Beyond the "Old Boys' Network": Social Networks and Job Finding at Community Colleges*

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Abstract

Much of the research and popular discourse on social networks in higher education has focused on elite, four-year universities. Little is known about the role of job networks outside of these institutions, despite the fact that the majority of college students do not attend so-called elite colleges. This paper fills a gap in our knowledge by analyzing how classmate networks at community colleges influence job finding. Using transcript data from a state community college system linked to matched employer-employee records, I investigate the effect of taking a class with a peer on the propensity for a student to get a job at the firm where their peer works. To address the concern that students sort into classes in ways that may affect job finding outcomes, I examine whether a student is more likely to get a job at a classmate's firm than at the the firm of a peer enrolled contemporaneously in a different section of the same course. Results indicate that students are 4.1 percent more likely to get a job at a classmate's firm in the three years after the class. This outcome holds up to various robustness checks addressing concerns about students sorting into sections. Results also indicate network effects vary significantly by location, educational performance, and gender. First, classmate networks are more important in rural areas than urban ones. Second, network formation displays positive assortative matching—higher performing students are more likely to get jobs through high performing classmates, and vice versa for lower performing students. Third, while women and men are equally likely to form networks with male classmates, women are significantly more likely to network with female classmates.

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1 Introduction

Social networks play an important role in determining where people work (Topa, 2011; Ioannides and Datcher Loury, 2004). Researchers estimate that at least 50 percent of new jobs are found through informal channels, rather than formal job search methods. (Granovetter, 1974; Topa, 2011). Social networks in college are potentially important in influencing not only early job finding but also career trajectory and lifetime earnings. Because people typically invest in higher education during the earlier parts of their working life, job outcomes out of college are especially critical. Poor job prospects out of college have persistent negative career effects (Kahn, 2010; Oreopoulos et al., 2012).

Social networks in higher education are often conceptualized as an elite school phenomenon—as evoked by the phrase the "old boys' network"—in which well-connected individuals provide exclusive access to opportunities for one another. However, this framing excludes the majority of college students who, by construction, attend a "non-elite" institution. Community colleges alone educate 42 percent of the college student population in the United States (Ma and Baum, 2016). These students on average come from very different backgrounds and go into different types of jobs than peers from elite schools, and they are likely to form and leverage social networks in different ways. How do social networks operate in the absence of the "old boys"?

This paper provides novel insight on how classmate networks at community colleges, also known as two-year colleges, affect job finding. Specifically, I use administrative data from community colleges in Arkansas to i) identify the causal effects of taking a class with a peer on getting a job at a firm where the peer works and ii) assess which factors influence network formation in this setting. To do so, I link student transcripts that contain detailed information on the courses students took from 2004 to 2012 with quarterly matched employer-employee records collected from Arkansas Unemployment Insurance (UI) data.

A key challenge to identification is disentangling network effects from other factors correlated with course selection that may also affect job finding. If classmates are more likely to end up working together than non-classmates, it is unclear a priori if this relationship is due to a network effect or unobservable factors that affect both students' class enrollment decisions and job finding. For example, students who are interested in health professions may be more likely to end up working at the same hospital later on due to shared professional interests, and these interests may also lead them to sign up for the same courses that are geared towards these jobs. Alternatively, some programs or fields at a school may have reputations or connections with certain firms, creating a pipeline effect to the firm for students in those courses. Both of these channels would show an increased propensity for students to end up working with classmates compared to peers who were not classmates, even in the absence of any network effects.

To identify the causal effects of classmate networks, I exploit quasi-random variation in class section enrollment within courses. A course consists of one or more sections that are taught to discrete sets of students but that offer the same content and amount of credit. I examine whether an individual is more likely to get a job at a firm where a classmate works than at the firm of a peer enrolled in a different section of the same course.[1] I interpret an increased propensity to get a job at a classmate's firm relative to a course peer's firm as indication that students use classmate networks to find jobs. My results indicate classmates at community colleges play a significant role in helping each other find jobs. Taking a class with a peer increases the propensity that a student will get a job at a firm where their peer works within three years of their last shared course by 4.1 percent.

The key identifying assumption underlying this design is that while selection into specific courses may be correlated with factors affecting job finding, enrollment into a given section of the same course does not suffer from the same issue. To test the validity of this assumption, I conduct several robustness checks. First, I show that once I condition on the course, there is minimal sorting into sections of the course on observable characteristics. Furthermore, the degree of residual sorting on observables does not predict a higher propensity for a student to get a job at a classmate's firm. Next, I augment the main specification with individual fixed effects, which controls for sorting on certain types of unobservable characteristics, to the degree that individuals who tend to sort on these characteristics also tend to end up in the same section of a course. My results are robust to this specification as well. Finally, I present evidence that my results are not being driven by students signing up for sections with pre-existing network contacts.

In addition to finding significant network effects among classmates, I find that this network effect varies by gender, educational performance, course type, and location. First, I

[1] I refer to a student's classmates in this setting as peers from the same section of a course, since these are the peers with whom a student shares a classroom setting.

find that women are more likely to use classmate networks than men. This result is driven entirely by differences in propensities to form networks with female classmates: Women and men do not differ in their propensity to network with male classmates. However, women are more likely to form networks with female classmates than they are with male classmates, while men do not display a statistically or economically significant to form networks with female classmates at all. Second, I find that no significant overall difference in the propensity for students to get a job through a classmate by academic performance. However, I do find positive assortative matching by performance—that is, high-performing students are significantly more likely to get jobs through high-performing peers and low-performing students are more likely to get jobs through low-performing peers. Third, I find that classmate networks play a more important role for job finding in vocational courses than in liberal arts (i.e. general study) courses. Finally, I find that students attending community colleges in more rural areas are significantly more likely to make use of classmate networks in job-finding than counterparts in urban areas.

This study relates to a large body of work on peer effects in education and contributes to growing research identifying job networks in a variety of social settings.[2] Prior research on education networks has overwhelmingly focused on the role of networks at elite institutions. Kramarz and Thesmar (2013) show that French CEOs from elite colleges are more likely to hire board members from the same institution, and Zimmerman (2019) finds similar results in management hiring patterns for graduates from the same degree cohort in elite Chilean schools.Marmaros and Sacerdote (2002) find that students at Dartmouth College use alumni and members of their fraternity or sorority for job-finding after graduation. Michelman et al. (2021) study exclusive campus clubs at Harvard University in the early 1900s, finding high socioeconomic returns to joining exclusive campus clubs, whose membership is dominated by students from prestigious private high schools. These studies provide important information to our understanding of social networks in higher education and reinforce the importance of the "old boys' network" in helping people at elite schools get jobs.

However, these results are not necessarily applicable to the broader student population. Although much of the rhetoric and research on educational networks focuses on elite settings,

[2]Residential neighbors: Topa (2001), Bayer et al. (2008), and Hellerstein et al. (2011). Former coworkers: Cingano and Rosolia (2012) and Hensvik and Skans (2016). Ethnic groups: Dustmann et al. (2016) and Beaman (2012). Family members: Kramarz and Skans (2014). See Sacerdote (2011) and Epple and Romano (2011) for a survey of the peer effects literature.

these schools educate a very small fraction of the population. Most students do not attend highly selective institutions with peers from privileged and connected backgrounds. Given that students who attend community colleges typically come from different social settings and work in a different part of the labor market than their elite college peers, it is unclear whether we should expect social networks to play the same role in job finding at these institutions. Moreover, empirical strategies used to identify network effects at elite institutions are often not applicable in non-elite settings. For example, Zimmerman (2019) tracks social networks through year- and degree program-specific cohorts, but students from communities colleges pursue a diverse array of education tracks and are thus not in well-defined cohorts. Kramarz and Thesmar (2013) focus on social networks in the boardroom using data from the Paris stock exchange, tracing networks through shared university and civil service backgrounds. However, unlike peers from elite colleges, community college students are not over-represented in high-profile positions that are readily tractable using public data. Marmaros and Sacerdote (2002) and Michelman et al. (2021) measure network relationships through campus residence and club membership, but community college students typically do not live on campus or participate in Greek life or other exclusive campus clubs. These aspects of two-year colleges pose challenges to using cohorts, roommates, club membership or public corporate data for identification, as prior studies have done. This paper makes a new contribution to the existing literature both by shedding light on the importance of classmate connections for job-finding at community colleges and in using a novel source of variation to identify networks at "non-elite" institutions.

In the remainder of the paper, Section 2 discusses the data and empirical setting for the paper. Section 3 describes the empirical strategy. Section 4 presents the main results of the analysis, as well as robustness checks and heterogeneity analyses. Section 5 concludes.

2 Data and Empirical Setting

This section begins by describing the data and empirical setting of this analysis. Next, I present summary statistics. Finally, I explain how the data are used to construct network links.

2.1 Data

Data for this paper come from the Arkansas Department of Higher Education. The dataset includes enrollment records for all students who attended a public college in Arkansas between academic years 2004 and 2012.[3] For each student, I observe information on background characteristics including gender, part-time or full-time attendance status, high school information, and college degree attainment. Additionally, transcript records provide information on the classes students take, instructor information, and credits earned for each class.

I link students to matched employer-employee labor market records using data collected from Arkansas Unemployment Insurance records.[4] These records contain quarterly observations on all individuals working for Arkansas from 2001-2011, minus uncovered sectors.[5] The panel allows me to track students over time through a firm identifier number, as well as a six-digit industry code of the firm.[6] If a student works multiple jobs in a quarter, the records report the job with the highest earnings in the quarter. If an individual does not appear in the labor market files in a given quarter, I am unable to disentangle whether she is unemployed, employed outside of Arkansas, or employed in an uncovered sector.[7]

This paper focuses on two-year college students. Arkansas has a total of 22 public two-year colleges, and during this time period, 44% of students enrolled in a public college in Arkansas in the data attend a two-year school, which is similar to the nation-wide share of college students enrolled in community colleges, 42% (Ma and Baum 2016). While I have data on four-year college students in Arkansas, I do not include them in this analysis because the research design is uniquely suited for a community college setting for multiple reasons. First, I look at classmate networks in this study, and classmates represent a relatively more prominent source of student interaction at two-year colleges. Four-year colleges often have a much stronger presence of potentially confounding sources of student networking such as residential dorms, Greek life, on-campus clubs and organizations, etc. Second, two-year college students are more likely to search for jobs in a local labor market, making them

[3] Academic year 2004 denotes semesters Fall 2003-Spring 2004 and so on for subsequent academic years.

[4] The information in these data are comparable to that found in the Longitudinal Employer-Household Dynamics (LEHD) dataset, although I only observe records for individuals working in Arkansas.

[5] Individuals working in uncovered sectors in this data line constitute a very small portion of overall employees in the state. These include self-employed individuals and federal government employees.

[6] Industries are classified using North American Industry Classification System (NAICS) codes.

[7] Analysis from the American Community Survey indicates that in 2000, approximately 12% of individuals in Arkansas with the education level of the sample in this dataset no longer lived in the state five years later.

more tractable in my data set, as well as potentially increasing the salience of peer networks. Third, two-year colleges have smaller classes on average than four-year counterparts and typically do not involve large lecture classes: mean class size for two-year colleges in this dataset is 17 students, and fewer than 5% of classes contain more than 30 students. This is important for the analysis because different sections of a course actually take place in separate classroom settings, as opposed to representing discussion sections within a large lecture class.

Table 1 describes the composition of students in the sample. From 2004-2012, I observe over 900,000 student-by-semester observations. Approximately 63% of students in the two-year college system are female, similar to national trends.[8] Slightly over half of students enroll as part-time, and 62% students are employed in a given term. The average student in the sample is 27 years old, with a median age of 24, and 94% of students attended high school in Arkansas.[9] Approximately one quarter of enrollees are transfer students, and students take an average of 3.09 classes a semester.

2.2 Class Structure

This section describes the structure of classes in this setting. Figure 1 shows a diagram of how classes are organized. Within a school and term, there are multiple courses offered on different topics. Below the level of courses are class sections. A course consists of one or more sections that are taught to discrete sets of students but offer the same content and amount of credit. I refer to a student's classmates in this setting as peers from the same section of a course, since these are the peers with whom a student shares a classroom setting.

The empirical strategy uses variation in section enrollment within courses to identify network effects. Accordingly, I make two sample restrictions: First, I limit the sample to students in courses containing multiple sections. Second, I restrict the sample to sections in a course taught by the same instructor to address the concern that instructors may affect job finding outcomes.[10] Approximately 42% of classes remain after these two restrictions.

Table 2 shows the characteristics of class sections in the sample. The mean GPA of

[8] In 2012, 57% of two-year college students and 56% of four-year college students nation-wide were female (USDOE, 2017).

[9] Nationally, the average of of two-year college students is 28 years old (Kolesnikova and Shimek (2008)).

[10] For example, if an instructor knows employers at a certain firm and helps her students get jobs there, we would see in the data that students in a section taught by her are more likely to work at this firm. However, this would not be due to a peer network effect.

Table 1: Student Characteristics

Female (%)	63.37
Part-time (%)	54.29
Employed (%)	61.42
In-State (%)	93.90
Transfer Student (%)	24.86
Age	26.87
	(9.07)
Number of Classes	3.09
	(1.82)
N	944,003

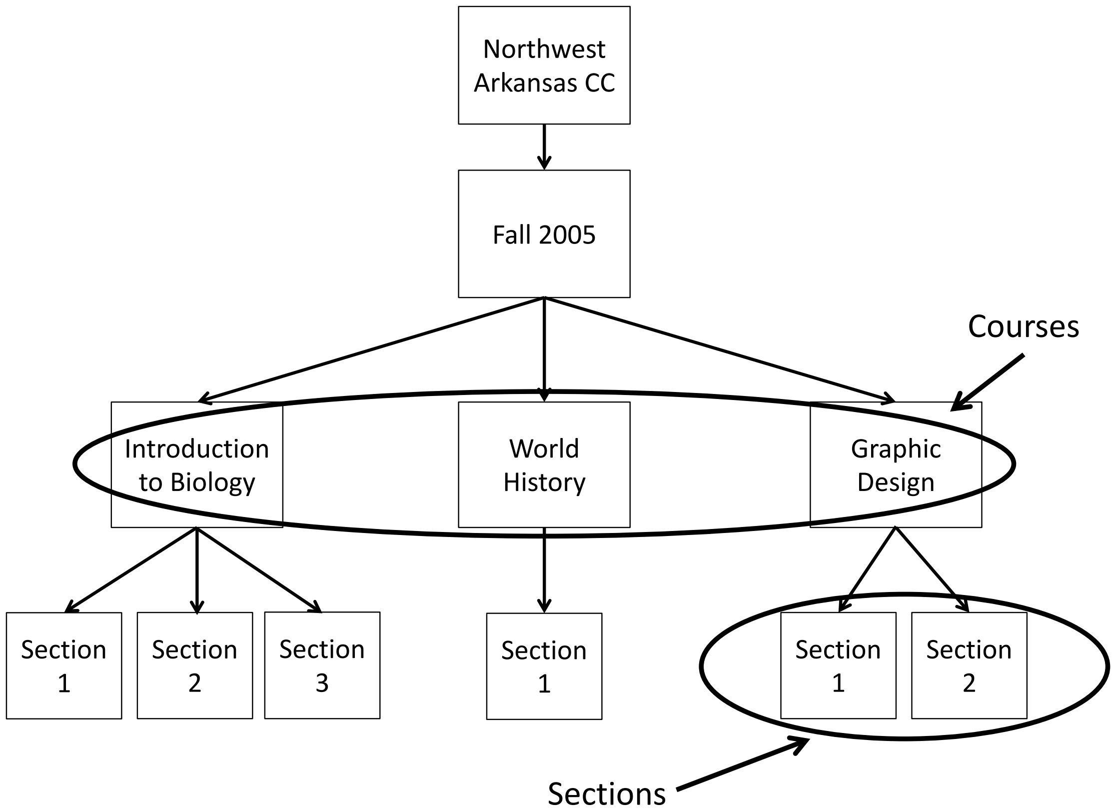
Arkansas Two-Year College Students, 2004-2012. Observations denote student×semester units. Table displays means (standard deviations in parentheses). Age is imputed from year of high school graduation, assuming students are 18 at the end of high school. Median age is 24.

students in a section is 2.62 (out of a 4 point scale), and 57% of sections are taught by female instructors.[11] On average, there are 17 students per section. Sections with one student are dropped from the sample since students in these classes do not have classmates with whom they can network ($\leq$ 1% of student×class observations). Figure 10 in the appendix shows the distribution of students per section. The modal class section has 21-25 students, and less than 5% of sections have more than 30 students. Table 2 also provides information on the subject classification of courses in the sample, classified using 2010 Classification of Instructor Program (CIP) codes. The most common subjects are Basic Skills and Remedial Education (19.2%), Social Sciences (14.2%), English (12.7%), Business, Management, and Marketing (9.4%), and Biology (5.6%)

To understand how the analysis sample compares with the full sample of students and classes, I include descriptive tables comparing the two samples in the appendix. Table 11 juxtaposes characteristics of students in the restricted sample with the original sample. Students in the analysis sample are very similar to the full sample of students both in terms

[11]Note: GPA data are inconsistently reported across sections, and I only observe GPA for 66% of the full sample of section observations.

Figure 1: Structure of Classes



Note: Figures displays a simplified example of a school that offers three courses in a term. Each course consists of a set of one or more sections that are taught to discrete sets of students but offer the same content and amount of credit.

of observable characteristics and the number of classes they take per semester. Table 12 compares characteristics of class sections in the analysis sample with the full sample. Sections in the analysis sample have a similar class size composition, mean GPA, and instructor gender distribution as the full sample. In both samples, Basic Skills and Remediation is the most prevalent course subject, although these courses occupy a higher share of classes taken in the analysis sample compared to the full sample. There are a slightly higher proportion of Social Sciences and English classes and lower proportion of Business and Health Professions classes in the analysis sample as well. The 14 most common subjects in the analysis sample make up 90% of the courses in the sample, and these same courses make up 86% of the courses in the full sample. Overall, Table 11 and 12 indicate the analysis sample is fairly representative of students and classes in Arkansas two-year colleges, at least on observable

Table 2: Class Section Characteristics

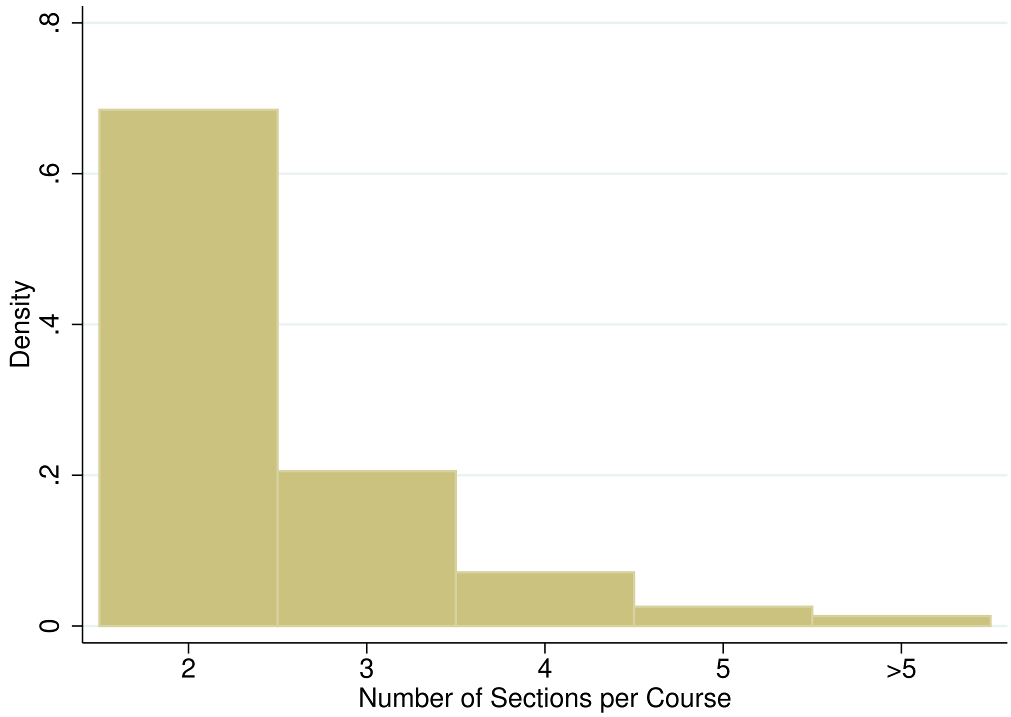
Section Size	17.37
	(8.20)
Mean GPA	2.62
	(0.96)
Female Instructor (%)	56.81
Course Subject (%)	
Basic Skills and Remedial	19.2
Social Sciences	14.2
English	12.7
Business, Management, and Marketing	9.4
Biology	5.6
Mathematics and Statistics	5.1
Computer and Information Sciences	4.5
Health Professions	4.1
Visual and Performing Arts	4.0
Humanities	3.2
Physical Sciences	2.2
Communication, Journalism	2.1
Mechanic and Repair	1.9
Engineering	1.7
Other	10.1
N	75,833

Arkansas Two-Year College Classes, 2004-2012. Units of observations are class sections. Table displays means (standard deviations in parentheses). Sections with one student have been dropped from the sample. Course subjects are categorized using 2010 Classification of Instructor Program (CIP) codes. Note: GPA data are inconsistently reported across sections, and I only observe GPA for 66% of the full sample of section observations.

characteristics.

The final sample consists of 75,833 sections nested in 31,590 courses. In this sample, each course contains multiple sections, and each section in a course group shares the same instructor. Figure 2 shows the distribution of sections per course. Approximately 68% of (instructor-specific) courses contain two classes, and fewer than 2% of courses contain more than five sections.

Figure 2: Distribution of Sections per Course



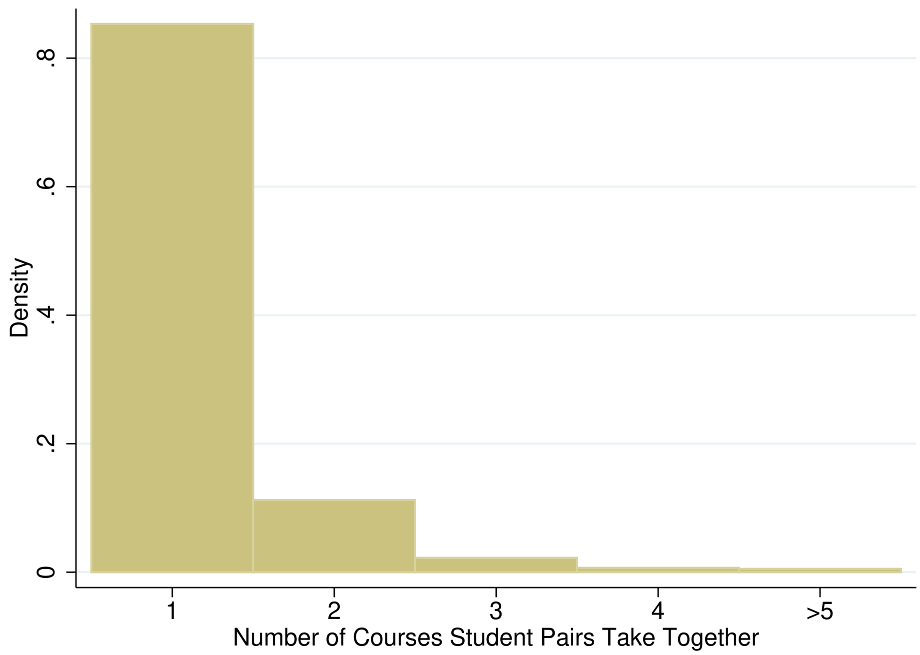
Note: Histogram the number of sections in each course of the final analytic sample of 31,590 courses.

2.3 Network Analysis: Data Set-up

To detect the use of classmate networks in job finding, I examine whether taking a class section with a peer increases the propensity for a student get a jot at the firm where their peer works. From the student-level observations in the raw data, I construct a dyadic data set consisting of students, i, matched with peers, j. I define a student's peers as the set of students with whom a student shares at least one course. For each dyadic observation, I observe in the data whether $\{i, j\}$ were former classmates for each course shared (i.e. whether they were in the same section of the course), as well as whether i ends up working in a firm where j was incumbent at time of hire. Figure 3 shows the distribution of the number of courses a pair of students share, conditional on sharing at least one course. The vast majority of student pairs, over 85%, only share one course. Note that matched pair observations are not interchangeable in this setting since order of getting hired matters: $\{i, j\} \neq \{j, i\}$, highlighting the inherent asymmetrical nature of network relationships.

To give a descriptive sense of the role of classmates in job-finding, Figure 4 displays the

Figure 3: Distribution of Number of Courses Student Pairs Share



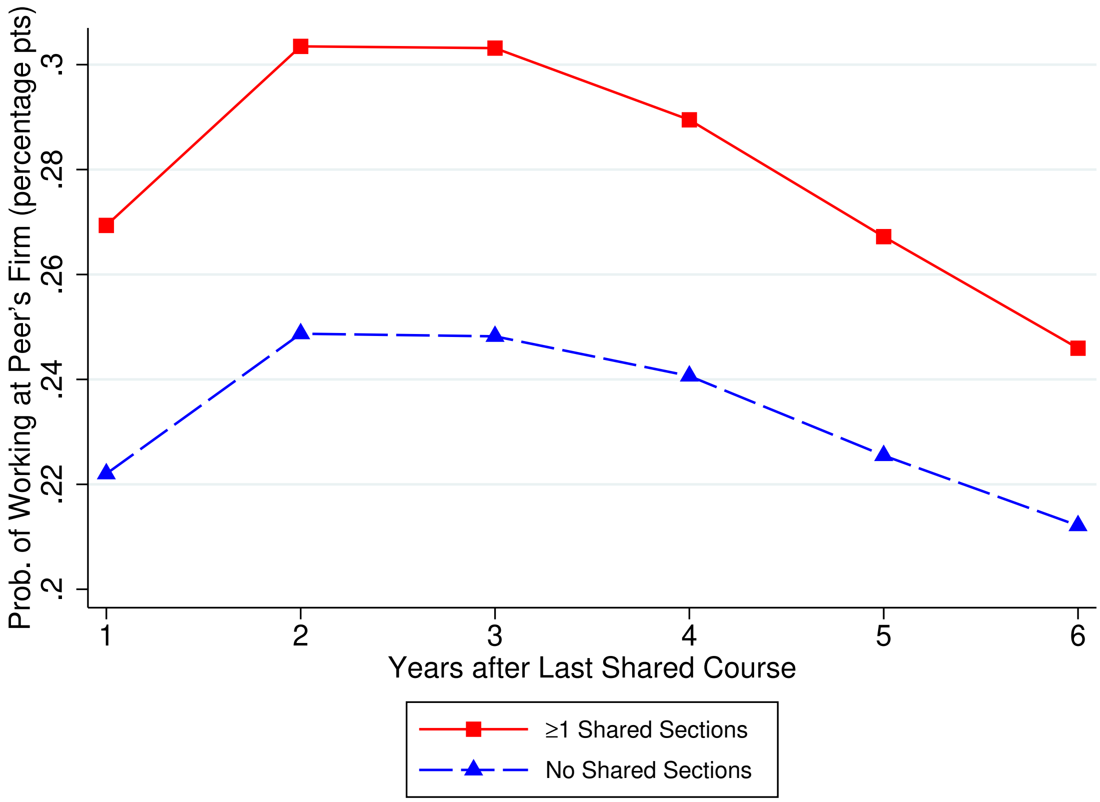
Note: Histogram displays number of courses a pair of students share at a two-year college, conditional on sharing at least one course.

probability that x years after their last course together, an individual works at a firm where her peer was incumbent at time of hire. The graph compares the propensity of i to get a job at a firm where j is incumbent for pairs $\{i, j\}$ who were former peers in the same section of a course, compared to pairs who were in different sections of a course a course. If $\{i, j\}$ enrolled in multiple shared courses, I categorize the pair as former classmates if they enrolled in the same section for at least one of the shared courses. The x-axis denotes the number of years since i and j took their last course together, and the y-axis denotes the probability that i works at a firm where j was working at the time of i's hire. I observe pairs up to six years after their last course together in the data.

For all years of analysis, the Figure 4 indicates a higher proportion of students start working at a peer's firm when the pair shared at least one section together, compared with pairs with no shared sections. A two-sample test of proportions shows that these values are significantly different at a 95% confidence level for each year.

While patterns in Figure 4 are suggestive that classroom networks may play a role in job-finding, the values in this graph should not be interpreted as causal for a couple of reasons.

Figure 4: Probability of Working at Peer's Firm



First, this figure does not control for what course(s) the pair enroll in. The propensity for a pair of students in a given course to end up that the same firm, independent of network effects, may vary across courses. For example, suppose a given location has only one healthcare firm (a hospital), which hires all healthcare workers in the area, and that there are 10 accounting firms in this same area that hire business professionals. If students who take health classes tend to go on to work in health professions and students who take business classes are more likely to go into business professions, this means students in health classes are mechanically going to be more likely to sort into the same firm than students in business classes, even without any social network effects. Without holding what course(s) the pair enroll in constant, it is not possible to disentangle network effects from baseline differences in finding jobs at the same firm. Second, Figure 4 does not allow for effects to vary based on the number of courses and/or classes within these courses that students share. This makes it infeasible to identify the effect of a marginal increase in an additional shared section on the propensity for a student to get a job at a firm where their peer works from the figure.

The next section introduces the empirical strategy, which addresses these limitations of the descriptive analysis to provide causal estimates.

3 Empirical Strategy

To identify the effects of classmate networks on job-finding, I run the following pair-level regression:

$$F_{ijc} = \rho_c + \gamma N_{ij} + \epsilon_{ijc} \tag{1}$$

where i and j represent two individuals who take a bundle of courses, c, together. The outcome of interest, F_{ijc} is an indicator variable equaling one if i works at a firm where j was incumbent when i was hired, and zero otherwise. As noted in the previous section, I can estimate F_{ijc} for different time frames after a pair's last course together. To capture the effect of classroom interaction, N_{ij} measures the number of sections i and j shared, and ϵ_{ij} denotes the error term. The coefficient of interest, γ, captures how much taking an additional section together increases the propensity for i to work at a firm where j is incumbent. A positive estimated value γ indicates classmates serve as a channel through which students are finding jobs.

One concern is that the correlation between the number of classes i and j take together and the propensity for i to get a job at a firm where j works may not be causal since students do not choose their courses randomly in this setting. Thus, other factors correlated with course selection could also affect job finding outcomes. First, since students select courses non-randomly, it may be that unobserved factors affecting course choice also affect the firms at which students seek employment. Second, some jobs may have certain degree or accreditation requirements, and consequently firms hiring in those jobs may disproportionately draw from courses associated with those degrees or programs. Finally, if certain programs or tracks of study have strong reputations or connections with certain firms, this could lead to a pipeline hiring effect in the associated courses. To control for these other factors correlated with course enrollment, I include a course bundle fixed effect, ρ_c, restricts comparison of observation $\{i, j\}$ to the set of pairs that took the same bundle of courses together as i and j. The course bundle fixed effect captures the baseline propensity for student to start working at a firm where a peer with whom she shares a set of courses c is incumbent, independent of classroom interaction effects. The course bundle fixed effect also holds constant the number of courses a pair takes together, isolating variation to sections shared within that set of courses. Intuitively, identification comes from comparing the number shared sections for a pair $\{i, j\}$ with the number of shared sections for other pairs of individuals who took the same set of courses together. Since the majority of pairs only ever share one course, ρ_c acts as a single course fixed effect for most observations.

The key identifying assumption in this strategy is that while individuals may sort non-randomly into the courses they choose to take, they do not sort into sections within a course in a way that also affects subsequent firm placement. This assumption is motivated by a few considerations. First, within a course, each section has the same course title and course description and offers the same number and type of credits, which eliminates much of the heterogeneity that drives student selection across courses. Furthermore, I have restricted analysis to variation in section enrollment within courses taught by the same instructor. This accounts for selection into certain instructors, as well as an instructor-specific job placement effects. Second, as indicated in Table 1, 61% percent of students hold jobs while in school and students take on average 3.1 classes per semester. Thus, even if students would like to select into sections, work or other academic obligations may place constraints on how much choice they have. Finally, since one limitation of the data is that I do not observe the time of day or day of week of a section in the data. I further augment Equation 1 by controlling for the attendance status (part-time vs. full-time) of both i and j to account for the fact that part-time students may be more constrained to courses that take place at certain times or days of the week.

Potential Threats to Identification

A causal interpretation of Equation 1 requires that students do not sort into sections within a course in ways that affect their propensity to end up working at the same firm. While the previous paragraph provides some motivation for why this holds, I also empirically test this assumption. Specifically, I assess two types of sorting: systematic and pair-wise. First, students may sort systematically into different sections of a course along unobservable characteristics. If these unobservable characteristics also affect firm choice later on, this could upwardly bias estimates of network effects. Second, students may enroll in the same sections on the basis of pre-existing friendships. If friends tend to share unobservable characteristics that make it more likely they will end up at the same firm, independently of network effects, this would also upwardly bias network estimates.

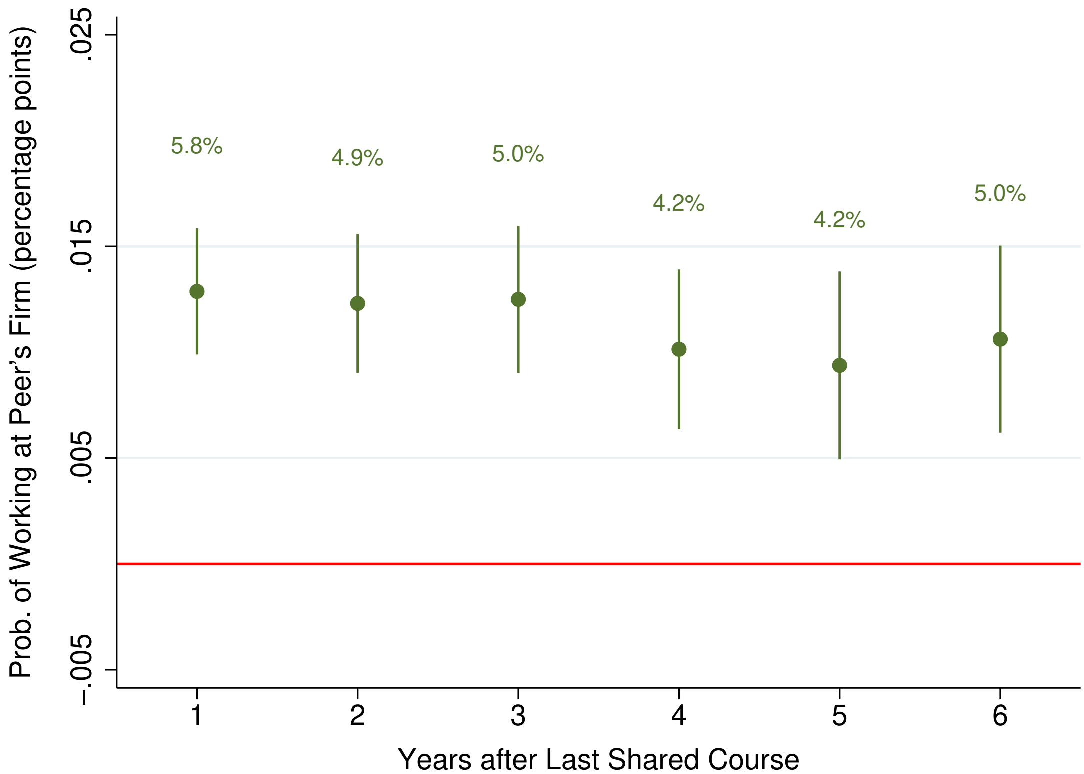
In Section 4.2, I conduct a number of empirical tests on the plausibility of the identification strategy against potential threats. First, I analyze the correlation on observable characteristics between students and peers in their section, conditioning on overall course demographics. While this evaluation does not explicitly provide information on the amount of sorting on unobservables, Altonji et al. (2005) show the amount selection on observables to be proportionally informative of the amount of selection on unobservables. Minimal amounts of selection on observables within sections of a course group would provide support that results are not being driven by student sorting. Second, I conduct two direct tests on the role of sorting on observables to see if heterogeneity in observable characteristics across sections is able to explain a statistically significant portion of the results. Third, I estimate an augmented version of Equation 1 using individual fixed effects, which addresses sorting on certain types of unobservables. Specifically, if some individuals tend to get a job at the same firm with those they take a course with and these individuals sort themselves into certain sections, Equation 1 would over-state the true classmate network effect. Finally, I test whether students tend to sign up for sections with pre-existing network contacts in a way that significantly affects the outcome of interest. I proxy for pre-existing network contacts using geographic proximity between a pair, as well as whether they worked together previously. Overall, these robustness checks provide support that the education main finding that taking a class with a peer increases the propensity that a student will get a job at a firm where their peer works is not driven by students sorting into sections within courses.

4 Results

4.1 Main Results

Figure 5 displays estimation results from Equation 1. Coefficients are estimated separately for each year. The x-axis denotes years after a pair $\{i, j\}$ takes their last course together. The outcome of interest is an indicator for whether x years after their last course together, individual i works at a firm where individual j was working at the time of i's hire. I observe individuals up to six years after their last shared course. Coefficient estimates have been multiplied by 100 to represent percentage points, and estimates include controls for the attendance status (part-time or full-time) of i and j I cluster standard errors by course bundle, and estimates are displayed with 95% confidence intervals. Numbers above point estimates represent the percent increase of the effect from baseline propensity for an individual to work at the firm of a peer who took the same set of courses.

Figure 5: Effects of Sharing Additional Class Sections on Probability of Working at Peer's Firm



Note: Coefficient estimates have been multiplied by 100 to reflect percentage changes, and standard errors are clustered by course bundle. Estimates are displayed with 95% confidence intervals. Numbers above point estimates represent the percent increase of the effect from baseline propensity for an individual to work at the firm of a peer who took the same set of courses. Results are displayed in table form with information on baseline value and sample sizes in Table 13 of the appendix. Estimates include controls for the attendance status (part-time or full-time) of i and j.

Results indicate taking an additional section with a peer significantly increases the propensity to work at a firm where the peer was incumbent at time of hire for each of the first six years after taking courses together. For example, taking an additional section together increases the propensity for an individual to work at a firm where her peer is incumbent three years after the course by 0.0125 percentage points. This represents a 5.0% increase in the baseline propensity for a student to work at a firm where a peer who took the same set of courses works, which is 0.248 percentage points. These results are presented in table form with information on baseline values and sample sizes in Table 13 of the appendix.

Since estimates are positive and statistically significant for all years of analysis, I multiple years together in Table 3 for subsequent analyses. Specifically, I look at the effects of taking a section with a peer on the propensity of getting a job at a firm where the peer is incumbent sometime within the first three years after the last course taken together. I choose this specification because while I observe students for up to six years in the data, I face a tradeoff between increasing the number of years I follow a pair and sample size, since I cannot observe later cohorts of pairs for as many years.[12] I aggregate outcomes over three years to balance observing student outcomes over more years and losing sample size.

Table 3 presents results on the aggregate effects of classmate networks on job finding within three years of sharing a course. The outcome of interest is an indicator variable taking a value one if student i gets a job at the firm where peer j works within three years of the last shared course and taking a value of zero otherwise. As before, coefficient estimates measure the effect of taking an additional section with a peer on the outcome, holding constant the bundle of courses the pair shares. Column (1) shows estimation results using a linear specification in number of sections, analogous to that in Equation 1. Column (2) incorporates a quadratic term in number of sections shared to capture non-linearities in sections shared on job-finding.

Coefficient estimates indicate taking an additional section with a peer has a positive and statistically significant effect on getting a job at a firm where a student's peer works within three years after the pair's last course together. The linear specification in column (1) indicates taking an additional sections with a peer increases the propensity that the student gets a job at a firm where their peer works within three years of their last course together by 0.025 percentage points. The quadratic specification in column (2) shows a statistically significant effect of 0.027 percentage points on the number of sections shared on the outcome of interest. The estimated coefficient on the quadratic term of number of sections shared is noisily estimated not statistically significant. Given these results, I cannot reject the hypothesis that the effect of a one-unit change in number of sections shared is linear. One

[12] For example, since data contain labor market earnings information through the first two quarters of 2012, I observe pairs who took their last course together in 2004 for up to six full years in the labor market. However, for a later cohort of pairs who took their last course together in in 2009, I only observe two years of labor market information. This can be seen from the sample sizes in Table 13, which decrease as I look at outcomes for more years out.

Table 3: Aggregate Effects of Sharing Additional Class Sections on Probability of Working at Peer's Firm

	(1)	(2)
Baseline	0.612	0.612
Number of Sections	0.0249***	0.0266***
	(0.00279)	(0.00363)
(Number of Sections)^2		-0.0602
		(0.0634)
Course Bundle FE	X	X
N	43,792,204	43,792,204

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Baseline and coefficient estimates are multiplied by 100, meaning estimates represent percentages. Outcome: whether student i gets a job at the firm where peer j works within three years of the last shared course.

reason for the lack of precision in coefficient estimates of the quadratic term may be that the vast majority of pairs (over 85%) only share one course together, as shown in Figure 3. The baseline propensity for an individual to get at a job at a firm where a peer who took the same set of courses works is 0.612%. Thus, taking an additional section with a peer increase the propensity for a student to start working at the peer's firm within three years by 4.1-4.3% from the baseline.

While estimated effects of classroom exposure on job-finding at a peer's firm are small in magnitude, they constitute a significant increase from the baseline probability of getting a job at a firm with an incumbent peer since baseline values are also very small. The reason for small baseline values is a function of the pair-level structure of the data: Each student has many classmates on average, who are spread out over many firms. Mechanically, this constrains the mean probability that for any given student pair observation, the student ends up working at her peer's firm. Thus, overall, findings indicate classmate networks play an economically and statistically significant role in helping students at two-year colleges find jobs.

4.2 Robustness

As detailed in Section 3, identification of network effects in this setting relies on the assumption that students do not sort into sections within a course in ways that affect their propensity to end up working at the same firm. This section provides multiple empirical checks on the validity of this assumption.

A. Examining Sorting on Observables

To assess whether student sorting on unobservable characteristics into sections within a course is driving results, I first analyze the correlation on observable characteristics between students and peers in their section, conditioning on overall course composition. While this evaluation does not explicitly provide information on the amount of sorting on unobservables, the degree of selection on observables is informative of the amount of selection on unobservables.[13] Following Bayer et al. (2008), for each section in the sample, I randomly select one student. Next, for each observable characteristic of interest in the data, I calculate the mean value of the characteristic of the non-selected students in the section, in order to construct a measure of average section characteristics. I sample only one individual per section in order to ensure that estimates are unbiased by the fact that each individual would significantly affect average group characteristics if multiple individuals per section were sampled.

Table 4 shows correlations along observable characteristics. Column 1 shows unconditional correlations, and column 2 shows correlations conditioned on course fixed effects. To obtain values in column 2, I first regress both individual and section measures separately on course fixed effects and then report the correlation between the residuals. These findings isolate the portion of the overall correlation to sorting patterns across sections within a course. As expected, results in column 1 show a significant degree of sorting across courses. Reassuringly, column 2 shows that with the addition course fixed effects, correlation on observable characteristics falls conosiderably. For example, the correlation between whether an individual is female and the proportion of peers in her section who are female is .344 overall, but this value falls to .068 with the addition of course fixed effects. On average, the addition of course fixed effects reduces estimated correlations by 76% for observable characteristics, and the average correlation between individuals and peers across characteristics is .049.

Although correlation of characteristics in Table 4 are much smaller after conditioning for course fixed effects, these values are not identical to zero. Thus, I next analyze whether remaining sorting into sections along observables after conditioning for course fixed effects would predict a significant higher probability of an individual getting a job at a firm with an

[13] Altonji et al. (2005) provide a detailed analysis of this relationship.

Table 4: Correlation between Individual and Average Characteristics of Peers

	Unconditional (1)	Conditional on Course (2)
Female	0.344	0.068
Employed	0.331	0.072
In-State	0.282	0.028
Transfer Student	0.340	0.065
Age 18-21	0.230	0.066
Age 22-26	0.056	0.021
Age 27+	0.078	0.026

Values shown represent correlations between individual characteristics and corresponding mean group characteristics of other individuals in the same section. Column 1 shows unconditional correlations, and the column 2 shows correlations conditional on course fixed effects.

incumbent same-section peer. The intuition behind this exercise is to understand whether differences in student composition on observables across sections explains any of the network effects measured in the main results. To do so, I extend Equation 1 to allow for heterogeneity along pair-level covariates:

$$F_{ijc} = \rho_c + \beta_1' X_{ij} + (\gamma + \beta_2' X_{ij}) N_{ij} + \epsilon_{ijc} \tag{2}$$

where X_{ij} represents a vector of pair-level covariates describing i and j for each characteristic listed in Table 4. In Equation 2, $\beta_1' X$ measures how the baseline propensity for an individual to start working at a firm with a course peer with whom they share no sections varies based on observable characteristics for each attribute of i and j. I estimate $\hat{\beta}_1'$ and use this estimation to test whether the correlation on observables across sections of a course would lead to a significantly higher predicted probability for a student to work at a firm where a peer with whom they a section works, compared to peers from the same course with no shared sections. I restrict this analysis to pairs who took one course together, which represents over 85% of pairs, in order to isolate predicted propensities due to variation in shared sections for pairs who shared the same number of courses. Specifically, I compare the estimated value of $\hat{\beta}_1' X$ for pairs who were not in the same section with the predicted value of $\hat{\beta}_1' X$ for pairs who were in the same section. This comparison indicates whether differences in block-level correlation on observable characteristics would lead to a higher predicted propensity for an individual to start working at the same firm as a same-section peer, as opposed to a different-section peer. If the estimated value of $\hat{\beta}_1'X$ is much higher for same-section pairs, this would suggest that sorting into section on observables may play a significant role in driving the finding that taking a section with a peer leads to a significant increase in the propensity to get a job at the firm where the peer works.

I estimate Equation 2 separately for each year τ after the pair's last course together, $\tau \in \{1, 2, ..., 6\}$. Table 5 presents predicted propensities for a student to get a job at the firm where their peer works τ years after a course, for pairs not in the same section with pairs who were in the same section. Results indicate that for all years of analysis, the estimated value of $\hat{\beta}_1'$ predicts that the propensity to work at a firm where a peer is incumbent is very similar for pairs who shared a section and those who did not. For example, three years after the course, the predicted probability that an individual works at a firm where a peer she shared a section with was incumbent at time of hire and the probability of working at a firm where a peer she didn't share a section with was incumbent are both .285 percent. Findings in Table 5 provide support that the small remaining amount of sorting on observables within courses do not drive the increased propensity for an individual to get a job at a firm where a peer from the same section works compared to a firm where a peer from a different section of the same course works.

Table 5: Counterfactual Predicted Propensities

τ	Different Section	Same Section
+1 year	0.239	0.238
+2 years	0.277	0.278
+3 years	0.285	0.285
+4 years	0.281	0.281
+5 years	0.264	0.265
+6 years	0.253	0.253

Numbers in table represent the predicted propensity for an individual to work at a firm where the peer is incumbent, τ years after their last course together. Estimates are reported as percentage points.

B. Estimation Using Restricted Sample

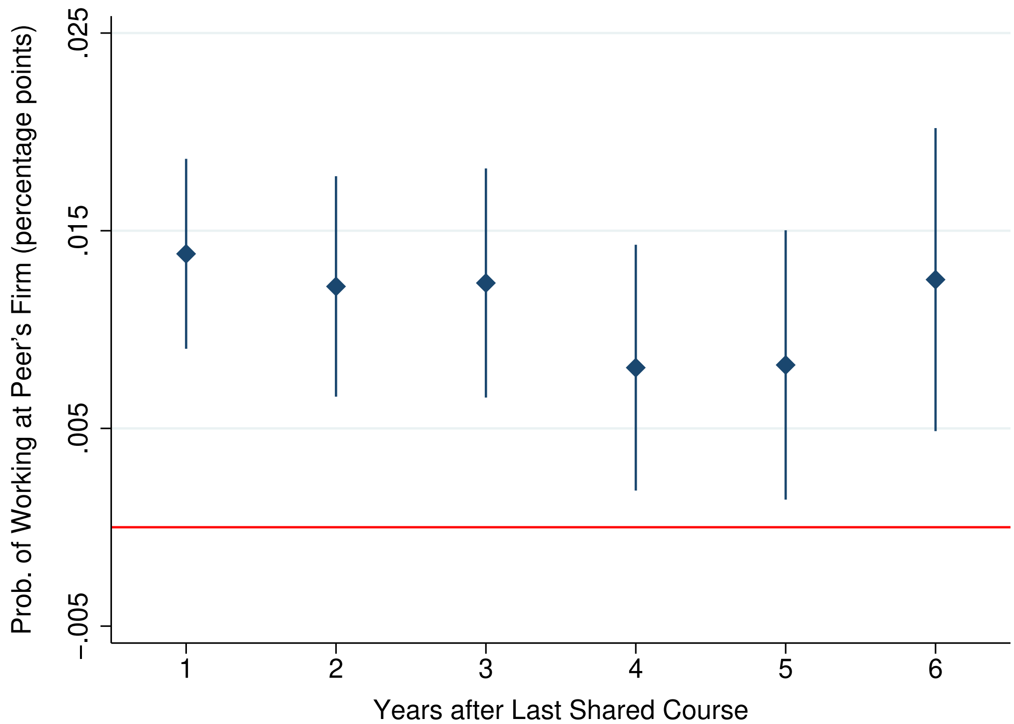
Next, I provide further testing for the robustness of results to sorting concerns by estimating network effects on subsamples of courses that display the least amount of within-course student sorting on observable characteristics. I run two analyses, one on the 50 percent of schools and oon on the 50 percent of course subjects that display the lowest sorting across sections within a course. To do so, for each school (or course subject) in the sample, I analyze the correlation between individual and average characteristics of peers in her section, conditional on course, as in column (2) of Table 4. I then take the average correlation across all observable characteristics. I select the 50% of schools (or course subjects) with the lowest average correlations to use for the restricted subsample.

Next, I re-estimate Equation 1 using these two subsamples and assess whether results still hold for these samples. Since these sample restrictions significantly change the composition of the courses analyzed, I do not expect results to be identical to main results in Figure 5 and Table 3. However, if I still observe significant estimated network effects in courses that experience the least amount of sorting sorting into sections on bservablles, this would provide further support to the ability of the research design to isolate the role of social interactions in the job finding process.

Figures 6 and 7 display results of this analysis for the subsample of schools and course subjects with the lowest degrees of sorting based on observables, respectively. Results indicate that for all years of analysis, the effects of taking an additional Section with a peer on the propensity for a student to work in a job where their peer was incumbent at time of higher are positive and statistically significant. Moreover, they are similar in magnitude to the estimates from the whole sample in Table 13, although in figures 6 and 7 have wider confidence bands, due to decreased sample size. Results are presented in table form with baseline values in Tables 14 and 15 in the appendix. These tables also display aggregate outcome results over the first three years after a pair's last shared course.

Overall, the subsample analyses find that estimated network effects are robust to subsamples displaying the lowest amount of sorting on observables. These findings provide further support that estimated network effects are not driven by student sorting into sections within a course.

Figure 6: Effects of Sharing Additional Class Section: Subsample of 50% of Schools with Lowest Amount of Sorting on Observables



Note: Coefficient estimates have been multiplied by 100 to reflect percentage changes, and standard errors are clustered by course bundle. Estimates are displayed with 95% confidence intervals. Results are displayed in table format with information on baseline value and sample sizes in Table 14 of the appendix.

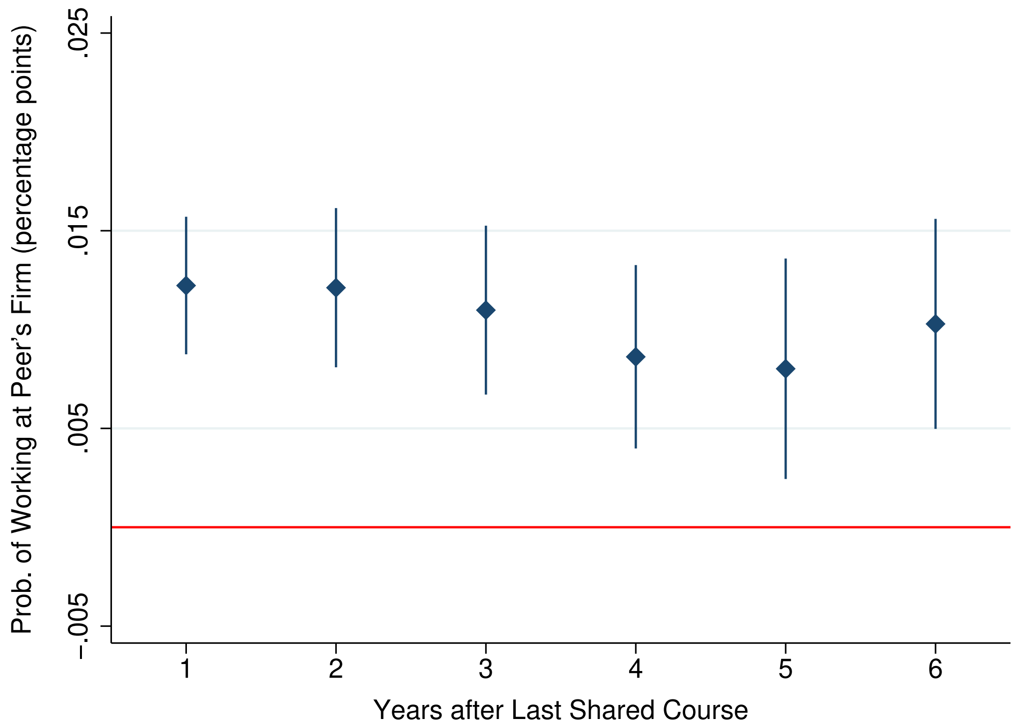
C. Specification with Individual Fixed Effects

While assessing sorting on observables is informative of sorting on unobservables, one concern with these analyses is that they cannot speak directly to this type off sorting. To analyze concerns that students sort into sections within a course based on unobservable characteristics, I next extend Equation 1 to include individual fixed effects for each member of the pair:

$$F_{ijc} = \tilde{\rho}_c + \tilde{\gamma} N_{ij} + \lambda_i + \lambda_j + \tilde{\epsilon}_{ijc} \tag{3}$$

where λ_i and λ_j represent fixed effects for i and j, respectively. Since each individual appear multiple times in the data, the inclusion of individual fixed effects can be used to test for one type sorting on unobservables. Specifically, this analysis accounts for sorting in situations where (i) certain types of workers are more likely to work with those in the same

Figure 7: Effects of Sharing Additional Class Section: Subsample of 50% of Course Subjects with Lowest Amount of Sorting on Observables



Note: Coefficient estimates have been multiplied by 100 to reflect percentage changes, and standard errors are clustered by course bundle. Estimates are displayed with 95% confidence intervals. Results are displayed in table format with information on baseline value and sample sizes in Table 15 of the appendix.

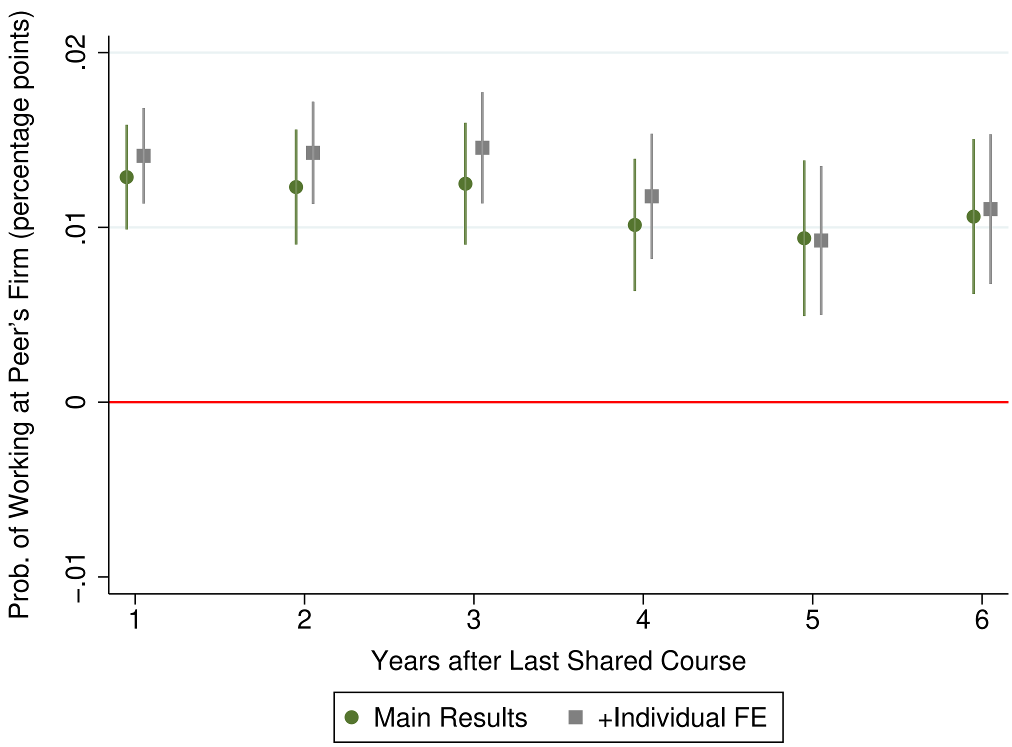
section for unobserved reasons, and (ii) these workers sort themselves into similar sections within a course. For example, suppose some students are more likely to work at firms with their peers because they prefer flexible work hours, and firms that offer flexible work hours attract a lot of students. If these students tend to sort into the same sections, perhaps if they sort into sections held at less conventional times of day, Equation 1 would over-estimate the effects of classmate networks on job-finding.[14] Equation 3 controls for this concern by capturing any inherent differences across individuals to work with peers with fixed effects.

Figure 8 shows estimated coefficients on the number of shared sections for Equation 3, compared to estimated coefficients for the primary specification in Equation 1. Results indicate that estimates including fixed effects produce very similar estimates to the original specification on the effect of taking an additional section together on the propensity for a

[14]I do not observe the time of day sections are held in the data, so I cannot control for this directly.

student to work at a firm with an incumbent peer for any of the years of analysis. For five out of the first six years after the last course, the specification with individual fixed effects actually estimates network effects that are actually slightly *higher* than estimates from the main specification. All results are reported with 95% confidence bars, and individual fixed effects results are reported numerically in Table 16 in the appendix. These results provide further reassurance that results are not being driven by students sorting into sections within a course on unobservable characteristics that also affect the outcome of interest.

Figure 8: Effects of Sharing Additional Class Section: Adding Individual Fixed Effects



Note: Coefficient estimates have been multiplied by 100 to reflect percentage changes, and standard errors are clustered by course bundle. Estimates are displayed with 95% confidence intervals. Estimation results from the main specification estimated using Equation 1 are displayed numerically in the appendix in Table 13. Results estimated using the augmented specification that includes individual fixed effects, Equation 3, are displayed in the appendix in Table 16.

D. Examining Role of Sorting on Pre-Existing Relationships

The previous robustness checks test for concerns regarding students sorting into sections along unobserved characteristics. In this section, I test for a different type of sorting, namely whether students sort into sections with pre-existing friends in a way that significantly affects the outcome of interest. This behavior would bias estimates if friends have correlated characteristics that make it more likely they will end up at the same firm, independent of classroom interactions. If certain pairs of students are more likely to sign up in sections with friends, this effect would not necessarily be picked up by the previous robustness tests of sorting along unobservables if sets of friends sort together, but not systematically along unobserved traits, across sections of a course.

Since I do not observe directly whether a pair of students share a pre-existing relationship, I proxy for this information by looking at geographic proximity between a pair, as well as whether they worked together previously. I measure residential proximity of a pair by calculating the travel distance between their high schools of attendance, and I measure prior coworker status using an indicator for whether the pair worked at the same place for at least one quarter in the three years prior to their first course together. This proxy is created on the intuition that pairs who live closer together or who were prior coworkers are more likely to have established social ties before taking a course together. These metrics are motivated by prior research showing both residential proximity and former coworkers serve as significant channels for networking.[15]

To test whether sorting on pre-existing relationships drives outcomes, I first analyze whether students do in fact exhibit a higher propensity to enroll in the same section with peers who they worked with previously or of closer geographic proximity:

$$N_{ijc} = \varphi_c + \phi_1 Prior\_Cowork_{ij} + \phi_2 Dist_{ij} + \nu_{ijc} \tag{4}$$

where $Prior\_Cowork_{ij}$ is an indicator for that takes on a value of one if i and j worked at the same firm in the three years prior to taking their first course together and zero otherwise. The variable $Dist_{ij}$ measures the travel distance in miles between the pair's high schools. The outcome of interest, N_{ijc}, which acts as the independent variable in Equation 1, represents the number of sections i and j share, and φ_c is a course bundle fixed effect. The coefficients ϕ_1 and ϕ_2 measure whether pairs who worked together previously or live closer enroll in more sections together, conditional on the courses in which they enroll.

Table 6 shows estimation results for Equation 4. Column (1) displays unconditional re-

[15] See Topa (2001), Bayer et al. (2008), Hellerstein et al. (2011), Schmutte (2015), Cingano and Rosolia (2012), Hensvik and Skans (2016), and Glitz (2017).

sults without course bundle fixed effects, and column (2) includes course bundle fixed effects. The inclusion of course bundle fixed effect reduces the magnitude of coefficient estimates on both previous coworkers and travel distance, although coefficient estimates remain statistically significant. Results from column (2) indicate pairs who were prior coworkers take approximately .037 more sections together, compared to pairs who did not work together before taking courses. An increase in the travel distance between pairs by one standard deviation decreases the number of sections individuals share by .007 sections. These findings indicate students display an increased propensity to enroll in sections with individuals with whom they were connected to previously, as measured by working together prior to the course and geographic proximity.

Table 6: Effects of Prior Coworkers and Travel Distance on Number of Class Sections Together

	(1)	(2)
Previous Coworker	0.131^{***}	0.037^{***}
	(0.006)	(0.001)
Travel Distance	-0.009^{***}	-0.007^{***}
	(0.002)	(0.001)
Course FE		X
N	39,434,472	39,434,472

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by course bundle. Travel distance is measured using z-scores. Outcome variable is number of sections pair i and j share.

Since students display an increased propensity to enroll in sections with peers they worked with or lived closer to, a concern to identification is that unobservable traits that lead people to sign up for the same section may also affect their propensity to work at the same firm, independent of network effects. In this situation, the coefficient γ in Equation 1 may overestimate the true effect of taking an additional section with a peer on the propensity of getting a job at the firm where a peer works.[16] To assess this concern, I extend Equation 1 to include controls for prior coworkers and travel distance:

[16] It is possible that friends are more likely to sign up for the same section and also more likely end up at the same firm, both through network effects. However, it is also possible that individuals tend to sign up for sections with friends, and friends share unobserved characteristics that make it more likely for them to end up at the same firm. The latter scenario is the one I am concerned about.

$$F_{ijc} = \check{\rho}_c + \check{\gamma} N_{ijc} + \phi_1 Prior\_Cowork_{ij} + \phi_2 Dist_{ij} + \check{\epsilon}_{ijc} \tag{5}$$

where F_{ijc} is an indicator variable taking a value of one if i works at a firm where j was working when i was hired, and zero otherwise The course bundle fixed effect, $\check{\rho}_c$, controls for sorting into courses, and N_{ijc} measures the number of sections i and j take together out of their shared courses. I add variables $Prior\_Cowork_{ij}$ and $Dist_{ij}$ to account for the role sorting into sections along pre-existing relationships plays in affecting subsequent job-finding outcomes. If estimates of $\check{\gamma}$ do not differ significantly from estimates of γ in Equation 1, this implies sorting into sections within a course group based on pre-existing relationships as captured by former coworkers and peers in closer geographical proximity does not drive results.[17]

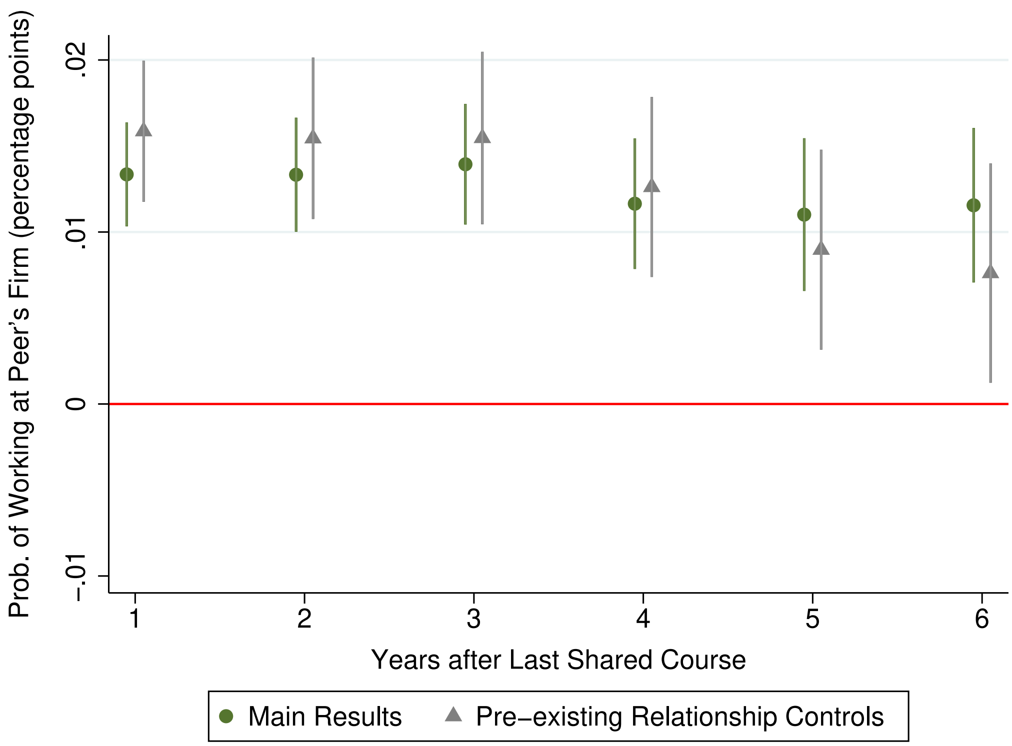
Figure 9 plots estimation results of Equation 5, in addition to original estimation results from Equation 1. All estimates are reported with 95% confidence bars. Results indicate that estimates including controls for travel distance (as measured by high school location) and whether a pair were prior coworkers produce very similar estimates to the original specification on the effect of taking an additional section together on the propensity for a student to work at a firm with an incumbent peer for any of the years of analysis. For four out of the first six years after the last course, the specification with prior relationship controls actually estimates network effects that are actually slightly *higher* than estimates from the main specification. All results are reported with 95% confidence bars, and individual fixed effects results are reported numerically in Table 17 in the appendix. The results provide support that results are not being driven by students sorting into sections within a course with peers based on pre-existing relationships.

4.3 Heterogeneity

This section looks at how network effects varies across different groups of students. Specifically, I look at differences in the use of classmate networks in job finding by gender, academic course performance, course type, and school location. All results in this section look at the

[17]Since students typically enroll in college either out of high school or after working for some time, geographic proximity based on high school and former workplace contacts intuitively should capture a significant portion of an individual's relationships. Furthermore, many other places where people form relationships will also be geographically correlated (e.g. family, places of worship, social groups). However, I cannot rule out the possibility that students systematically form pre-existing relationships in ways that are not captured by residential proximity or prior work history.

Figure 9: Effects of Sharing Additional Class Section: Controlling for Pre-existing Relationships



Note: Coefficient estimates have been multiplied by 100 to reflect percentage changes, and standard errors are clustered by course bundle. Estimates are displayed with 95% confidence intervals. Estimation results from the main specification estimated using Equation 1 are displayed numerically in the appendix in Table 13. Results estimated using the augmented specification that includes controls for proxies for pre-existing relationships, Equation 5, are displayed in Table 17.

aggregate outcome of whether i gets a job at peer j's firm within three years of the pair's last shared course.

Gender

Table 7 examines network effects across different gender pairings of students i and j. The variable "Female" is an indicator for whether i is female, and "Peer Female" is an indicator for whether j is female. Column (1) looks at the overall differences in propensity for men and women to use classmate networks in job finding. I include interactions of an indicator variable for female with the course bundle fixed effect to account for the possibility that women sort into courses with different baseline rates of job-finding at peers' firms than men. This interaction also subsumes gender fixed effects. Results indicate women are significantly more likely to find a job through a classmate peer. For men, sharing an additional section with a peer increases the propensity of getting a job at a firm where their peer is incumbent by 0.013 percentage points. For women, this effect is 0.018 percentage points larger than it is for men, indicating that taking a class with a peer increases the propensity for women to get a job at the peer's firm by slightly more than twice the amount it does for men.

Table 7: Student Gender: Effects of Additional Section on Prob. of Working at Peer's Firm

Sample	All	Male	Female	All
	(1)	(2)	(3)	(4)
Number of Sections	0.013***	0.021***	0.020***	0.021***
	(0.004)	(0.005)	(0.005)	(0.005)
Num. Sections×Female	0.018***			-0.000
	(0.005)			(0.007)
Num. Sections×Peer Female		-0.020***	0.013**	
		(0.006)	(0.006)	
Num. Sections×Female×Peer Female				0.013**
				(0.006)
Num. Sections×Male×Peer Female				-0.020***
				(0.006)
Peer Female		-0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Male×Peer Female				-0.002***
				(0.000)
Course Bundle FE	X	X	X	X
Female×Cse Bundle FE	X			X
N	43,416,171	14,676,591	28,739,580	43,416,171

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Baseline and coefficient estimates are multiplied by 100, meaning estimates represent percentages. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student i starts working at firm where peer j is incumbent within three years of last shared course. "Female" is an indicator for whether i is female, and "Peer Female" is an indicator for whether j is female.

Columns (2) and (3) look at the role of the gender of the student's peer, j, on networking. Column (2) restricts the sample to male students, and column (3) restricts the sample to female students. Results indicate that taking a section with a male peer increases the the propensity for both men and women to get a job at a firm where the peer is incumbent by about the same amount, 0.020-0.021 percentage points. However, men are significantly less likely to get a job through a female classmates, while women are more likely to do so. For men, taking an additional section with a female peer leads to a 0.020 percentage point lower propensity of getting a job at the peer's firm relative to taking a section with a male peer. This essentially indicates men do not use female peers for job finding at all in this setting. In contrast, for women, taking an additional section with a female peer leads to a 0.013 percentage point higher propensity of getting a job at the peer's firm relative to taking a section with a male peer.

Column (4) includes both men and women in the sample and looks at differences in classmate network effects across both student and peer genders. Reinforcing findings in columns (2) and (3), results indicate that for men, taking an additional section with a male peer increases the propensity that the student will start working at a firm where their peer is incumbent within three years of their last shared course by 0.021 percentage points. Additionally, this effect is the same for women taking an additional section with a male peer. Taking a section with a female peer increases the propensity that a woman will get a job at a firm where her peer works by 0.013 percentage points more than the effect of taking a section with a male. However, taking a section with a female peer decreases the propensity that a man will get a job at a firm where his peer works by 0.020 percentage points more than the effect of taking a section with a male, indicating men get no job-finding network benefit from female classmates under this metric.

To summarize, results in Table 7 indicate women are more likely to use classmates for job-finding than men in this setting. Further analysis reveals that this effect comes entirely from differences in propensities for men and women to find jobs through female classmates. Namely, students of both genders use male classmates for job-finding at comparable rates. However, while women display a higher propensity to find jobs through female classmate networks than through male classmate networks, men are significantly less likely to find jobs through female classmate networks.

Course Performance

Table 8 looks at whether the propensity for students to use peers for job-finding differs based on the whether the student is academically high-performing or low-performing. The variable "Grade" denotes the z-score of the grade student i received in the section, and "Peer Grade" denotes the z-score of the grade for her peer j. I only observe grade information for about 66% of sections in the sample, so as a starting point, column (1) re-estimates the main specification from equation 1 on the sample of observations for which I observe a section grade for both i and j. I find that for this sample, taking an additional section with a peer increases the propensity for the individual to get a job at a the firm where their peer works within three years of their last course together by .025 percentage points. This is the same effect I find when estimating this specification on the full sample in Table 3, indicating classmate networks play a similar role in the subset of observations for which I observe student grades.

Table 8: Course Performance: Effects of Additional Section on Prob. of Working at Peer's Firm

	(1)	(2)	(3)	(4)
Number of Sections	0.025***	0.025***	0.025***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)
Num. Sections×Grade		0.005		0.006
		(0.004)		(0.004)
Num. Sections×Peer Grade			0.008**	0.008**
			(0.003)	(0.003)
Num. Sections×Grade×Peer Grade				0.016***
				(0.004)
Grade		0.000		0.000
		(0.000)		(0.000)
Peer Grade			0.000***	0.000***
			(0.000)	(0.000)
Grade×Peer Grade				0.000***
				(0.000)
Course Bundle FE	X	X	X	X
N	20,139,030	20,139,030	20,139,030	20,139,030

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Baseline and coefficient estimates are multiplied by 100, meaning estimates represent percentages. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student i starts working at firm where peer j is incumbent within three years of last shared course. "Grade" is the z-score of student i's grade is female, and "Peer Grade" is the z-score of student j's grade.

Next, column (2) assesses how the propensity for a student to get a job through their peer varies by the student's performance in their class section. I find no evidence of significant differences in network effects based on student i's grade in the class. Column (3) examines how the propensity for a student to get a to through their peer varies by the peer's performance in class. I find some suggestive evidence that peer's with stronger academic performance are more likely to serve as network contacts. A one standard deviation in peer

j's performance in the section increases the propensity for individual i to get a job at a firm where j is incumbent within three years of their last shared course by .008 percentage points, and this effect is statistically significant at the 5% level. Column (4) looks at interaction of student and peer performance on classmate network formation propensities. Results indicate a positive and statistically significant effect on student grade and peer grade, indicating students are relatively more likely to get jobs through peers who are of a similar academic caliber to themselves. In other words, I find evidence of assortative matching along academic performance in network formation.

Course Type

Community colleges offer a mix of vocational courses and general study, or liberal arts, courses. Table 9 looks at whether the propensity for students to use peers for job-finding differs across course types. Table 18 in the appendix shows the breakdown of courses into vocational or liberal arts by course subject. I do not observe course subject information for a small portion courses in the sample, so as a starting point, column (1) re-estimates the main specification from equation 1 on the sample of observations for which I observe courses. I find that for this sample, taking an additional section with a peer increases the propensity for the individual to get a job at a firm where their peer is incumbent within three years of their last course together by .023 percentage points. This is very similar to the effect I find when estimating this specification on the full sample in Table 3.

Next, column (2) analyzes differences in propensity for a student to find a job through her peer in vocational vs. liberal arts classes. I find that for a pair of students in liberal arts classes, taking an additional section with a peer increases the propensity that the student will get a job at a firm where their peer is incumbent within three years of their last shared course by 0.016 percentage points. This effect is 0.020 percentage points larger for a pair of students in vocational classes. Thus, findings indicate classmate networks play a bigger role in job finding for students in vocational classes compared to general interest, at least in the near future. One potential explanation of this effect may be driven by the fact that students in liberal arts classes are more focused on transferring to a four-year college than on finding a job. Another possibility is that students who take vocational courses tend to be more similar in their career interests and thus more useful to each other in the job search process.

Table 9: Course Type: Effects of Additional Section on Prob. of Working at Peer's Firm

	(1)	(2)
Number of Sections	0.023***	0.016***
	(0.003)	(0.004)
Number of Sections×Vocational Course		0.020***
		(0.008)
Course Bundle FE	X	X
N	39,097,551	39,097,551

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Baseline and coefficient estimates are multiplied by 100, meaning estimates represent percentages. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student i starts working at firm where peer j is incumbent within three years of last shared course. Courses that are not vocational are classified as "liberal arts". Table 18 in the appendix contains a detailed classification of courses by.

School Location

Table 10 examines whether there is heterogeneity in classmate networks use across urban and rural areas of the state. To do so, I first classify schools as being located in metropolitan statistical areas, micro statistical areas, or neither, based on the Office of Management and Budget (OMB) 2013 county-level classifications. Table 19 in the appendix shows the classification of individual schools.

Column (1) of table 10 augments the main specification in Equation 1 with interactions of number of sections shared with whether the pair attend a school located in a micropolitan or metropolitan area. The omitted category are schools that are not located in either type of region, i.e. schools in more rural counties. Results indicate the effect of taking an additional section with a peer for students at schools that are located in more rural counties is significantly higher than for students in schools located in micropolitan or metropolitan counties. Column (2), the preferred specification, includes interaction terms of number of sections with school size and school instructional classification.[18]. Results in column (2) show similar patterns to those in column (1). At schools that are not in metropolitan or micropolitan areas, taking an additional section with a peer increases the propensity that a student will

[18]Instructional classifications are obtained from The Carnegie Classification of Institutions fo Higher Education, and community colleges in this setting fall into one of three categories: High Transfer, High Vocational and Technical, and Mixed Transfer/Vocational and Technical

Table 10: Urbanicity: Effects of Additional Section on Prob. of Working at Peer's Firm

	(1)	(2)
Number of Sections	0.057***	0.092***
	(0.007)	(0.022)
Num. Sections×Micropolitan	-0.037***	-0.033***
	(0.008)	(0.009)
Num. Sections×Metropolitan	-0.043***	-0.041***
	(0.009)	(0.011)
Num Sections×School Enrollment		-0.000*
		(0.000)
Num Sections×High Vocational+Technical		-0.030
		(0.019)
Num Sections×Mixed Transfer/Voc.+Tech.		-0.023
		(0.016)
Course Bundle FE	X	X
N	39,129,871	39,129,871

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Baseline and coefficient estimates are multiplied by 100, meaning estimates represent percentages. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student i starts working at firm where peer j is incumbent within three years of last shared course. Omitted category: schools located in counties that are neither metropolitan nor micropolitan areas. Table 19 in the appendix shows the breakdown of schools in the sample by geographic area classification.

get a job at a firm where their peer is incumbent within three years of their last shared course by 0.092 percentage points. The effect of taking an additional section together on network effects is 0.033 percentage points lower at schools in micropolitan areas and 0.041 percentage points lower at schools in metropolitan areas. These results suggest that classmate networks play an especially important role in the job finding process for community college students in rural areas.

5 Conclusion and Discussion

Prior studies on social networks in college have predominantly focused on elite, four-year college settings. However, these elite institutions educate only a small subset of students, and the vast majority of college students attend a "non-elite institution". This study sheds novel insight on the role of social networks in job finding at community colleges, which educate over 40% of the college population in the US. On average, these students come from very different socioeconomic backgrounds and go into different types of jobs and parts of the labor market compared to peers at elite schools, so it's not clear a priori if findings on the role of social networks at elite schools will be applicable to these settings. Furthermore, due to differences institutional setting, existing methods used to measure networks at elite schools are typically not applicable to a community college setting, requiring the innovation of new methods of examining social networks.

Using transcript data from Arkansas community colleges linked to employer-employee records, this study investigates the effect on enrolling in a class section with a peer on the propensity or a student to get a job at a firm where their peer works. To address the concern that students sort into sections in ways that may affect job finding outcomes, I examine whether a student is more likely to get a job at a firm where a classmate works, as opposed to a peer enrolled contemporaneously in a different section of the same course.

Results indicate classmate networks do play a significant role in helping community college students find jobs. Taking a section with a peer increases the probability of the student getting a job at her peer's firm within three years of their last shared course by 4.1%. I conduct several validity checks to address concerns that results are driven by students sorting non-randomly into sections along characteristics that would also affect the outcome of interest and find that results are robust to these checks. Additionally, I find that the effects of networking vary significantly across different student and school contexts. First, students use classmate networks for job finding more in rural settings compared to more urban areas. Second, students use classmates for job finding more in vocational courses compared to general study courses. Third, classmate network formation displays positive assortative matching, in that higher performing students are more likely to get jobs through high performing peers, and vice versa for lower performing students. Finally, women are more likely to use classmate network for job finding than men. This effect is driven entirely by women being significantly more likely than men to get jobs through female classmates. Men and women display similar propensities to get jobs through male classmates.

Overall, my findings indicate social networks likely play a significant role in job-finding beyond the realm of highly selective, elite institutions. Specifically, my results suggest that classmates play an important and nuanced role in job finding at community colleges. From a policy perspective, one implication of these results is that it may be beneficial for community colleges to put resources toward encouraging and/or facilitating more opportunities for students to form networks, such as clubs and organizations, alumni groups, social spaces, etc. These findings also have implications for the evaluation of the returns to college. Ignoring the role of social networks would provide an underestimate the true returns to attending college. One avenue of future research that would help shed light on the role of social connections in these settings is to examine the role of networks on earnings.

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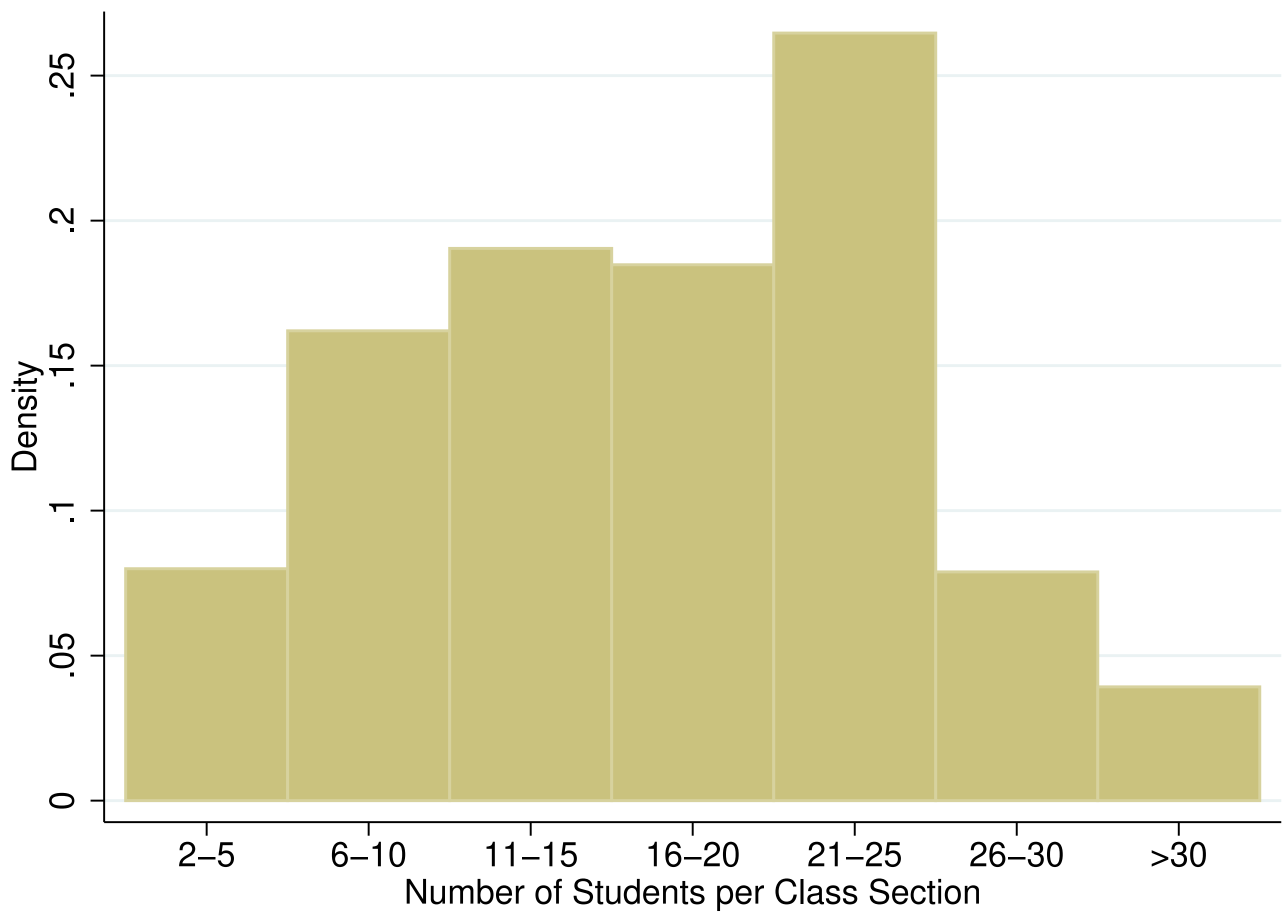
Appendix A Additional Tables and Figures

Figure 10: Distribution of Students per Section



Note: Class sections with one student are dropped from the sample.

Table 11: Student Characteristics: Analysis Sample vs. All Students

	Analysis Sample (1)	All Students (2)
Female (%)	63.75	63.37
Part-time (%)	52.68	54.30
Employed (%)	62.29	61.42
In-State (%)	94.94	93.90
Transfer Student (%)	24.42	24.86
Age	26.22	26.87
	(8.76)	(9.07)
Number of Sections	3.16	3.09
	(1.70)	(1.82)
N	422,022	944,003

Arkansas Two-Year College Students, 2004-2012. Observations denote student×semester units. Table displays means (standard deviations in parentheses). Age is imputed from year of high school graduation, assuming students are 18 at the end of high school. Column (1) represents observations that appear in the analysis sample for this paper. Column (2) represents observations of all students from Table 1.

Table 12: Class Section Characteristics: Analysis Sample vs. All Classes

	Analysis Sample (1)	All Classes (2)
Class Section Size	17.37	15.74
	(8.20)	(8.42)
Mean GPA	2.62	2.80
	(0.96)	(0.95)
Female Instructor	0.57	0.55
	(0.50)	(0.50)
Class Subject (%)		
Basic Skills and Remedial	19.2	14.3
Social Sciences	14.2	12.4
English	12.7	9.8
Business, Management, and Marketing	9.4	11.4
Biology	5.6	4.5
Mathematics and Statistics	5.1	4.6
Computer and Information Sciences	4.5	4.2
Health Professions	4.1	9.0
Visual and Performing Arts	4.0	4.2
Humanities	3.2	2.9
Physical Sciences	2.2	2.4
Communication, Journalism	2.1	1.2
Mechanic and Repair	1.9	2.8
Engineering	1.7	2.6
Other	10.1	13.7
Observations	75,833	181,413

Arkansas two-Year college class sections, 2004-2012. Units of observations are class sections. Table displays means (standard deviations in parentheses). Sections with one student have been dropped from the sample. Course subjects are categorized using 2010 Classification of Instructor Program (CIP) codes.

Table 13: Effects of Sharing Additional Class Section on Probability of Finding Job at Peer's Firm (Year-by-year Breakdown)

	+1yr	+2yrs	+3yrs	+4yrs	+5yrs	+6yrs
Baseline	0.222	0.249	0.248	0.241	0.226	0.212
Number of Sections	0.0129***	0.0123***	0.0125***	0.0101***	0.00938***	0.0106***
	(0.00152)	(0.00167)	(0.00177)	(0.00192)	(0.00227)	(0.00225)
Course Bundle FE	X	X	X	X	X	X
N	59,192,230	52,294,258	43,748,074	34,621,106	26,337,746	18,624,800

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Column headers denote years x after pair's last shared course. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student starts working at firm where peer is incumbent x years after their last course together. Baseline and coefficient estimates multiplied by 100, meaning estimates represent percentages.

Table 14: Effects of Sharing Additional Class Section, Subsample 50% Schools with Lowest Sorting

	(1)	(2)	(3)	(4)	(4)	(6)	(7)
	Aggregate	+1yr	+2yrs	+3yrs	+4yrs	+5yrs	+6yrs
Baseline	0.549	0.199	0.229	0.226	0.228	0.220	0.208
Number of Sections	0.014***	0.012***	0.012***	0.008**	0.008**	0.013***	0.028***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Course Bundle FE	X	X	X	X	X	X	X
N	27,921,800	25,414,596	21,537,676	17,073,772	13,041,922	9,163,112	21,556,137

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Coefficients represent estimates of Equation 1 on a subsample of the 50% of schools that display the lowest amount of sorting on observables. Observations represent matched pairs of students with peers, $\{i, j\}$. Column headers denote years x after pair's last shared course. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student starts working at firm where peer is incumbent x years after their last course together. Baseline and coefficient estimates multiplied by 100, meaning estimates represent percentages. Outcome variable in column (1) is whether student starts working at firm where peer is incumbent within three years of last shared course, and columns (2)-(7) show year-by-year estimates.

Table 15: Effects of Sharing Additional Class Section, Subsample 50% Course Subjects with Lowest Sorting

	(1)	(2)	(3)	(4)	(4)	(6)	(7)
	Aggregate	+1yr	+2yrs	+3yrs	+4yrs	+5yrs	+6yrs
Baseline	0.606	0.218	0.251	0.257	0.252	0.235	0.222
Number of Sections	0.012***	0.012***	0.011***	0.009***	0.008***	0.010***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Course Bundle FE	X	X	X	X	X	X	X
N	38,768,591	34,489,985	29,007,065	22,970,397	17607068	12,545,731	29 033,737

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Coefficients represent estimates of Equation 1 on a subsample of the 50% of course subjects that display the lowest amount of sorting on observables. Observations represent matched pairs of students with peers, $\{i, j\}$. Column headers denote years x after pair's last shared course. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student starts working at firm where peer is incumbent x years after their last course together. Baseline and coefficient estimates multiplied by 100, meaning estimates represent percentages. Outcome variable in column (1) is whether student starts working at firm where peer is incumbent within three years of last shared course, and columns (2)-(7) show year-by-year estimates.

Table 16: Effects of Sharing Additional Class Section, Specification with Individual Fixed Effects

	(1) Aggregate	(2) +1yr	(3) +2yrs	(4) +3yrs	(4) +4yrs	(6) +5yrs	(7) +6yrs
Baseline	0.222	0.249	0.248	0.241	0.226	0.212	
Number of Sections	0.028***	0.014***	0.014***	0.015***	0.012***	0.009***	0.011***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Course Bundle FE	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X
N	43,782,809	59,191,320	52,293,618	43,747,556	34,620,382	26,337,200	18,624,298

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Coefficients represent estimates of Equation 3. Observations represent matched pairs of students with peers, $\{i, j\}$. Column headers denote years x after pair's last shared course. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student starts working at firm where peer is incumbent x years after their last course together. Baseline and coefficient estimates multiplied by 100, meaning estimates represent percentages. Outcome variable in column (1) is whether student starts working at firm where peer is incumbent within three years of last shared course, and columns (2)-(7) show year-by-year estimates.

Table 17: Effects of Sharing Additional Class Section, Controlling for Pre-existing Relationships

	(1) Aggregate	(2) +1yr	(3) +2yrs	(4) +3yrs	(4) +4yrs	(6) +5yrs	(7) +6yrs
Baseline	0.222	0.249	0.248	0.241	0.226	0.212	
Number of Sections	0.030***	0.016***	0.015***	0.015***	0.013***	0.009***	0.008**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Course Bundle FE	X	X	X	X	X	X	X
N	23,409,171	31,352,210	27,767,060	23,385,438	18,722,176	14,383,020	10,267,360

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by course bundle. Observations represent matched pairs of students with peers, $\{i, j\}$. Coefficients represent estimates of Equation 5, which includes controls for pre-existing relationships. Specifically, I control for whether i and j were previously coworkers, as well as the travel distance between the pair, as measured by the distance between their high schools. There are notably fewer observations for these estimates than corresponding estimates of main results in Table 13 because high school information is missing for a number of students. Column headers denote years x after pair's last shared course. Estimates include controls for the attendance status (part-time vs. full-time) of i and j. Outcome: whether student starts working at firm where peer is incumbent x years after their last course together. Baseline and coefficient estimates multiplied by 100, meaning estimates represent percentages. Outcome variable in column (1) is whether student starts working at firm where peer is incumbent within three years of last shared course, and columns (2)-(7) show year-by-year estimates.

Table 18: Course Subject Classification

Liberal Arts	Social Sciences
	Basic Skills
	English Language and Literature
	Biological and Biomedical Sciences
	Mathematics and Statistics
	Computer and Information Sciences
	Visual and Performing Arts
	Humanities
	Physical Sciences
	Liberal Arts and sciences
	Multi/Interdisciplinary Studies
Vocational	Business, Management, and Marketing
	Health Professions
	Homeland Security, Law Enforcement, and Service
	Mechanic and Repair Technologies
	Engineering Technologies/Technicians
	Education
	Family and Consumer Sciences
	Parks, Recreation, Leisure, and Fitness
	Communication and Journalism
	Leisure and Recreation Activities
	Precision Production
	Personal and. Culinary Services
	Transportation and Materials Moving
	Personal Awareness and Self-Improvement
	Legal Professions
	Agriculture
	Library Science
	Construction Trades
	Communications Technologies/Technicians
	Natural Resources and Conservation
	Public Administration and Social Services
	Interpersonal and Social Skills
	Military Technollogies
	Military Science, Leadership, and Operations
	Science Technologies/Technicians

Classification of course subjects into liberal arts and vocational categories. Course subjects are classified using 2010 Classification of Instructional Program (CIP) codes.

Table 19: School Location Classification

Metropolitan	National Park Community College
	Northwest Arkansas Community College
	Pulaski Technical College
	Mid-South Community College
Micropolitan	East Arkansas Community Colege
	Arkansas State University–Mountain Home
	Univ. of Ark. Community College at Batesville
	Southern Arkansas University Tech.
	North Arkansas College
	Arkansas State University–Beebe
	Arkansas Northeastern College
	College of the Ouachitas
Neither	Rich Mountain Community College
	Univ. of Ark. Community College at Morrilton
	Cossatot Community College
	Ozarka College
	Black River Technical College
	Univ. of Ark. Community College at Hope

Schools are classified based on the county in which the school is located. Classification are based on 2013 definitions of statistical areas from the Office of Management and Budget (OMB).