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IZA DP No. 17541

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ISSN: 2365-9793

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ABSTRACT

Coworker Networks from Student Jobs: A Flying Start at Labor Market Entry?

This paper analyzes the impact of college students' coworker networks formed during student jobs on their labor market outcomes after graduation. For our analysis, we use novel data that links students' administrative university records with their pre- and post-graduation employment registry data and their coworker networks. Our empirical strategy exploits variation in the timing and duration of student jobs, controlling for a variety of individual and network characteristics, as well as firm-by-occupation fixed effects, eliminating potential selection bias arising from non-random entry into student jobs and networks. The results show that students who work alongside higher-earning coworkers during their student jobs earn higher wages in their first post-graduation employment. Two key mechanisms appear to drive this effect: (1) sorting into higher-paying firms after graduation, facilitated by coworker referrals, and (2) enhanced field-specific human capital through exposure to skilled colleagues. However, the initial wage advantage from higher-earning coworker networks diminishes over time as students with worse networks catch up. Our findings contribute to the understanding of how early career networks shape labor market outcomes and facilitate a smoother transition from higher education to graduate employment.

JEL Classification: I23, J24, J31
Keywords: coworker networks, student jobs, labor market entry, wages

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1 Introduction

Networks play an important role in accessing job opportunities and enhancing career advancement (Granovetter, 1973). 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), and former or recent coworkers in regular employment (e.g. Cingano and Rosolia, 2012; Glitz, 2017; Saygin et al., 2021; Eliason et al., 2022; Cornelissen et al., 2017).

However, evidence is lacking on the role of networks formed during student jobs in accessing job opportunities and enhancing career advancement. This gap in the literature is surprising given the potential significance of such networks for at least three reasons. First, student employment is a prevalent and growing phenomenon. In recent years, approximately 40 % of students in the United States and over 60 % in Germany work in student jobs (Irwin et al., 2022; Staneva, 2015). Second, the transition from higher education to the workforce is characterized by significant information asymmetries: employers lack reliable signals about students' abilities, while students are similarly uncertain about potential employers. Student jobs provide an early opportunity to build professional networks in a work-related environment, which may help reduce these information frictions. Thus, coworkers in these settings can provide valuable insights, guidance, and act as role models, potentially exerting a lasting influence on labor market outcomes. Third, as the transition from higher education to employment is a critical career stage with lasting implications (e.g. Oyer, 2006; Oreopoulos et al., 2012; Wachter, 2020), the networks formed during this period could have enduring benefits for a graduate's professional trajectory.

This paper examines the benefits college students gain from coworker networks formed during student jobs. Specifically, we investigate whether working alongside higher-earning coworkers in student jobs leads to higher wages in graduates' first post-graduation job. To explore this question, we leverage a unique dataset that links various administrative records of students and their coworkers in student jobs. The dataset combines students' university records, their pre- and post-graduation employment registry data, and the social security data of all individuals employed in the same firm and during the same time as the student. This linkage enables us to track both students' career trajectories and the professional networks they form through their student jobs. Within this novel dataset, we define a coworker as any individual working in the same occupation and firm as the student during the same time period.[1] By tracking both students and their coworkers over time and across multiple jobs and firms, we provide a dynamic view of the effect of students' professional networks beyond graduation.

To solve the identification challenge stemming from the non-random sorting of students into specific firms and occupations, our main specification includes firm-by-occupation fixed effects and controls for an exhaustive set of individual and network characteristics. The variation used in this empirical strategy arises exclusively from the timing and duration of a student's employment within a particular firm and occupation. Specifically, by employing firm-by-occupation fixed effects, we compare two students who worked at the same establishment and in the same occupation, but who began their student jobs at different times and had different job durations. As a result, these students interacted with different coworkers, reflecting changes in the workforce composition within the same firm-occupation cell over time.

Conditioning on firm-by-occupation fixed effects provides several benefits for our identification strategy. First, it mitigates bias from potential sorting of high-ability students into more productive firms or high-quality coworker networks, as students working in the same occupation within the same firm are likely to share similar characteristics. Second, changes in the composition of coworkers within a firm-occupation cell are plausibly exogenous to the students, making the variation in coworker quality more likely to be independent of student characteristics.

[1] In the text we use the terms establishment and firm interchangeably.

To address potential remaining selection bias, we assess the quality of the student's professional network at the time of graduation, instead of during the student job. Furthermore, we use changes in network quality between the student job and graduation as a proxy for network quality. These approaches mitigate concerns that students may intentionally choose firms or occupations with the expectation of gaining access to more advantageous coworker networks upon graduation. However, the composition of the network at graduation is determined solely by the workforce within the specific firm-occupation cell, making it exogenous to the student's earlier choice of student job. Additionally, we incorporate graduation cohort fixed effects to control for variations in labor market conditions at the time of graduation. As part of further robustness checks, we include year-by-occupation and time period-by-firm-by-occupation fixed effects to capture potential variations in labor market conditions across different occupations, even within the same firm, over time (Wachter, 2020). Finally, we conduct placebo tests by estimating the effects of coworkers who are employed in the same firm but in a different occupation than the student. Since these coworkers are less likely to have interacted closely with the student, we expect the results of these tests to show no significant effects.

Our results demonstrate that graduates benefit from their student job coworker networks by receiving significantly higher wages after graduating from college. Specifically, our estimates reveal that independent of the specification a 10 % increase in the average coworkers' wages at the time of a graduate's labor market entry is associated with approximately a 1 % higher wage for the graduate's first full-time job. The magnitude of the estimated network effects is substantial: It is more than two times larger than if the share of workers from the same minority increases within the same firm (Dustmann et al., 2016) and ten times larger than the general peer effects on wages identified by Cornelissen et al. (2017). Yet, we expect larger effect sizes in our setting because knowledge gaps and information frictions are potentially strong during labor market entry. In contrast, Dustmann et al. (2016) and Cornelissen et al. (2017) focus on already established workers, where such frictions are likely to be weaker.

The effects on entry wages are partly explained by students sorting into better-paying firms, suggesting that successful coworkers help them navigate the labor market and make more informed job choices. Additionally, we find that referrals may also play a role in shaping these outcomes, as the largest wage gains are observed among students who followed a former coworker to a new firm. In contrast, we find no significant wage effects when students remain at the same firm where they worked during their student job. Our findings are consistent with the idea that professional networks mitigate knowledge gaps and reduce information frictions in the labor market. Similarly, we observe that better networks do not affect graduate's wages if they worked in student jobs unrelated to their field of study. This finding suggests that better coworkers help the student to acquire firm- and field-specific human capital or to understand the industry-specific labor market, rather than enhancing general human capital. Confirming this channel, we find no significant relationship between better networks and students' GPA, indicating that the observed wage effects are driven by work-related skills and experience, rather than academic achievement.

In addition to the graduates' acquisition of industry-related information and the sorting into higher paying firms, we also find that graduates with stronger coworker networks from their student jobs tend to experience lower job separation rates, suggesting better job matching in the initial stages of their careers. However, while graduates with higher-paid networks enjoy a wage premium at the start of their careers, this advantage diminishes as they gain experience. Wage convergence occurs over time, with graduates from lower-paid networks catching up as they may likely acquire relevant skills for their careers. Thus, although the initial benefits of a better coworker network are significant, both in terms of entry wage and job stability, these effects tend to fade as career development factors like experience and performance take precedence.

We make four novel contributions to the literature. First, 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 a more pronounced effect 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, these previous studies present evidence that coworker quality is important for individuals who are already in the labor market. In contrast to these studies, we show that coworker networks from student jobs also have effects on individuals who are yet not attached to the labor market.

Second, we add to the broader literature on peer effects in college that exploits variation in the assignment of students to dormitories, classes, or introductory courses. In contrast to our study, this literature examines the effects of student peers, rather than coworker, 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 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.[2]

Third, we also contribute 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 channels that influence the transition

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

from college to the labor market. For example, Oreopoulos et al. (2012) show that economic situation at labor market entry is an important factor for earnings even 10 years after labor market entry. Furthermore, Hensvik et al. (2023) identified referrals as an important channel for transition from school to work. Our findings add to these findings that the network quality established during student jobs is also an important channel in the successful college to labor market transition.

Fourth, this paper contributes to the more general literature on the effect of student jobs. Although some studies show that working during university or high school studies can have positive effects on later wages (e.g. Hotz et al., 2002; Margaryan et al., 2022; 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 2 describes the data and our sample. Section 3 presents the empirical strategy and describes the large set of control variables we include to account for different endogeneity issues. Section 4 presents and discusses our results as well as possible underlying mechanisms. Finally, Section 5 concludes.

2 Data and Descriptive Statistics

The data include detailed labor market and college information for each student, social security records of their coworkers, and administrative records of the establishments in which the students worked during their studies. We describe the datasets and their linkage in the following paragraphs.

Student-level data

The core of our dataset is a newly established linkage between social security records and administrative data from a large German university. These social security records come from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) and cover the universe of employees in Germany.[3] They contain detailed daily information on employment, benefit receipt, and job search.

The university's administrative records comprise detailed information on every student who graduated from that university between 1995 and 2016. The data include information on individual characteristics (e.g., gender, year of birth) as well as on pre-college and college education (e.g., field of study, high school and college GPA, time of enrollment and graduation). These individual records of the students are linked to their social security records based on a student's name, date of birth, and gender. The linkage combines information on the students' educational trajectory as well as each student's entire labor market history, including their student and graduate employment (e.g., firm, start and end dates, occupation, employment type, wage). The linkage thereby allows to uniquely identify students in the data who worked in student jobs while attending university.

Coworker networks

Building on the identification of student jobs, we extract data on potential coworkers from the comprehensive social security records of the German workforce. Using the data linkage, we have detailed information on each student's employment spell, including the establishment, occupation code, and precise start and end dates. This allows us to identify all employees who worked at the *same establishment* during the *same time* period as the student, enabling us to pinpoint coworkers who potentially interacted with the student during their employment.

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

[3] 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, marginal part-time employment, receipt of benefits, officially registered as job-seekers with the Federal Employment Agency, or (planned) participation in active labor market policy programs.

work in the social security system after graduation and who had at least one student job while studying.[4] A student job is defined as any employment spell of the student that occurred while the student was enrolled in college (up to 5 years before graduation, see Figure 1). However, we restrict our sample to the last employment spell (and thus student job) the student had.

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. In addition, we distinguish between close coworkers, i.e., those coworkers who work in the same three-digit occupation and establishment as the student[5], and less close coworkers, i.e., all other coworkers in the same 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 after graduating from college between 2000 and 2016, 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.[6] 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 1). If the coworkers have multiple employment spells at the time of graduation of the student, we

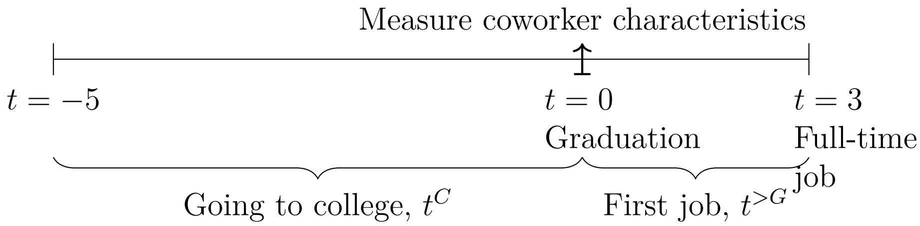
[4]This means that we exclude all students enrolled in teacher training programs, as they often become civil servants shortly after entering the labor market and thus do not work in the social security system. We also exclude bachelor's students because they may enroll in a master's program after completing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

[5]Also Cornelissen et al. (2017) define coworkers as employees working in the same three-digit occupation within the same establishment.

[6]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.

keep the spell with the longest tenure to measure these characteristics.

Figure 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 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.[7]

2.2 Descriptive statistics

The resulting sample comprises 6,243 individual graduates who had a student job besides studying and started their first full-time job within three years upon graduating from college between 2000 and 2016. Table 1 presents descriptive statistics on the graduates, their coworker networks, and their first full-time job.

53 % of the graduates are female and 2 % have a non-German citizenship. The average age at first full-time employment is 27.46 years and the average high school GPA is 2.22, with a range from 1 (best) to 4 (passed). Most graduates in our sample studied either humanities and social sciences (37 %) or economics and business (26 %). 22 % of the graduates studied a medical subject and 15 % studied mathematics and natural sciences. Table 1 also shows the top industries of their student jobs: The industries *Education* (28 %), *Human Health*

[7] 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).

and Social Work Activities (16 %) and Manufacturing (14 %) provide the majority of jobs for students followed by *Accommodation and food service activities* (10 %) and *Wholesale and Retail Trade* (8 %).

During their studies, students worked on average 2.77 different student jobs in rather small establishments with slightly above-average productivity, as indicated by the positive average AKM fixed effect of 0.04. The average coworker network can be described as predominantly female (57 %), mostly employed (69 %) and composed of German citizens (93 %), and with rather lower levels of education (59 %). Figures A.1 and A.2 in the Appendix show the right-skewed distribution of the network size of graduates with a median network size of 132 coworkers working in the same firm-occupation cell. The large network size is due to the fact that students tend to work in the same job (and thus same establishment-occupation cell) as many other people because jobs in industries like retail, food service, and customer support often have high turnover rates and are geared towards temporary, part-time or entry-level workers. This is in stark contrast to existing research on coworkers within firms (e.g. Cornelissen et al. (2017) where networks are much smaller, mostly due to the more specialized jobs more senior workers and employees do. As we will show later, the vast majority of students (83.13 %) do not start their first job upon graduation in the firm in which they worked as students. Also, our empirical identification is not sensitive to the network size as we account for the average network quality.

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.[8] 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 between graduation and the first full-time job. Figure A.4 in the Appendix shows the distribution of days to first full-time job. The distribution is right-skewed with a median of 112 days (about 3-4 months).

[8] Figure A.3 in the Appendix shows the distribution of daily wages of graduates in their first full-time job.

Table 1: Descriptive Statistics

	Mean	SD
First Job after Graduation Characteristics		
Log Daily Wage at the First Job After Graduation	3.992	0.67
Log Days to Start First Job After Graduation	4.703	1.31
Network Quality at Graduation		
Average Log Daily Wage of Close Coworkers	3.90	0.66
Graduate Characteristics		
Female	0.53	0.50
Non-German	0.02	0.13
Age at the First Job After Graduation	27.46	2.53
Final High School GPA	2.22	0.61
Number of Student Jobs	2.77	2.79
Log Average Wage in Student Jobs	2.47	0.96
Field of Study		
Economics and Business	0.26	0.44
Mathematics and Natural Sciences	0.15	0.36
Humanities and Social Sciences	0.37	0.48
Medical Studies	0.22	0.41
Student Jobs Characteristics		
Average AKM Establishment FE	0.04	0.37
Industry of Student Jobs		
Education	0.28	0.45
Human Health and Social Work Activities	0.16	0.37
Manufacturing	0.14	0.34
Accommodation and Food Service Activities	0.10	0.30
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycle	0.08	0.27
Information and communication	0.04	0.19
Occupation in Student Job		
University teachers, lecturers at higher technical schools and academies	0.18	0.38
Office Specialists	0.11	0.31
Senior government officials	0.10	0.30
Waiters, Stewards	0.08	0.27
Nursing assistants	0.07	0.26
Office Auxiliary Workers	0.05	0.22
Network Characteristics		
Network Size (Median)	132	–
Employment Rate of Coworkers	0.69	0.19

Continued on next page

Table 1 – continued from previous page

	Mean	SD
Share of Female	0.57	0.24
Share of Non-German	0.07	0.09
Mean Age of Employees	32.44	6.68
Share of Middle Educated	0.16	0.24
Share of Highly Educated	0.25	0.26
Individuals	6,243	

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 A.1. Network coworker characteristics are measured at the time of graduation. First job characteristics are based on the first full-time job after graduation.

3 Empirical Strategy

The relationship of interest is whether the network of coworkers a student builds during their student jobs affects the student's labor market outcomes after graduation. Our empirical analysis accounts for the non-random allocation of students to their student jobs and the underlying unobserved motivation for choosing one job over another by exploiting the variation in coworkers induced by the variation in timing and duration of students jobs. To make the idea clear, we compare two students who worked in the same establishment in the same occupation but worked with different coworkers because the student jobs started and/ or ended at different points in time. As a consequence, students have met different coworkers.

We estimate the following baseline wage equation:

$$
\begin{aligned}
log\, w_{i,t^G} = & \beta_1 log\, \overline{w}_{\sim i,jot^G} + \beta_2 log\, \overline{w}_{\sim o,ijt^G} + \\
& \gamma \mathbf{x'}_{i,t^G} + \delta_1 \mathbf{p'}_{\sim i,jot^G} + \delta_2 \mathbf{p'}_{\sim o,ijt^G} + \\
& \theta_{jot^C} + \eta_{t^G} + \epsilon_{i,jot^C}
\end{aligned}
\tag{1}
$$

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 wage of all former coworkers from the students' last student job, measured at the time when the student graduates. Coworkers are defined as working in the same establishment j in the same (three-digit) occupation o at exactly the same time t^C as the student. We use the coworker wages at the time of the student's graduation, i.e. $log\, \overline{w}_{\sim i,jot^G}$, as a proxy for coworker quality. We relax on that in a robustness check in which we use the coworkers' wage increases instead. The corresponding β_1 is our main coefficient of interest, determining the effect of coworker networks from student jobs on a graduate's entry wage.

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 establishment 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 establishment-occupation cell of the student job, θ_{jot^C}. The characteristics of the establishment and of the occupation of the student's job could have been observable to the student when choosing the student job. Thus, students may have chosen certain establishments or occupations in order to build a network of high quality colleagues. By including the firm-by-occupation fixed effect θ_{jot^C}, we account for self-selection into specific establishment-occupation cells.

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.[9]

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). Overall, including the set of aforementioned variables allows us to control for students' and networks' characteristics, for student sorting into specific student jobs, and also for labor market conditions at graduation. ϵ_{ijot^C} is the residual error term. We argue that the error term is uncorrelated with both our dependent variable and all covariates. In two robustness checks we also use occupation-by-year fixed effects and firm-by-occupation-by-time period fixed effects to account for occupation-specific cohort effects, even within firms. The results, as will be shown in the next section, are robust to these additional additional adjustments to the empirical strategy.

There are two remaining threats to identification that could introduce bias into the re-

[9]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 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 same 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.

sults. First, workers may choose a particular establishment and occupation after a student has joined the workplace, which could give rise to the reflection problem discussed by Manski (1993). However, we believe it is unlikely that workers actually anticipate knowledge spillovers from students, and argue that knowledge spillovers rather flow uni-directionally from regular employees to students, rather than the reverse. Second, we cannot directly observe the occupation-specific knowledge of the students. For instance, consider a scenario where a new technology is introduced across multiple establishments just before a student graduates from university, and the coworkers in the network are already benefiting from this technology (by experiencing higher productivity and wages). If the student is unfamiliar with the new technology, the superior wage and productivity of their coworkers may not be reflected in the graduate's wages. This could lead to a downward bias in the estimated effect of the network, underestimating the true impact of coworker quality on the graduate's wage.

4 Results

4.1 Main results

Table 2 shows results for our main outcome log of a graduate's wage in the first full-time job after graduation from different specifications and variations of the coworker quality measure as described in Section 3. Column (1) reports the results for our main specification from Equation 1 with firm-by-occupation fixed effects. Column (2) adds occupation-by-year fixed effects to control for occupation-specific time trends as described by Wachter (2020). In Column (3) we present results from including firm-by-occupation-by-time fixed effects where we use time intervals of the student job start year.[10]

In Table 2, Panel A, we use the log of the average wage as our proxy for coworker quality.

[10] Specifically, the time periods capture the student job start years in the pre-IT bubble burst (1999 – 2001), the pre-global financial crisis (2002 – 2007), post-financial crisis (2008 – 2012), Eurozone recovery (2013 – 2016). The choice of time period involves a trade-off: it should be narrow enough so that we capture students who are affected by the same firm-occupation shocks, but broad enough so that we still allow for enough variation in coworker wages and exposure to different coworkers.

Table 2: Effects of Student Job Coworker Networks on first job upon graduation

	Dependent variable:		
	Entry wage (log) in first job:		
	(1)	(2)	(3)
Panel A: Quality proxied by average coworker wages (log)			
Log avg. coworker wage - Same occupation	0.105***	0.099**	0.124***
	(0.039)	(0.040)	(0.042)
Log avg. coworker wage - Other occupation	0.061	0.038	0.048
	(0.059)	(0.066)	(0.071)
Adjusted R-squared	0.169	0.219	0.173
Individuals	6,243	6,243	6,243
Panel B: Quality proxied by change in coworker wages			
Change in coworker wages - same occupation	0.063*	0.108**	0.088**
	(0.033)	(0.045)	(0.039)
Change in coworker wages - other occupation	0.042	0.044	0.078
	(0.074)	(0.088)	(0.083)
Adjusted R-squared	0.168	0.219	0.173
Individuals	6,239	6,239	6,239
Coworker network controls	yes	yes	yes
Graduate controls	yes	yes	yes
Graduation cohort FE	yes	yes	yes
Establ. x occ. FE	yes	yes	no
Occ. x year FE	no	yes	no
Establ. x occ. x time FE	no	no	yes

Notes: Column (1) shows OLS estimation results from the regression specified in Equation 1, column (2) adds occupation-by-year fixed effects, column (3) uses firm-by-occupation-by-time fixed effects. 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, age, and vocational education. Coworker network controls (by same vs. other occupation) include student's log network size, the employment rate of coworkers, the share of female and non-German coworkers, the coworkers' mean age and its square, and their education. We also include graduation cohort fixed effects in all specifications. Standard errors (in parentheses) are clustered at the level of the student job establishment. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results 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 in all specifications. Specifically, we find that a 10 % increase in the average wage of coworkers is associated with a 1.05 % higher wage of the graduates' first full-time job. 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.

However, one could argue that average wages may not be a perfect measure of coworker quality, or that they could be correlated with unobserved characteristics of either the student or the establishment. To address this, we also consider the change in the average coworker wage between the time of the student job and the student's graduation as an additional proxy for coworker quality in Panel B. This wage change may be particularly useful, as students cannot foresee the future wage trajectories of their coworkers and, therefore, are unlikely to self-select into positions based on those future wage outcomes. Moreover, by subtracting the average coworker wage at the time of the student job from the wage at the time of the student's graduation, we relax the assumption made in Section 3 that the coworker wage at graduation is unrelated to the non-random assignment of students to their student jobs. Reassuring for our empirical approach, the results using the change in coworker wages as the independent variable show a similar effect on entry wages than the coworker wages at graduation (see Table 2, Panel B).

4.2 Channels

In this section, we analyse the channels why higher quality co-worker during student jobs increase wages at graduation. We test the two most likely channels: i) the role of referrals and professional networks and ii) the acquisition of relevant skills and knowledge through experienced coworkers.

Both mechanisms may help reduce information frictions in the labor market. The first mechanism highlights the importance of social connections, particularly the influence of former coworkers in facilitating access to higher-paying job opportunities. The second mechanism involves the development of human capital, where students gain valuable occupation- or industry-specific expertise. This experience improves the student's ability to signal their capabilities to potential employers, addressing the information asymmetries that typically exist between job seekers and hiring firms. Both professional networks and skill acquisition may play crucial roles in mitigating information gaps, allowing students to secure better job opportunities and higher wages.

Our results indicate that professional networks, specifically referrals from former coworkers, play a significant part in shaping students' career outcomes. As Table 3 (column 2) indicates the largest wage premium occurs when students begin working at a firm where a former coworker is employed, with the effect being twice as large as the baseline. This finding suggests that referrals or recommendations from previous coworkers play a significant role in facilitating job placement and enhancing wage outcomes. Importantly, better-paid coworkers increase the graduate's probability to start at the same firm of the coworker (column 3a), even if the coworker has since the student job moved to a different employer (column 3c). Thus, the influence of a former coworker extends beyond just working at the same firm of the student job. This result highlights the value of these professional connections that appear to go beyond the student job. Moreover, students who have worked with higher-paid coworkers are more likely to sort into better-paying firms indicated by an increase in the probability to start in a firm with above mean AKM (4a) or paying above average wages (column 4b).

Interestingly, firm-specific human capital does not appear to play a significant role in explaining the wage effects observed. If firm-specific human capital were a major driver, we would expect that students who remain at the same firm after their student job would experience significantly higher wage returns due to their accumulated firm-specific knowledge. However, the coefficients remain unchanged even when we exclude all graduates who start working at the firm where they completed their student job (column (2) of Table 4). This suggests that the observed wage effects are not driven by the firm-specific skills students acquire during their student employment. Yet, this relationship is not true for internships: The coefficients become smaller when we exclude firms where students completed internships (column (3) of Table 4), further suggesting that referrals play a significant role in explaining the observed wage effects. It appears that internships, that often provide students with more structured, skill-based work experiences, foster stronger professional connections.

In addition to the role of referrals, the acquisition of relevant skills through work experience significantly influences wage outcomes. Students who gain work experience in positions closer related to their field of study – as indicated in column (4b) of Table 4 – tend to earn higher wages upon graduation than those working in jobs unrelated to their field of study. The latter jobs include, for instance, bartending or cashiering - and we show that better-paid coworkers in these jobs don't affect a graduate's entry wage (column (4a) in Table 4).[11] These results suggest that jobs closer aligned with a student's academic background provide practical exposure to the industry, fostering the development of specialized expertise and offering valuable insights into the specific industry and its labor market.

While working alongside better-paid coworkers within the university also contributes to higher wages (column (5) in Table 4), the underlying mechanism does not appear to be an increase in knowledge directly relevant to achieving high exam grades, as we do not observe any effect on the overall college GPA as shown in column (6). Therefore, we cannot confirm that better-paid coworkers motivate students to intensify their study efforts, nor can we assert that students with higher-paid coworkers gain specific knowledge that directly supports their academic studies.

[11] Specifically, we define "unrelated" student jobs as student jobs that are in the industries "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 1 shows that students disproportionately choose these industries.

Table 3: Channels: Sorting and referrals

	Dependent variable: Entry wage (log)		*Dependent variable: Probability to start in a firm...*				
	Baseline (1)	Followed former coworker (2)	with former coworker (3a)	of student job (3b)	with coworker but not of student job (3c)	Above median AKM (4a)	Above median wage (4b)
Log avg. coworker wage - Same occupation	0.105***	0.234**	0.061***	0.015	0.046**	0.075***	0.112**
	(-0.039)	(-0.11)	(-0.022)	(-0.017)	(-0.021)	(-0.029)	(-0.054)
Log avg. coworker wage - Other occupation	0.061	0.02	-0.009	-0.008	-0.001	-0.03	-0.043
	(-0.059)	(-0.152)	(-0.039)	(-0.025)	(-0.034)	(-0.049)	(-0.05)
Mean Outcome	4.403	4.47	0.307	0.169	0.139	0.5	0.5
Adjusted R-squared	0.169	0.367	0.048	0.080	0.043	0.132	0.119
Individuals	6,243	866	6,243	6,243	6,243	6,038	6,170
Coworker network controls	yes	yes	yes	yes	yes	yes	yes
Graduate controls	yes	yes	yes	yes	yes	yes	yes
Graduation cohort fixed effects	yes	yes	yes	yes	yes	yes	yes
Estab. x occ. FE	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the entry wage (log) of first job in columns (1) and (2). In columns (3a) to (3c), the dependent variable is the probability to start the first employment in a firm in which a former coworker is working (3a), in the firm of the student job (3b), or in the firm in which a former coworker is now working but that is different from the student job (3c). In columns (4a) and (4b), the dependent variable is the probability to start the first employment in a firm that has an above median AKM (4a) or pays above median wages (4b). All results are based on OLS estimates of the regression specified in Equation 1 on different subsets of the data. The unit of observation is an individual graduate. For the description of covariates, please refer to the notes in Table 2. Standard errors (in parentheses) are clustered at the level of the student job establishment. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Channels: Human Capital

		Firm–specific human capital		Field-specific human capital			
				Type of student job			
	Baseline	Sample w/o firms of the student job	Sample w/o internship	Unrelated to field of study	Related to field of study	Sample w/o uni as empl.	*College GPA*
	(1)	(2)	(3)	(4a)	(4b)	(5)	(6)
Log avg. coworker wage – Same occupation	0.105***	0.102**	0.083*	0.001	0.147***	0.089*	0.082
	(0.039)	(0.042)	(0.048)	(0.114)	(0.038)	(0.045)	(0.061)
Adjusted R-squared	0.169	0.186	0.18	0.321	0.168	0.158	0.268
Individuals	6,243	5,190	5,154	984	5,262	4,526	5,300
Coworker network controls	yes	yes	yes	yes	yes	yes	yes
Graduate controls	yes	yes	yes	yes	yes	yes	yes
Graduation cohort fixed effects	yes	yes	yes	yes	yes	yes	yes
Estab. x occ. FE	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the entry wage (log) of first job in columns (1) to (5) and college GPA in column (6). Columns (1) to (5) show OLS estimation results from the regression specified in Equation 1 on different subsets of the data. The unit of observation is an individual graduate. College GPA is not available for all graduates (in column (6)). For the description of covariates, please refer to the notes in Table 2. Standard errors (in parentheses) are clustered at the level of the student job establishment. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Overall, the results in Tables 3 and 4 suggest that the quality of the student's initial coworker network can have a lasting impact on their career trajectory, with better-connected and higher-paid coworkers opening doors to higher-paying job opportunities. Thus, referrals and networking play a critical role in shaping students' early career choices and wage outcomes, emphasizing the importance of social capital alongside human capital in determining labor market success.

4.3 Dynamic effects over time

In the following, we focus on dynamic effects over time to show how coworker networks influence not only initial job acquisition but also the dynamics of job retention over time. In Table 5, we provide evidence that students who worked with higher-paid coworkers are able to secure a job more quickly after graduation (column (1)), effectively narrowing the time between finishing their studies and entering the workforce by an average of 2 % for every 10 % increase in close coworker wages. This suggests that high-quality coworkers can help students overcome the typical challenges associated with the transition from college to employment. By providing valuable professional guidance, sharing industry-specific knowledge, and possibly offering job leads or referrals, better-paid coworkers play a crucial role in improving the students' job search. As a result, students with higher-paid (and thereby maybe more influential) coworkers are able to access networks that streamline the job search process, reducing the lag between graduation and job entry compared to students with less advantaged networks.

The results also show that students who worked with higher-paid coworkers are less likely to separate from their first employer within the first six months of employment, suggesting that these coworker networks contribute to better job matching and improved retention during the initial phase of employment. However, after the first six months, we do not observe any significant effect on job separation rates. This indicates that while the influence of high-quality coworkers can enhance job stability in the early stages of employment, the

Table 5: Effects of Job Finding and Separation

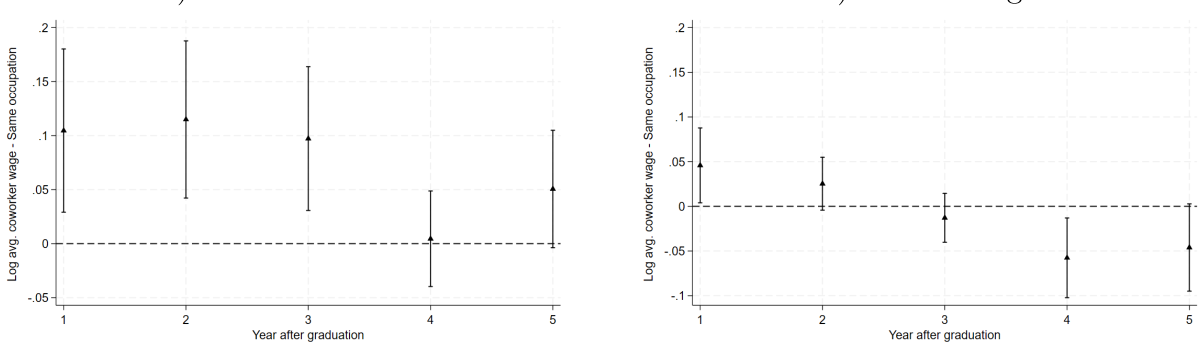
	Dependent variable:			
	Log days to start first job	*Separation within*		
		6 months	*12 months*	*24 months*
	(1)	(2a)	(2b)	(2c)
Log avg. coworker wage - Same occupation	-0.204***	-0.054*	-0.022	-0.043
	(0.074)	(0.028)	(0.039)	(0.037)
Mean Outcome		0.175	0.306	0.512
Adjusted R-squared	0.116	0.021	0.041	0.118
Individuals	6,243	6,243	6,243	6,243
Coworker network controls	yes	yes	yes	yes
Graduate controls	yes	yes	yes	yes
Graduation cohort FE	yes	yes	yes	yes
Establ. $\times$ occ. FE	yes	yes	yes	yes

Notes: The table shows OLS estimation results using the following outcome variables: log days to start first job (Column (1)) and separation rate (Columns (2a) to Columns (2c). The unit of observation is an individual graduate. For the description of covariates, please refer to the notes in Table 2. Standard errors (in parentheses) are clustered at the level of the student job establishment. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

effect diminishes over time. In the longer term, other factors such as career progression, job satisfaction, and individual preferences likely become more important in shaping employees' decisions to stay or leave their jobs.

Figure 2: Dynamic Effects

A) Baseline results B) De-meaning



Notes: Panel A shows the results of estimating five of our baseline specifications of Equation 1 using the log wage of full-time employment for up to five years after graduation in each specification. In Panel B, we estimate a similar specification but demean the outcome variable using the average individual log wage within 5 years of graduation.

To investigate the dynamic wage effects over time, we employed an alternative empirical specification that allows us to account for unobserved heterogeneity by de-meaning the outcome variable. In this specification, we compute the outcome variable for each student as the deviation from their own average wage over a five-year post-graduation period. This method effectively removes individual fixed effects, which were not feasible in our previous estimations. By controlling for individual unobserved factors, this approach provides a clearer picture of the long-term wage effects and confirms the robustness of our results.

Our findings in Figure 2 show that the wage effect associated with working with higher-paid coworkers is initially pronounced in the first year after graduation, with students from higher-quality networks earning higher wages during this period. This early wage premium is likely driven by the students' sorting into better-paying establishments, as we demonstrated earlier in Table 3. However, over time, the wage advantage diminishes, and we find no significant effect beyond the first year using this specification. This suggests that other students, who may not have had access to high-quality networks, catch up over time, e.g. by separating from their initial employer as indicated in Table 5. The lack of persistent wage effects in the longer term implies that while initial job placement and networking can provide a short-term wage boost, the influence of early coworker networks on wages diminishes as graduates gain additional experience.

4.4 Heterogeneity across gender and ability

Table 6 explores two different types of heterogeneity: Panel A splits the sample by High school GPA because it is a proxy for ability and a potential proxy for socioeconomic status (SES). As network quality may compensate for missing family networks it may be especially helpful for low SES students. Specifically, we split the sample at the median GPA and classify all students above the median as having a "high GPA" and those below the median as having a "low GPA". The coefficients are slightly higher for students with a GPA below the median, but due to the small differences in the coefficients, there is no evidence that students with a low high school GPA are driving our results and that better networks from student jobs compensate for missing other networks.

Table 6: Wage Effects of Student Job Coworker Networks: Heterogeneity Analysis

	Log (Daily) Wage at the First Job		
	(1)	(2)	(3)
Panel A: By High-School GPA			
	All Students	**Low GPA**	**High GPA**
Log avg. coworker wage - Same occupation	0.105***	0.095*	0.078
	(0.039)	(0.055)	(0.065)
Adjusted R-squared	0.169	0.192	0.164
Individuals	6,243	3,262	2,981
Panel B: By Gender			
	All Students	**Female**	**Male**
Log avg. coworker wage - Same occupation	0.105***	0.128*	0.106
	(0.039)	(0.076)	(0.069)
Adjusted R-squared	0.169	0.169	0.185
Individuals	6,243	3,280	2,963

Notes: The table shows OLS estimation results from the regression specified in Equation 1 and separately by High School GPA and gender. We split the sample by median GPA and classify those students with a 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 2. Standard errors (in parentheses) are clustered at the level of the student job establishment. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 for both female and male graduate although they are only statistically significant for females. However, the point estimates demonstrate a rather low difference between the genders indicating that no gender benefits more from higher quality coworkers.

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 networks from student jobs are also helpful to improve labor market outcomes at beginning of the career. These coworker networks help students sort into higher-paying firms after graduation, facilitated by coworker referrals, and enhance students' field-specific human capital through exposure to skilled colleagues. However, the initial wage advantage diminishes over time as graduates with worse coworker networks catch-up. Although we lack exogenous variation in network quality, the richness of our data and extensive controls allow us to account for selection into student jobs, student characteristics, and network composition. Moreover, our results are robust to different specifications and additional checks that allow us to account for unobserved network and unobserved student characteristics.

The size of our effects are remarkable. A 10 % increase in the average wage of former coworkers is associated with a 1.05 % higher wage in the first full-time job. This effect is more than 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 10 times larger than the spillover effects of working with productive coworkers (Cornelissen et al., 2017), in the German context, and similar to 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.

Overall, our findings highlight that student jobs matter beyond their purpose of providing a living. Specifically, our results suggest that networks from student jobs including better quality coworkers improve the transition from college to the labor market. Our study shows that students appear to benefit from student job networks because they receive field-specific knowledge and referrals from good coworkers. Moreover, we present evidence that these elements appear important for labor market transition. Hence, policies aimed at smoothing the transition from higher education to employment should focus on providing graduates with similar access to information, mentorship, and professional connections, helping to replicate the advantages gained from high quality student job networks.

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A Appendix

A.1 Additional figures

Figure A.1: Distribution of Network Size per Student

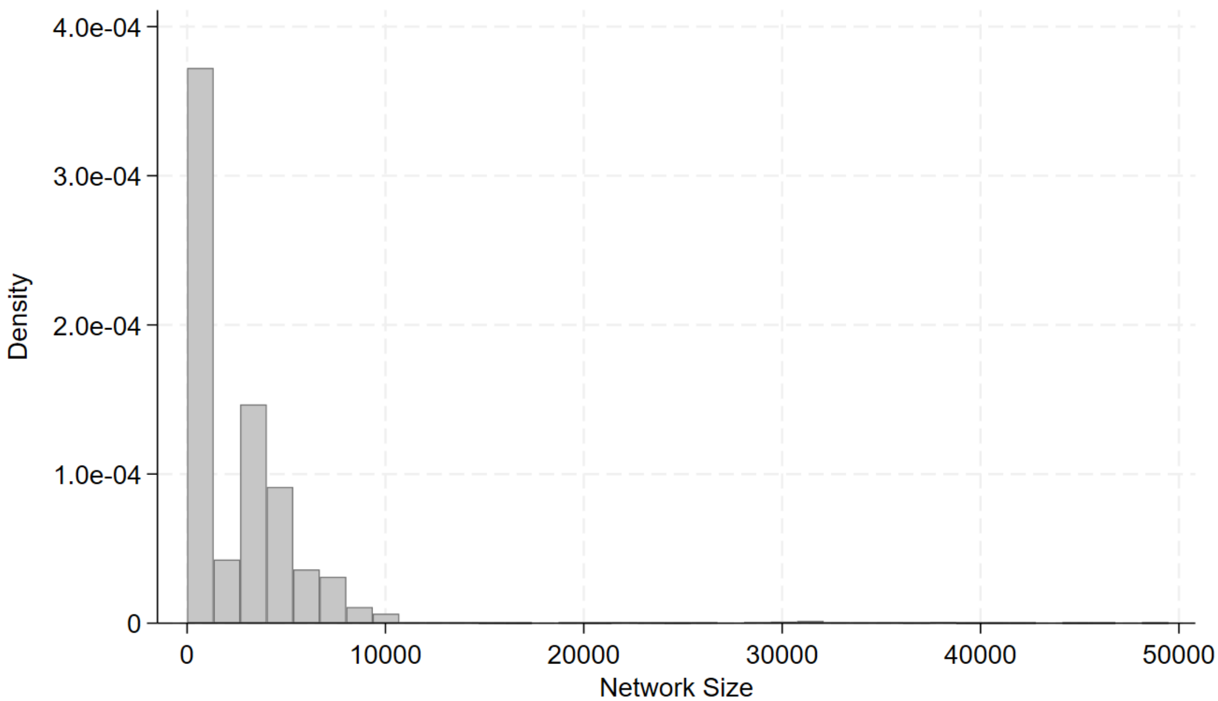


Figure A.2: Distribution of Network Size per Student- Less than 1000 Employees

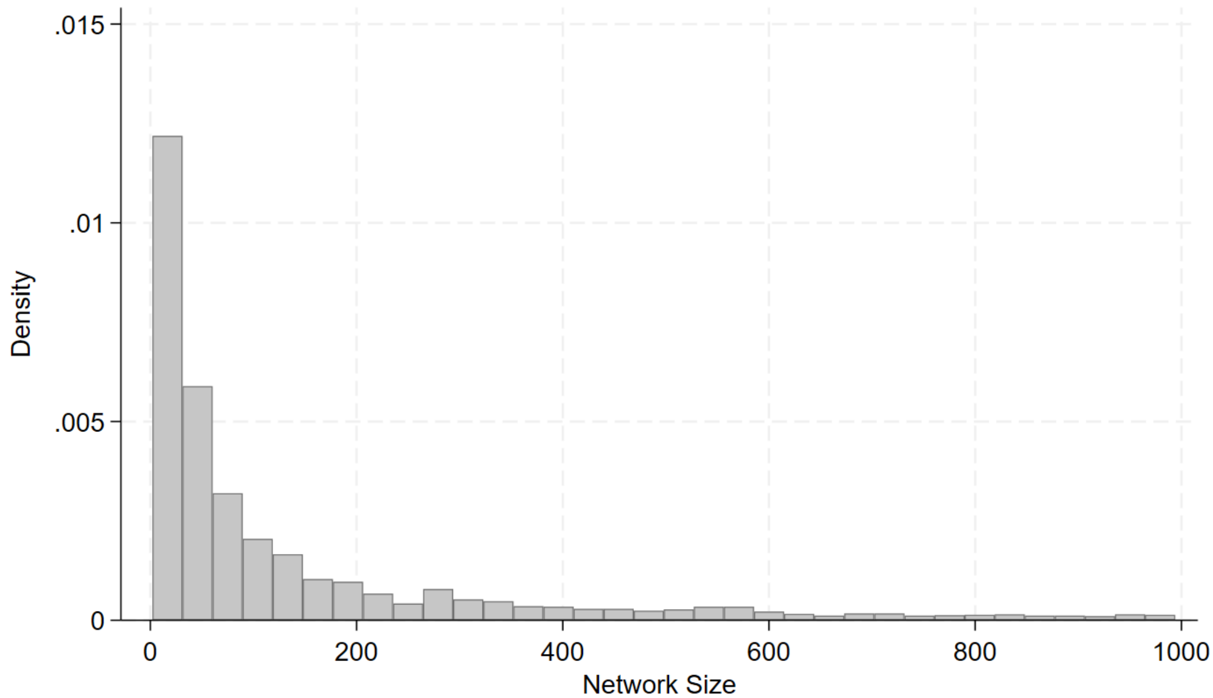


Figure A.3: Daily Wage at the first Full-Time Job after Graduation

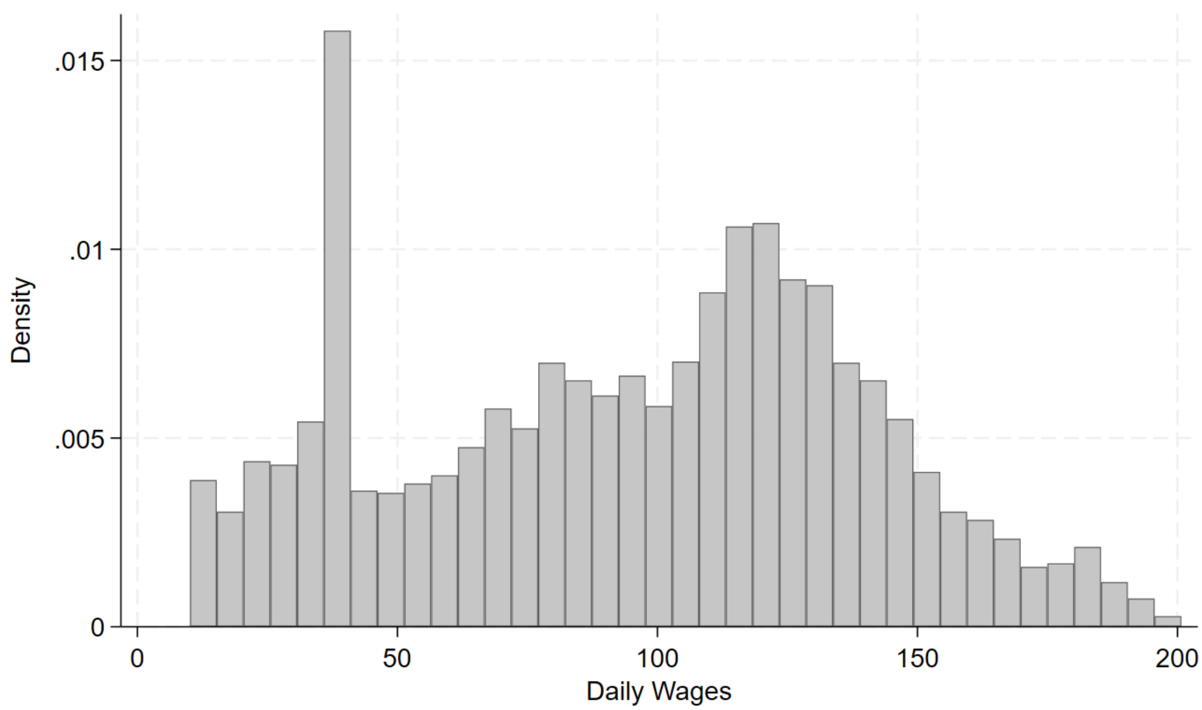
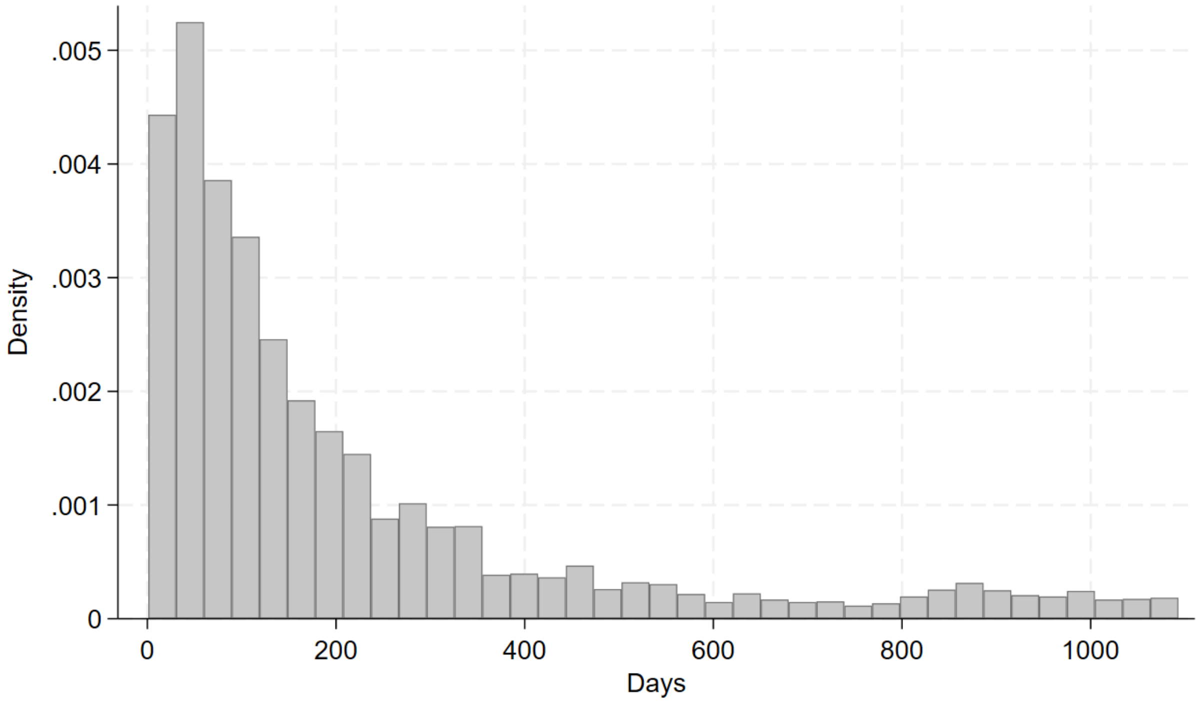


Figure A.4: Days to Find First Full-time Job After Graduation



A.2 Additional tables

Table A.1: Network Characteristics in Other Occupations

	Mean	SD
Student Jobs Network Characteristics - Other Occupations		
Log Average Coworker Wage	4.38	0.60
Log Network Size	5.60	2.65
Employment Rate of Coworkers	0.82	0.16
Share of Female Coworkers	0.55	0.24
Share of Non-German Coworkers	0.07	0.12
Mean Age of Coworkers	39.64	5.60
Share of Middle Educated Coworkers	0.31	0.25
Share of Highly Educated Coworkers	0.20	0.18
Individuals	6,242	

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.