characteristics as in Table 4.2. Heteroscedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In addition to varying our network quality measure, we also perform four robustness checks on our definition of which coworkers are included in a student's network. First, we vary the definition of which coworkers work within the same occupation. In our main specification, we define as coworkers only those workers who work in the same 3-digit occupation code as the student. As a robustness check, we examine whether the results are sensitive to a broader definition of coworker based on 2-digit occupation. Column (2) of Appendix Table C.2 demonstrates that the effect size is slightly reduced when considering broader occupational code categories. This similar effect is plausible because even when focusing on broader occupational groups, students may still benefit from networks that are employed in occupations closely related to their own.

Appendix Table C.3 reveals that the effects are more pronounced in jobs lasting 3 months compared to those lasting less than 3 months. As expected, this result shows that the effect is more pronounced when students interact with their coworkers for a longer period of time. As a third variation of the network definition, we alter the network definition to a size of 100 instead of 250 in our main specification. Column (3) of Appendix Table C.2 shows that changing the network size does not alter the effect sizes of coworker wages. As shown in Figure C.3, students work predominantly at smaller establishments with fewer coworkers and likely work closely with those closest to them. Thus, the consistent results are plausible.

Finally, Appendix Table C.4 presents the results of regressions in which we measure network characteristics separately for full-time and part-time coworkers at the time of the student's graduation. We find that only *full-time* coworkers significantly affect the wage of the graduate's first full-time job. If better-quality peers generally have more information about, e.g., potential job openings or better-paying establishments, then all coworkers should affect the entry wage of a graduate's first full-time job. However, because we focus only on a graduate's first full-time job, the advice, inspiration, or anchoring of full-time coworkers may be more important. In this case, we would expect only the characteristics of full-time coworkers to matter in our estimations. However, it could also be that full-time coworkers mechanically have more time to interact with the student.

All findings from the variation in the network definition support our main specification, as they show that coworkers who work less closely together (2-digit occupation, larger network size, shorter duration, part-time coworkers) have a smaller or similar impact on the labor market transition of graduates.

4.4.3 Channels

The quality of former coworkers from student jobs may help graduates in their transition to the labor market through a variety of channels. In this section, we investigate several of these potential channels.

First, the coworker quality may help in case a graduate starts his or her career at the same establishment as a coworker or in the same establishment as the student job. If students have worked with good coworkers prior to moving to such an establishment, it may be especially beneficial for the student. For example, better-quality coworkers could improve the students' bargaining position through better information on possible wages in such a scenario. Second, better coworkers may increase in students' effort at university and consequently better grades are a potential channel for the positive effect on labor market entry. Third, we examine whether better coworkers lead to higher entry wages but longer job searching, or higher job separations at 6, 12 and 24 months after graduation. If the days to find a job are longer or the matches are less sustainable for graduates with good coworkers, this would indicate that good coworkers are a noisy hiring signal for employers, leading to higher wages in the first job but slower employment transitions and no productivity gains.

Fourth, we investigate different types of student jobs as potential channels. On the one hand, coworker quality may be particularly important for jobs that are related to the students' studies if coworker quality is complementary to the subject content. On the other hand, coworker quality may be particularly relevant for jobs that are unrelated to the students' studies assuming that students working in these jobs have worse networks in general, and coworker quality can substitute a lacking network. Finally, we investigate further heterogeneities, such as gender and university performance.

Referrals

A relatively high share of college graduates start their first full-time job at an establishment where a former coworker is employed or at the same establishment where they previously worked as a student (about 20% in our estimation sample). In general, student jobs may act as a screening device for both students and employers and as a referral tool independent of the quality of the coworkers. However, good coworkers may also be more helpful to make a referral or start in the establishment of student jobs more successful than bad coworkers. Good coworkers may give better advice or suggestions to the student to find better jobs with higher wages.

In Column (2) of Table 4.4, we investigate the effects of former coworker quality on graduates who started their first full-time job in the same establishment where a former coworker worked at the time of graduation. Column (3) presents the results for graduates who started their first full-time job in the same establishment where they worked during their studies. Finally, Column (4) show the results for graduates who neither work in an establishment of a former coworker or the establishment of the student job.

We find that the quality of coworkers is important for starting wages when college graduates start their careers in an establishment where a former coworker works (referrals) or in the establishment of the student job. This provides evidence for the importance of referrals, as a coworker may refer a student in our sample to his or her employer.

The results also show that good coworkers are particularly valuable in helping students find jobs after graduation. However, as the results in Column (4) show, even for those graduates who do not start in an establishment of a former coworker or the establishment of the student job, coworker quality is still related to higher wages at the first job, although the effect is now smaller.

Table 4.4: Wage Effects: By Individuals Working in an Establishment of a Former Coworker or their Former Student Job

	Log (Daily) Wage at the First Job			
	All Student Jobs	Jobs in Establishments of a Former Coworker	Jobs in Establishments of their Student Job	Excluding jobs in the Establishments of Columns 2 and 3
	(1)	(2)	(3)	(4)
Log avg. coworker wage – Same occupation	0.076***	0.187***	0.162***	0.046*
	(0.022)	(0.058)	(0.054)	(0.025)
Log avg. coworker wage – Other occupation	0.030	-0.023	0.011	0.038
	(0.024)	(0.077)	(0.071)	(0.027)
Adjusted R-squared	0.248	0.321	0.181	0.256
Individuals	3,261	654	655	2,446

Notes: The table shows OLS estimation results from the regression specified in Equation 4.1. In column (2), we focus only on establishments of the first full-time job of a graduate in which a former coworker works. In column (3), we focus only on establishments in which the student worked prior to graduation as a student job according to our definition. In column (4), we exclude columns (2) and (3) from our baseline specification in column (1). We consider only the first full-time job after graduation as the first job. We include all variables as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Effects on College GPA, Job Finding Time, and Job Separation

Another channel for the positive and significant effects of coworker quality may be that students exposed to better coworker quality increase their study effort, for example, because they are more motivated or receive information that higher grades increase the likelihood of getting a higher-paying job. Conversely, students could also reduce their study effort if job-specific human capital (student job) and general human capital (university study) are substitutes. Therefore, in Column (1) of Table 4.5, we use college GPA as the outcome variable and find no effect of coworker quality on college GPA.

In addition, Column (2) of Table 4.5 show that the former coworker quality increases the speed of starting the first full-time job. A 10% increase in the average coworker wage is associated with a reduction in the days to start a full-time job by 1.24%.

Finally, coworker quality may also affect the match stability of the graduate's first full-time job, as coworker quality may affect employer and employee screening, and coworker quality leads to faster matches, which may reduce match stability. However, in Columns (3a) to (3c), we do not find that coworker quality affects the probability of separation within the first 24 months of full-time employment.

Table 4.5: Effects of Student Job Coworker Networks on College Grade, Job Finding Time and Separation Rate

	College GPA	**Log Days to Start First Job**	**Separation within 6 Months**	**Separation within 12 Months**	**Separation within 24 Months**
	(1)	(2)	(3a)	(3b)	(3c)
Log avg. coworker wage – Same occupation	0.002	-0.124***	0.004	-0.002	0.001
	(0.019)	(0.048)	(0.014)	(0.017)	(0.018)
Log avg. coworker wage – Other occupation	-0.017	-0.013	0.010	0.023	0.035*
	(0.024)	(0.050)	(0.016)	(0.019)	(0.020)
Adjusted R-squared	0.369	0.141	0.025	0.054	0.137
Individuals	2,633	3,261	3,261	3,261	3,261
Graduate controls	yes	yes	yes	yes	yes
Coworker network controls	yes	yes	yes	yes	yes
Other employee controls	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Establishment effects	yes	yes	yes	yes	yes
Occupation fixed effects	yes	yes	yes	yes	yes
Graduation cohort fixed effects	yes	yes	yes	yes	yes

Notes: The table shows OLS estimation results using the following outcome variables: College GPA (Column (1)), log days to start first job (Column (2)) and separation rate (Columns (3a) to Columns (3c). The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. Graduate characteristics include gender, nationality, high school GPA, number of student jobs, log average wage in student jobs, field of study, and age. Coworker network and other employee controls include student's log network size, the employment rate of coworkers, the share of female and non-German coworkers, the coworkers' mean age and their education. Establishment effects are the average AKM establishment effects across student jobs. Industry fixed effects and occupation fixed effects are included for the last student job prior to graduation. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Related vs. Unrelated Student Jobs

In Table 4.6, we distinguish between student jobs that were most likely chosen by students simply to earn money and student jobs that were more likely chosen in expectation of better future labor market outcomes. Specifically, we define "unrelated" student jobs as student jobs that are in "Wholesale and retail trade; repair of motor vehicles and motorcycles" or "Accommodation and food service activities" and are not internships or student worker jobs (*Werkstudent*). Any other student job is classified as a "related" student job. We assume that student jobs in unrelated industries are more likely to be typical student jobs to earn extra money, such as working in a bar, restaurant, or supermarket. Consistent with the assumption that jobs in unrelated industries are typical student jobs to earn money, Table 4.1 shows that students disproportionately choose these industries.

Table 4.6 shows the results of our estimations separately for students who worked in unrelated student jobs in Column (2) and those who worked in related student jobs in Column (3). Because some students worked in both unrelated and related student jobs, the number of observations does not add up to our baseline specifications in Column (1). The results in Table 4.6 show that our effects for log wages as an outcome are driven by coworker networks from related jobs. In other words, conditional on our variables controlling for selection into student jobs, these results suggest that higher coworker quality in related jobs improves the quality of the initial job.

Further Heterogeneities

Table 4.7 explores two different types of heterogeneity: In Panel A, we split the sample by college GPA because college GPA may be a proxy for socioeconomic status (SES) and network quality may be especially helpful for low SES students to compensate for missing

Table 4.6: Wage Effects of Student Job Coworker Networks - Unrelated vs. Related Jobs

	Log (Daily) Wage at the First Job		
	All Student Jobs	Only Unrelated Jobs	Only Related Jobs
	(1)	(2)	(3)
Log avg. coworker wage – Same occupation	0.076***	0.006	0.086***
	(0.022)	(0.035)	(0.025)
Log avg. coworker wage – Other occupation	0.030	0.051	-0.001
	(0.024)	(0.034)	(0.030)
Adjusted R-squared	0.248	0.219	0.255
Individuals	3,261	1,441	2,329

Notes: The table shows OLS estimation results from the regression specified in Equation 4.1 and separately estimated by unrelated and related jobs. Unrelated jobs are in sectors which are not related to the graduates' field of studies and are not internships or student worker jobs. These sectors are whole sale and retail trade; repair of motor vehicles and motorcycles, and accommodation and food service activities. Related jobs are all other student jobs. The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. We include all variables as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

family networks. Specifically, we split the sample at the median GPA and classify all graduates above the median as having a "high grade" and those below the median as having a "low grade". The coefficients are slightly lower for students with a GPA below the median, but due to the small differences in the coefficients, we argue that college GPA is not driving our results.

In Panel B, we split our sample by gender and distinguish between female and male graduates. The relationship between coworker quality and a graduate's wage at labor market entry remains positive and statistically significant for both female and male graduates.

Table 4.7: Wage Effects of Student Job Coworker Networks: Heterogeneity Analysis

	Log (Daily) Wage at the First Job		
	(1)	(2)	(3)
Panel A: By Graduation Grade			
	All Students	**High Grade**	**Low Grade**
Log avg. coworker wage – Same occupation	0.076***	0.082***	0.069*
	(0.022)	(0.031)	(0.038)
Log avg. coworker wage – Other occupation	0.030	-0.002	0.041
	(0.024)	(0.037)	(0.039)
Adjusted R-squared	0.248	0.198	0.225
Individuals	3,261	1,561	1,072
Panel B: By Gender			
	All Students	**Female**	**Male**
Log avg. coworker wage – Same occupation	0.076***	0.089***	0.077**
	(0.022)	(0.031)	(0.034)
Log avg. coworker wage – Other occupation	0.030	0.013	0.066*
	(0.024)	(0.032)	(0.037)
Adjusted R-squared	0.248	0.210	0.232
Individuals	3,261	1,893	1,368

Notes: The table shows OLS estimation results from the regression specified in Equation 4.1 and separately by college GPA and gender. We split the sample by median GPA and classify those students with a college GPA above the median as "High Grade" and those below the median as "Low Grade". The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. We include all variables as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.5 Conclusion

This paper provides new insights into the role of coworker networks from student jobs in enhancing career advancement and access to job opportunities. While previous studies have focused on more institutionalized networks such as classmates or roommates, we show that more informal networks from student jobs are also relevant. These networks of coworkers can help reduce information frictions, which are likely to be highest at the beginning of a career.

Our findings indicate that graduates benefit from the quality of their coworker networks in the form of higher entry wages. Although we do not have exogenous variation in network quality, the strength of our data, in particular the large set of control variables, allows us to come close to a causal effect. Moreover, our results are robust to different specifications and robustness checks. Our results first show that graduates tend to benefit more if they start their careers in establishments where a former coworker is employed or where they worked during their studies. Interestingly, we do not find much heterogeneity across gender or student ability. However, the results show that the type of student job matters, with the quality of coworkers in related jobs having a positive effect on the quality of the first job.

The size of our effects are remarkable. A 10% increase in the average wage of former coworkers is associated with a 0.76% higher wage in the first full-time job. This effect is about twice as large compared to a 10 percentage point increase in the share of workers from the same minority in the same establishment (Dustmann et al., 2016), about 7 times larger than the spillover effects of working with productive coworkers (Cornelissen et al., 2017), both in the German context, and 3 times larger than the peer quality effect on future wages stated by Hong and Lattanzio (2022). However, while our paper estimates the effect of having better quality coworkers in student jobs on wages at a later point in time, the paper by Cornelissen et al. (2017) estimates the immediate spillover effects of having better quality coworkers in the same establishment and occupation, which can explain much of the difference in the magnitude of the results. These results point into the same direction as the study by Kramarz and Skans (2014), who analyze the effect of having a parent working in the same plant. Given that a parent is much closer to the student than a former coworker, it is plausible that their result is about eleven times higher in magnitude.[7]

Overall, we show that student jobs matter beyond their purpose of providing a living. Our results clearly suggest that networks of better quality coworkers built during student jobs improve the transition from college to the labor market, most likely by reducing information frictions very early in a person's career. This study highlights the importance of considering coworker networks in policies aimed at smoothing the transition from higher education to employment and provides valuable insights for future research on the topic.

[7] Note also, that Kramarz and Skans (2014) employ a different definition of the first job than we do.

5 Conclusion

The transition from university to the labor market is an important stage for graduates as it has long-lasting effects on their careers (e.g., Gerhart, 1990; Kahn, 2010; Oreopoulos et al., 2012). During the job search period at this stage, both job seekers and employers face significant information frictions, which may result in lower starting salaries for recent graduates and a higher probability of job mismatches. Moreover, if these information frictions differ across demographic groups, they may foster labor market discrimination against certain groups, such as women, thereby contributing to labor market inequalities, in particular the gender wage gap.

This dissertation examines the transition from university to the labor market, focusing on gender differences and the role of information in early career labor market outcomes. The dissertation consists of two parts: The first part (Chapters 2 and 3) examines gender differences and the role of information in the transition from university to the labor market, with the chapters specifically addressing the gender negotiation gap and the early career gender wage gap. The second part (Chapter 4) explores how networks from student jobs might improve entry wages by reducing information frictions. The overarching themes include the critical transition period from university to the labor market, information frictions during this period and ways to reduce them, and a focus on master's graduates with higher labor market attachment. Finally, all analyses are based on data from Germany, where the employment rate of university graduates after graduation and during their studies is high and the gender wage gap is pronounced.

In Chapter 2, I conduct a large online field experiment to reduce gender differences in negotiation behavior that may contribute to the gender wage gap. In this chapter, I aim to provide causal evidence on the role of information on graduates' negotiation intentions and behavior in a real-world setting. I implement a randomized control trial (RCT) with final-year master's students at German universities prior to graduation. In the baseline survey, I randomly assign participants to two short experimental treatments. The statistics treatment provides information on gender differences in negotiation and wages, while the role-model treatment provides personalized information on negotiation experiences conveyed by successful role models. Following the treatments, I use follow-up surveys to track the participants as they enter the labor market after graduation. The baseline results show that there is a pronounced gender gap in negotiation intentions for base salary and other monetary components. For the treatment effects, I first find that both the statistics and the role-model treatments significantly increase females' negotiation intentions, while only the role-model treatment increases males' negotiation intentions. However, despite the increase in negotiation intentions resulting from the interventions, the treatments do not affect actual negotiation behavior for the first job after graduation for either gender.

In Chapter 3, together with Malte Sandner, we analyze the gender wage gap at labor market entry and its evolution during the initial years of a career. Using a unique dataset that links graduates of a large German university with detailed employment records from German social security registers, we find that a significant gender wage gap already exists in the first full-time job after graduation. However, the gender wage gap narrows in the first year after the first job, before slowly widening over time. As an explanation for the narrowing of the gender wage gap, we find that female graduates have higher returns to firm and occupation changes than their male counterparts. In particular, women may use firm and occupation changes to correct for a skill mismatch, which is more common for women than for men in the first job.

The second part of this dissertation, Chapter 4, co-authored with Gökay Demir, Friederike Hertweck, and Malte Sandner, also focuses on the transition from university to the labor market and examines whether and to what extent graduates' coworker networks from student jobs affect their early career wages. The empirical analysis is based on administrative data covering all job-related networks before and after graduation. In this chapter, we focus on university students who graduated from a large German university between 1995 and 2016. Our identification strategy overcomes potential bias due to non-random selection into networks by controlling for an extensive set of individual, network, and establishment characteristics, as well as establishment fixed effects, and by distinguishing between close and less close colleagues in the same establishment. Our results suggest that university graduates benefit from the quality of their coworkers in student jobs by earning higher wages in their first job after graduation. These findings can contribute to understanding which factors are important for a successful transition from higher education to the labor market.

Taken together, the first part of this dissertation demonstrates that gender differences affecting graduates' labor market outcomes begin even before the initial job search period, when information frictions are high. In particular, it reveals a gender gap in negotiation intentions that can be mitigated by a short and low-cost information intervention, although changing actual behavior in high-stakes situations remains challenging. In addition, I document the existence of a gender wage gap in graduates' first jobs, which narrows after one year due to occupational and firm changes. This may be because women initially take more mismatched jobs, possibly due to information asymmetries, which they correct within a year of entering the labor market. The second part of the dissertation, which focuses on co-worker networks in student jobs, shows that the quality of networks can mitigate these information frictions, leading to higher starting wages after graduation.

Overall, this dissertation provides valuable insights into the critical transition from university to the labor market, which has long-lasting effects on graduates' careers. The findings of this dissertation are key to understanding the gender gap at the beginning of a career and identifying factors that are crucial for a successful transition into the labor market. In addition, it highlights the role of information frictions during this period and how reducing them can affect labor market outcomes. This understanding can help inform policies and practices aimed at smoothing the transition of graduates from university to the labor market and at reducing the gender gaps in the early stages of careers.

Bibliography

Abebe, G., Caria, A. S., Fafchamps, M., Falco, P., Franklin, S., and Quinn, S. (2021). Anonymity or distance? Job search and labour market exclusion in a growing African city. *The Review of Economic Studies*, 88(3), 1279–1310.

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2), 251–333.

Acemoglu, D. and Shimer, R. (1999). Efficient unemployment insurance. *Journal of Political Economy*, 107(5), 893–928.

Adamecz-Völgyi, A. and Shure, N. (2022). The gender gap in top jobs – the role of overconfidence. *Labour Economics*, 79, 102283.

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.

Altmann, S., Falk, A., Jäger, S., and Zimmermann, F. (2018). Learning about job search: A field experiment with job seekers in Germany. *Journal of Public Economics*, 164, 33–49.

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, 305–396. Elsevier.

Altonji, J. G. and Blank, R. M. (1999). Chapter 48: Race and gender in the labor market. *Handbook of Labor Economics*, 3(C), 3143–3259.

Altonji, J. G., Blom, E., and Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics*, 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, 04, 2016. Institute for Employment Research (IAB), Nuremberg, Germany.

Antoninis, M. (2006). The wage effects from the use of personal contacts as hiring channels. *Journal of Economic Behavior & Organization*, 59(1), 133–146.

Ashraf, N., Bau, N., Low, C., and McGinn, K. (2020). Negotiating a better future: How interpersonal skills facilitate intergenerational investment. *The Quarterly Journal of Economics*, 135(2), 1095–1151.

Babcock, L. and Laschever, S. (2003). *Women don't ask: Negotiation and the gender divide*. Princeton University Press.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261–292.

Bartel, A. P. and Borjas, G. J. (1981). Wage growth and job turnover: An empirical analysis. *Studies in Labor Markets*, 65–90.

Battisti, M. (2017). High wage workers and high wage peers. *Labour Economics*, 46, 47–63.

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.

Bellmann, L., Lochner, B., Seth, S., and Wolter, S. (2020). AKM effects for german labour market data. FDZ-Methodenreport, 01, 2020. Institute for Employment Research (IAB), Nuremberg, Germany.

Belot, M., Kircher, P., and Muller, P. (2019). Providing advice to jobseekers at low cost: An experimental study on online advice. *The Review of Economic Studies*, 86(4), 1411–1447.

Belot, M., Kircher, P., and Muller, P. (2022). How wage announcements affect job search—a field experiment. *American Economic Journal: Macroeconomics*, 14(4), 1–67.

Bertrand, M. (2011). New perspectives on gender. In *Handbook of Labor Economics*, Volume 4, 1543–1590. Elsevier.

Bertrand, M. (2020). Gender in the twenty-first century. *AEA Papers and Proceedings*, 110, 1–24.

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.

Biasi, B. and Sarsons, H. (2021). Information, confidence, and the gender gap in bargaining. *AEA Papers and Proceedings*, 111, 174–178.

Biasi, B. and Sarsons, H. (2022). Flexible wages, bargaining, and the gender gap. *The Quarterly Journal of Economics*, 137(1), 215–266.

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.

Bleemer, Z. and Zafar, B. (2018). Intended college attendance: Evidence from an experiment on college returns and costs. *Journal of Public Economics*, 157, 184–211.

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.

Bowles, H. R., Babcock, L., and McGinn, K. L. (2005). Constraints and triggers: Situational mechanics of gender in negotiation. *Journal of Personality and Social Psychology*, 89(6), 951.

Breda, T., Grenet, J., Monnet, M., Van Effenterre, C., et al. (2020). Do female role models reduce the gender gap in science? Evidence from French high schools. IZA Discussion Papers 13163, Institute of Labor Economics (IZA).

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.

Brenzel, H., Gartner, H., and Schnabel, C. (2014). Wage bargaining or wage posting? Evidence from the employers' side. *Labour Economics*, 29, 41–48.

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

Bursztyn, L., González, A. L., and Yanagizawa-Drott, D. (2020a). Misperceived social norms: Women working outside the home in Saudi Arabia. *American Economic Review*, 110(10), 2997–3029.

Bursztyn, L., Rao, A., Roth, C. P., and Yanagizawa-Drott, D. H. (2020b). Misinformation during a pandemic. Working Paper 27417, National Bureau of Economic Research.

Caldwell, S. and Harmon, N. (2019). Outside options, bargaining, and wages: Evidence from coworker networks. Unpublished.

Cappellari, L. and Tatsiramos, K. (2015). With a little help from my friends? Quality of social networks, job finding and job match quality. *European Economic Review*, 78, 55–75.

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

Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics*, 138(3), 967–1015.

Card, D., Kluve, J., and Weber, A. (2010). Active labour market policy evaluations: A meta-analysis. *The Economic Journal*, 120(548), F452–F477.

Carranza, E., Garlick, R., Orkin, K., and Rankin, N. (2022). Job search and hiring with limited information about workseekers' skills. *American Economic Review*, 112(11), 3547–83.

Chetty, R., Looney, A., and Kroft, K. (2009). Salience and taxation: Theory and evidence. *American Economic Review*, 99(4), 1145–1177.

Chotiputsilp, B. and Kim, T. (2021). Can negotiation training help close the gender pay gap? Available at SSRN 3899997.

Cingano, F. and Rosolia, A. (2012). People I know: Job search and social networks. *Journal of Labor Economics*, 30(2), 291–332.

Cornelissen, T., Dustmann, C., and Schönberg, U. (2017). Peer effects in the workplace. *American Economic Review*, 107(2), 425–456.

Cortés, P. and Pan, J. (2023). Children and the remaining gender gaps in the labor market. *Journal of Economic Literature*, 61(4), 1359–1409.

Cortés, P., Pan, J., Pilossoph, L., Reuben, E., and Zafar, B. (2023). Gender differences in job search and the earnings gap: Evidence from the field and lab. *The Quarterly Journal of Economics*, 138(4), 2069–2126.

Cox, J. C. and Oaxaca, R. L. (1992). Direct tests of the reservation wage property. *The Economic Journal*, 102(415), 1423–1432.

Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, 47(2), 448–74.

De Schouwer, T. and Kesternich, I. (2022). It's all about the meaning: Work meaning, job flexibility, and the gender wage gap. KU Leuven, Department of Economics.

Del Bono, E. and Vuri, D. (2011). Job mobility and the gender wage gap in Italy. *Labour Economics*, 18(1), 130–142.

Del Carpio, L. and Guadalupe, M. (2022). More women in tech? Evidence from a field experiment addressing social identity. *Management Science*, 68(5), 3196–3218.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2), 315–372.

Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics*, 135(4), 1965–2005.

Demir, G. (2023). Labor market frictions and spillover effects from publicly announced sectoral minimum wages. Available at SSRN 4306501.

Dorner, M., Heining, J. Jacobebbinghaus, P., and Seth, S. (2010). Stichprobe der Integrierten Arbeitsmarktbiografien (SIAB) 1975-2008. FDZ-Methodenreport, 01, 2010. Institute for Employment Research (IAB), Nuremberg, Germany.

Dreber, A., Heikensten, E., and Säve-Söderbergh, J. (2022). Why do women ask for less? *Labour Economics*, 78, 102204.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2), 514–546.

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

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior*, 23(4), 281–295.

Eliason, M., Hensvik, L., Kramarz, F., and Skans, O. N. (2023). Social connections and the sorting of workers to firms. *Journal of Econometrics*, 233(2), 468–506.

Eurofound (2022). *Moving with the times: Emerging practices and provisions in collective bargaining*. Publications Office of the European Union, Luxembourg.

Eurostat (2023a). *Employment rates of recent graduates*.

Eurostat (2023b). *Gender pay gap statistics*.

Exley, C. L., Niederle, M., and Vesterlund, L. (2020). Knowing when to ask: The cost of leaning in. *Journal of Political Economy*, 128(3), 816–854.

Farber, H. S. and Gibbons, R. (1996). Learning and wage dynamics. *The Quarterly Journal of Economics*, 111(4), 1007–1047.

Federal Statistical Office (2022). *Mothers at 1st birth and Länder.*

Federal Statistical Office (2023). *Bildung und Kultur.*

Feinberg, R. M. (1977). Risk aversion, risk, and the duration of unemployment. *The Review of Economics and Statistics*, 59(3), 264–271.

Feld, J. and Zölitz, U. (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labor Economics*, 35(2), 387–428.

Filippin, A. and Ichino, A. (2005). Gender wage gap in expectations and realizations. *Labour Economics*, 12(1), 125–145.

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, 1–102. Elsevier.

Francesconi, M. and Parey, M. (2018). Early gender gaps among university graduates. *European Economic Review*, 109, 63–82.

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.

Fröberg, E., Säve-Söderbergh, J., Wahlund, R., and Wakeman, S. W. (2023). The promise (and peril) in approaching gender parity: Preregistered survey experiments addressing gender inequality in negotiations. *Labour Economics*, 102401.

Gerhart, B. (1990). Gender differences in current and starting salaries: The role of performance, college major, and job title. *ILR Review*, 43(4), 418–433.

Glitz, A. (2017). Coworker networks in the labour market. *Labour Economics*, 44, 218–230.

Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American Economic Review*, 96(2), 1–21.

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.

Gonzalez, F. M. and Shi, S. (2010). An equilibrium theory of learning, search, and wages. *Econometrica*, 78(2), 509–537.

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.

Grewenig, E., Lergetporer, P., and Werner, K. (2020). Gender norms and labor-supply expectations: Experimental evidence from adolescents. CESifo Working Paper 8611, CESifo.

Haaland, I. and Roth, C. (2023). Beliefs about racial discrimination and support for pro-black policies. *Review of Economics and Statistics*, 105(1), 40–53.

Haaland, I., Roth, C., and Wohlfart, J. (2023). Designing information provision experiments. *Journal of Economic Literature*, 61(1), 3–40.

Hansen, B. and McNichols, D. (2020). Information and the persistence of the gender wage gap: Early evidence from California's salary history ban. NBER Working Papers 27054, National Bureau of Economic Research.

Hassan, L. M., Shiu, E., and Shaw, D. (2016). Who says there is an intention–behaviour gap? Assessing the empirical evidence of an intention–behaviour gap in ethical consumption. *Journal of Business Ethics*, 136, 219–236.

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.

Heller, S. B. and Kessler, J. B. (2021). Information frictions and skill signaling in the youth labor market. NBER Working Papers 29579, National Bureau of Economic Research.

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.

Hensvik, L., Müller, D., and Skans, O. N. (2023). Connecting the young: High school graduates' matching to first jobs in booms and great recessions. *The Economic Journal*, 133(652), 1466–1509.

Herber, S. P. (2018). The role of information in the application for highly selective scholarships: Evidence from a randomized field experiment. *Economics of Education Review*, 62, 287–301.

Hernandez-Arenaz, I. and Iriberri, N. (2019). A review of gender differences in negotiation. *Oxford Research Encyclopedia of Economics and Finance*.

Holzer, H. J. (1988). Search method use by unemployed youth. *Journal of Labor Economics*, 6(1), 1–20.

Hong, L. and Lattanzio, S. (2022). The peer effect on future wages in the workplace. Available at SSRN 4052587.

Hotz, V. J., Xu, L. C., Tienda, M., and Ahituv, A. (2002). Are there returns to the wages of young men from working while in school? *Review of Economics and Statistics*, 84(2), 221–236.

Hsieh, C.-T., Hurst, E., Jones, C. I., and Klenow, P. J. (2019). The allocation of talent and U.S. economic growth. *Econometrica*, 87(5), 1439–1474.

Ioannides, Y. M. and Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature*, 42(4), 1056–1093.

Irwin, V., De La Rosa, J., Wang, K., Hein, S., Zhang, J., Burr, R., Roberts, A., Barmer, A., Bullock Mann, F., Dilig, R., et al. (2022). Condition of Education 2022. NCES.

Jäger, S., Roth, C., Roussille, N., and Schoefer, B. (2022). Worker Beliefs About Outside Options. NBER Working Paper 29623, National Bureau of Economic Research.

Jann, B. et al. (2008). The Blinder-Oaxaca decomposition for linear regression models. *The Stata Journal*, 8(4), 453–479.

Jarosch, G., Oberfield, E., and Rossi-Hansberg, E. (2021). Learning from coworkers. *Econometrica*, 89(2), 647–676.

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.

Kiessling, L., Pinger, P., Seegers, P., and Bergerhoff, J. (2024). Gender differences in wage expectations and negotiation. *Labour Economics*, 87, 102505.

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. *AEA Papers and Proceedings*, 109, 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.

Kramarz, F. and Skans, O. N. (2014). When strong ties are strong: Networks and youth labour market entry. *The Review of Economic Studies*, 81(3), 1164–1200.

Kugler, K. G., Reif, J. A., Kaschner, T., and Brodbeck, F. C. (2018). Gender differences in the initiation of negotiations: A meta-analysis. *Psychological Bulletin*, 144(2), 198.

Kunze, A. (2003). Gender differences in entry wages and early career wages. *Annales d'Economie et de Statistique*, 245–265.

Kunze, A. (2005). The evolution of the gender wage gap. *Labour Economics*, 12(1), 73–97.

Kuziemko, I., Norton, M. I., Saez, E., and Stantcheva, S. (2015). How elastic are preferences for redistribution? Evidence from randomized survey experiments. *American Economic Review*, 105(4), 1478–1508.

Kuziemko, I., Pan, J., Shen, J., and Washington, E. (2018). The mommy effect: Do women anticipate the employment effects of motherhood? NBER Working Paper 24740, National Bureau of Economic Research.

Le Barbanchon, T., Ubfal, D., and Araya, F. (2023). The effects of working while in school: Evidence from employment lotteries. *American Economic Journal: Applied Economics*, 15(1), 383–410.

Levitt, S. D. and Dubner, S. J. (2023). *Freakonomics: A New Nobel Laureate Explains the Gender Pay Gap (Replay)*. Harper Trophy.

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.

Maier, F. (2007). The persistence of the gender wage gap in Germany. Discussion Paper, 01, 2007. Harriet Taylor Mill–Institut für Ökonomie und Geschlechterforschung, Berlin.

Manning, A. and Swaffield, J. (2008). The gender gap in early-career wage growth. *The Economic Journal*, 118(530), 983–1024.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3), 531–542.

Marmaros, D. and Sacerdote, B. (2002). Peer and social networks in job search. *European Economic Review*, 46(4-5), 870–879.

Mazei, J., Hüffmeier, J., Freund, P. A., Stuhlmacher, A. F., Bilke, L., and Hertel, G. (2015). A meta-analysis on gender differences in negotiation outcomes and their moderators. *Psychological Bulletin*, 141(1), 85.

Mengel, F. (2020). Gender differences in networking. *The Economic Journal*, 130(630), 1842–1873.

Moghavvemi, S., Salleh, N. A. M., Sulaiman, A., and Abessi, M. (2015). Effect of external factors on intention–behaviour gap. *Behaviour & Information Technology*, 34(12), 1171–1185.

Möller, J. and Rust, C. (2018). The role of a local university in regional development: The case of Regensburg. *Entrepreneurship and Local Economic Development*, 247–280.

Müller, D., Strauch, K., et al. (2017). Identifying mothers in administrative data. FDZ-Methodenreport, 13, 2017. Institute for Employment Research (IAB), Nuremberg, Germany.

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 (2022). *Education at a Glance 2022: OECD Indicators.* OECD Publishing, Paris.

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.

Palffy, P., Lehnert, P., and Backes-Gellner, U. (2023). Countering gender-typicality in occupational choices: An information intervention targeted at adolescents. Working Papers, 207, Department of Business Administration (IBW), University of Zurich.

Pannenberg, M. (2010). Risk attitudes and reservation wages of unemployed workers: Evidence from panel data. *Economics Letters*, 106(3), 223–226.

Peter, F., Spiess, C. K., and Zambre, V. (2021). Informing students about college: Increasing enrollment using a behavioral intervention? *Journal of Economic Behavior & Organization*, 190, 524–549.

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.

Porterfield, S. L. and Winkler, A. E. (2007). Teen time use and parental education: Evidence from the CPS, MTF, and ATUS. *Monthly Labor Review*, 130(5), 37–56.

Recalde, M. P. and Vesterlund, L. (2023). Gender differences in negotiation: Can interventions reduce the gap? *Annual Review of Economics*, 15.

Reuben, E., Wiswall, M., and Zafar, B. (2017). Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender. *The Economic Journal*, 127(604), 2153–2186.

Rigdon, M. L. (2012). An experimental investigation of gender differences in wage negotiations. Available at SSRN 2165253.

Riley, E. (2022). Role models in movies: The impact of Queen of Katwe on students' educational attainment. *Review of Economics and Statistics*, 1–48.

Robst, J. (2007). Education and job match: The relatedness of college major and work. *Economics of Education Review*, 26(4), 397–407.

Rockoff, J. E., Staiger, D. O., Kane, T. J., and Taylor, E. S. (2012). Information and employee evaluation: Evidence from a randomized intervention in public schools. *American Economic Review*, 102(7), 3184–3213.

Roussille, N. (2024). The role of the ask gap in gender pay inequality. *The Quarterly Journal of Economics*, qjae004.

Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *The Quarterly Journal of Economics*, 116(2), 681–704.

Sacerdote, B. (2014). Experimental and quasi-experimental analysis of peer effects: Two steps forward? *Annual Review Economics*, 6(1), 253–272.

Säve-Söderbergh, J. (2019). Gender gaps in salary negotiations: Salary requests and starting salaries in the field. *Journal of Economic Behavior & Organization*, 161, 35–51.

Saygin, P. O., Weber, A., and Weynandt, M. A. (2021). Coworkers, networks, and job-search outcomes among displaced workers. *ILR Review*, 74(1), 95–130.

Schwandt, H. and Von Wachter, T. (2019). Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets. *Journal of Labor Economics*, 37(S1), S161–S198.

Schwarz, N. and Vaughn, L. A. (2002). The availability heuristic revisited: Ease of recall and content of recall as distinct sources of information. In *Heuristics and Biases: The Psychology of Intuitive Judgement*, 103–119. Cambridge, England: Cambridge University Press.

Schwieren, C. (2012). The gender wage gap in experimental labor markets. *Economics Letters*, 117(3), 592–595.

Settele, S. (2022). How do beliefs about the gender wage gap affect the demand for public policy? *American Economic Journal: Economic Policy*, 14(2), 475–508.

Sevilla, A. (2020). Gender economics: An assessment. *Oxford Review of Economic Policy*, 36(4), 725–742.

Sheeran, P. (2002). Intention—behavior relations: A conceptual and empirical review. *European Review of Social Psychology*, 12(1), 1–36.

Simeaner, H., Ramm, M., and Kolbert-Ramm, C. (2014). Datenalmanach studierendensurvey 1993–2013: Studiensituation und studierende an universitäten und fachhochschulen. Hefte zur Bildungs– und Hochschulforschung. AG Hochschulforschung, Universität Konstanz.

Small, D. A., Gelfand, M., Babcock, L., and Gettman, H. (2007). Who goes to the bargaining table? The influence of gender and framing on the initiation of negotiation. *Journal of Personality and Social Psychology*, 93(4), 600.

Staneva, M. (2015). *Studieren und Arbeiten: die Bedeutung der studentischen Erwerbstätigkeit für den Studienerfolg und den Übergang in den Arbeitsmarkt.* DIW Roundup: Politik im Fokus, No. 70, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.

Stuhlmacher, A. F. and Walters, A. E. (1999). Gender differences in negotiation outcome: A meta-analysis. *Personnel Psychology*, 52(3), 653–677.

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. Department of Economics, University of Pittsburgh.

Wachter, T. V. (2020). The persistent effects of initial labor market conditions for young adults and their sources. *Journal of Economic Perspectives*, 34(4), 168–194.

Wiedemann, A. U., Schüz, B., Sniehotta, F., Scholz, U., and Schwarzer, R. (2009). Disentangling the relation between intentions, planning, and behaviour: A moderated mediation analysis. *Psychology and Health*, 24(1), 67–79.

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.

Zhu, M. (2022). Beyond the “old boys’ network”: Social networks and job finding at community colleges. *Journal of Human Resources*.

Zimmerman, S. D. (2019). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review*, 109(1), 1–47.

Zölitz, U. and Feld, J. (2018). The effect of peer gender on major choice. Unpublished Manuscript. Department of Economics, University of Zurich.

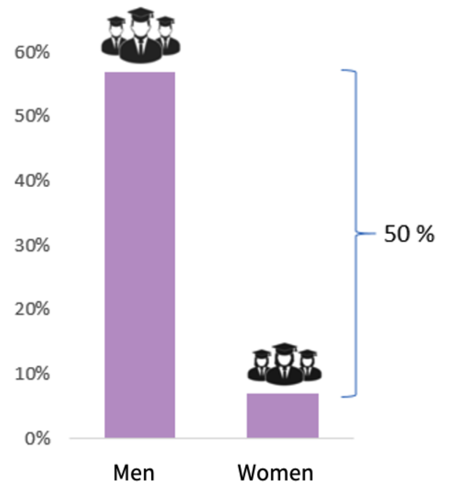
Appendix A: Chapter 2

A.1 Additional Figures and Tables

Figure A.1: Statistics Treatment: Example Pages

(a)

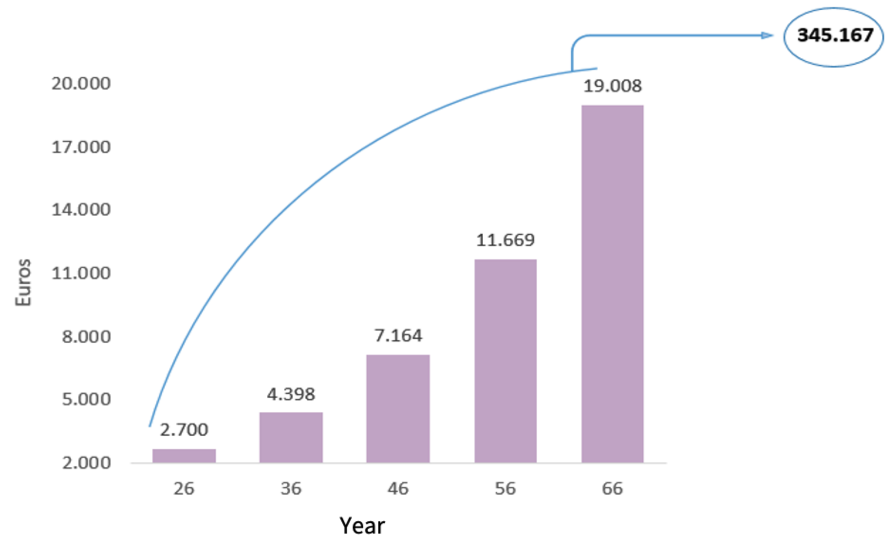
The negotiation behavior of university graduates



A U.S. study by Carnegie Mellon University shows that among master's graduates, only **7 percent of women** negotiate their salaries when entering the workforce. By contrast, **57 percent of men** negotiate in their first job interviews: the gender negotiation gap is thus 50 percentage points. Male graduates are eight times more likely to negotiate than female graduates.

(b)

Annual wage differentials through salary negotiation increase over the working life.



Annual wage differences between Anna and Felix by age

Over the entire period, Felix earns a total of **345,167 euros more** than Anna by the age of 66.

Notes: These figures show example pages from the statistics treatment. These pages are translated from the original language (German). For complete survey questions and treatments in the original language (German), see link `https://doku.iab.de/grauepap/Supplementary_Materials.pdf`.

Figure A.2: Role-Model Treatment: Example of An Interview With Selected Questions

Photo

Name: Jeannine

Age: 39

Education: Diploma, English/American studies

Occupation: Executive Chairwoman of the Board

Current position: CEO & Chairwoman of the Board

Did you negotiate your salary for your first job after graduation?
Yes

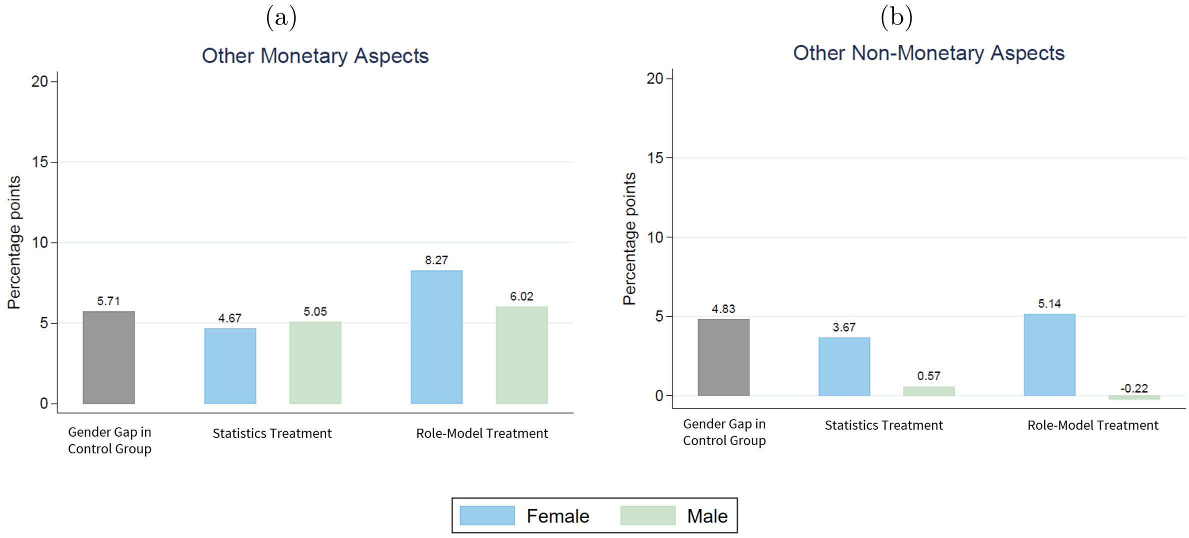
How likely do you think applicants' salaries would increase as a result of negotiation?
Very likely. (Depending on what the base salary was. Is it a good offer when measured against the market? Does it reflect my skills and is it fair in the overall context and comparable to salaries of others in similar positions, with similar experience levels?)

By what percentage do you think the salary would increase?
5-15%

What is the best way to prepare for salary negotiations?
Inquire: What are the salaries currently in similar industries, for people in similar positions, with similar experience and skills? Make healthy self-assessments and develop healthy self-esteem. Adopt an attitude.

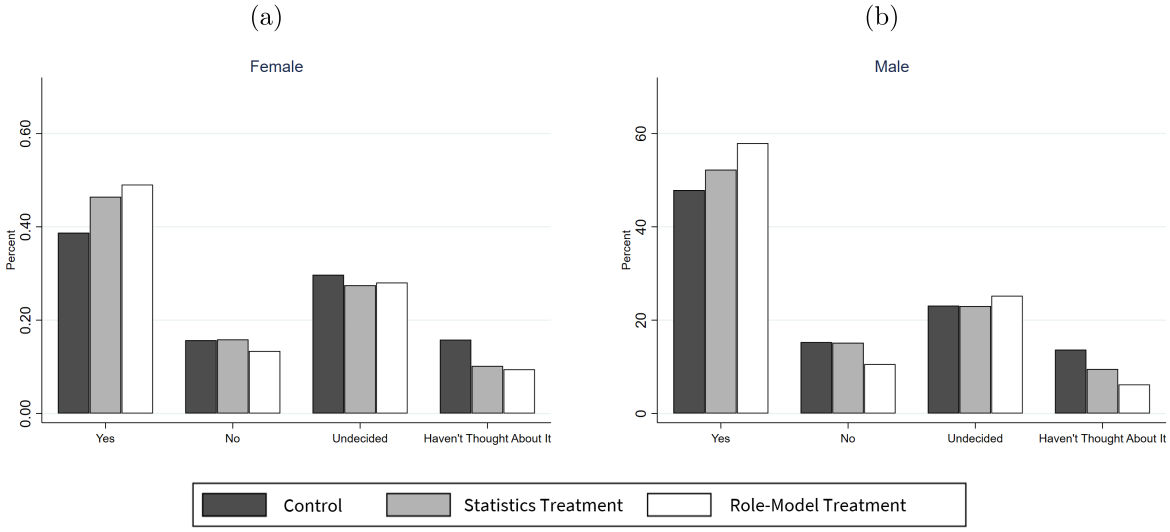
Notes: This figure shows part of an example page from the role-model treatment. This page is translated from the original language (German). For complete survey questions and treatments in the original language (German), see the following link https://doku.iab.de/grauepap/Supplementary_Materials.pdf.

Figure A.3: The Treatment Effects on Negotiation Intentions for Other Monetary and Non-Monetary Aspects



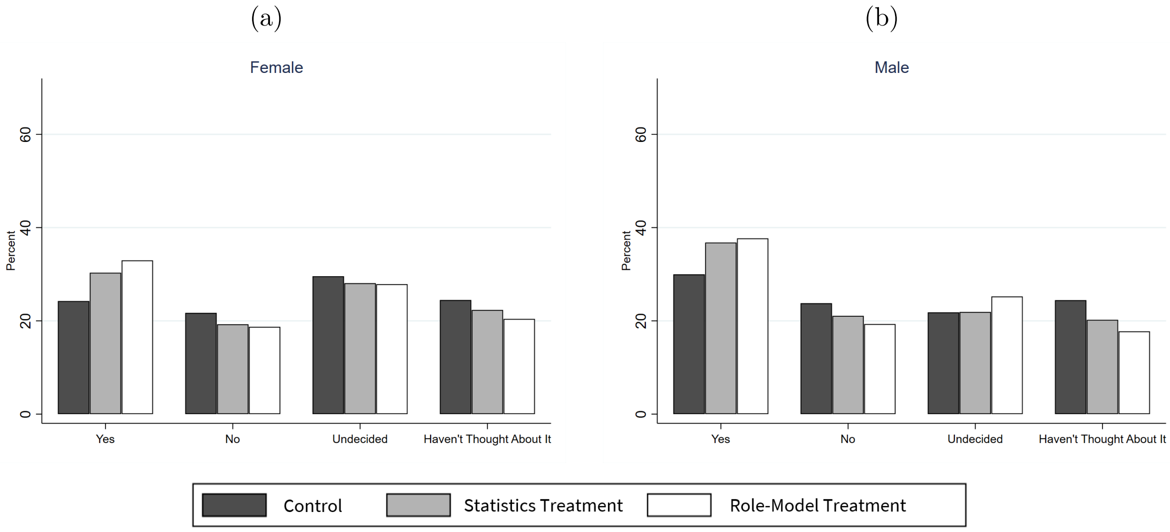
Notes: The figure shows the effects of treatments on the outcomes of the negotiation intention for other monetary aspects (left panel) and other non-monetary aspects (right panel), based on the estimation equation 2.1. The effects of treatments are also shown in Table 2.3, Columns (3) to (4), and Columns (5) to (6), respectively. The gray bar represents the gender gap in the control group at follow-up 1. Blue (green) bars represent the treatment effect on the negotiation intention for females (the males). The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the variables of interest and controls, refer to Table 2.3.

Figure A.4: The Treatment Effects on Negotiation Intentions for Base Salary - All Response Categories



Notes: The figure shows the effects of treatments on the outcomes of the negotiation intention for base salary for females (left panel) and for males (right panel). The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the controls, refer to Table 2.3.

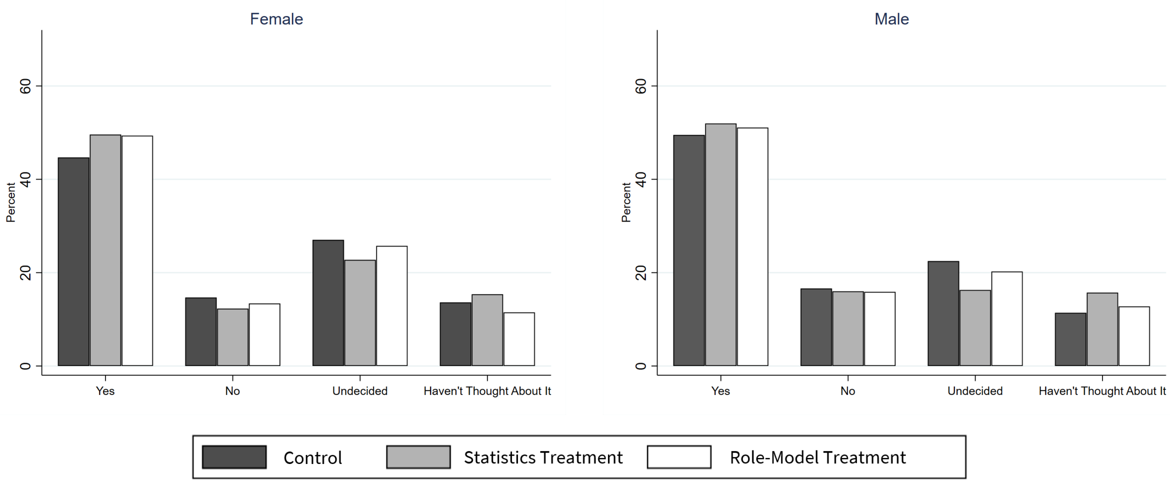
Figure A.5: The Treatment Effects on Negotiation Intentions for Other Monetary Aspects - All Response Categories



Notes: The figure shows the effects of treatments on the outcomes of the negotiation intention for other monetary aspects for females (left panel) and males (right panel). The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the controls, refer to Table 2.3.

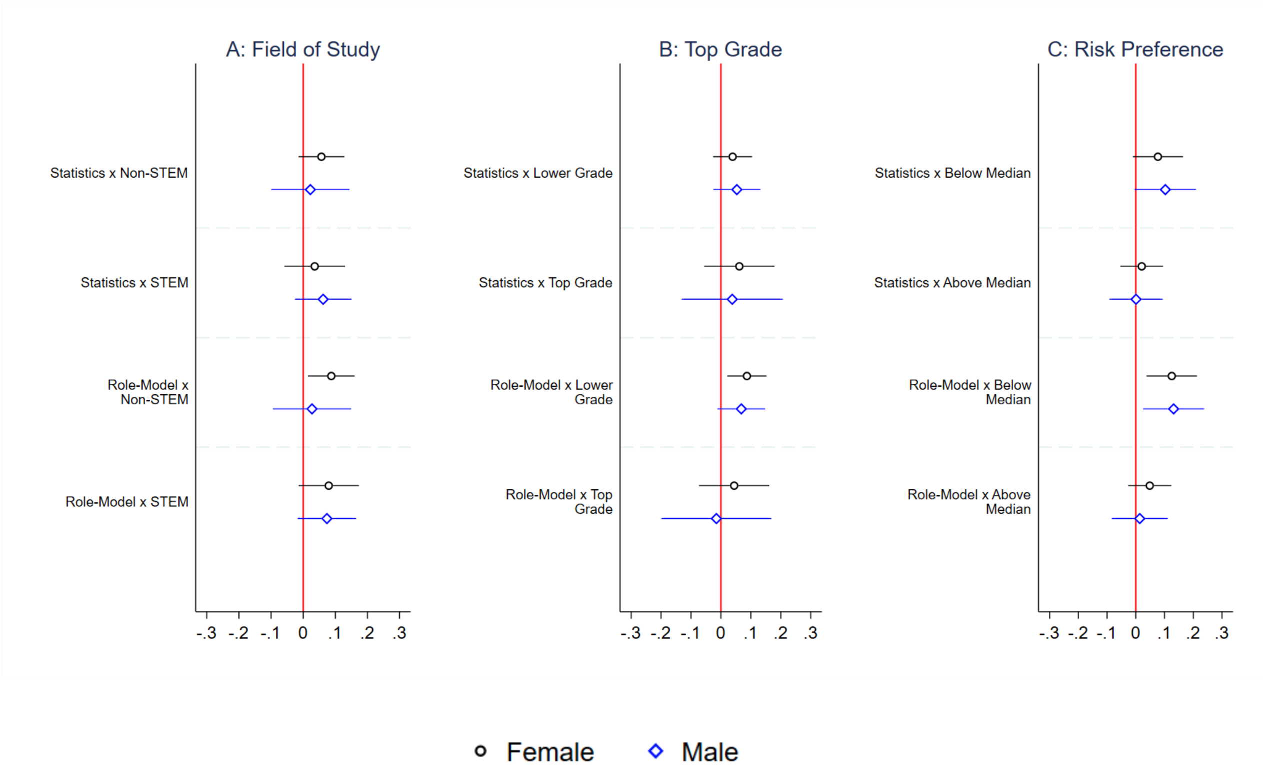
Figure A.6: The Treatment on Negotiation Intentions for Other Non-Monetary Aspects - All Response Categories

(a) (b)



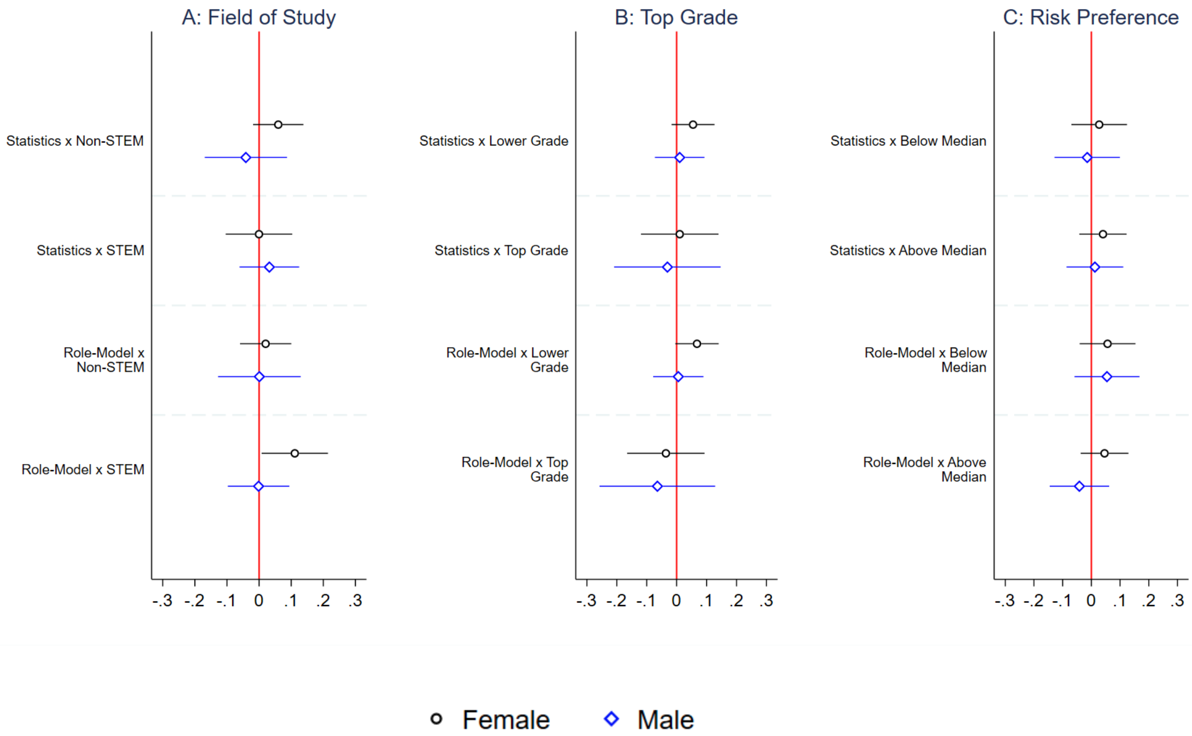
Notes: The figure shows the effects of treatments on the outcomes of the negotiation intention for other non-monetary aspects for females (left panel) and males (right panel). The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the controls, refer to Table 2.3.

Figure A.7: Heterogeneity in the Treatment Effect: Other Monetary Aspects



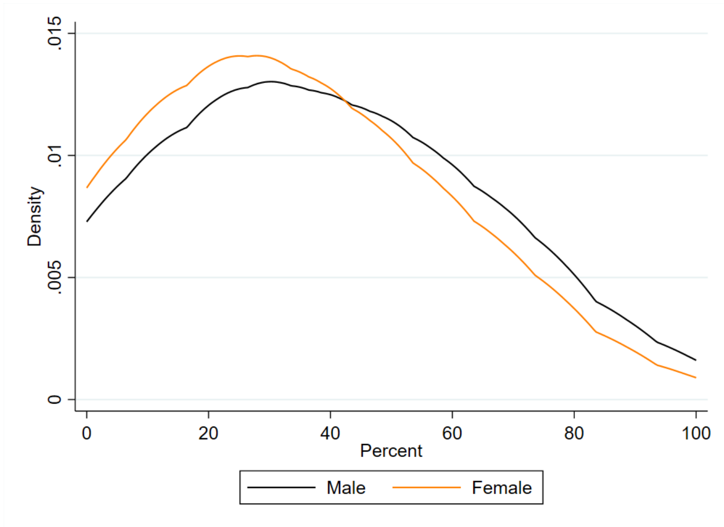
Notes: The figure shows heterogeneous treatment effects on the negotiation intention for other monetary aspects. The effects of treatments are also shown in Columns (3) and (4) of Table A.6. The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the variables of interest and controls, refer to Table 2.3.

Figure A.8: Heterogeneity in the Treatment Effect: Other Non-Monetary Aspects



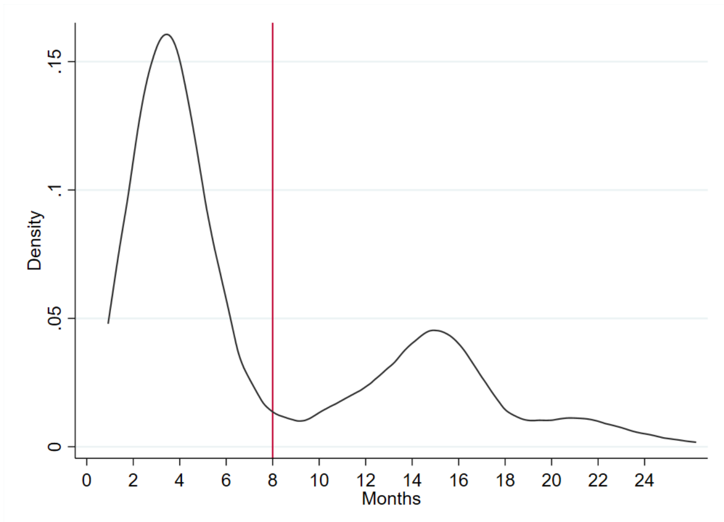
Notes: The figure shows heterogeneous treatment effects on the negotiation intention for other non-monetary aspects. The effects of treatments are also shown in Columns (5) and (6) of Table A.6. The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up. For explanations of the variables of interest and controls, refer to Table 2.3.

Figure A.9: Percentage Chance of Increase of Base Salary, Conditional on Negotiation



Notes: The figure shows the distribution of the outcome variable by gender. The outcome variable is the percentage chance increase in the base salary. Gray (orange) line represents the distribution of male's (female's) answer. The outcomes are measured 2-4 months after the intervention at follow-up 1. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and have given an answer to the negotiation intention to all outcomes (base, other monetary and non-monetary aspects) in the first wave and first follow-up.

Figure A.10: Months Between Response to Negotiation Question and Intervention



Notes: The figure illustrates the density of months between the intervention and the response to the base salary negotiation question. To examine the timing effect, I divide individuals into two groups based on whether the time between intervention and response was less than 8 months or more. The vertical red line represents this 8-month threshold.

Table A.1: Summary Statistics: Balance in Covariates - Sample Intention Negotiation Outcomes

	Pooled		Control (C)	Statistics Treatment (T1)	Role-Model Treatment (T2)	C - T1	C - T2	T1 - T2
	Mean (1)	SD (2)	Mean (3)	Mean (4)	Mean (5)	*p*-value (6)	*p*-value (7)	*p*-value (8)
Female	0.595	0.578	0.595	0.578	0.594	0.479	0.970	0.512
Top Grade (<= 1.7)	0.575	0.494	0.582	0.566	0.575	0.507	0.773	0.717
Planned Graduation before May	0.154	0.122	0.846	0.878	0.861	0.057	0.392	0.311
Field of Study								
Languages, Humanities and Social Sciences	0.326	0.310	0.326	0.310	0.306	0.503	0.393	0.845
Economics, Business and Law	0.190	0.211	0.190	0.211	0.220	0.287	0.134	0.656
Mathematics and Natural Sciences	0.180	0.185	0.180	0.185	0.176	0.784	0.833	0.632
Engineering and IT	0.305	0.294	0.305	0.294	0.298	0.630	0.784	0.842
Age	26.684	26.867	26.684	26.867	26.584	0.207	0.490	0.049
Born in Germany	0.881	0.882	0.881	0.882	0.876	0.973	0.762	0.738
College Family Background	0.392	0.488	0.405	0.382	0.389	0.324	0.520	0.744
Having Siblings	0.850	0.357	0.844	0.852	0.855	0.636	0.535	0.877
Worked During Studying								
No	0.098	0.298	0.110	0.091	0.094	0.206	0.276	0.877
Yes, entirely	0.444	0.497	0.438	0.456	0.437	0.470	0.978	0.462
Yes, occasionally	0.457	0.498	0.452	0.452	0.469	0.995	0.491	0.489
Risk Preferences	4.714	3.356	4.770	4.717	4.650	0.720	0.529	0.660
Started Applying For a Job	0.272	0.445	0.259	0.270	0.288	0.604	0.184	0.415
Reservation Wage	2948.348	902.458	2925.647	2961.400	2959.015	0.424	0.459	0.957
Expected Monthly Wage	3541.144	951.614	3511.793	3572.843	3539.184	0.199	0.565	0.472
Perceived Share of Women Who Negotiate the Wage of Their First Job	31.507	19.437	30.963	32.178	31.357	0.233	0.703	0.424
Perceived Share of Women Who Negotiate the Wage of Their First Job	31.507	19.437	57.915	58.124	57.825	0.847	0.935	0.783
Perceived Wage Increase after Women Negotiated Their Wage	57.959	20.759	9.437	10.069	10.048	0.274	0.310	0.973
Perceived Wage Increase after Men Negotiated Their Wage	14.687	12.945	14.028	15.053	14.996	0.158	0.203	0.942
Individuals	2,492		857	844	791			

Notes: This table shows summary statistics. The sample includes final-year master students who gave an answer to negotiation intention questions in waves 1 and 2. Columns (1) to (4) document mean values for all individuals who participated in the first wave and treatments, for the control group, for the statistics treatment group and for the role-model treatment group, respectively. Columns (5) to (8) show the p-value for t-tests of the difference in means for the control and statistics treatment groups, the control and role-model treatment groups, and the statistics and role-model treatment groups. All variables are measured prior to treatment. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.2: Summary Statistics: Balance in Covariates - Sample Realized Negotiation Outcomes

	Pooled		Control (C)	Statistics Treatment (T1)	Role-Model Treatment (T2)	C - T1	C - T2	T1 - T2
	Mean (1)	SD (2)	Mean (3)	Mean (4)	Mean (5)	*p*-value (6)	*p*-value (7)	*p*-value (8)
Female	0.536	0.499	0.547	0.522	0.541	0.356	0.486	0.814
Top Grade (<= 1.7)	0.603	0.489	0.590	0.602	0.614	0.669	0.644	0.378
Planned Graduation before May	0.325	0.469	0.333	0.324	0.319	0.742	0.856	0.612
Field of Study								
Languages, Humanities and Social Sciences	0.240	0.427	0.234	0.253	0.233	0.408	0.397	0.994
Economics, Business and Law	0.229	0.420	0.237	0.228	0.221	0.709	0.772	0.511
Mathematics and Natural Sciences	0.176	0.367	0.173	0.180	0.173	0.723	0.733	0.985
Engineering and IT	0.356	0.479	0.357	0.338	0.372	0.485	0.199	0.572
Age	26.852	2.667	26.731	26.998	26.821	0.087	0.257	0.243
Born in Germany	0.908	0.290	0.907	0.915	0.901	0.620	0.362	0.688
College Family Background	0.396	0.489	0.400	0.395	0.393	0.852	0.945	0.800
Having Siblings	0.855	0.353	0.845	0.849	0.869	0.819	0.306	0.215
University Type								
University	0.689	0.463	0.686	0.705	0.676	0.469	0.257	0.695
University of Applied Sciences	0.288	0.453	0.291	0.270	0.304	0.390	0.164	0.610
Worked During Studying								
No	0.059	0.235	0.059	0.061	0.056	0.886	0.675	0.789
Yes, Entirely	0.533	0.499	0.544	0.525	0.530	0.484	0.840	0.618
Yes, Occasionally	0.381	0.486	0.371	0.383	0.389	0.661	0.835	0.522
Risk Preferences	4.688	2.963	4.696	4.766	4.602	0.706	0.366	0.410
Started Applying For a Job	0.534	0.499	0.534	0.529	0.539	0.848	0.712	0.864
Reservation Wage	3163.512	857.494	3162.453	3160.785	3167.242	0.973	0.890	0.921
Expected Monthly Wage	3736.118	911.871	3711.889	3759.982	3734.923	0.360	0.610	0.653
Perceived Share of Women Who Negotiate the Wage of Their First Job	34.946	21.465	35.223	35.012	34.608	0.868	0.745	0.632
Perceived Share of Men Who Negotiate the Wage of Their First Job	60.371	20.823	60.943	60.209	59.993	0.547	0.859	0.439
Perceived Wage Increase after Women Negotiated Their Wage	9.245	10.061	9.649	9.110	8.985	0.394	0.841	0.326
Perceived Wage Increase after Men Negotiated Their Wage	13.930	13.406	14.277	13.622	13.914	0.431	0.729	0.687
Individuals	1,958		625	671	664			

Notes: This table shows summary statistics. The sample includes final-year master students who gave an answer to realized negotiation questions in wave 2 or 3. Columns (1) to (4) document mean values for all individuals who participated in the first wave and treatments, for the control group, for the statistics treatment group and for the role-model treatment group, respectively. Columns (5) to (8) show the p-value for t-tests of the difference in means for the control and statistics treatment groups, the control and role-model treatment groups, and the statistics and role-model treatment groups. All variables are measured prior to treatment. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.3: Summary Statistics: Gender Differences

	Female (1)	Male (2)	Diff. (Female-Male) (3)	s.e. (4)
Top Grade (<= 1.7)	0.602	0.493	0.109***	0.013
Planned Graduation before May	0.238	0.248	-0.010	0.011
Field of Study				
Languages, Humanities and Social Sciences	0.395	0.136	0.259***	0.011
Economics, Business and Law	0.234	0.213	0.022**	0.011
Mathematics and Natural Sciences	0.173	0.144	0.030***	0.009
Engineering and IT	0.197	0.508	-0.311***	0.012
Age	26.875	27.256	-0.380***	0.083
Born in Germany	0.873	0.807	0.066***	0.009
College Family Background	0.378	0.388	-0.010	0.013
Having Siblings	0.838	0.837	0.001	0.010
University Type				
University	0.706	0.645	0.060***	0.012
University of Applied Sciences	0.265	0.331	-0.065***	0.012
Worked During Studying				
No	0.069	0.101	-0.033***	0.007
Yes, Entirely	0.529	0.436	0.093***	0.013
Yes, Occasionally	0.366	0.443	-0.077***	0.013
General Risk Attitude	4.505	5.404	-0.899***	0.088
Started Applying for a Job During the Survey	0.431	0.450	-0.018	0.013
Reservation Wage	2835.501	3358.775	-523.275***	22.595
Expected Monthly Wage	3386.980	3972.491	-585.511***	23.724
Individuals	3,338	2,705		

Notes: This table shows summary statistics of female and male participants. The sample includes final-year master students who participated in the main survey (wave 1). Column (1) and (2) document mean values for females and males, respectively. Column (3) shows the difference in means by gender. Column (4) shows the p-value for t-tests of the difference in means for females and males. All variables are measured prior to treatment. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.4: The Treatment Effects by Baseline Intentions

	Base Salary				Other Monetary Aspects				Other Non-Monetary Aspects			
	Not Intent in Baseline		Intent in Baseline		Not Intent in Baseline		Intent in Baseline		Not Intent in Baseline		Intent in Baseline	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Statistics Treatment	0.089***	0.047	0.054	0.039	0.047*	0.058	0.051	0.053	-0.000	-0.006	0.085*	0.008
	(0.032)	(0.045)	(0.055)	(0.045)	(0.028)	(0.037)	(0.088)	(0.077)	(0.038)	(0.049)	(0.044)	(0.050)
Role-Model Treatment	0.091***	0.132***	0.052	0.060	0.056**	0.059	0.150*	0.096	0.061	0.013	0.042	0.042
	(0.033)	(0.048)	(0.054)	(0.047)	(0.028)	(0.037)	(0.085)	(0.075)	(0.040)	(0.049)	(0.046)	(0.051)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.178	0.250	0.712	0.786	0.175	0.178	0.629	0.671	0.276	0.294	0.687	0.745
Individuals	1,034	612	434	412	1,227	793	241	231	837	573	631	451

Notes: The table reports the treatment effects on the negotiation intention outcomes by baseline intentions (reported in wave 1) 2-4 months after the intervention. The outcome variables are binary and equal to 1 if respondents intend to negotiate for base salary (Columns (1) and (4)), for other monetary aspects (Columns (5) and (8)), and other non-monetary aspects (Columns (9) and (12)), and equal to 0 otherwise. For explanations of the variables of interest and controls, refer to Table 2.3. *Mean of Control Group* is the respective mean outcome in the control group at follow-up 1. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.5: The Effects of Training Treatment on Negotiation Intention

	First Stage		2SLS					
	Impact of Receiving an Invitation on Attending the Training Treatment		Impact of Training Treatment on Negotiation Intention					
			for Base Salary		for Other Monetary Aspects		for Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Negotiation Training Participation			0.093	0.202	-0.051	0.241*	0.076	0.305**
			(0.014)	(0.014)	(0.031)	(0.031)	(0.145)	(0.145)
Invitation Receipt	0.179***	0.217***						
	(0.014)	(0.018)						
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	1,468	1,024	1,468	1,024	1,468	1,024	1,468	1,024

Notes: The table reports the effects of the training treatment on negotiation intention outcomes 2-4 months after the intervention. Columns (1) to (2) report the first stage results for females and males, respectively. The Local Average Treatment Effect (LATE) results are reported in Columns (3) to (8). The outcome variables for the 2SLS are binary and equal to 1 if respondents intend to negotiate for base salary (Columns (3) and (4)), for other monetary aspects (Columns (5) and (6)), or other non-monetary aspects (Columns (7) and (8)), and equal to 0 otherwise. The training treatment is represented by dummy variables that take the value 1 if the respondent received the corresponding treatment and 0 for those in the control group. The sample includes individuals who participated in Wave 1 and Follow-up 1 (Wave 2) and who responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in Wave 1 and Follow-up 1. See Table 2.3 for an explanation of the controls. Robust standard errors are in parentheses. ***, ** and * indicate significance at the 1, 5 and 10% levels.

Table A.6: Heterogeneity in the Treatment Effects on Negotiation Intention by Field of Study, Top Grade and Risk Preferences

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Field of Study						
Non-STEM	0.398***	0.522***	0.283***	0.305***	0.404***	0.588***
	(0.089)	(0.119)	(0.083)	(0.115)	(0.091)	(0.121)
Statistics x Non-STEM	0.048	-0.055	0.057	0.022	0.060	-0.041
	(0.039)	(0.064)	(0.036)	(0.062)	(0.040)	(0.065)
Role-Model x Non-STEM	0.103***	0.088	0.087**	0.027	0.020	0.001
	(0.040)	(0.065)	(0.037)	(0.062)	(0.041)	(0.066)
STEM	0.364***	0.504***	0.271***	0.218**	0.380***	0.512***
	(0.090)	(0.115)	(0.084)	(0.111)	(0.092)	(0.117)
Statistics x STEM	0.133***	0.066	0.036	0.062	-0.000	0.032
	(0.052)	(0.047)	(0.048)	(0.045)	(0.053)	(0.047)
Role-Model x STEM	0.079	0.092*	0.080*	0.074	0.111**	-0.001
	(0.051)	(0.048)	(0.048)	(0.046)	(0.053)	(0.049)
Panel B: By Top Grade						
Lower Grade	0.337***	0.433***	0.251***	0.299***	0.437***	0.624***
	(0.089)	(0.065)	(0.044)	(0.062)	(0.049)	(0.065)
Statistics x Lower Grade	0.098***	0.032	0.039	0.053	0.055	0.010
	(0.036)	(0.042)	(0.033)	(0.040)	(0.037)	(0.042)
Role-Model x Lower Grade	0.090**	0.087**	0.087***	0.068*	0.068*	0.006
	(0.036)	(0.042)	(0.033)	(0.041)	(0.037)	(0.043)
Top Grade	0.334***	0.388***	0.265***	0.311***	0.490***	0.637***
	(0.098)	(0.084)	(0.055)	(0.080)	(0.061)	(0.085)
Statistics x Top Grade	0.017	-0.026	0.061	0.038	0.010	-0.031
	(0.064)	(0.090)	(0.060)	(0.086)	(0.066)	(0.091)
Role-Model x Top Grade	0.098	0.072	0.044	-0.015	-0.036	-0.064
	(0.064)	(0.097)	(0.060)	(0.093)	(0.066)	(0.098)
Panel C: Risk Preferences						
Below Median	0.274***	0.345***	0.172**	0.102	0.341***	0.543***
	(0.094)	(0.120)	(0.087)	(0.116)	(0.097)	(0.124)
Statistics x Below Median	0.081*	0.001	0.077*	0.103*	0.027	-0.014
	(0.048)	(0.056)	(0.045)	(0.054)	(0.049)	(0.058)
Role-Model x Below Median	0.072	0.183***	0.126***	0.132**	0.057	0.054
	(0.048)	(0.056)	(0.045)	(0.054)	(0.050)	(0.058)
Above Median	0.394***	0.569***	0.290***	0.343***	0.397***	0.681***
	(0.090)	(0.119)	(0.084)	(0.114)	(0.093)	(0.122)
Statistics x Above Median	0.065	0.032	0.023	0.001	0.039	0.012
	(0.041)	(0.049)	(0.038)	(0.047)	(0.042)	(0.050)
Role-Model x Above Median	0.099**	0.028	0.049	0.014	0.043	-0.042
	(0.041)	(0.051)	(0.038)	(0.050)	(0.042)	(0.053)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of the treatments on the negotiation intention outcomes 2-4 months after the intervention, based on the estimation of Equation 2.1. For explanations of the outcome variables, the sample, the variables of interest, and the controls, see Table 2.3.

Table A.7: The Role of Belief in Treatment Effect

	Perceived Gender Gap in Negotiation				Perceived Wage Increases as a Result of Negotiation			
	Gender Gap in Belief		Negotiation Intention		Gender Gap in Belief		Negotiation Intention	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Statistics Treatment	3.538***	5.663***	0.106***	0.086	-0.556	-0.232	0.095**	0.001
	(1.026)	(2.137)	(0.035)	(0.075)	(0.554)	(0.748)	(0.040)	(0.048)
Role-Model Treatment					0.525	-0.246	0.088**	0.134***
					(0.553)	(0.777)	(0.040)	(0.050)
Error	0.457***	0.401***	0.002	0.003*				
	(0.036)	(0.051)	(0.001)	(0.002)				
Statistics x Error	-0.184***	-0.090	0.002	0.003				
	(0.051)	(0.076)	(0.002)	(0.003)				
Error-Female					0.283***		0.004	
					(0.046)		(0.003)	
Statistics x Error-Female					-0.009		0.000	
					(0.062)		(0.004)	
Role-Model x Error-Female					0.064		-0.002	
					(0.063)		(0.005)	
Error-Male						0.316***		0.001
						(0.044)		(0.003)
Statistics x Error-Male						-0.071		0.001
						(0.063)		(0.004)
Role-Model x Error-Male						-0.016		-0.002
						(0.060)		(0.004)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	29.174	17.210	0.329	0.478	9.135	11.413	0.329	0.478
Individuals	927	558	927	558	995	734	995	734

Notes: This table reports the treatment effects on the perceived gender gap, based on the estimation of Equation 2.2 and on the perceived wage increase based on the estimation of Equation 2.3. The statistics treatment is represented by a dummy variable equal to 1 if respondents received the statistics treatment and 0 for those in the control group. The sample includes individuals who participated in wave 1 and follow-up 1 (wave 2) and responded to the negotiation intention questions for all outcomes (base salary, other monetary aspects, non-monetary aspects) in wave 1 and follow-up 1. For explanations of the controls, refer to Table 2.3. *Mean of Control Group* is the respective mean outcome in the control group at follow-up 1. Robust standard errors in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.8: The Treatment Effects on Realized Negotiation Behavior: Excluding Inconsistent Answers Across Waves

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Statistics Treatment	-0.022	-0.005	0.033	-0.027	-0.050	-0.040
	(0.040)	(0.043)	(0.029)	(0.035)	(0.032)	(0.033)
Role-Model Treatment	-0.023	0.021	0.005	-0.025	-0.022	0.005
	(0.039)	(0.044)	(0.027)	(0.036)	(0.032)	(0.034)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.406	0.465	0.132	0.200	0.228	0.181
Individuals	928	799	928	799	928	799

Notes: This table shows the treatment effects on realized negotiation outcomes, excluding individual answers this question in both waves (wave 2 and wave 3), and who give different answers. For explanations of the outcome variables and the sample, see Table 2.5. For explanations of the variables of interest and the controls, refer to Table 2.3.

Table A.9: The Treatment Effects on Realized Negotiation by Field of Study, Top Grade and Risk Preferences

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Field of Study						
Non-STEM	0.653***	0.596***	0.273***	0.296**	0.389***	0.278**
	(0.107)	(0.143)	(0.082)	(0.117)	(0.089)	(0.112)
Statistics x Non-STEM	-0.079	0.053	0.005	-0.019	-0.035	-0.048
	(0.049)	(0.069)	(0.037)	(0.056)	(0.041)	(0.054)
Role-Model x Non-STEM	-0.023	-0.046	0.010	-0.017	0.015	0.068
	(0.049)	(0.072)	(0.038)	(0.059)	(0.041)	(0.057)
STEM	0.538***	0.622***	0.236***	0.276**	0.347***	0.231**
	(0.108)	(0.136)	(0.083)	(0.111)	(0.090)	(0.107)
Statistics x STEM	0.094	-0.038	0.063	-0.005	-0.026	0.019
	(0.058)	(0.050)	(0.045)	(0.041)	(0.048)	(0.040)
Role-Model x STEM	0.022	0.028	0.067	-0.025	-0.013	0.018
	(0.057)	(0.050)	(0.044)	(0.041)	(0.047)	(0.039)
Panel B: By Top Grade						
Low Grade	0.598***	0.519***	0.224***	0.278**	0.420***	0.301***
	(0.106)	(0.142)	(0.081)	(0.117)	(0.089)	(0.113)
Statistics x Low Grade	-0.012	0.022	0.032	0.002	-0.041	0.010
	(0.043)	(0.045)	(0.033)	(0.037)	(0.036)	(0.036)
Role-Model x Low Grade	-0.014	0.053	0.051	0.009	-0.005	0.038
	(0.042)	(0.046)	(0.033)	(0.038)	(0.035)	(0.036)
High Grade	0.574***	0.565***	0.261***	0.294**	0.424***	0.280**
	(0.120)	(0.153)	(0.092)	(0.126)	(0.100)	(0.122)
Statistics x High Grade	0.013	-0.073	0.020	-0.046	0.006	-0.062
	(0.077)	(0.087)	(0.059)	(0.072)	(0.065)	(0.069)
Role-Model x High Grade	0.012	-0.167*	-0.022	-0.166**	0.031	-0.004
	(0.075)	(0.093)	(0.057)	(0.077)	(0.062)	(0.074)
Panel C: By Risk Preferences						
Below Median	0.544***	0.567***	0.267**	0.183**	0.247**	0.344***
	(0.146)	(0.112)	(0.120)	(0.085)	(0.116)	(0.093)
Statistics x Below Median	-0.049	0.020	0.029	0.046	0.044	0.040
	(0.060)	(0.056)	(0.050)	(0.043)	(0.048)	(0.047)
Role-Model x Below Median	-0.014	-0.020	-0.043	0.039	0.065	0.075
	(0.061)	(0.056)	(0.050)	(0.043)	(0.048)	(0.046)
Above Median	0.577***	0.607***	0.330***	0.249***	0.331***	0.459***
	(0.142)	(0.107)	(0.117)	(0.082)	(0.113)	(0.089)
Statistics x Above Median	0.043	-0.026	-0.040	0.018	-0.044	-0.085**
	(0.054)	(0.050)	(0.044)	(0.038)	(0.043)	(0.042)
Role-Model x Above Median	0.036	0.003	-0.000	0.028	0.008	-0.051
	(0.055)	(0.049)	(0.045)	(0.038)	(0.044)	(0.041)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the treatment effects on realized negotiation outcomes, based on the estimation of Equation 2.1. For explanations of the outcome variables and the sample, see Table 2.5. For explanations of the variables of interest and the controls, refer to Table 2.3.

Table A.10: Reasons for Not Negotiating: A Comparison of Female and Male

	Female (1)	Male (2)	Female-Male (3)
Base Salary Was Fixed	0.668	0.531	0.136***
Salary Did Not Matter	0.049	0.074	-0.026
Fear of Not Getting the Job	0.204	0.130	0.074**
Fear of Having Proposal Rejected	0.092	0.051	0.041
Unsure What Amount to Propose	0.194	0.098	0.097***
Unsure How to Negotiate	0.194	0.116	0.078**
Thought the Salary Was Fixed	0.049	0.033	0.016
Salary Was Not Discussed	0.286	0.256	0.031
Would Not Want to Be Perceived as Too Aggressive	0.058	0.047	0.012
Already Negotiated Other Aspects	0.029	0.056	-0.027
Concern about Negative Relationship with Employer	0.092	0.056	0.036
Salary Offer Was Reasonable	0.388	0.488	-0.100**
I Don't Know	0.005	0.037	-0.032**
Other Reason	0.228	0.233	-0.004
Individuals	352	238	

Notes: This table shows reasons for not negotiating by gender by pooling the control and treatment groups, which presented in Table 2.6. Specifically, the question "What were the main reasons for not negotiating the base salary of your first regular job after your master's degree?" was asked only of participants who reported not negotiating the salary of their first job. Column (1) shows the response of females, Columns (2) show the response of males, and Column (3) compares the response of the control and treatment groups. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.11: The Treatment Effect by the Waves in Which Questions Were Answered

	Base Salary				Other Monetary Aspects				Other Non-Monetary Aspects			
	2. Wave		3. Wave		2. Wave		3. Wave		2. Wave		3. Wave	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Statistics Treatment	0.037	0.038	-0.039	-0.012	-0.005	0.051	0.013	-0.025	0.003	0.009	-0.063**	0.030
	(0.027)	(0.035)	(0.030)	(0.036)	(0.038)	(0.045)	(0.024)	(0.032)	(0.044)	(0.041)	(0.029)	(0.032)
Role-Model Treatment	0.060**	0.052	-0.047	-0.022	0.086**	-0.009	-0.008	-0.029	0.060**	0.052	-0.036	0.007
	(0.028)	(0.035)	(0.030)	(0.037)	(0.039)	(0.042)	(0.024)	(0.033)	(0.044)	(0.042)	(0.029)	(0.032)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.198	0.273	0.319	0.388	0.148	0.182	0.120	0.182	0.245	0.155	0.223	0.161
Individuals	1306	1025	1379	1057	568	536	1146	889	566	535	1146	888

Notes: This table reports treatment effects by two groups: those who answered the negotiation questions during Wave 2 (2-4 months after the intervention) and those who answered during Wave 3 (6-8 months after the planned graduation date). See Table 2.5 for explanations of the outcome variables and the sample. For explanations of the variables of interest and controls, refer to Table 2.3. *Mean of control group* is the respective mean outcome in the control group at Follow-up 1 (Wave 2). Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.12: The Treatment Effect by the Months After the Intervention

	Base Salary			
	Months After the Intervention			
	Less than 8 Months		Longer than 8 Months	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Statistics Treatment	0.036	0.038	-0.053	-0.039
	(0.028)	(0.035)	(0.044)	(0.056)
Role-Model Treatment	0.059**	0.054	-0.046	-0.034
	(0.028)	(0.035)	(0.044)	(0.060)
Strata FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of Control Group	0.148	0.182	0.120	0.182
Individuals	1,305	1,027	644	486

Note: This table reports treatment effects by two groups: those who answered the negotiation questions within less than 8 months after the intervention, and those who answered more than 8 months after the intervention. See Table 2.5 for explanations of the outcome variables and the sample. For explanations of the variables of interest and controls, refer to Table 2.3. *Mean of Control Group* is the respective mean outcome in the control group at follow-up 1. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels.

Table A.13: The Treatment Effects on Negotiation During the Search for the First Job

	Base Salary	
	Female	Male
	(1)	(2)
Statistics Treatment	-0.035	-0.019
	(0.038)	(0.040)
Role-Model Treatment	-0.021	-0.012
	(0.037)	(0.041)
Strata FE	Yes	Yes
Controls	Yes	Yes
Mean of Control Group	0.470	0.547
Individuals	1,051	909

Note: This table shows the treatment effects on the realized negotiation for a base salary during the job search period for the first job. For explanations of the sample, see Table 2.5. For explanations of the variables of interest and the controls, refer to Table 2.3.

Table A.14: The Treatment Effects on Realized Negotiation Behavior: Alternative Sample

	Base Salary		Other Monetary Aspects		Other Non-Monetary Aspects	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Statistics Treatment	0.003	0.016	0.028	-0.009	-0.031	-0.006
	(0.023)	(0.029)	(0.028)	(0.034)	(0.031)	(0.031)
Role-Model Treatment	0.022	0.032	0.033	-0.021	0.004	0.032
	(0.024)	(0.030)	(0.027)	(0.033)	(0.031)	(0.033)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Control Group	0.240	0.308	0.147	0.192	0.236	0.176
Individuals	1,949	1,513	1,053	911	1,051	909

Note: This table shows treatment effects on realized negotiation outcomes, not excluding those with missing data on other monetary and non-monetary aspects. See Table 2.5 for explanations of the outcome variables. For explanations of the variables of interest and controls, refer to Table 2.3.

Appendix B: Chapter 3

B.1 Data and Additional Descriptive Statistics

This section describes all the data preparation steps taken 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, to eliminate errors in daily wages for full-time employees, we follow the literature and exclude daily wages less than 10 euros 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 few censored wages in our restricted sample; censored wages account for only 1.3% for the first job and approximately 4.7% a year after the first job, with a small increase in subsequent years after graduation.

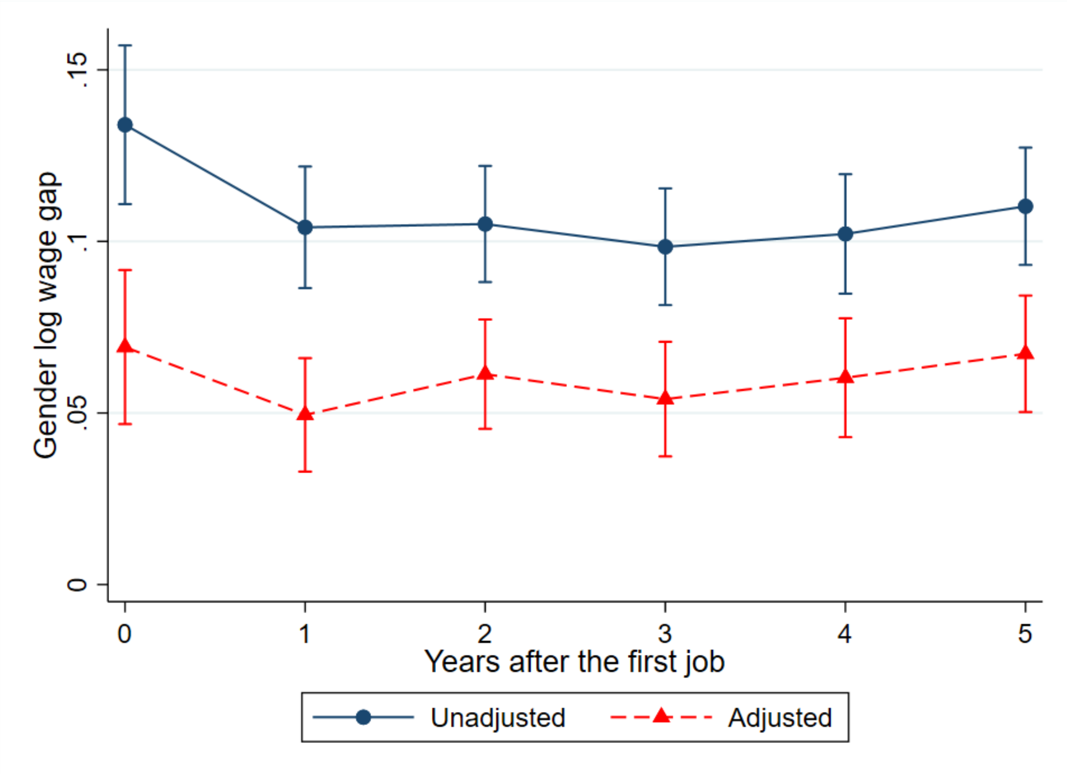
Moreover, working hours are not recorded in the IEB dataset, as only information about whether a person works full-time or part-time (working more or less than 30 hours per week) is available. For this reason, we focus only on graduates who have a full-time job in their first job after graduation. An 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 the next missing spells if the place of residence and work, industry code and establishment ID did not change. Following this procedure, the number of missing values in the occupation code decreases significantly for 2011.

Finally, 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 childbirth.

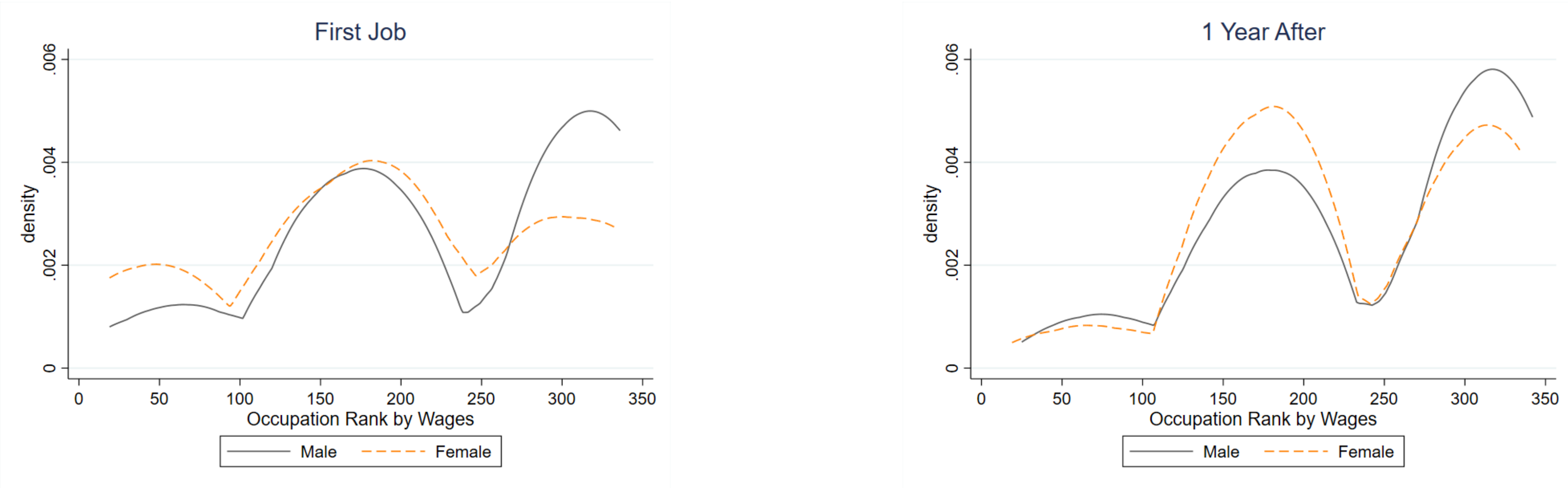
B.2 Additional Figures

Figure B.1: Unbalanced Sample: Dynamics of the Gender Wage Gap Over Years After Labor Market Entry



Note: The sample size is 3,409 (2,262 male, 1,147 female). The sample consists of graduates who work in a full-time job as their first job after graduation. The dependent variable is the 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 as controls. The personal characteristics include age and having German citizenship. The pre-graduation characteristics include duration of study, place of high school final exam and working during study. All estimations include the beginning month of the first job as a control. Additionally, we control for having a child between the years.

Figure B.2: Distribution of Occupations for Female and Male Job Changers



Note: The figure shows the distribution of male and female job changers across occupations. The sample size is 312 and includes only firm and occupation changers (Column 5, Table 3.4). The plot on the left shows the distribution before the job change (at the first job), and the plot on the right shows that 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, which represents a 2% sample of the entire IEB dataset.

B.3 Additional Tables

Table B.1: Descriptive Statistics – Sample Comparison to Population

	Estimation Sample	Population
Share of Females[1]	0.498	0.457
Economics and Business	0.415	0.484
Mathematics and Natural Sciences	0.182	0.353
Humanities and Social Sciences	0.761	0.713
Medical Studies	0.518	0.581
Final High-school GPA[2]	2.20	2.15
Economics and Business	2.36	2.45
Mathematics and Natural Sciences	2.17	1.99
Humanities and Social Sciences	2.31	2.27
Medical Studies	1.81	1.88
University GPA[3]	2.04	2.02
Graduation Age[1]	27.37	27.80
Share of Non-German Graduates[3]	0.217	0.110

Note: This table presents summary statistics on the characteristics of graduates before and after graduation and compares them with official register data and representative survey data from other studies. Our estimation sample consists of graduates with a master's degree or equivalent working full-time in their first job after graduation.
1. The reference year for both sets of data is 2010. Source: Federal Statistical Office, 2011.
2. The reference year is WS 2006/2007 according to the survey data from Simeaner et al. (2014) and 2007 in our sample.
3. The years are pooled for 1993-2009 in the survey data from Francesconi and Parey (2018) and pooled for 1995-2010 in our data.

Table B.2: 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 B.3: 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
Explained by:				
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: This table shows the Oaxaca-Blinder decomposition results. 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 twofold decomposition. Fortin et al. (2011) provide detailed information on the methodology, and Jann et al. (2008) provide a description of the STATA application.

Table B.4: Gender Wage Gap in all Types of First Jobs

Dependent Variable: Log Daily Wage								
	Personal and Pre-Graduation Characteristics						Additional Post-Graduation Characteristics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.271***	-0.201***	-0.212***	-0.109***	-0.101***	-0.097***	-0.045***	-0.045***
	(0.018)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
Graduation year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full-time employment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of study FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Final university grade	No	No	No	Yes	Yes	Yes	Yes	Yes
Pre-graduation characteristics	No	No	No	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	No	Yes	Yes	Yes
Post-graduation characteristics	No	No	No	No	No	Yes	No	Yes
R-squared	0.050	0.417	0.424	0.493	0.498	0.501	0.630	0.652
Individuals	10,149	10,149	10,149	10,149	10,149	10,149	10,149	10,149

Note: This table shows the gender wage gap at labor market entry based on the OLS model specified in equation 3.1. The sample consists of all individuals who work in any kind of job after the graduation. The dependent variable is the log gross daily wage at the first job. The control variables are added gradually. Column (1) shows the results with only the graduation year as a control. Column (2) adds a full-time indicator. Column (3) adds personal characteristics such as age and (not) having German citizenship and Column (4) adds field of study (17 categories). Column (5) adds the final university grades, and Column (6) adds pre-graduation characteristics, i.e., duration of study, location of the final high-school examination, a dummy for apprenticeship and a dummy for working while studying. Column (7) adds 3-digit occupation fixed effects. Column (8) shows the results after adding post-graduation characteristics, i.e., job search time, job location, 1-digit industry fixed effects, firm size (7 categories), the share of women in firms (3 categories), and the beginning month of the first job. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10% levels.

Table B.5: Descriptive Statistics - Stayers and Firm and Occupation Changers

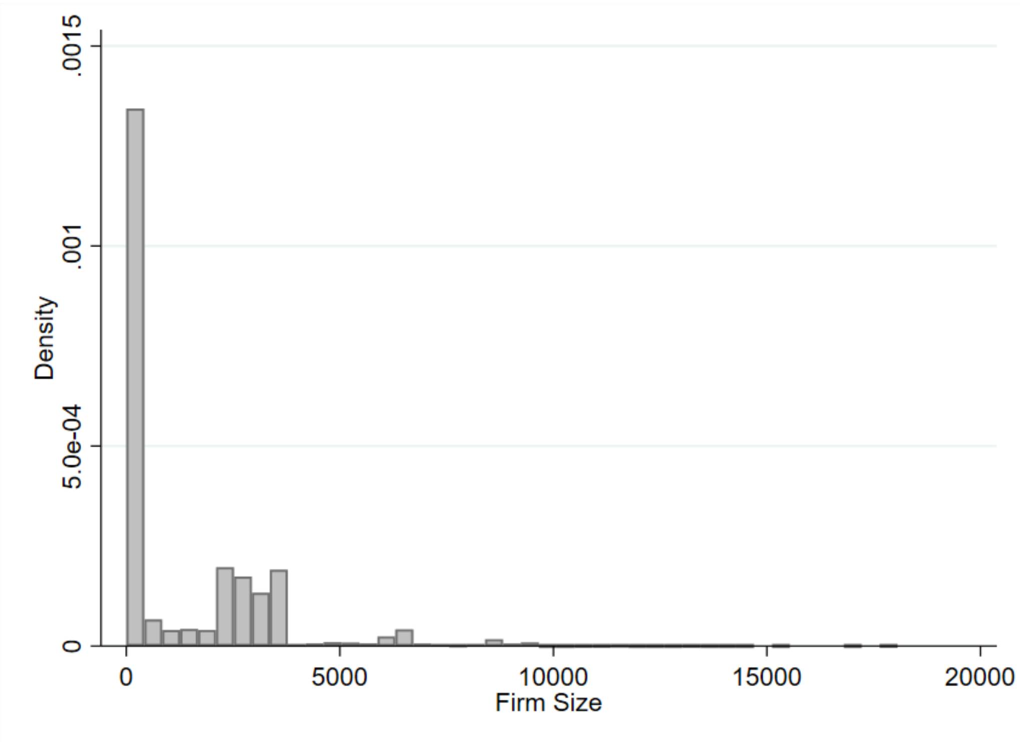
	Stayers			Firm and Occupation Changers		
	Male	Female	Male-Female	Male	Female	Male-Female
Panel A: Economics, Business, Humanities and Social Sciences						
Age at the First Job	27.467	26.674	0.793***	27.899	26.990	0.908***
non-German	0.014	0.038	-0.024***	0.017	0.015	0.003
Duration of Study	5.527	5.463	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	
Panel B: Mathematics, Natural Sciences and Medical Studies						
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	

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

Appendix C: Chapter 4

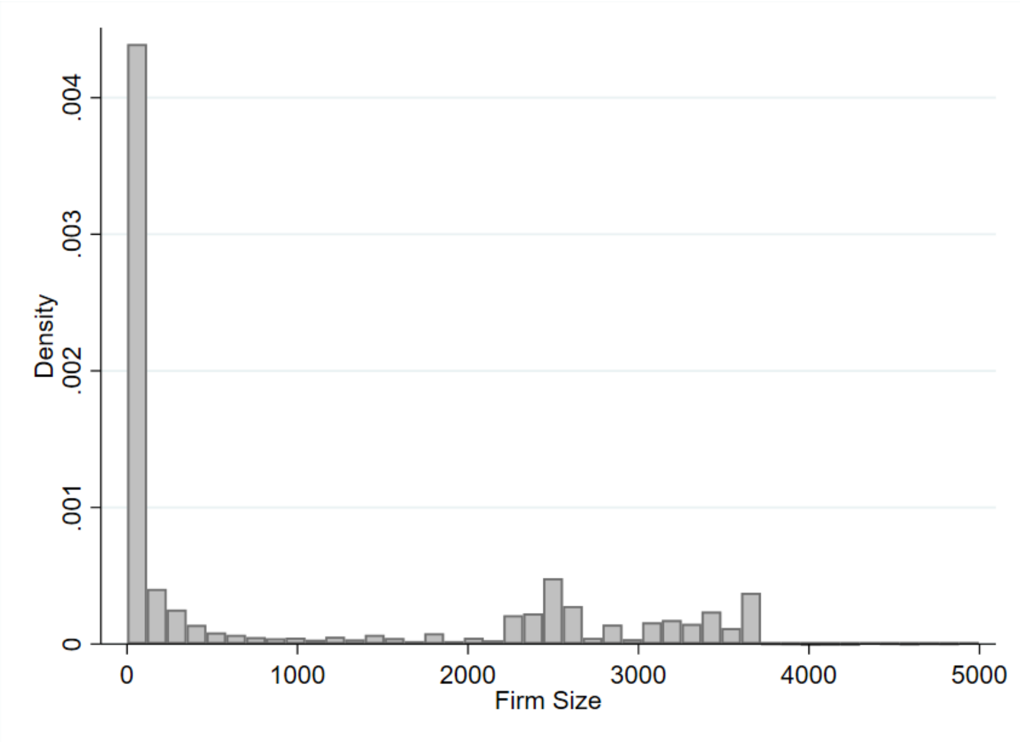
C.1 Additional Figures and Table

Figure C.1: Establishment Size of Student Jobs



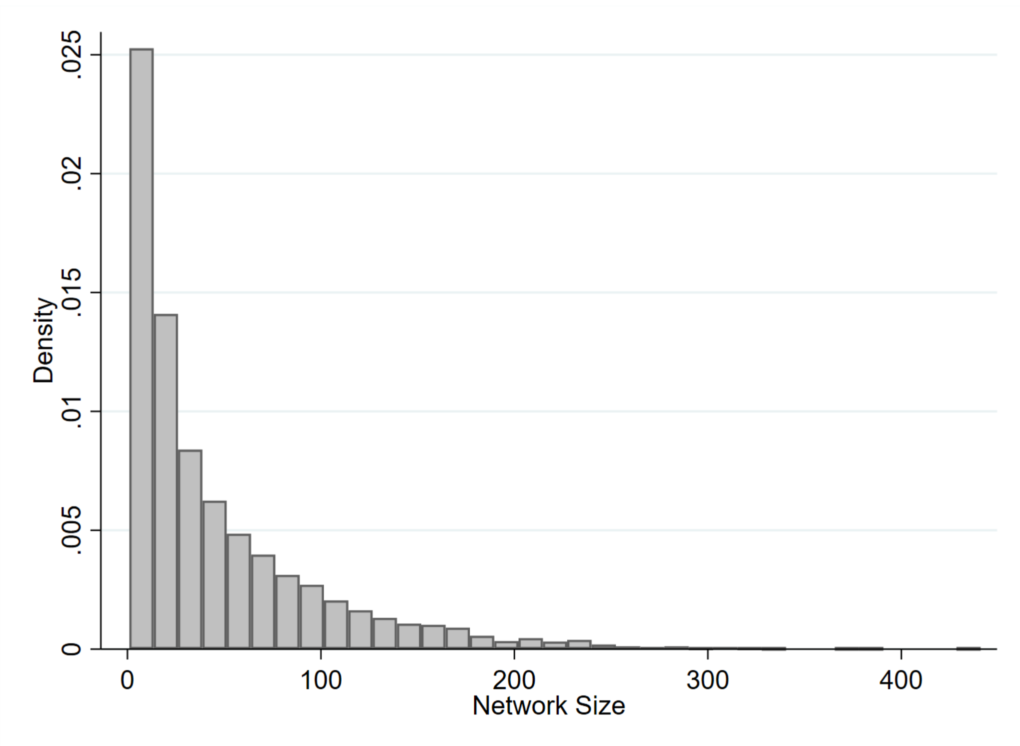
Notes: This figure shows the distribution of establishment size of student jobs. Student jobs longer than three months and with a network size of 250 or more coworkers are excluded.

Figure C.2: Establishment Size of Student Jobs - Less than 5000 Employees



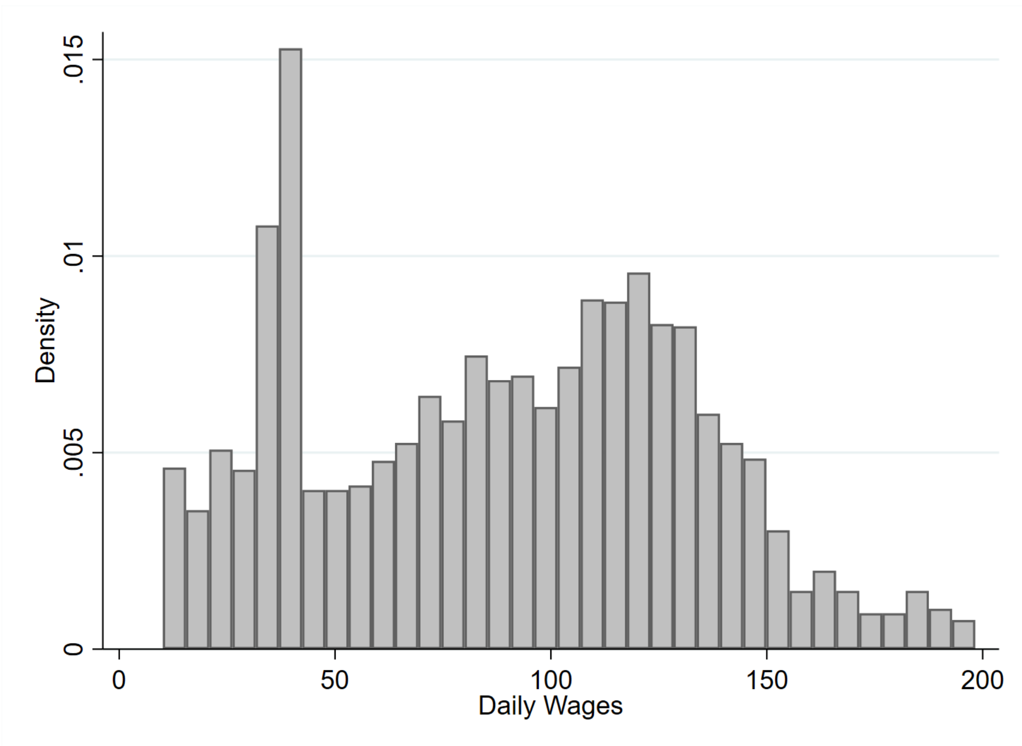
Notes: This figure shows the distribution of establishment size of student jobs with less than 5000 employees. Student jobs longer than three months and with a network size of 250 or more coworkers are excluded.

Figure C.3: Distribution of Network Size per Student



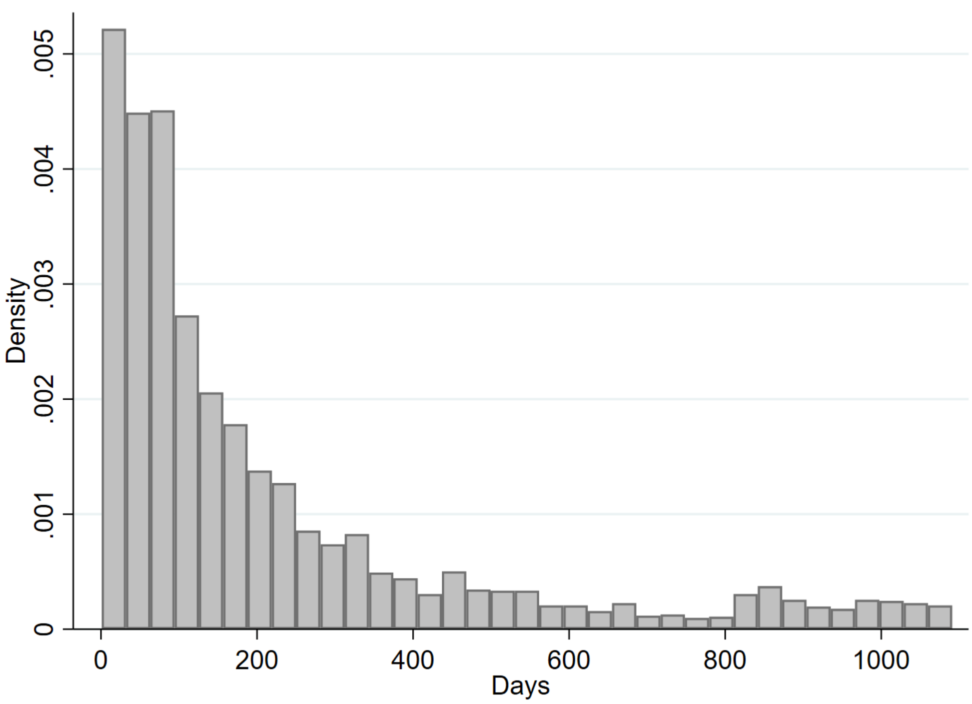
Notes: This figure shows the distribution of network size for each student. Network size measures the number of coworkers a student has over 5 years prior to graduation. Student jobs longer than three months and with a network size of 250 or more coworkers are excluded. The reason for having a network size greater than 250 is that students can work in several student jobs during their study.

Figure C.4: Daily Wage at the First Full-Time Job After Graduation



Notes: This figure shows the distribution of daily wages of graduates in their first full-time job. We compute the deflated daily wage of the graduate using the Consumer Price Index from the Federal Statistical Office.

Figure C.5: Days to Find the First Full-Time Job After Graduation



Notes: This figure shows the distribution of time (in days) between graduation and the first full-time job.

Table C.1: Network Characteristics in Other Occupations

	Mean	SD
Student Jobs Network Characteristics - Other Occupations		
Log Average Coworker Wage	4.12	0.61
Log Network Size	3.24	1.28
Employment Rate of Coworkers	0.65	0.20
Share of Female Coworkers	0.58	0.27
Share of Non-German Coworkers	0.09	0.15
Mean Age of Coworkers	38.48	6.84
Share of Middle Educated Coworkers	0.26	0.27
Share of Highly Educated Coworkers	0.09	0.16
Individuals	3,261	

Notes: This table reports the means and standard deviations of the network characteristics of less close coworkers. Less close coworkers work in the same establishment but in another occupation as college students in their student jobs. Network coworkers characteristics are measured at the time of graduation.

Table C.2: Effects of Student Job Coworker Networks - Robustness to Different Network Definitions

	Log (Daily) Wage at the First Job		
	Main Sample	Different Network Definitions	
	3 digits Occupation	2 digits Occupation	Network Size Max 100
	(1)	(2)	(3)
Log avg. coworker wage – Same occupation	0.076***	0.070***	0.075***
	(0.022)	(0.023)	(0.023)
Log avg. coworker wage – Other occupation	0.030	0.039*	0.030
	(0.024)	(0.022)	(0.025)
Adjusted R-squared	0.248	0.246	0.258
Individuals	3,261	3,311	2,699

Notes: The table shows OLS estimation results from the regression specified in Equation 4.1 and separately estimated by using 3-digits occupation code (Column (1)), 2-digits occupation code (Column (2)) and network size maximum 100 (Column (3)). The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. We include all variables as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table C.3: Effects of Student Job Coworker Networks - Robustness to Different Student Job Durations

	Log (Daily) Wage at the First Job	
	Main Sample Student Job Longer than 3 Months	Different Student Job Duration Student Job Shorter than 3 Months
	(1)	(2)
Log avg. coworker wage – Same occupation	0.076***	0.039
	(0.022)	(0.025)
Log avg. coworker wage – Other occupation	0.030	0.045
	(0.024)	(0.029)
Adjusted R-squared	0.248	0.241
Individuals	3,261	2,191

Notes: The table shows OLS estimation results from the regression specified in Equation 4.1. Column (1) define student jobs last longer than 3 months (our main student job definition, Column (2) defines student job last shorter than 3 months. The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. We include all variables as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.4: Wage Effects: Full-time vs. Part-time Network Members

	Log (Daily) Wage at the First Job
	(1)
Log avg. coworker wage - Full-time - Same occupation	0.119***
	(0.033)
Log avg. coworker wage - Full-time - Other occupation	0.040
	(0.043)
Log avg. coworker wage - Part-time - Same occupation	0.009
	(0.023)
Log avg. coworker wage - Part-time - Other occupation	0.026
	(0.022)
Adjusted R-squared	0.257
Individuals	2,391
Graduate characteristics	yes
Network characteristics	yes
Average AKM establishment effect	yes
Industry and occupation in student job	yes

Notes: The table shows the OLS estimation results from a regression specified similar to Equation 4.1. We further distinguish between network characteristics by full-time and part-time employment at time of graduation. Thus, e.g., we measure the share of female former coworkers in the same (and other) occupation who are either in full-time employment or part-time employment at time of graduation. The unit of observation is an individual graduate. We consider only the first full-time job after graduation as the first job. We include all other variables, besides the network characteristics, as in Table 4.2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.