Students' Coworker Networks and Labor Market Entry

Gökay Demir* Friederike Hertweck† Malte Sandner‡ Ipek Yükselen§¶

Abstract

This paper analyzes whether and to what extent college students' coworker networks from student jobs affect their labor market transition after graduation. The empirical analysis is based on administrative data, which includes all pre- and post-graduation job-related networks of college 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 coherent sets of individual, network, and firm characteristics, as well as firm fixed effects, and by distinguishing between close and less close colleagues in the same firm. Our results suggest that college graduates benefit from the quality of their coworkers in student jobs by speeding up their transition to the labor market and earning higher wages in their first job after graduation. Our results are important for understanding the relevant ingredients for a successful transition from higher education to the labor market.

JEL codes: I23, J24, J31

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*RWI – Leibniz Institute for Economic Research and Heinrich-Heine-Universität Düsseldorf. E-Mail: demir@rwi-essen.de.

†RWI – Leibniz Institute for Economic Research

‡Nuremberg Institute of Technology and Institute for Employment Research (IAB)

§Institute for Employment Research (IAB)

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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. Saygin et al., 2021; Glitz, 2017; Cingano and Rosolia, 2012; Eliason et al., 2022).

However, little is known 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). Therefore, additional knowledge about the mechanisms and important factors of the transition process is important for designing effective policies to smooth transitions.

In this paper, we go beyond the existing literature 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 is challenging, first, because the data must include 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, it is challenging because students are not randomly selected into student jobs and thus into coworker networks.

To solve the data challenge, our study uses data which links the administrative university records of students from a large German university with their social security records. This 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 firm. The data also allow us to identify those coworkers who work with the student in the same firm and in the same (or another) occupation as the student, which we use to indicate close or less close 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 address the endogeneity issue that students with better coworkers also work in more productive firms, which may have positive effects on the transition from college to employment, we control for detailed student job characteristics, industry characteristics, and a proxy for firm productivity suggested by Abowd et al. (1999). In addition, we focus on the close coworkers and control for the less close coworkers. If we expect unobserved firm shocks or policies, such as firm training policies, to positively bias our network quality indicator, we should expect the same bias for coworkers who work in the same firm but not closely with the student. Finally, we run an estimation including firm fixed effects, estimating the coworker effect for students with different coworker networks within the same firm, which prevents specific firm 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 cannot use student fixed effect because we are interested in the coworker network during studying on wages after graduation. However, we control for a wide range of individual pre-college characteristics and a reliable measure of pre-college ability, students' high school GPA.

Our results show that graduates benefit from their embedded coworker networks by speeding up the labor market transition and 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. 0.78 % higher entry wage at the graduate's first full-time job and a 1.5 % reduction in the time between graduation and first job. Our results also indicate that the network quality has no effect on the probability that the graduate separates from the first employer after 6, 12, or 24 months. These results are robust to the different specifications and robustness checks we apply.

In a series of heterogeneity analyses, we 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 related jobs drive the effects on wages, while coworkers in unrelated jobs drive the effects on the time between graduation and first job. These results suggest that the quality of coworkers in more related jobs improves the quality of the first job, while the quality of coworkers in unrelated jobs leads to faster employment. One might be concerned that the faster entry into the labor market leads to a worse match. However, this negative effect does not appear as the coefficient on wages for the unrelated job is not negative. When we look at potential heterogeneity across gender and student ability, measured by college GPA, our results do not show much difference across 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).

One possible channel explaining the coworker effects on transition is an increase in students' effort at university. However, we can rule out this channel as we do not find any effects of coworker quality on graduation grades. Another channel is that students benefit from good coworkers if they start their career in the same firm where they worked as a student. If only this channel explains the effects, we should see no effects after excluding students who start in their student job firm after graduation, which is not the case. Excluding these two channels, a likely remaining explanation for why student job coworkers may improve graduates' labor market entry is information frictions on potential outside options, which are high during labor market entry: Jäger et al. (2022) shows that these frictions partly explain wage differentials between similar workers, and Belot et al. (2019); Carranza et al. (2022); Demir (2022) 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 networks of coworkers can help reduce information frictions for individual workers. However, we can not 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 dorms, 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.

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. We show that the network of students' jobs is also important for this important transition. This knowledge can help improve policies to smooth the transition, such as career counseling.

Finally, this paper contributes to the literature on the effect of working while studying. While 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), this literature rarely identifies channels why working during studies has positive effects on wages. With our results, we 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 sample selection, and presents descriptive statistics. Section 3 describes our empirical strategy. Section 4 presents and discusses our results. Finally, Section 5 concludes.

2 Data and Descriptives

Our data include detailed labor market and college data for each student, social security records for their coworkers, and information on the firms where the students worked during their studies. All datasets and links are described below.

Student-level data

The core of our dataset is the detailed social security records of all students who graduated from a large German university between 1995 and 2016. These records come from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) and the administrative records of the university. The IEB covers the universe of employees in Germany[1] and contain detailed daily information on employment, benefit receipt, and job search. Since the IEB does not include educational trajectories, 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 studying.

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 student and graduate employment (e.g., start and end dates, occupation, employment type, wage).

Coworker networks

For each student job, we know the firm 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 firm at the same time as the student. We define these individuals as potential coworkers of student i in student job k and all potential coworkers as the student coworker network. In a final step of data preparation, we then extract socio-demographic characteristics (gender, age, nationality, educational

[1]The IEB allows the employment status of an individual to be tracked 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)

attainment) and labor market history (employment status, deflated (daily) wage) of each of these potential coworkers.

AKM data

We also add AKM fixed effects, provided by Bellmann et al. (2020), to our data. The establishment AKM fixed effect measures the proportional wage premium 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.

2.1 Sample selection

The relationship of interest is whether students' networks of coworkers 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 a student job while studying.[2] We consider any job up to 5 years before graduation as a student job (Figure 1).

To ensure that students and their coworkers have sufficient contacts and interactions, we drop student jobs (and thus coworker networks) that last less than three months, as well as student jobs in firms with more than 250 employees.[3] In addition, we distinguish between close coworkers, those coworkers in the same 3-digit occupation and firm, and less close co-workers, all other coworkers in the same firm.

Our outcomes of interest relate to a graduate's transition to the labor market. We restrict our analysis to the first full-time job, dropping all graduates who did not find a full-time job within three years of graduation and dropping some implausible cases (i.e., graduates who earn less than 10 Euro per day in a full-time job).

We select the daily wage of the graduate and compute the deflated log daily wage of the graduate using the Consumer Price Index from the Federal Statistical Office and the number of days until the graduate starts full-time employment.[4]

For coworkers, we assign a missing value to observations with a wage below the first percentile of the wage distribution for coworkers. We convert gross daily wages to real daily wages using the Consumer Price

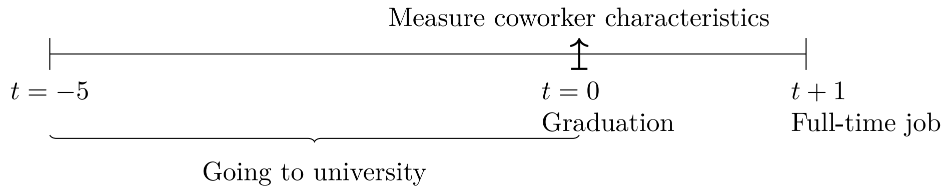
[2] This means that we exclude all students enrolled in teacher training programs, as they often become civil servants shortly after entering the labor market and thus do not work in the social security system. We also exclude bachelor students because they may enroll in a master's program after completing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

[3] Figures A.5 and A.6 show that students tend to work in smaller firms during their studies anyway.

[4] 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 the graduates' wages are censored. Thus, censored wages are unlikely to affect our results.

Index from the Federal Statistical Office. We measure coworker characteristics at the exact time the student graduates from college ($t = 0$ in Figure 1). If employees have multiple employment spells at this time, we keep the spell with the longest tenure.

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.

2.2 Descriptive statistics

Our sample restrictions leave us with 3,285 individual graduates who worked in student jobs and started their first full-time job within three years of graduation between 2000 and 2016. Table 1 presents descriptive statistics on the graduates, their coworker networks, and their first full-time job.

58 % of the graduates are female. 2 % of the graduates have a non-German citizenship. The average age at first full-time employment is 28. Average high school GPA is 2.33 – it ranges from 1 (best) to 4 (passed). Most graduates in our sample studied either Humanities and Social Sciences (43 %) or Economics and Business (29 %). 17 % of the graduates studied a medical subject, 11 % studied a program in Mathematics and Natural Sciences. Table 1 also displays the top last industry in which students worked besides their studies: The industries ”Wholesale and retail trade; repair of motor vehicles and motorcycles” and ”Accommodation and food service activities” have the highest share of graduates with 20% and 22 % respectively. Furthermore, Table 1 displays the top last occupations of students. Students in our sample are most likely to work as waiters or office specialists.

In the five years prior to graduation, 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 A.2 in the appendix shows the distribution of the network size of graduates. The average coworker network can be described as female-dominated (64 %), mostly employed (61%), of German citizenship (94 %), and lower educated (71 %).

The average daily wage of graduates in their first full-time job after graduation is about 76 Euro, which is about 2,280 Euro per month. Figure A.3 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 seven months. Because we focus on the first full-time job after graduation, if students work in other types of jobs before their first full-time job, that time is also included in the number of days to the first job. Figure A.4 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 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	0.14
Age at the First Job After Graduation	27.45	2.57
Final High School GPA	2.33	0.60
Number of Student Jobs	3.65	3.30
Log Average Wage in Student Jobs	2.41	0.87
Field of Study		
Economics and Business	0.29	0.45
Mathematics and Natural Sciences	0.11	0.31
Humanities and Social Sciences	0.43	0.50
Medical Studies	0.17	0.38
Student Jobs Characteristics		
Average AKM Establishment FE	-0.14	0.44

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Table 1 – continued from previous page

	Mean	SD
Industry of Student Jobs		
Acommodation and Food Service Activities	0.22	0.41
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcyle	0.20	0.40
Professional, Scientific and Technical Activities	0.14	0.34
Human Health and Social Work Activities	0.10	0.30
Information and Communication	0.08	0.26
Manufacturing	0.05	0.21
Administrative and Support Service Activities	0.05	0.21
Occupation in Student Job		
Waiters, Stewards	0.16	0.37
Office Specialists	0.14	0.35
Salespersons	0.11	0.31
Office Auxiliary Workers	0.07	0.25
Others Attending on Guests	0.05	0.22
Network Characteristics		
Log Network Size	3.20	1.33
Employment Rate of Coworkers	0.61	0.20
Share of Female	0.64	0.29
Share of Non-German	0.06	0.11
Mean Age of employes	34.23	7.44
Share of Middle Educated	0.20	0.27
Share of Highly Educated	0.09	0.19

Individuals	3,285

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 firm and occupation) of college students from their student jobs. We present descriptive statistics on the network characteristics of less close coworkers (same firm but other occupation) in Table A1. Network coworkers 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 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.

Our empirical analysis relies on the fact that student jobs are typically fixed in time and associated with unidirectional knowledge spillovers from coworkers to students. We observe the local labor market from 1995 to 2016 and can exploit the variation in coworker networks induced by individual students having multiple student jobs, and by different students working in the same firm but at different times (and thus having different coworkers).

We estimate the following baseline wage equation:

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

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 firm 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 firms during their student jobs (i.e., at time t^C), 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. 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 firm at the same time as the student but in different occupations ($\sim o$) than the student: $log\, \overline{w}_{\sim o,ijt^G}$ thereby controlling for shocks common to all workers who worked at the same time and in the same firms as the student. An example of such a shock is a common training for all workers.

To control for high ability students sorting into jobs with high quality coworkers, we include a large set of individual, firm, 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 firm of the student job, s_{jt^C}, the occupation of the student, θ_{ot^C}, and the characteristics of the firm, μ_{jt^C}. The firm and occupation characteristics of the student's job were observable to the student. Students may have chosen certain firms 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 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 firm, $p'_{\sim o,ijt^G}$. 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.[5]

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 firm and occupation *after* a student joins the firm, 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. Suppose that a new technology is adopted by various firms shortly 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 wage of the graduate. This would lead to a downward bias, underestimating the true effect of the network on the graduate's wage.

[5] This strategy accounts for the fact that former coworkers may have been promoted, taken parental leave, or changed employers since the student left the firm. Of course, in an alternative specification, we could also include these network characteristics at the time of the student job. Including all $p'_{\cdot,t^C}$ 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 firm, or career counselors who have close ties to some firms. We believe that these cases are rare and are already captured by including occupation and firm effects.

4 Results

4.1 Main Results

Table 2 shows our main results from estimating equation 1. Column (1) reports the regression results for our main outcome - a graduate's log wage in the first full-time job after graduation. In columns (2) to (4c), we report the coefficients on a set of additional outcomes regressed on coworker quality and respective controls.

Table 2 shows a positive and statistically significant relationship between coworker quality and the log wage of the graduate's first full-time job. Former coworkers positively affect the first wage after graduation (column (1)) and increase the speed of starting the first full-time job (column (2)). More specifically, we find that a 10% increase in the average wage of coworkers is associated with a 0.78% higher wage of graduates' first full-time job and a 1.45% reduction in the number of days to start a full-time job.

In column (3) of Table 2, we use college GPA as the outcome variable. Students with higher coworker quality might increase their study effort, for example, because they are more motivated or because they 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. We find no effect of coworker quality on college GPA. 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 (4a) to (4c), we do not find that coworker quality affects the probability of separation within the first 24 months of full-time employment.

In our subsequent analysis, we focus on the first two outcomes of Table 2 as these are the most relevant indicators for transition quality.

Table 2: Effects of Student Job Coworker Networks

	Log daily wage at first job (1)	Log days to start first job (2)	College GPA (3)	Separation within 6 months (4a)	Separation within 12 months (4b)	Separation within 24 months (4c)
Log avg. coworker wage	0.078***	-0.145***	0.011	0.007	0.006	0.014
– Same occupation	(0.022)	(0.047)	(0.015)	(0.017)	(0.018)	(0.019)
Log avg. coworker wage	0.024	0.002	0.026	0.032*	0.029	-0.019
– Other occupation	(0.024)	(0.051)	(0.017)	(0.019)	(0.020)	(0.025)
Adjusted R-squared	0.241	0.137	0.027	0.054	0.130	0.355
Individuals	3,285	3,285	3,285	3,285	3,285	2,665
Graduate controls	yes	yes	yes	yes	yes	yes
Coworker network controls	yes	yes	yes	yes	yes	yes
Other employee controls	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Firm effects	yes	yes	yes	yes	yes	yes
Occupation fixed effects	yes	yes	yes	yes	yes	yes
Graduation cohort fixed effects	yes	yes	yes	yes	yes	yes

Notes: The table shows OLS estimation results from the regression specified in Equation 1. 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. Firm 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: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

4.2 Heterogeneity

Table 3 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 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 larger 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. Regarding the speed of entry, we find a stronger effect for female graduates: Columns (5) and (6) in Panel B of Table 3 show that female graduates benefit more from a high quality network than male graduates.

In Table 4, 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

Table 3: Wage and Job Finding Effects of Student Job Coworker Networks: Heterogeneity Analysis

	Log (Daily) Wage at the First Job			**Log Days to Find First Job**		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Graduation Grade						
	All Students	**High Grade**	**Low Grade**	**All Students**	**High Grade**	**Low Grade**
Log avg. coworker wage	0.078***	0.088**	0.099***	-0.145***	-0.137*	-0.174**
– Same occupation	(0.022)	(0.035)	(0.033)	(0.047)	(0.077)	(0.078)
Log avg. coworker wage	0.024	-0.020	0.025	0.002	0.006	-0.068
– Other occupation	(0.024)	(0.043)	(0.032)	(0.051)	(0.096)	(0.082)
Adjusted R-squared	0.241	0.221	0.173	0.137	0.134	0.117
Observations	3,285	1,333	1,332	3,285	1,333	1,332
Panel B: By Gender						
	All Students	**Female**	**Male**	**All Students**	**Female**	**Male**
Log avg. coworker wage	0.078***	0.088***	0.075**	-0.145***	-0.151**	-0.108
– Same occupation	(0.022)	(0.032)	(0.033)	(0.047)	(0.059)	(0.078)
Log avg. coworker wage	0.024	0.006	0.057	0.002	-0.001	0.043
– Other occupation	(0.024)	(0.033)	(0.036)	(0.051)	(0.065)	(0.095)
Adjusted R-squared	0.241	0.203	0.225	0.137	0.149	0.107
Observations	3,285	1,898	1,387	3,285	1,898	1,387

Notes: The table shows OLS estimation results from the regression specified in Equation 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 2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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 4 shows the results of our estimations separately for students who worked in unrelated student jobs in columns (2) and (5) and those who worked in related student jobs in columns (3) and (6). Because some students worked in both unrelated and related student jobs, the number of observations does not add up to our baseline specifications in columns (1) and (3). The results in Table 4 show that our effects for log wages as an outcome are driven by coworker networks from related jobs, while the effects for the time to find a first full-time job are driven by coworker networks from unrelated jobs. In other words, these results suggest that higher coworker quality in related jobs improves the quality of the initial job, while higher coworker quality in unrelated jobs accelerates the transition to employment.

Table 4: Wage and Job Finding Effects of Student Job Coworker Networks - Unrelated vs. Related Jobs

	Log (Daily) Wage at the First Job			**Log Days to Start First Job**		
	All student jobs	**Only unrelated jobs**	**Only related jobs**	**All student jobs**	**Only unrelated jobs**	**Only related jobs**
	(1)	(2)	(3)	(4)	(5)	(6)
Log avg. coworker wage – Same occupation	0.078***	0.002	0.083***	-0.145***	-0.188***	-0.083
	(0.022)	(0.034)	(0.025)	(0.047)	(0.067)	(0.057)
Log avg. coworker wage – Other occupation	0.024	0.051	0.004	0.002	-0.004	-0.006
	(0.024)	(0.034)	(0.031)	(0.051)	(0.066)	(0.071)
Adjusted R-squared	0.241	0.219	0.236	0.137	0.194	0.122
Observations	3,285	1,451	2,265	3,285	1,451	2,265

Notes: The table shows OLS estimation results from the regression specified in Equation 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 2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

4.3 Channels

A relatively high share of college graduates start their first full-time job at the same establishment where they previously worked as a student (about 20% in our estimation sample). Student jobs may act as a screening device for both students and employers. Higher average coworkers' wages in an establishment may increase the likelihood that the student stays in the establishment and earns a higher wage in her first full-time job compared to other students who selected to lower-paying establishments. We account for this feature of student jobs by excluding graduates who started their first full-time job in any of the establishments where they worked as a student in columns (2) and (5) of Table 5. In columns (3) and (6), we only exclude graduates who started their first full-time job in the last establishment where they worked as a student. We find that our main results, namely a positive and statistically significant association between log average coworker wages and the log wage of the first full-time job, remain even after excluding these graduates. Thus, although starting as a full-time employee in an establishment where the student previously worked is an important feature of student jobs, it cannot fully explain why having quality coworkers helps graduates earn higher wages in their first job.

In Table 6, we present 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. Consistent with an advice, inspiration, or anchoring mechanism, we find that only *full-time* coworkers affect the wage of the graduate's first full-time job. However, we find no effect on the speed of entry into the first full-time job. A 10% increase in the average wage of coworkers working full-time at the time of graduation is associated with a 1.39% higher wage of the graduate.

If better-quality coworkers generally have more information about, say, potential job openings or better-

Table 5: Wage and Job Finding Effects: With and without Students who Started in Student Job Establishment

	Log (Daily) Wage at the First Job			**Log Days to Start First Job**		
	All Student Jobs	**Excluding Job in Same Establishment**	**Excluding Job in Last Establishment**	**All Student Jobs**	**Excluding Job in Same Establishment**	**Excluding Job in Last Establishment**
	(1)	(2)	(3)	(4)	(5)	(6)
Log avg. coworker wage	0.078***	0.049**	0.055**	-0.145***	-0.137***	-0.145***
– Same occupation	(0.022)	(0.025)	(0.024)	(0.047)	(0.051)	(0.050)
Log avg. coworker wage	0.024	0.031	0.036	0.002	0.024	0.030
– Other occupation	(0.024)	(0.026)	(0.026)	(0.051)	(0.054)	(0.054)
Adjusted R-squared	0.241	0.266	0.260	0.137	0.171	0.172
Individuals	3,285	2,628	2,730	3,285	2,628	2,730

Notes: The table shows OLS estimation results from the regression specified in Equation 1. In columns (2) and (5), we exclude any establishment in which the student has worked before. In columns (3) and (6), we exclude the last establishment in which the student worked before graduating. 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. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

paying establishments, then all coworkers should affect the entry wage of the graduate's first full-time job. On the other hand, if advice, inspiration, or anchoring by full-time coworkers is important, then we would expect only the characteristics of full-time coworkers to matter in our estimates and no effect for part-time coworkers, since we focus only on graduates' first full-time job. However, it could also be that full-time coworkers simply had more opportunities to interact with the student.

4.4 Robustness

Our main results in Section 4.1 and illustrated in Table 2 use an extensive set of covariates that control for the selection of observably better students into better student jobs. We believe that our controls are good measures of student ability and the quality of potential peers. However, we cannot rule out the possibility that unobservable factors jointly affect our key independent variable and the outcomes. Therefore, to test the robustness of our results, we use another empirical strategy to assess the effect of higher earning student job coworkers on labor market entry.

We perform two robustness checks to validate our results. First, we use establishment fixed effects rather than relying only on the AKM establishment effect. As a result, we restrict the variation in our variables to only coming from at least two different students employed at the same establishment. The timing of the student job – students work in the same place but at different times –, the date of graduation – students may work in the same place at the same time but graduate at different times –, or students working in the same establishment but in different occupations are the main sources of variation in average coworker quality in this case. In Panel B of Table 7, we use establishment fixed effects and show that the coefficient is similar in magnitude to the baseline, but lacks statistical power because the variation comes from only a small subset

Table 6: Wage and Job Finding Effects: Full-time vs. Part-time Network Members

	Log (Daily) Wage at the First Job (1)	**Log Days to Find First Job** (2)
Log avg. coworker wage - Full-time - Same occupation	0.139***	0.073
	(0.036)	(0.080)
Log avg. coworker wage - Full-time - Other occupation	0.045	-0.007
	(0.044)	(0.104)
Log avg. coworker wage - Part-time - Same occupation	0.005	-0.035
	(0.023)	(0.056)
Log avg. coworker wage - Part-time - Other occupation	0.021	0.004
	(0.022)	(0.055)
Adjusted R-squared	0.248	0.147
Observations	2,413	2,413
Graduate characteristics	yes	yes
Network characteristics	yes	yes
Average AKM establishment effect	yes	yes
Industry and occupation in student job	yes	yes

Notes: The table shows the OLS estimation results from a regression specified similar to Equation 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 2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

of our sample.

Second, one might argue that average wages are not an adequate proxy for quality. Despite our confidence in the ability of our control variables to reduce bias in our measure of coworker quality due to non-random sorting, we perform a robustness check by using an alternative measure of coworker quality. Specifically, we use the person AKM effect provided by Bellmann et al. (2020). The person AKM effect is estimated through a regression with worker and establishment fixed effects, and can be interpreted as a combination of skills and other factors that are equally valued 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 C of Table 7. Our results 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. Similar to Table 6, we find that the quality of full-time coworkers has no effect on the time it takes for a graduate to find his or her first full-time job.

Table 7: Wage and Job Finding Effects of Student Job Coworker Networks

	Log (Daily) Wage at the First Job	**Log Days to Start First Job**
Panel A: Baseline		
Log avg. coworker wage - Same occupation	0.078***	-0.145***
	(0.022)	(0.047)
Adjusted R-squared	0.241	0.137
Individuals	3,285	3,285
Panel B: Establishment Fixed Effects		
Log avg. coworker wage - Same occupation	0.066	-0.163
	(0.048)	(0.109)
Adjusted R-squared	0.268	0.229
Individuals	3,285	3,285
Panel C: Worker AKM Effects		
Avg. coworker AKM - Same occupation	0.077	-0.017
	(0.050)	(0.098)
Adjusted R-squared	0.240	0.135
Individuals	3,040	3,040

Notes: The table shows robustness checks of our baseline estimation in Equation 1. In panel A, we present the baseline specification. In panel B, we add establishment fixed effects and include the same control variables as in our baseline specification. In panel C, 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 from the estimation in panel C. 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 2. Heteroskedasticity-robust standard errors in parentheses. Significance levels: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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 faster labor market transitions and 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. 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, while better-quality coworkers in unrelated jobs lead to faster employment.

The size of our effects are remarkable. A 10 % increase in the average wage of former coworkers is associated with a 0.78 % 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 firm (Dustmann et al., 2016) and about 7 times larger than the spillover effects of working with productive coworkers (Cornelissen et al., 2017), both in the German context. Note, however, that 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 firm and occupation, which can explain much of the difference in the size of our and their results. Moreover, a back-of-the-envelope calculation suggests that a 100 % increase in coworker quality would reduce the number of days to find a first full-time job by approximately 16 days from the median. 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.[6]

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.

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

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A Appendix

Figure A.1: Mean Daily Wage of Coworkers per Student

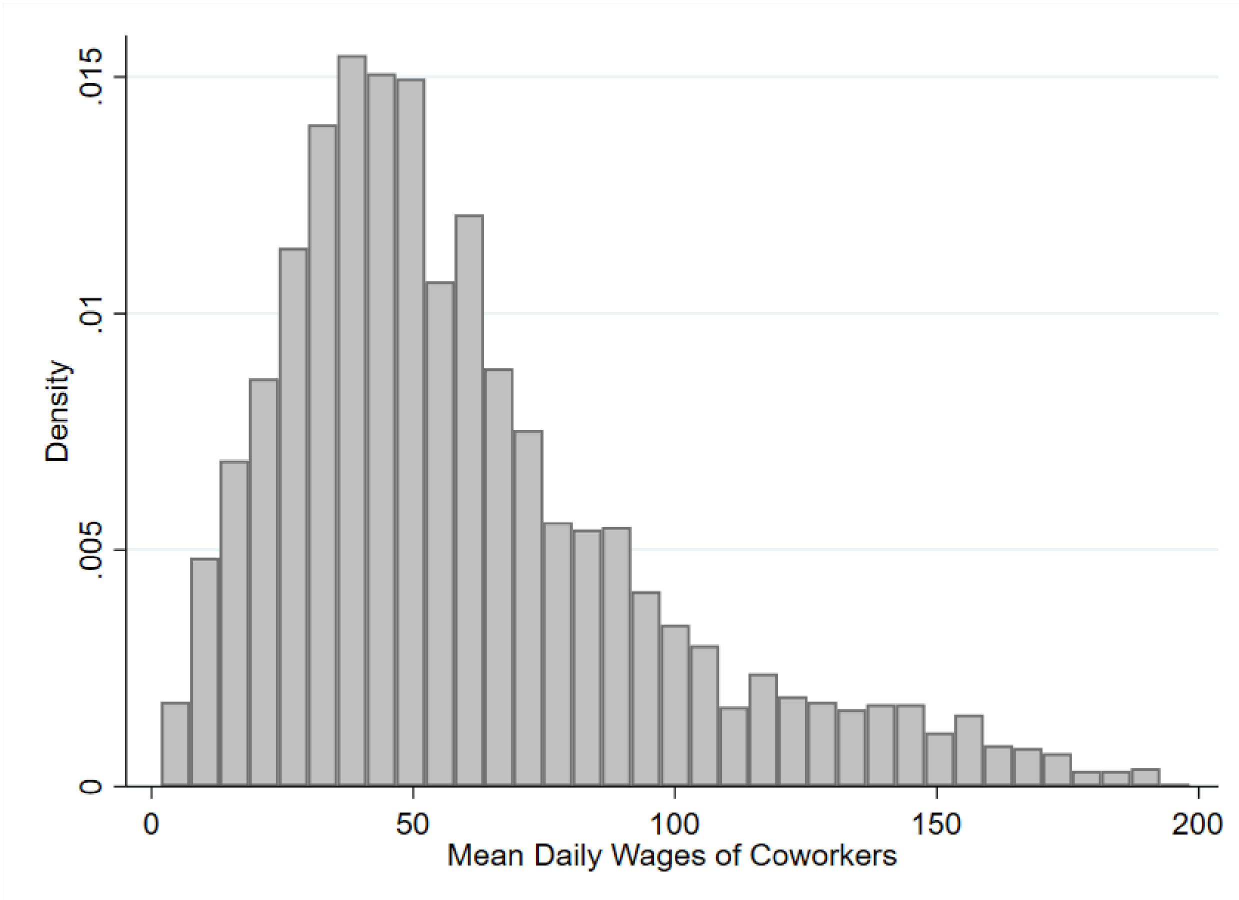
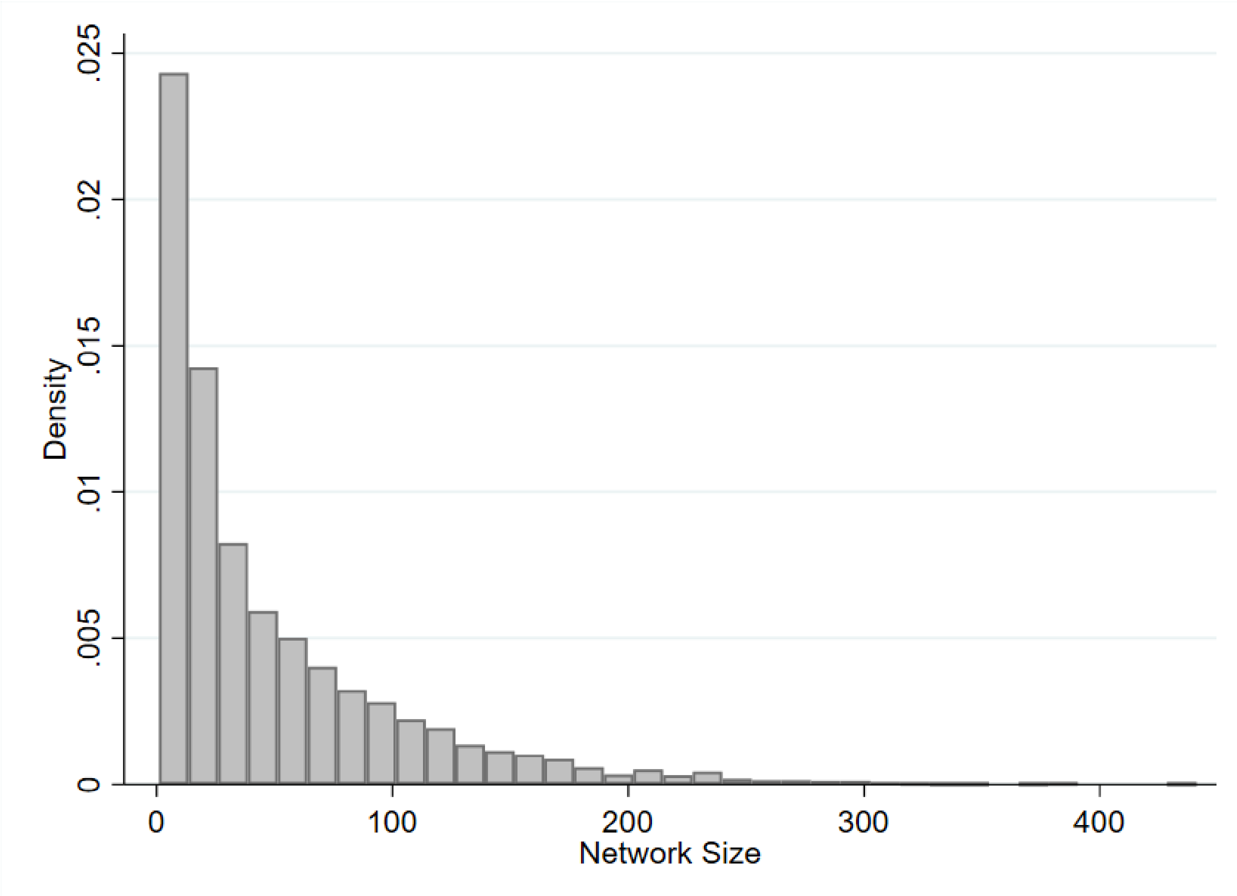


Figure A.2: Distribution of Network Size per Student



Note: This figure shows the distribution of network size for each student. Network size measures the number of coworkers a student has over 5 year prior to the graduation. Students with jobs longer than three months and a network size of 250 coworkers per job 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 A.3: Daily Wage at the first Full-Time Job after Graduation

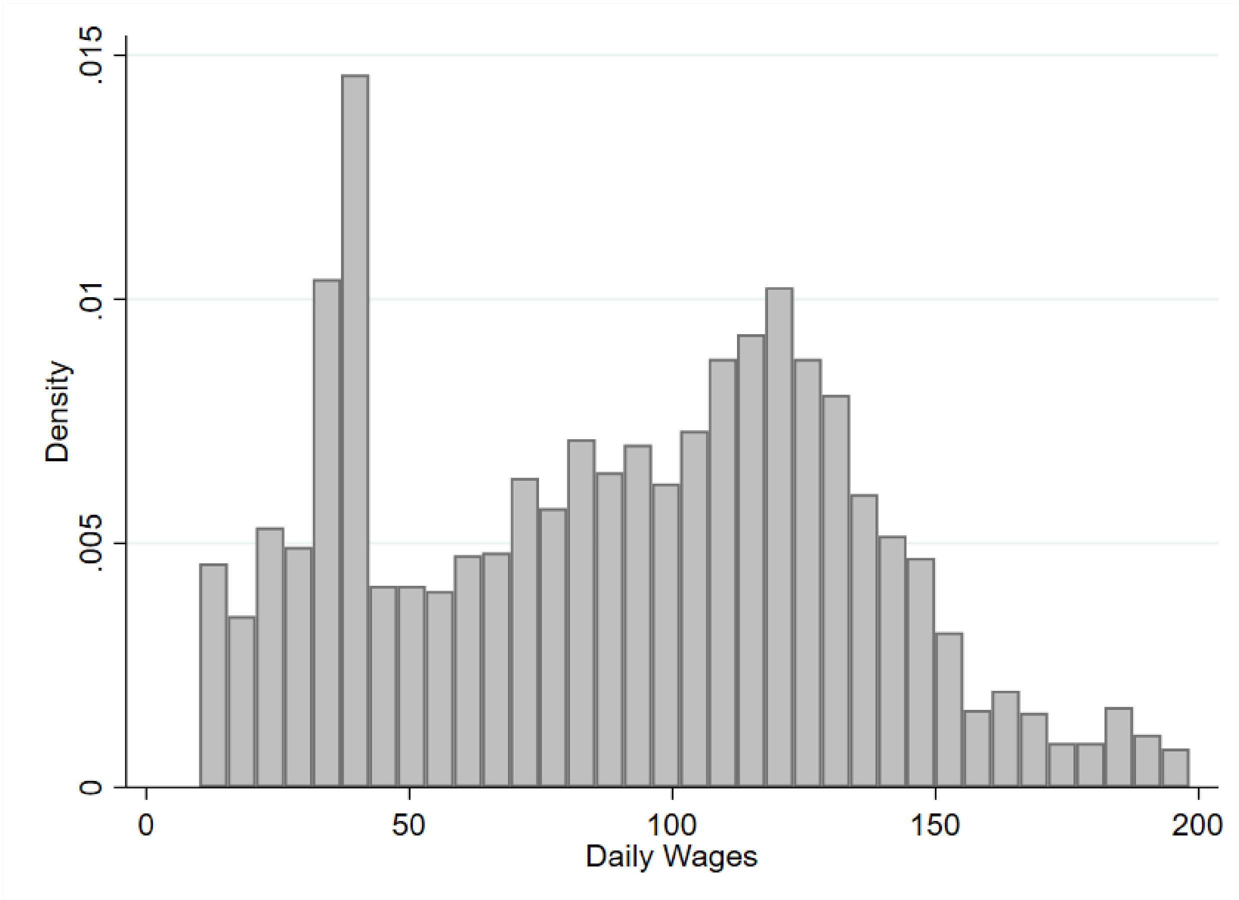


Figure A.4: Days to Find First Full-time Job After Graduation

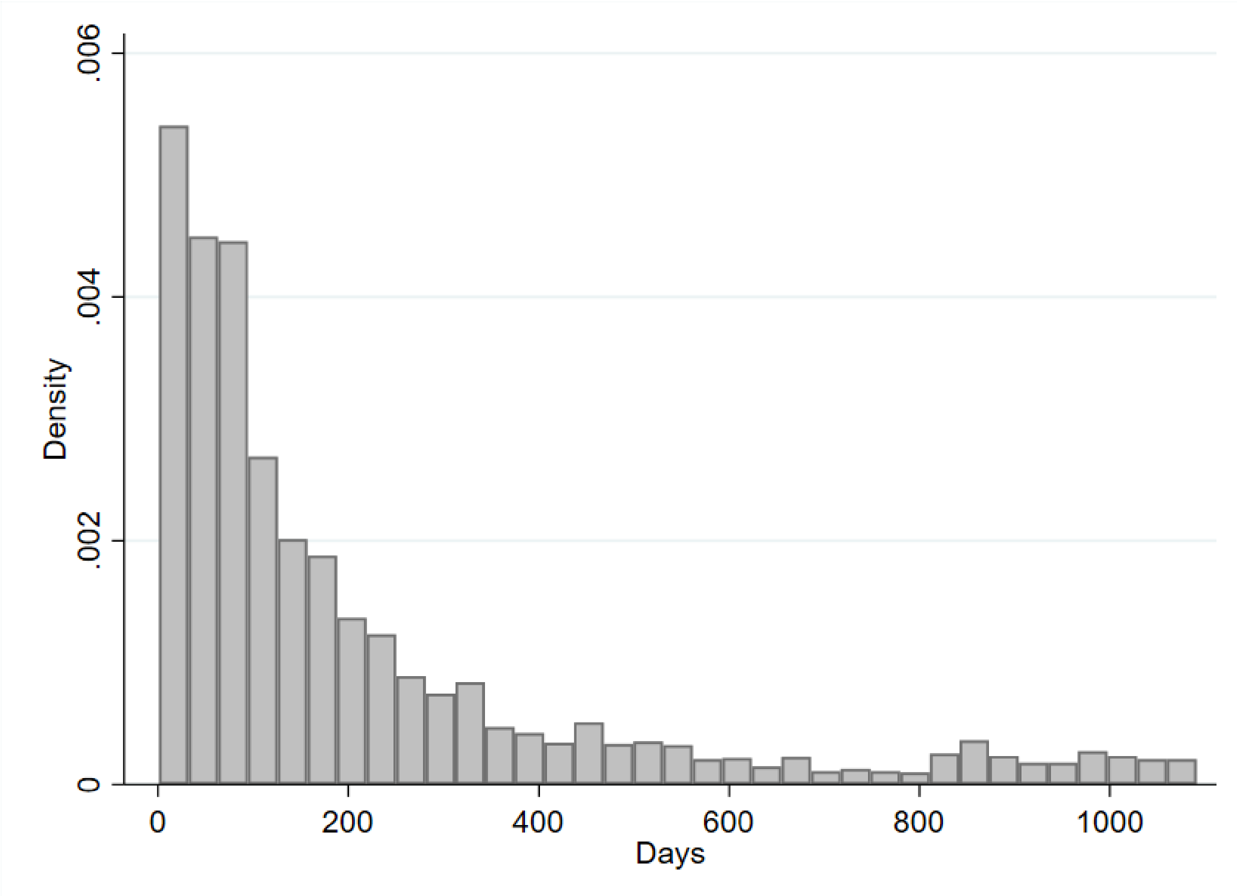


Figure A.5: Establishment Size of Student Jobs

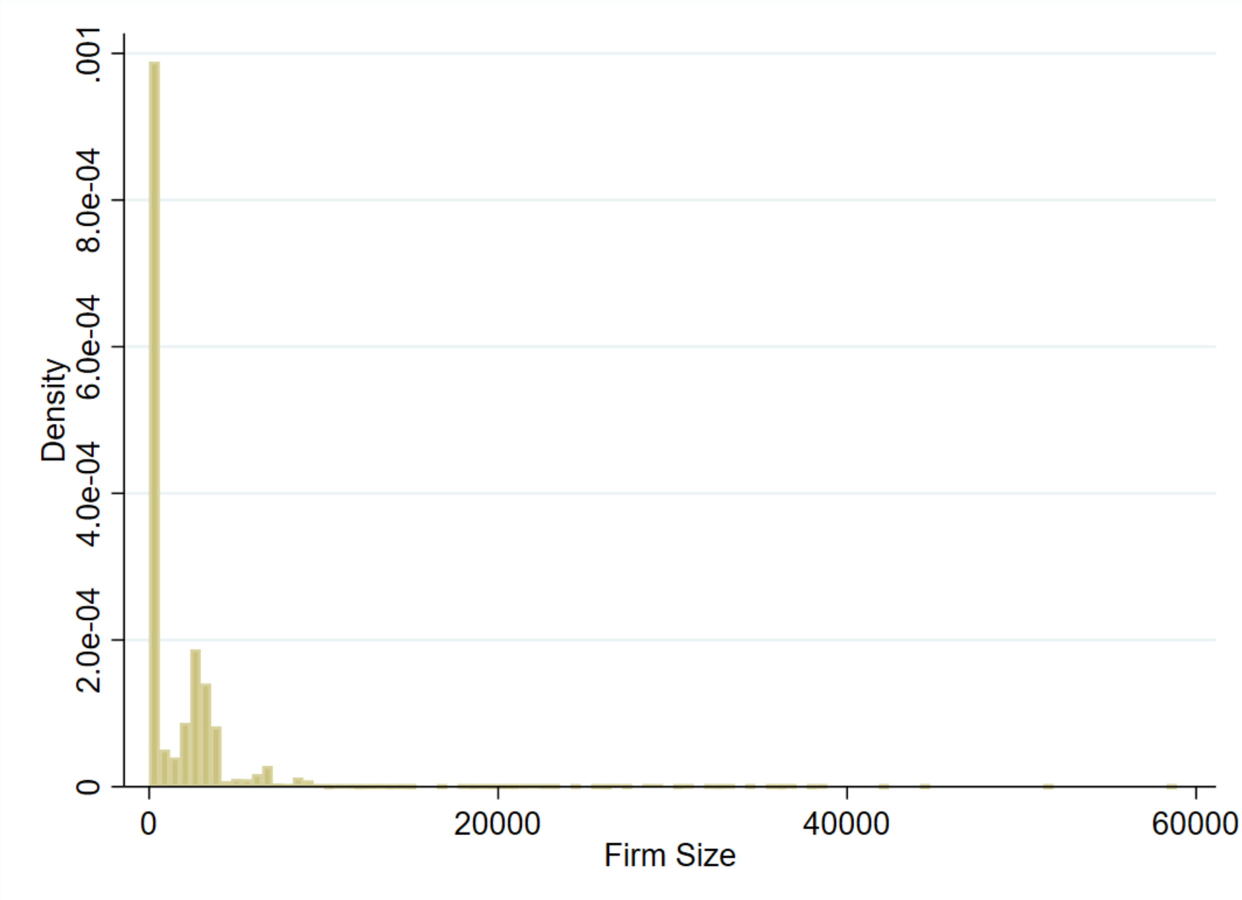


Figure A.6: Establishment Size of Student Jobs- Less than 5000 Employees

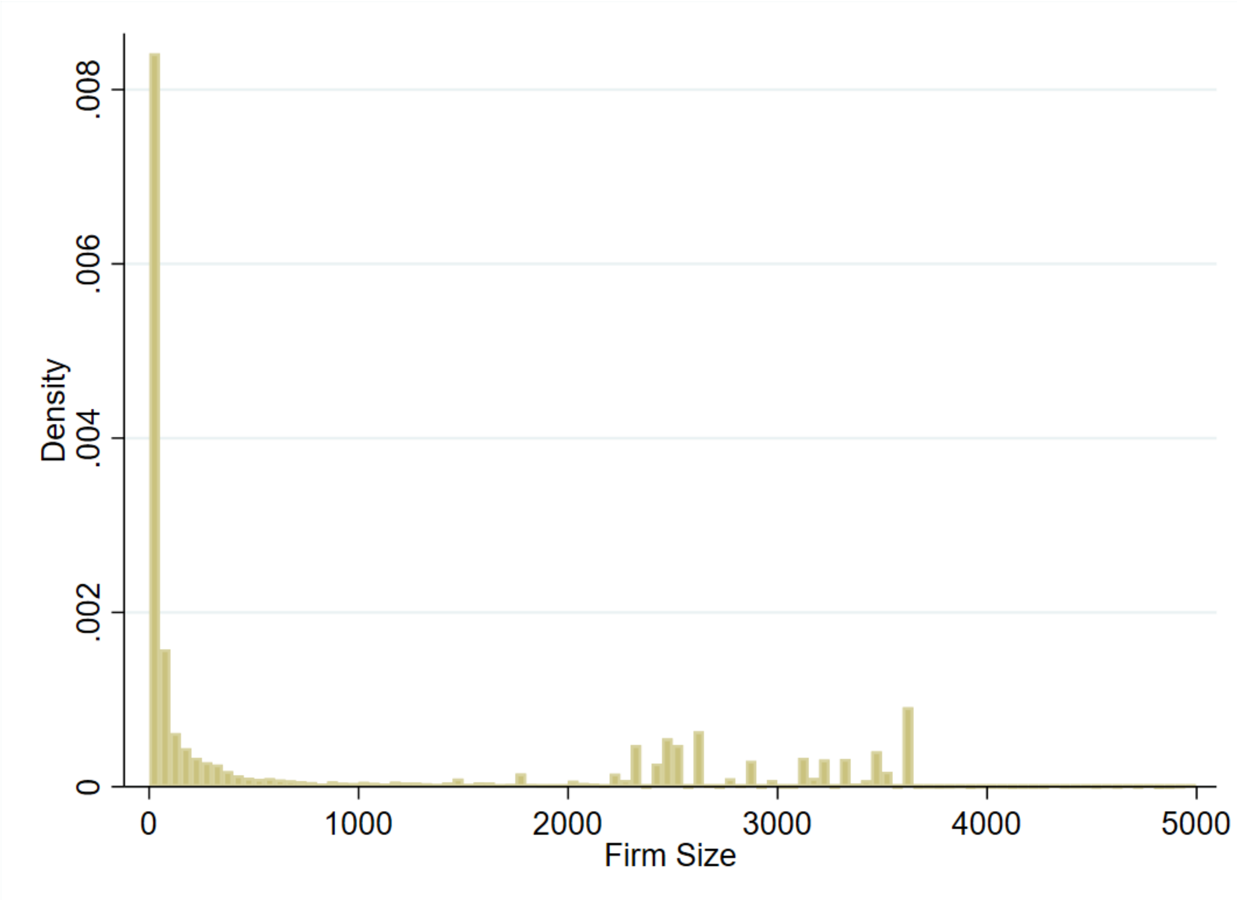


Table A1: Network Characteristics in Other Occupations

	Mean	SD
Student Jobs Network Characteristics - Other Occupations		
Log Average Coworker Wage	4.12	0.61
Log Network Size	3.27	1.29
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	38.76	6.85
Share of Middle Educated Coworkers	0.26	0.27
Share of Highly Educated Coworkers	0.10	0.17
Individuals	3,285	

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