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Who Gets the Job? The Consequences of Strategic Information Sharing within Social Networks
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ABSTRACT

We study how job-seekers share information about jobs within their social network, and its implications for the quality of applicants and hires. We randomly increase the amount of competition for a job that we created and find that jobseekers are less likely to share information about the job, especially with their high ability peers. This lowers the quality of applicants, hires, and performance on the job —suggesting that disseminating job information through social networks may result in lower quality applicants than expected for competitive positions. While randomly offering higher wages attracts better talent, it is not able to fully overcome these strategic disincentives.

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A randomized controlled trials registry entry is available at
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1 Introduction

A well-functioning labor market relies on firms' ability to identify and match with the most qualified candidates. Firms aim to attract the best candidates by promoting their job vacancies (through advertising or referral networks), and enhancing their jobs' appeal (by offering higher wages or improved benefits). However, the success of these strategies depends on how well this information reaches suitable candidates (Caria et al., 2024). Since jobs are competitive, information is unlikely to flow smoothly within social networks – when a job-seeker shares details about a job with their peers, it reduces their own chance of securing the position (Beaman et al., 2018). This means that the effectiveness of common hiring strategies depends on job-seekers' strategic response to the perceived competition for a job. While accurately measuring how hiring strategies and job-seeker behaviors interact is crucial for understanding the efficiency of job matches and its resulting impact on the labor market, it is also challenging to do, since these behaviors are usually determined in equilibrium.

In this paper, we aim to disentangle these dynamics by isolating job seekers' strategic behavior and examining how they interact with common hiring strategies. Specifically, we design a randomized control trial to achieve three goals – first, to document whether job-seekers exhibit "strategic disincentives" in information sharing i.e., share less information about jobs with specific types of peers when the competition for these jobs is made salient to them. Second, we explore how these strategic disincentives impact the talent pool of applicants received, the hires that are made, and their performance on the job. Finally, we assess how they interact with a common strategy that can be used to attract better talent – offering higher wages.

We partnered with six colleges in Mumbai, India to design an experiment that allows us to precisely identify how information flows through a network and the role competition plays, while specifically shutting down other mechanisms that could affect labor market outcomes. The colleges we worked with had multiple programs of study (henceforth referred to as a 'batch'). Every week, the research team created a job where students were given 45 minutes to search and summarize articles on a particular topic of interest for a renowned international institution. Each student had to complete their task individually, and there was no interaction between them on the job. Information on this job opportunity was shared with randomly selected students ('entry-points') within each batch. A new group of students were selected to hear about the jobs each week for six weeks. Each job we shared was either 'rival' or 'non-rival' across batches. A 'rival' job meant that students we informed about the job (the entry-points) would have to apply and compete with their peers for these positions. A 'non-rival' job meant that entry-point students were guaranteed the position, but could still share the information with their peers (who had to submit an application). To further test whether the dynamics we observe change as the quality of the job improves, we also varied whether the job offered a high wage (INR 1,000 or 12 USD) relative to the status-quo (INR 500 or 6 USD). The assignment of whether a job was categorized as rival/non-rival, and high wage or not, was done randomly at the batch-week level. In other words, all participating batches were randomly allocated to receive information about a rival or high-wage job each week, and a random subset of students *within* the batch were selected as entry-points and heard about the job directly from the research team.

This experimental setup allows us to cleanly isolate the role of competition in a way that would not be possible within a real firm. By creating our own jobs, we could easily vary whether they were rival or non-rival. Additionally, working with the same group of students within a college setting allowed us to keep track of interactions within the social network over time. Finally, offering short-term employment allowed us to repeat the hiring exercise weekly and quickly gather performance data. As such, it's difficult to determine whether our results represent an upper or lower bound compared to more traditional firm settings where competitive distortions may be higher or lower. However, the goal of this paper is to identify the underlying mechanism. We therefore view it as a proof of concept that highlights the important role competition and strategic disincentives play in the labor market. Moreover, we argue that our findings are likely relevant to contexts where short-term jobs or casual daily labor is prevalent – a widespread form of employment globally and a primary livelihood for hundreds of millions of workers in India alone (Breza et al., 2021).

Next, we provide a stylized conceptual framework to motivate our analysis. Specifically, we show that an individual's decision to share information is determined by two channels: a "competition channel", where sharing job information with friends reduces one's own probability of getting the job; and a "utility channel", where sharing information with friends provides utility (from feelings of reciprocity or warm glow, for example). The decision to share information depends on which of these two channels dominates. This in turn depends on whether the job is rival or not, and on the characteristics of the individuals sharing the job relative to their peers (their ability, how closely connected they are, their homophily, etc.).

We document four main findings. First, we find that job-seekers were more likely to share information about a job when they did not have to worry about competing for it. On average, students in non-rival batches were 5 p.p. (30%) more likely to hear about the job we shared with entry-points relative to students in rival batches. Moreover, students with no direct connection to entry-point students were 3 p.p. (25%) more likely to hear about the job when it was non-rival relative to rival. This indicates that job information was more likely to spread beyond immediate connections to the entry-points when it was non-rival in nature.

Second, we investigate three factors that may exacerbate (or mitigate) the nature of competition between job-seekers. We find that job-seekers were strategic about *who* they shared information with when the job was rival and they knew they had to compete for it. First, students were 7.5 p.p. *less* likely to hear about a job from lower ability entry-point peers (relative to higher or same ability peers) when the job was rival. Conversely, they were 8.5 p.p. *more* likely to hear about a job from lower ability entry-point peers (relative to higher or same ability peers) when the job was non-rival. This difference is statistically significant, and suggests that entry-points were taking the relative ability of their peers into account when deciding whether to share information or not. Second, we investigate the strength of close friendship connections. Students who reported a close connection to an entry-point at baseline (as compared to those who did not) were more likely to hear about this information, regardless of whether the job was rival or not. Specifically, students were 10.8 p.p. more likely to hear about a rival job when they were closely connected to the entry point, and 9.3 p.p. more likely to hear about a non-rival job. This suggests that closer social bonds can mitigate competitive concerns. Finally, we investigate the role of homophily. We find that when the job was rival, students were 5.3 p.p. less likely to share job information with another student of the same gender but when the job was non-rival they were 5.7 p.p more likely to share the job with their same gender friend. This suggests that students perceived competition from others of the same gender. These effects on ability and homophily were driven entirely by men, who appear less likely to share information with other high-ability, male peers when the job information was rival. This result is consistent with a larger literature that finds more competitive behavior among men in the labor market (Cashdan, 1998; Niederle and Vesterlund, 2011; Boudreau and Kaushik, 2023).

Third, we establish that the above results have implications for the quality of candidates (as measured by their GPA scores) who hear about, apply for, and are hired for a job, as well as their performance on the job. The GPA of students who *heard* about the job was 0.08σ higher on average when the job was non-rival relative to rival. This improved the ability of the applicant pool (0.13σ), and of those who were hired (0.38σ). This also improved job performance across multiple indicators. Students hired from non-rival batches were 11.5% more likely to show up for the job and 32% more likely to finish within the allotted 45 minutes, compared to those from rival batches. Additionally, they completed the task more quickly and submitted higher-quality work.

These results suggest that relying heavily on social networks to spread job information for highly competitive jobs may screen out high-ability candidates. In theory, one approach to counter this effect, and attract stronger applicants, is to offer higher wages to make positions more desirable. If higher quality candidates demand higher compensation, then offering higher wages is essential to attracting such candidates (Dal Bó et al., 2013). However, increasing the wage can amplify both the competition and utility channels presented in the conceptual framework above. On the one hand, the cost of sharing job information (competition channel) increases, as informed job-seekers lose more if their peers secure the higher-paying job. On the other, the benefits of sharing the job (utility channel) also increase, as informed job-seekers derive greater satisfaction from helping their friends access a higher-paying job. Since these channels work in opposite directions, it is theoretically ambiguous whether increasing wages overcomes the strategic disincentives of sharing job information or not.

In our fourth result, we find that doubling the wage among rival jobs attracted a better pool of applicants (0.10σ) and hires (0.08σ), relative to the status-quo rival job. These hires also scored 14.5% higher on their submissions. This confirms that higher wages can indeed attract better talent. However, a key advantage of our setting is that we can also identify how much better candidates' ability would have been, if higher wages could be offered without triggering a competitive response among job-seekers i.e., if the job information was non-rival in nature. We find that the ability of hired candidates among high-wage *non-rival* jobs and the evaluation score on their submissions, increases by an additional 0.35σ and 19.1% respectively, relative to high-wage *rival* jobs. Put differently, firms would have to increase the wage by 3-6 times (rather than doubling it, like we did for the experiment) to get the same increase in ability induced by eliminating strategic disincentives.

To summarize, these results suggest that job-seekers strategically shared less information about jobs when they were concerned about having to compete for them. In particular, they shared less with peers they perceived to be higher ability than themselves, and thus a greater competitive threat. This behavior has significant implications, as it led to a reduction in the overall quality of applications and hired candidates received. While offering more attractive (higher paying) wages could help overcome this in principle, our results suggest that this increase in wages would have to be substantial to attract higher quality candidates in the presence of strategic disincentives. Taken together, these results highlight how competition shapes hiring dynamics. While firms may have limited ability to address this in the labor market—especially because most jobs are inherently rival—one key takeaway is the potential downside of relying solely on social networks to share job opportunities, and the potential benefit of interventions that promote a broader dissemination of job information.[1]

This study contributes to multiple strands of the literature. First, we contribute to a recent and growing literature that examines strategic incentives of sharing information within a social network, and how individual characteristics influence these decisions. Recent work has documented that factors ranging from political affiliation (Bandiera et al., 2023) to race (Miller and Schmutte, 2021) impact information sharing with important implications for the efficiency and fairness of information flows. Most related to our study is a small literature that documents how competition can limit the transmission of information among small firms and farms (Cai and Szeidl, 2018; Hardy and McCasland, 2021; Cefalà et al., 2024). We focus on a different source of labor market competition – between job seekers themselves – where social networks introduce dynamics that can, in theory, trigger a utility channel capable of offsetting competitive pressures. Unlike previous studies, we also show how competition among job seekers can shape outcomes on the other side of the labor market, influencing both the quality of hires and the impact of strategies used to attract them.

Second, we contribute to the literature on labor market frictions in low-income countries (as reviewed in Caria et al. (2024)). We show that strategic considerations can restrict the flow of job-related information within social networks, reducing the quality of applicants and hires. Our results complement Caria et al. (2023), who find that active labor market policies limit information sharing between program recipients and non-recipients. In contrast, we study how information is exchanged in the absence of such policies and demonstrate that competition itself discourages treated job-seekers from sharing information with peers.

Finally, we contribute to a large literature on the importance of social networks in referring job-seekers in the labor market that follows the seminal work of Granovetter (1973) and Montgomery (1991). More recent work has demonstrated how referrals can reduce asymmetric information (Beaman and Magruder, 2012; Brown et al., 2016; Pallais and Sands, 2016; Dustmann et al., 2016) and induce effort on the job (Kugler, 2003; Heath, 2018). On the other hand, if individuals lack pertinent information about their peers that employers seek, or if they prioritize recommending friends regardless of their quality, referral-based hiring can distort the recruitment process (Beaman and Magruder, 2012; Fafchamps and Moradi, 2015). Unlike previous work, we design an experiment that precisely isolates the role of competition in the referral process and shows how it interacts with hiring strategies such as wage increases. Interesting, our results might help explain why the impact of referrals varies across contexts. When

[1] Online job portals have the potential to fulfill this role, but their matching algorithms must be sophisticated enough to ensure that firms are not overwhelmed with irrelevant applications.

competition is minimal, as seen among full-time existing employees (Dustmann et al., 2016), referrals tend to be higher quality. However, in contexts where competition is more pronounced, such as among day laborers (Beaman and Magruder, 2012), the quality of referrals can decline. This may also explain why individuals need incentives to make better referrals.

The rest of this paper is organized as follows: Section 2 describes our setting, the experiment, and data collection, Section 3 lays out a conceptual framework to formalize the role of competition in impacting job sharing, while Section 4 reports results. Section 5 concludes.

2 Experimental Design and Data

2.1 Experimental Design

Recruitment: We worked with six private colleges in Mumbai, India. These colleges cater to lower-income students across the city. Each college consists of students across different programs of study (such as commerce, marketing, finance, HR, etc.), which we term as a 'batch' (i.e. a major). We worked with students from 23 batches who were about to complete their final year of college and intended to look for jobs once they graduated. Students from these colleges typically go on to work as BPO telecallers or back-office assistants. Unemployment rates are relatively high for students graduating from private colleges across India, and there is some debate as to the quality of education students receive at these institutions (Beniwal, 2023).

To recruit our sample within each college, we publicly advertised a three-hour complementary "employability training" course that we would be offering to anyone who participated in the study. This course covered topics such as how to look for jobs using job-portals, how to build a professional CV, and how to get ready for an interview. There was no module in the training that mentioned the importance of social networks in job search or otherwise primed the students to share job information. Anyone who registered for the course became part of our sample, and we subsequently engaged them for the next six weeks. The reason for offering this training course was twofold. First, the participating colleges wanted us to help their students improve their job search process; and second, the training course helped us get students who were actually interested in looking for a job and for whom the intervention (described below) would be relevant. At the end of the course, students received a completion certificate and were informed they might be contacted about a short-term gig in the coming weeks.

There were 496 students in these batches who registered for the training course out of a total of 2,834 students. We conducted a comprehensive baseline survey with these 496 students, where we collected detailed socio-demographic information, as well as English, logical, and quantitative abilities, information on students' social networks, who they talked to about employment opportunities, and the strength of their connection with their friends.

The students: Students in our baseline sample were 20 years old on average, 60% were female, 82% were Hindu, and 60% came from the general castes (see Table A1). Students in our sample were from lower-middle income households with less than 25% reporting a monthly family income exceeding INR 30,000 (USD 350). Their parents typically did not have higher education: only 13% of fathers and 6% of mothers had a college degree. Students reported speaking to their friends regularly about jobs. Just over half of the students reported having helped friends find a job in the past, 42% relied on friends to find jobs for themselves, and 87% discussed jobs more generally with their friends. Compared to a nationally representative sample of the 68th Round of the National Sample Survey (NSS) from 2011-12 as in Banerjee and Chiplunkar (2024), our sample was slightly younger, with a lower concentration from scheduled castes/ schedules tribes/ other backward classes. We also find that our sample is comparable to college graduates in the CMIE, a nationally representative panel of Indian households, both in terms of parental income and religion. However, our sample has a slightly higher proportion of women and general caste individuals (Table A2).

The job: Our experiment engaged this sample for six weeks after the completion of the training program (students were unaware of duration of the study). Each week, we called all 496 students to conduct a brief survey, asking about their job-search strategies, the jobs they learned about, and the jobs they applied to. For the subset of students who were randomly selected to receive information about a job (detailed below), we also informed them about the opportunity during these midline calls. We mentioned that we had designed a small task (henceforth, our "job") that would require them to spend 45 minutes searching for five articles on a particular topic on Indian public policy that was of interest to a researcher at a renowned international institution. We informed students the job was a one time opportunity, with a fixed wage. The application process would be simple: they would only need to fill out a Google Sheet with their contact information and GPA. They would also receive a certificate of recognition for completing the work. In both rival and non-rival scenarios, students were informed that we needed multiple people to perform this task so they should feel free (but were not required) to share their referral code. They were not told exactly how many slots were available, nor the criteria that we would use to select students for the job. We ended the phone call by sending a brief WhatsApp message that included details about the job opportunity and a link to the application.

Our hiring process ranked applicants based on their GPA and given our budget constraints, we were willing to hire a maximum of a third of the batch. Each student who was hired for the job (detailed below) was tasked with finding relevant articles and summarizing them in a few sentences. We changed the topics weekly and covered issues in agricultural policy, women empowerment, education, etc. This job (and research topic) was the *same* across all college-batches in a particular week. The selected students joined remotely via a Google link at a pre-determined time to complete the job. Each student had to complete their task individually and there was no interaction between them on the job. While some students completed their task online and submitted their summaries to the team, others submitted handwritten summaries via WhatsApp. These summaries were anonymously graded by the research team on a scale from 1-10. Students who completed this task received their payment of INR 500 (USD 6.5) and their completion certificate that same day.

Randomization Procedure: We varied two aspects of the job before sharing it with a randomly selected group students within a batch: (a) whether the job was "rival" or not (which we detail further below); and (b) whether it offered double the wage i.e., INR 1000, or not. Everything else about the job (such as the topic students had to summarize) remained the same across all batches during a given week. The experimental design then followed a two-stage process. In the first stage, for a given week, a batch was randomly allocated to receive information about one of the four categories of jobs: (i) rival high-wage; (ii) rival normal-wage; (iii) non-rival high-wage; and (iv) non-rival normal wage. In the second stage, for a given week, we then randomly selected 20% of students within each batch to receive information about this job. We call these students our 'entry-points'. To track the spread of information, entry-points received a unique referral code along with an application link via WhatsApp, which they could easily share and forward to other classmates.[2] Anyone who

[2]This unique referral code was created using a random number generator in R alongside the treatment assignment. If a student heard about a job through a friend-of-a-friend of an entry point, they would still need to use the referral code of the original entry point. Around 95% of referral codes submitted by applicants were from within the same batch. This is likely because students had little opportunity to interact across batches, given the lack of overlapping classes or shared dormitories.

was not assigned to hearing about these jobs are henceforth labelled as 'students'.[3] Note that since a new group of students within a batch was selected to hear about the job, the entry-points changed every week. Table A1 shows that the characteristics of these entry-points relative to the other students was balanced across weeks. Lastly, the entry-point students were randomly picked every week and 73% of students were either never treated or treated only once, mitigating strategic considerations across weeks in information sharing.

Rival and Non-Rival Jobs: We now elaborate on the distinction between a rival and non-rival job. The distinction between a rival job and a non-rival job influenced the strategic incentives that the entry-points faced when sharing information about the job opportunity within their social network. For a batch that was allocated to a rival job, entry-points were invited to apply for the job and would be notified if they were selected for it. For a non-rival job on the other hand, entry-points were *guaranteed* the job if they applied for it (we did not provide any further details on the selection criteria, and no one asked). In both cases (rival and non-rival), entry-points were encouraged to share this job opportunity with their peers (who would have to apply and were not guaranteed a position) since we were prepared to hire multiple students from a batch for the job. Finally, in rival batches we ranked all applicants by GPA and hired the most qualified set. In non-rival batches, we hired all entry-point students (if they applied), along with other students with the highest GPA. In both cases, students were unaware of the selection criteria or the total number of slots available in any given week.

External Validity It's important to note that our setting is unique in several ways. First, we created our own firm to hire job seekers, allowing us to easily vary whether a position was guaranteed (non-rival) or competitive (rival). We recruited from a pool of students whose social network we could capture, for short-term, one-off jobs that we could hire repeatedly for and quickly observe productivity. We had limited opportunity to learn about students' abilities over time, and the students did not interact with one another during the job.

The advantage of designing the experiment the way we did is that it allows us to precisely identify how information flows through a network and the role competition plays, while shutting down other mechanisms that could affect labor market outcomes in a real-world setting. Moreover, our design allows us to disentangle equilibrium

[3] Note that by definition, 'students' include *all* students in a batch who were not assigned to receiving the job information, including those who were not in our baseline.

dynamics that would otherwise be challenging to separate: by experimentally varying both the wage and the level of competition for a job, we can examine how the two dynamics interact. In other words, this experimental design created the necessary conditions to identify the underlying mechanisms of interest. The paper thus serves as a proof of concept for how strategic disincentives shape hiring outcomes and influence the effectiveness of firms' hiring strategies.

However, it's important to acknowledge that these features distinguish our setting from other labor markets, and the effects we observe could represent either an upper or lower bound—depending on whether competition is more or less salient in these other contexts. For example, in settings where firms rely heavily on current employees for referrals—and where those employees are held accountable for the performance of their referrals (e.g., through performance-based incentives)—competitive distortions may be less pronounced than in our context. In such cases, our estimated effects could represent an upper bound. Conversely, if these new hires then become competition for future promotions and may affect current employees' standing within the company, then competitive distortions may be higher — implying that our effects could represent a lower bound.[4]

Nevertheless, the types of students we engaged, and the short-term nature of the job are not unusual in India, where job turnover is common among job seekers. According to the CMIE, a nationally representative panel dataset of Indian households, approximately 25% of job seekers change jobs (as defined by narrow industry-occupation pairs) every three months, 30% leave after 6 months, and approximately 50% do not stay in the same job for more than a year (Figure A1). We also use data from the CMIE and India's National Sample Survey (NSS) to show that our students are similar to the overall college population in these datasets, particularly in terms of parental income and religious backgrounds, with a slightly higher proportion of general caste students. Moreover, the short-term, casual hiring model we employ in our study is similar to those examined in Breza et al. (2021) and Varun (2024).

2.2 Data

We collected four datasets. First, a baseline survey with 496 students captured detailed information about job-seekers' demographics (gender, GPA score, social norms).

[4]Ultimately, there are several underlying factors that can influence the strength of competitive distortions in a given setting. These include whether the job is long-term or short-term, the availability of alternative job opportunities, how attractive the job is, whether the job seeker has prior experience with the employer, and whether the employer is hiring for a single position or multiple roles (to name a few).

The survey asked respondents to list all the friends in their batch who they talk to about jobs and the strength of their connection. This allowed us to map out their social network.[5] Second, we conducted *weekly* midline surveys with our baseline sample to understand whether they had heard about our job opportunity, as well as who they heard it from.[6] Third, we complement these data with information collected on applications. All applicants had to apply via google-forms so we could track applications. These forms asked for the applicant's name, gender, GPA, and a referral code. The referral code was unique to each entry-point in a week, which enabled us to perfectly track which entry-points applicants heard the job from, thus fully characterizing the flow of information within the network.[7] Fourth, we tracked who was hired each week as well as several measures of their performance on the job (such as time taken, quality of submission, etc.). Note that both the data on applications and hires included information about applicants and hires regardless of whether they were in our baseline sample or not. This enabled us to capture a comprehensive spread of information within the batch as opposed to just within our sample.

We create two datasets for our analysis. The first is a student-by-week panel, which includes 496 students who completed the baseline survey (each student can appear up to six times). Additionally, there are 110 students who did not complete the baseline because they did not register for the initial employability program, but later heard about the job through another source and decided to apply (appearing 147 times in total). It is important to note that when analyzing whether individuals heard about these job opportunities, we focus on the non-entry points, which represent 80% of the sample (approximately 2535 observations).

Second, to understand how information spreads and who shares information with whom, we create a bi-directional student pairs-week dataset. These data consist of all student pairs (for each week) where at least one of i and j report (in the baseline survey) being in each others social network. Like the previous dataset, for each week, we restrict our attention to all pairs of *non-entry point students* that were in our baseline sample, and therefore eligible to be entry points themselves (approximately 3740 observations).

These datasets allow us to generate three key outcomes of interest: whether a student (i) heard about the job; (ii) applied to the job; and (iii) was hired for the job. We also

[5]30.6% of students report talking to no friends about jobs, another 43.7% report talking to 1 person, while the remaining 25.7% report talking to 2-4 students.

[6]Specifically, we ask "We know some college students apply to short-term roles, did you see/hear about any last week? This includes - one time short gigs, weekend jobs, 1 day tasks, 30 min task run by the employability training program, etc."

[7]Only one referral code was entered in the application. Therefore, if a applicant received the information from more than one entry point, we only capture one of these.

examine the average GPA of the students in each of these three groups.[8] Lastly, it enables us to measure various indicators of job performance, including attendance, task completion, completion time, and submission quality.

3 Conceptual Framework

Before discussing the results, we present a simple and stylized conceptual framework to help guide our empirical analysis and interpret the results. The aim of this framework is to highlight two key tradeoffs faced by individuals in deciding whether to share job information with peers or not: first, competing with their peers for the job; and second, the utility gains derived from sharing this job information with peers. This provides us with a parsimonious way to interpret the results.

Setup: Consider a pair of friends i and j who are indexed by a characteristic (such as gender, ability, etc.) X_i and X_j respectively. A job is indexed by a quality measure w (such as wage, amenities, etc.) so that a higher w implies a better quality job. We model the decision of an individual i who hears about a job w and has to decide whether to share this information with their friend j. The utility of individual i is given by:

$$\mathcal{U}_i = \Pr\left(X_i, X_j, \mathbb{1}_i\{\text{Share}\}\right)U(w) + \mathbb{1}_i\{\text{Share}\} \times \underbrace{\eta_{ij}\theta(w)}_{\text{Utility Channel}} \tag{1}$$

We define each term in turn. $U(w)$ is the utility derived by an individual i from working in a job w. $\Pr(X_i, X_j, \mathbb{1}_i\{\text{Share}\})$ is the probability that i is hired for a job w. This depends on the individuals own characteristics (X_i), the (endogenous) decision to share this information with j (denoted by $\mathbb{1}_i\{\text{Share}\}$) and if shared, the characteristics of j (X_j). Lastly, we refer to $\eta_{ij}\theta(w)$ as a "utility channel". We assume that sharing information might have non-employment utility benefits for the individual, denoted by $\theta(w)$. This utility may stem from altruistic preferences—a genuine desire

[8]Our trial was registered on the AEA RCT Registry (# AEARCTR-0007564). Although we did not create a pre-analysis plan (PAP), we identified a very parsimonious set of primary outcomes to investigate. First, we specified two primary outcomes of interest in the registry: hearing about job opportunities and actively applying for jobs. We expanded our analysis to include an investigation of who was hired, as this represents a natural extension of who applies. Second, we also specified two dimensions of heterogeneity (that we discuss in subsequent sections), namely ability and homophily. We expanded our analysis to include an investigation of the impact of being closely connected to a peer, as such connections are expected to reduce the impact of competition (in contrast to ability, which would intensify it). Following the guidance of Banerjee, Duflo, Finkelstein, Katz, Olken and Sautmann (2020), our readers may wish to interpret heterogeneity analysis on close connections as secondary analysis.

to share—or from the expectation of reciprocity, where the individual anticipates being repaid in the future and gains utility from that prospect.η_{ij} captures how much an individual cares about sharing this information, which could for example be proxied by the strength of their connection or homophily considerations.[9] Furthermore, $\Pr(X_i, X_j, \mathbb{1}_i\{\text{Share}\})$ is defined as follows:

$$\Pr\left(X_i, X_j, \mathbb{1}\{\text{Share}\}\right) = p(X_i) - \mathbb{1}_i\{\text{Share}\} \underbrace{\lambda(X_i, X_j)}_{\text{Competition Channel}} \tag{2}$$

Consider the case where there is no job sharing i.e., $\mathbb{1}_i\{\text{Share}\} = 0$. Then we denote the probability that an individual i is hired for a job w by $p(X_i)$, where $\partial p/\partial X_i \geq 0$ i.e., conditional on the job, individuals with "better" characteristics (higher ability for example) are more likely to be hired.[10]

Now consider the case where an individual decides to share information i.e., $\mathbb{1}_i\{\text{Share}\} = 1$. We assume (in a reduced-form way) that sharing information on jobs with friends might reduce the possibility that the individual gets the job. We term this the "competition channel". Moreover, the extent to which this competition matters depends on the characteristics of j relative to i. To put it more formally, we assume that sharing jobs reduces own-probability of getting a job by a function $\lambda(X_i, X_j)$, where $\partial\lambda/\partial X_j > 0$ i.e., conditional on X_i, a higher X_j would reduce i's probability of getting the job.

Decision to share information: Given this setup, an individual i will share a job with their peer j as long as s/he receives higher utility from doing so i.e., $\mathcal{U}_i(\mathbb{1}_i\{\text{Share}\} = 1) \geq \mathcal{U}_i(\mathbb{1}_i\{\text{Share}\} = 0)$. From Equations (1) and (2), this implies:

$$\begin{aligned} \Delta\mathcal{U} &= \mathcal{U}_i(\mathbb{1}_i\{\text{Share}\} = 1) - \mathcal{U}_i(\mathbb{1}_i\{\text{Share}\} = 0) \geq 0 \\ &= \underbrace{\eta_{ij}\theta(w)}_{\text{Utility channel}} - \underbrace{\lambda(X_i, X_j)U(w)}_{\text{Competition channel}} \geq 0 \end{aligned} \tag{3}$$

i.e., the utility benefits of sharing the job outweigh the costs of competing for it.

[9]Note, that the utility conferred to the agent i does not depend on whether their friend j actually receives the job. While this assumption could be relaxed, for simplicity we do not allow it here.

[10]There are two clarifications of note: first, we do not endogenously solve for $p(X_i)$ in equilibrium, but rather assume that it depends on the characteristics of an individual. Second, we do not distinguish between the probability of hearing and applying for the job. As we will show later, conditional on hearing about a job 75-80% of individuals apply for it, indicating that this is not an important margin.

4 Empirical Analysis

4.1 Does Information Flow?

There were two ways for students in our sample to hear about these jobs. Entry-points heard about the job directly from us (by design), while other students could only hear about the job from their entry-point peers (or from someone connected to an entry-point). Since our primary goal is to understand the flow of job information and how it changes with the rival nature of the job information, we restrict our analysis to the non-entry point students. We begin by estimating the following regression:

$$Y_{ibt} = \alpha_b + \alpha_t + \beta_1 \text{Non-Rival}_{bt} + \gamma X_i + \varepsilon_{ibt} \tag{4}$$

where Y_{ibt} takes the value 1 if an individual i in batch b in week t heard about (or applies to) a job and 0 otherwise; Non-Rival_{bt} takes the value 1 if the job shared in individual i's batch (b) was non-rival in week t and 0 otherwise; α_b and α_t are batch and week fixed effects that we include to account for the stratification of treatment, and X_i controls for the number of friends individual i has. We cluster standard errors at the batch-week and individual level. The former is to account for how the treatment was administered, while the latter allows for correlations within individual across weeks. From our conceptual framework (Equation 3) we anticipate that individuals will be more likely to share information about the job when the job is non-rival and the competition channel is shut down ($\beta_1 > 0$).

We find that 21% of non-entry-point students heard about the job (pooled across batches and weeks), and among those who did, 80% applied. This suggests that limited access to job information may be a more significant barrier in our setting than students' willingness to apply. In Panel A of Table 1, we then turn to examining how information sharing (and hence applications) varied with the competition of the job. The probability that a student heard about (Column 1) or applied to a job (Column 2) increased by 5.3 p.p. and 4.7 p.p. respectively, if the job we advertised in their batch was non-rival relative to when it is rival. This represents a 30% increase.

Furthermore, we can test whether the probability that a student heard about a job increased when they were directly connected to an entry-point who received this information from us, and how this varied with the rival nature of the job information. Specifically, we estimate the following regression specification:

$$Y_{it} = \alpha_b + \alpha_t + \beta_1 \text{Non-Rival}_{bt} + \beta_{2A} \text{Non-Rival}_{bt} \times \text{T}_{it} + \beta_{2B} \text{Rival}_{bt} \times \text{T}_{it} + \gamma X_i + \varepsilon_{it} \tag{5}$$

where (Non-)Rival$_{bt}$ takes the value 1 if the job we shared in batch b was (Non-)rival and 0 otherwise; T_{it} takes the value 1 if at least one friend in i's social network was selected as the entry-point in week t and 0 otherwise. The coefficient β_1 measures the change in the probability of hearing about a job for individuals who are *not* connected with entry points for a non-rival job compared to a rival job (as being unconnected in a rival job is the omitted group). The coefficient β_{2A} measures the change in the probability that an individual hears about a non-rival job when they are connected to an entry point compared to an individual who had no direct connections to entry points. Similarly, β_{2B} does the same for rival jobs. Lastly, X_i controls for the total number of friends that individual i reported.

The results are reported in Panel B of Table 1. Column 1 shows that individuals were 25.5 p.p. (24.1 p.p.) more likely to hear about the job when they were connected to an entry-point, relative to when they were not connected to any entry-point, and the job information was non-rival (rival). This confirms that being directly connected matters regardless of whether the job information is rival or not (β_{2A} and β_{2B} are not significantly different from one another). Nevertheless, individuals with no connections to entry-points were also 3 p.p. (25%) more likely to hear about the job when it was non-rival relative to rival (β_1 is significant). This suggests that information disseminated more widely to non-connected peers when information was non-rival. We see a similar pattern emerge for applications (Column 2) as well. The probability of applying increased by 2 p.p for unconnected students when the job was non-rival relative to rival (though the point estimate is not statistically significant at conventional levels).[11]

Taken together, these results highlight two essential aspects of how the competitive nature of job information affects its dissemination within social networks. First, we illustrate the role of strategic disincentives in sharing labor market opportunities. Jobs classified as "rival" were less likely to be shared within a group. Second, an individual's chances of hearing about a job significantly improved *on average* when someone they knew directly received the information – both when the job was rival or non-rival. That said, we examine the characteristics of these relationships and show that there is meaningful heterogeneity in which connections share information.[12]

[11] Among those who heard about a job from an entry-point, 93% received the information from an entry-point who also applied for the job. This makes it unlikely that information sharing was driven by entry-points who chose not to apply themselves.

[12] In Table A6, we show that our results are robust to controlling for an individual's treatment status from the previous week.

4.2 Who Shares Information, and With Whom?

Having established that information about non-rival jobs is more likely to be shared than rival ones, we now examine whether these strategic decisions to share information were influenced by additional factors that could exacerbate or mitigate perceived competition for a job. First, we examine whether individuals shared job information less with their higher-ability peers when the job was rival versus non-rival. Second, we explore whether a (self-reported) measure of the closeness of their friendship was able to overcome job-seekers' tendency to withhold rival job information. Finally, we investigate information sharing between same-gender friends, building on a literature on homophily.

For this analysis, we shift focus on friend pairs between which information is most likely to flow and for whom personal information (e.g. GPA) is most likely to be known. As noted earlier in Section 2.2, these data include all student pairs (for each week) in which at least one of the two students, i or j, reported in the baseline survey discussing employment opportunities and job search with the other. As in the previous section, we focus exclusively on pairs where student i is not the entry point in a given week. It follows that the analysis is conducted at the pair-level (instead of at the individual level), where each pair consists of a non-entry point student (the respondent) i and their friend j, who we observe in a week t.

Ability of the Individual: If individuals know they have to compete for a job they may be less likely to share information about it. One feature that could exacerbate this dynamic is if an individual j perceives their peer i to be of higher ability. Indeed, sharing information about a job with i means potentially competing with a stronger applicant pool, thus mechanically reducing j's chance of getting the job. Through the lens of our conceptual framework (Equation 3), $\partial \Delta \mathcal{U} / \partial X_j = -U(w) \partial \lambda / \partial X_j < 0$ i.e., individuals are less likely to share job information with their higher-ability peers.

We can test this hypothesis by looking at whether students were less likely to hear about the job from a lower ability entry-point peer when the job information was rival (as opposed to non-rival). Using a student's GPA score as measure of ability, we construct a binary variable for each pair ij, denoted by $1(\text{Ability}_i > \text{Ability}_j)$, that takes the value 1 if an individual i has a higher GPA score (and thus higher ability) relative to j. We then estimate the following specification for the pair ij in a week t:

$$\begin{aligned} Y_{ijt} = \alpha_b + \alpha_t + \beta_{1A}\text{Rival}_{jt} + \beta_{1B}\text{Rival}_{jt} \times 1(\text{Ability}_i > \text{Ability}_j) \\ + \beta_{2A}\text{Non-Rival}_{jt} + \beta_{2B}\text{Non-Rival}_{jt} \times 1(\text{Ability}_i > \text{Ability}_j) \\ + \beta_3 1(\text{Ability}_i > \text{Ability}_j) + \beta_4\text{Non-Rival}_{bt} + \gamma X_i + \varepsilon_{ijt} \end{aligned} \tag{6}$$

where Y_{ijt} is a binary variable that takes the value 1 if the respondent i hears about a job from their friend j in a week t. Non-Rival$_{bt}$ takes the value 1 if a batch b was non-rival in week t. (Non-)Rival$_{jt}$ takes the value 1 if their friend j is an entry-point and receives information about a (non-)rival job from us in week t i.e., it is a short-hand for (Non-)Rival$_{bt} \times T_{jt}$.[13] Lastly, like in previous specifications, X_i controls for the number of friends for i, and α_b and α_t are batch and week fixed effects (the level of treatment stratification). Our coefficients of interest are β_{1B} and β_{2B}. The coefficient β_{1B} measures the change in the probability that an individual hears about a *rival* job when they have relatively higher ability than their entry-point friend, as compared to when they have relatively lower ability entry-point friend. β_{2B} captures the same comparison for *non-rival* jobs. A key test of the significance of the competition channel (in line with the conceptual framework) is if $\beta_{1B} < \beta_{2B}$ i.e., if rival jobs are less likely to be shared with high ability peers than non-rival ones.

The results are reported in Column 1 of Table 2. First, we find similar results to those discussed in Table 1– being connected to an entry-point increased the probability of hearing about a job in both rival and non-rival batches i.e., across all columns in the table, $\widehat{\beta}_{1A} > 0$ and $\widehat{\beta}_{2A} > 0$. However, *who* received this job information varies widely based on whether the job is rival or not. A higher ability student was 7.5 p.p. (39.2%) *less* likely to hear about a rival job when their lower ability entry-point friend heard about it. On the other hand, they were 8.5 p.p. (51.5%) *more* likely to hear about it from their lower ability entry-point friend when the job was non-rival. We can comfortably reject the null hypothesis that $\hat{\beta}_{1B} = \hat{\beta}_{2B}$ (p-value: 0.02). This implies that the probability that a high-ability individual heard about a job from her low-ability entry-point friend was indeed different based on whether the job was rival or not.

Strength of the Connection: While perceptions of someone's higher-ability may reduce information sharing for rival jobs, being closely connected to someone may have

[13] While we control for Non-Rival$_{bt}$ and $1(\text{Ability}_i > \text{Ability}_j)$ separately, we cannot control for T_{jt}, which is perfectly collinear with Non-Rival$_{jt}$ and Rival$_{jt}$. In other words, (β_{2A}) β_{1A} measure the change in the probability that an individual hears about a (non-)rival job from their (lower-ability) entry-point friend, relative to their (lower-ability) non-entry point friend (the reference group).

the opposite effect. There may be utility gains to sharing jobs with friends if individuals are altruistic and want to help their friends find jobs; if they believe that by sharing a job with their friends they are more likely to hear about an opportunity themselves in the future; or if they benefit from creating opportunities to interact with their friend by sharing job information. These channels could mitigate an individual's disutility from sharing competitive employment opportunities with their close friends. More formally through the lens of our conceptual framework (Equation 3), $\partial \Delta \mathcal{U} / \partial \eta_{ij} = \theta(w) \geq 0$.[14]

In our baseline survey, we asked respondents to tell us for each friend, on a scale of 1 (Not Close) to 5 (Very Close), how frequently they talked to each other about employment and jobs. We then classified each pair as "close" if the respondent rated the frequency of interactions to be 4 or higher.[15] Similar to Equation (6), we estimate the following specification and report the results in Column (2) of Table 2:

$$\begin{aligned} Y_{ijt} = \alpha_b + \alpha_t + \beta_{1A}\text{Rival}_{jt} + \beta_{1B}\text{Rival}_{jt} \times \text{Close Friends}_{ij} \\ + \beta_{2A}\text{Non-Rival}_{jt} + \beta_{2B}\text{Non-Rival}_{jt} \times \text{Close Friends}_{ij} \\ + \beta_{3A}\text{Close Friends}_{ij} + \beta_{3B}\text{Non-Rival}_{bt} + \gamma X_i + \varepsilon_{ijt} \end{aligned} \tag{7}$$

Turning to the results, we see that individuals were 10.8 p.p. and 9.3 p.p. more likely to hear information on jobs from their close connections entry-point peers (relative to connections that weren't close) when the jobs were rival and non-rival respectively. That is, individuals were more likely to hear about jobs from their close connections entry-point peers regardless of the competition for the job ($\hat{\beta}_{1B} = \hat{\beta}_{2B}$, p-value: 0.76). This suggests that close friendships boost information flow regardless of whether the job is rival or not, indicating that close friendships can overcome competitive concerns.

Same Gender: Lazarsfeld et al. (1954) coined the term "homophily" to capture the fact that socially connected individuals tend to be similar to one another. While a large literature has studied the causes and consequences of homophily in various contexts (McPherson et al., 2001; Jackson, 2025), how it affects information sharing about jobs in the presence of strategic disincentives is unclear (Batista et al., 2018). On the one hand, individuals that share an identity (gender in our case) may be able to relate more to one another, and may be more likely to share job information with each other – a "homophily channel" (a higher η_{ij} in our theory). On the other hand, job-seekers

[14] This assumes that being closely connected is uncorrelated with other characteristics X_j that matter for competition. If there is a correlation, then the effect of being a close connection on the probability of sharing is ambiguous when jobs are rival, but unambiguously positive when the job is non-rival.

[15] Our results are robust to alternate cutoffs (for example, 3 or 5) as reported in Table A4.

that share a certain characteristic may feel like they are more directly in competition with one-another for the job, which could reduce their propensity to share information – a "competition channel" (a higher λ in our theory). The probability of sharing information about a job with individuals of a similar identity ultimately depends on the strength of both these channels (which operate in different directions), and is therefore ambiguous when the job information is rival in nature. However, if a job is non-rival (i.e., $\lambda = 0$), then we should expect more information transmission across individuals under homophily (since $\partial \Delta \mathcal{U} / \partial \eta_{ij} \geq 0$).

We investigate this by defining a binary variable that takes the value 1 if both individuals in a ij pair are of the same gender and 0 otherwise. We then estimate the following specification for a pair of individuals ij in a week t:

$$\begin{aligned} Y_{ijt} = \alpha_b + \alpha_t + \beta_{1A}\text{Rival}_{jt} + \beta_{1B}\text{Rival}_{jt} \times \text{Same Gender}_{ij} \\ + \beta_{2A}\text{Non-Rival}_{jt} + \beta_{2B}\text{Non-Rival}_{jt} \times \text{Same Gender}_{ij} \\ + \beta_{3A}\text{Same Gender}_{ij} + \beta_{3B}\text{Non-Rival}_{bt} + \gamma X_i + \varepsilon_{ijt} \end{aligned} \tag{8}$$

The results are reported in Column (3) of Table 2. We find that individuals were 5.3 p.p. (5.7 p.p.) less (more) likely to hear about the job information from their same gender entry-point friends (relative to different gender entry-point friends) when the job was rival (non-rival). These magnitudes are statistically different from each other (p-val: 0.09). This suggests that when the competition channel is absent, homophily induces more sharing. However, the competition channel dominates homophily when jobs are rival, and same-gender friends are less likely to share this rival job information.

Taken together our results indicate that the rival nature of job information can lead to certain types of job seekers being screened out of receiving job information from their peers. In particular, higher ability job-seekers were less (more) likely to receive information on a job when it was rival (non-rival) by their relatively lower ability entry-point peers. Conversely, the strength of a friendship could mitigate these competitive effects of information sharing: individuals were more likely to share job information with their closest friends even if they had to compete with them for it. Lastly, homophily can induce more information sharing only when the information shared is non-rival.[16]

Gender Differences in Information Sharing: Extensive research indicates that women are often more hesitant to engage in labor market competition compared to men

[16] In Table A7, we show that our results are robust to controlling for an individual's treatment status from the previous week.

(Cashdan, 1998; Niederle and Vesterlund, 2011; Boudreau and Kaushik, 2023). Recent studies explore how this dynamic impacts career decisions (Buser et al., 2014), self-promotion behaviors (Exley and Kessler, 2022), and workplace outcomes (Flory et al., 2015). Our current context provides an opportunity to investigate a novel avenue that has yet to be explored in the literature: gender disparities in sharing competitive information. We examine this by conducting a distinct analysis for male and female job-seekers. The results, detailed in Panels A and B of Table A3, indicate that men are less likely to share job information with both high-ability peers (p-value = 0.00) and other men (p-value = 0.12) when the job is rival. We observe no such impacts among women: the estimated effects are small and statistically insignificant.

4.3 Impact on Application Pool, Hiring, and Job Performance

Having established that strategic disincentives can systematically lead to certain individuals in a social network being excluded from hearing about job information, we now delve into the repercussions of this on the quality of applications received by firms. Recall from Table 1 that approximately 80% of individuals applied for a job conditional on hearing about it. This implies that the pool of applicants we received was directly linked to who heard about the job. We therefore first focus on investigating how the composition of applicants and hires changed when the job was rival or not. For measuring ability, we focus on a students' GPA, which is an observable characteristic that employers routinely use to make hiring decisions.[17] Lastly, we use several measures to examine how this impacts students' performance on the job.

Pool of Applicants and Hires: Pooling applications across all batches b and weeks t, we first examine the entire ability distribution of applicants for non-rival and rival jobs.[18]. In Figure 1, we see that the distribution is shifted to the right for non-rival jobs relative to rival ones. We formalize this by re-estimating Equation (4) with applicants' standardized GPA as the outcome variable. As reported in Column (1) of Table 3, the ability of students who heard about the job was 0.08σ higher when the job was non-rival relative to rival. Considering the substantial conversion rate from learning about a job to applying for it, this translated into a 0.13σ increase in the quality of the applicant pool as well (Column 2). Our hiring rule was straightforward: we ranked our applicants according to their GPA and hired them until all the slots for the position were filled. Figure 1 shows a similar rightward shift in the ability distribution among

[17] To ease interpretation, we standardize GPA scores to have mean 0 and standard deviation 1.

[18] We exclude entry points in non-rival jobs because they were mechanically selected for the job and not subject to the hiring rule based on ability

hires when the job was non-rival.[19] More formally, in Column (3) of Table 3, we observe that the ability of hires was 0.38σ higher when the job was non-rival relative to rival.

Performance on the Job: We use several measures of job performance and re-estimate Equation (4) to examine differences between the job performance of students hired through rival and non-rival batches. First, we create binary variables that take the value 1 if a student was either: (i) present for the task; (ii) completed the task; and (iii) completed the task within the stipulated time (45 mins), and 0 otherwise. While 83% of students who were hired in rival batches showed up for the job (Table 4, Column 1), students hired from non-rival batches were 9.6 p.p. (11.5%) more likely to be present. Students from non-rival batches were also 15.3 p.p. (21%) more likely to finish the task (Table 4, Column 2), and 20.4 p.p. (32%) more likely to finish it within the stipulated time (Table 4, Column 3). Lastly, we use two other measures of job performance, namely the time taken (in minutes) to finish the job, and the quality of the submission, as measured by the score students received on their submission (1-10). Students from non-rival batches finished their jobs 3.6 minutes (9.1%) faster (Table 4, Column 4), and their scores were 22% higher as well (Table 4, Column 5).

Taken together, these results confirm that the strategic disincentives in information sharing can meaningfully impact the quality of applications that a firm receives, as well as the hires that the firm can make, which ultimately impacts the quality of the work being performed.

4.4 Can Offering Higher Wages Help?

In previous sections, we show that job-seekers share less information with their peers in a competitive setting, and this has consequences for labor market hiring. Specifically, it suggests that firms that rely heavily on social networks to spread information about job opportunities might end up with lower quality applicant pools and hires than expected. To mitigate this effect, and motivate high-quality candidates to apply for their job openings, firms could enhance the job's appeal by increasing the wage.

While conventional labor supply models would suggest that higher wages should attract higher quality candidates, these models do not consider the dynamics that come into play within social networks. In particular, while increasing the wage makes

[19] Having a better pool of applicants on average doesn't necessarily guarantee better hires. What matters is the quantity and quality of candidates at the top of the distribution, as those are the ones we ultimately hire.

a job more appealing, this could elicit two distinct responses from job-seekers thinking about whether or not to share the job opportunity. First, there is the competition channel: a higher paying job is less enticing to share because the cost of losing the job to a potential fellow applicant has increased. Second, there is the utility channel: a higher paying job is more attractive to share because of the warm glow from sharing information about a better job with a friend. Captured more formally (Equation 3), $\partial \triangle \mathcal{U} / \partial w = \eta_{ij}\theta'(w) - \lambda(X_i, X_j)U'(w)$. Therefore, whether $\partial \triangle \mathcal{U} / \partial w$ is greater than or less than 0 depends on how strongly a change in wages impacts the competition and utility channels. It is entirely possible that job-seekers would share less if the competition channel outweighed the altruism channel, resulting in a lower quality applicant pool for firms to choose from despite an increase in wages.

To investigate this further, we embedded a sub-experiment by cross-randomizing whether the job was rival or not with a high or normal wage. This meant that in some batch-weeks we doubled the wage to INR 1000 for 45 mins work (high-wage category), as compared to the status-quo "normal-wage" of INR 500. This created four types of jobs that could be shared in any given week: "high-wage, rival", "high-wage, non-rival", "normal-wage, rival", "normal-wage, rival".

Similar to Equation (4), we can then estimate the following regression specification:

$$Y_{ibt} = \alpha_b + \alpha_t + \beta_1 \text{High Wage}_{bt} + \beta_2 \text{Non-Rival}_{bt} + \beta_3 \text{High Wage}_{bt} \times \text{Non-Rival}_{bt} + \gamma X_{it} + \varepsilon_{ibt} \tag{9}$$

where all the variables remain the same as in Equation (4). In addition, High-Wage$_{bt}$ takes the value 1 if the job shared in individual i's batch (b) was high-wage in week t, and and 0 otherwise.

The above experimental design provides us with multiple insights on how competition interacts with changes in the quality of the job (wages in our case) and subsequently impacts information sharing within the social network. First, β_1 estimates the causal impact of doubling the wage of a rival job (the status-quo), on information sharing within the social network (and subsequently on the quality of applicants and hires). Second, we can isolate whether competition dampens how much information about high-wage jobs is shared by comparing the information sharing of high-wage rival jobs (β_1) to high-wage, non-rival jobs ($\beta_1 + \beta_2 + \beta_3$) i.e., we can test whether $\beta_2 + \beta_3 = 0$. Lastly, we can benchmark the magnitude of competition's effect on information sharing (β_2) to that of a common strategy firms usually follow to attract better talent: increasing wages (β_1).

Table 5 shows that doubling the wage (for rival jobs) did not significantly increase the probability that individuals heard about it (Column 1) or applied to it (Column 2). Indeed the coefficients– $\hat{\beta}_1 = -0.009$ (Column 1), and $\hat{\beta}_1 = -0.007$ (Column 2) – are very small in magnitude and statistically insignificant at conventional levels. However, it is possible that shutting down competition by making the high-wage job non-rival could significantly increase its information-sharing. We find that the probability that a student heard and applied to this high-wage job when it was non-rival increased by 8.2 p.p (Column 1) and 7.9 p.p (Column 2) respectively (we recover these estimates by adding $\beta_2 + \beta_3$). We can comfortably reject the null hypothesis that $\beta_2 + \beta_3 = 0$ (p-val ≤ 0.02).

Lastly, we investigate how the quality of applicants and hires was affected in Table 6. Note, that when examining applications and hiring, interpreting effects becomes more complicated because there is selection into which job seekers apply to the job (conditional on hearing about it) and then selection into final hires (we hired students with the highest GPA). For example, if high wages encourage both high- and low-ability students to apply more often, the average GPA of applicants may remain unchanged since the proportion of high- and low-ability students stays the same. However, the absolute increase in high-ability students in the candidate pool could result in a higher GPA among those who were hired.

We find that doubling the wage (for rival jobs) improved the quality of applicants and hires by around 0.1σ and 0.08σ respectively (Columns 2 and 3), and their final evaluation score (ranging from 1-10) on the task by almost 1 point or 14.5% (Column 4). The difference between this positive impact and the absence of an effect on the likelihood of hearing about a job can be clarified by the observation that high-ability students were more inclined to apply when they heard about a high-wage job. Consequently, they were more likely to be hired compared to their lower-ability peers. An advantage of our setting is that we can also identify how much stronger candidates ability would have been if higher wages could be offered without triggering a competitive response among job-seekers i.e., if the jobs were non-rival in nature. Specifically, the quality of hires (applicants) improved by 0.35σ (0.04σ) when the high-wage job was non-rival relative to rival and these candidates had a 1.3 points (19.1%) higher evaluation score on the task as well (we recover these estimates by adding $\beta_2 + \beta_3$). Lastly, to gauge the importance of the competition channel, a simple back-of-the envelope calculation comparing β_1 and β_2 suggests that to get the same increase in ability among the pool of hires (applicants), a firm would have to increase wages by 5.8 (3.3 times).[20] Similarly, firms would increase wages by 2.7 times to maintain the same quality of job

[20] To see this, note from Column (3) that the average quality of hires is 0.08σ higher when wages are doubled, and 0.39σ higher when information is non-rival. Therefore, to get the *same* increase in the average applicant quality (assuming linear treatment effects), wages would have to be 1+0.391/0.081 ($1+\beta_2/\beta_1$) i.e., 5.8 times higher.

performance (Column 4).[21] In other words, these results underscore the importance of strategic disincentives in information sharing. Specifically, they suggest that firms would have to offer substantially higher wages to attract the same pool of applicants they would have attracted in the absence of these disincentives.

5 Conclusion

Social networks are central to well functioning labor markets in low income countries. Firms rely on these networks to disseminate information about new job openings and attract high quality candidates. Any frictions that are created by job-seekers competing for jobs could have negative impacts on the quality of matches. We explore this phenomenon empirically with Indian college students about to enter the job market. We create our own firm and randomly seed their social networks with jobs that are either rival or non-rival. We find that when a job is rival, information about that job is less likely to travel in the network, and is less likely to reach high ability job seekers. This is especially true among men. We find that offering higher wages helps attract better quality candidates. However, the improvement is smaller than it would be if competition were not discouraging job-seekers from sharing information.

We view these results as a proof of concept for how an important mechanism like competition shapes labor market dynamics—specifically, its influence on hiring outcomes and the effectiveness of different hiring strategies. Interestingly, these results might explain why the literature finds that the impact of referrals varies across contexts. Specifically, they suggest that whenever competition-related worries are prominent (as seen among day laborers, for instance as in Beaman and Magruder (2012)), the quality of referrals might be lower compared to situations where job-seekers are less concerned about their future job prospects (such as among full-time employees as in (Dustmann et al., 2016)). While firms are limited in their ability to fully eliminate competitive distortions (most jobs are inherently rival), our results suggest there is value in supporting technologies and strategies that help job information reach beyond close social networks—for example, through job portals or information campaigns at universities; or ensuring that referees are properly incentivized.

[21] The results for other job performance indicators are reported in Table A5.

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Tables

Table 1: Heard About and Applied to a Job

	(1) Heard	(2) Applied
Panel A:		
Non-Rival$_{bt}$	0.053	0.047
	(0.020)**	(0.022)**
Control Mean	0.18	0.14
Observations	2535	2535
Panel B:		
Non-Rival$_{bt}$	0.030	0.020
	(0.017)*	(0.017)
Non-Rival$_{bt}$ $\times$ T$_{it}$	0.255	0.230
	(0.057)***	(0.054)***
Rival$_{bt}$ $\times$ T$_{it}$	0.241	0.188
	(0.048)***	(0.044)***
Control Mean	0.12	0.08
Observations	2388	2388

Notes: This table shows whether the rival/non-rival nature of the job affects the probability of hearing (Column 1) or applying (Column 2) to the job. The sample is restricted to non-entry point students in week t. The dependent variable in Column 1 takes the value 1 if i has heard about the job in week t and 0 otherwise. The dependent variable in Column 2 takes the value 1 if i has applied to the job in week t and 0 otherwise. In Panel B, we drop the 147 respondents who were not in the baseline sample but applied for a job. (Non-)Rival$_{bt}$ takes the value 1 if batch b was assigned to the (Non-)Rival treatment in week t and 0 otherwise. T_{it} takes the value 1 if at least one friend of individual i was an entry-point in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table 2: Heard About and Job-Seeker Characteristics

	(1) Ability	(2) Close Friends	(3) Same Gender
Rival_{jt} (β_{1A})	0.191	0.090	0.190
	(0.036)***	(0.022)***	(0.048)***
$\text{Rival}_{jt} \times$ X (β_{1B})	-0.075	0.108	-0.053
	(0.038)*	(0.029)***	(0.045)
Non-Rival_{jt} (β_{2A})	0.165	0.143	0.143
	(0.033)***	(0.033)***	(0.041)***
$\text{Non-Rival}_{jt} \times$ X (β_{2B})	0.085	0.093	0.057
	(0.061)	(0.045)**	(0.049)
$\beta_{1B} = \beta_{2B}$	0.02	0.76	0.09
Observations	2781	3470	3470

Notes: This table shows whether individual characteristics affect how information disseminates when a job is rival or not. The sample is restricted to ij pairs where individual i was assigned to the non-entry point group in week t. The dependent variable takes the value 1 if i heard about the job in week t from friend j, and 0 otherwise. (Non-)Rival_{jt} takes the value 1 if friend j was assigned to the (Non-)Rival treatment in week t and 0 otherwise. In Column (1), X is an indicator for 1($\text{Ability}_i >\text{Ability}_j$), which takes the value 1 if individual i has a higher ability than j. Column (1) has fewer observations because we are missing GPA for some dyads. In Column (2), X is an indicator for Close Friend_j, which takes the value 1 if both i and j are "close friends" and 0 otherwise. Similarly, in Column (3), X is an indicator for Same Gender_{ij}, which takes the value 1 if both i and j are of the same gender and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

Table 3: Ability of Students

	(1) Heard	(2) Applied	(3) Hired
Non-Rival_{bt}	0.083	0.130	0.381
	(0.037)**	(0.045)***	(0.082)***
Control Mean	0.08	0.07	0.13
Observations	688	462	304

Notes: This table shows how the ability of students who hear (Column 1), apply (Column 2) and are hired (Column 3) changes when a job is rival or not. The sample is restricted to respondents assigned to non-entry point group in week t and respondents who were entry-points when the job was rival in week t. In Column (1), the sample is restricted to students who heard about the job, in Column (2) the sample is restricted to students who applied for the job, and in Column (3) the sample is restricted to students who were hired. The dependent variable is the respondent's standardized GPA score. Non-Rival_{bt} takes the value 1 if the batch b was assigned to the non-rival treatment in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

Table 4: Performance of Students on the Job

	(1) Present	(2) Complete	(3) Complete Ontime	(4) Time Taken	(5) Eval. Score
Non-Rival$_{bt}$	0.096	0.153	0.204	-3.576	1.619
	(0.038)**	(0.041)***	(0.058)***	(1.842)*	(0.395)***
Control Mean	0.83	0.74	0.64	39.21	7.26
Observations	304	304	304	304	304

Notes: This table shows how the performance of hired students changes when a job is rival or not. The sample is restricted to hired respondents who were assigned to non-entry point group in week t and respondents who were entry-points when the job was rival in week t. The dependent variables in Columns (1)-(3) are binary variables that take the value 1 if a student showed up for a task, submitted, and submitted within the stipulated time limit (45 mins), and 0 otherwise. The dependent variables in Columns (4) and (5) are the time taken (in minutes) to complete the task and the quality of submission, which is a score from 1-10. Non-Rival$_{bt}$ takes the value 1 if the batch b was assigned to the non-rival treatment in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Table 5: Heard About and Applied to a Job (High-Wage)

	(1) Heard	(2) Applied
High-wage$_{bt}$ (β_1)	-0.009	-0.007
	(0.024)	(0.025)
Non-Rival$_{bt}$ (β_2)	0.022	0.013
	(0.024)	(0.027)
High-wage$_{bt}$ $\times$ Non-Rival$_{bt}$ (β_3)	0.060	0.066
	(0.039)	(0.044)
$\beta_1 = \beta_2$	0.13	0.45
$\beta_2 + \beta_3 = 0$	0.01	0.02
Control Mean	0.19	0.14
Observations	2535	2535

Notes: This table shows whether the rival/non-rival/high-wage/normal-wage nature of the job affects the probability of hearing (Column 1) or applying (Column 2) to the job. The sample is restricted to respondents assigned to non-entry point group in week t. The dependent variable in Column 1 takes the value 1 if i has heard about the job in week t and 0 otherwise. The dependent variable in Column 2 takes the value 1 if i has applied to the job in week t and 0 otherwise. High-wage$_{bt}$ takes the value 1 if the batch b was assigned to the high-wage treatment in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

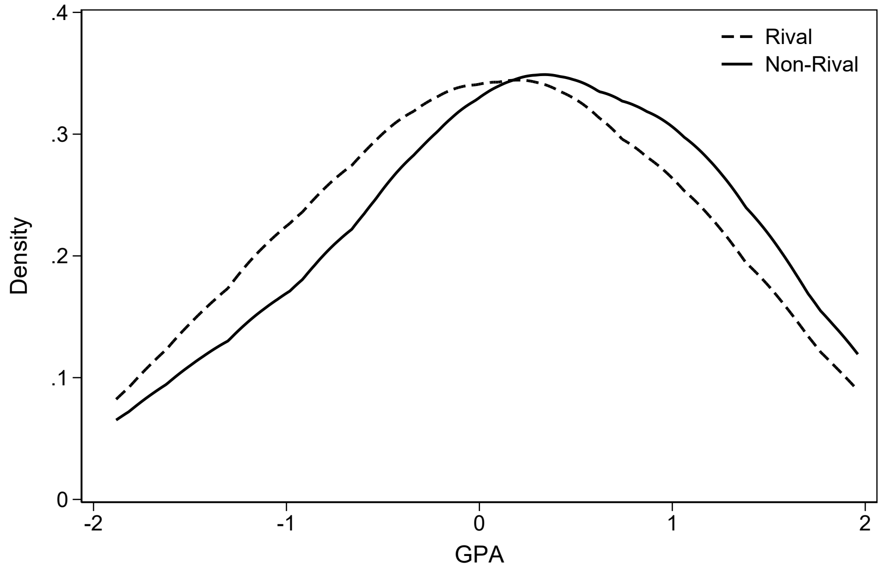
Table 6: Ability of Students (High-Wage)

	Std. GPA Score			Eval. Score
	(1) Heard	(2) Applied	(3) Hired	(4) Hired
High-wage$_{bt}$	-0.036	0.100	0.081	0.989
	(0.051)	(0.028)***	(0.047)*	(0.320)***
Non-Rival$_{bt}$	0.117	0.232	0.391	1.723
	(0.080)	(0.045)***	(0.035)***	(0.568)***
Non-Rival$_{bt}$ $\times$ High-wage$_{bt}$	-0.059	-0.195	-0.037	-0.407
	(0.103)	(0.028)***	(0.144)	(0.774)
$\beta_1 = \beta_2$	0.06	0.05	0.00	0.18
$\beta_2 + \beta_3 = 0$	0.41	0.43	0.01	0.01
Control Mean	0.03	0.00	0.04	6.80
Observations	688	462	304	304

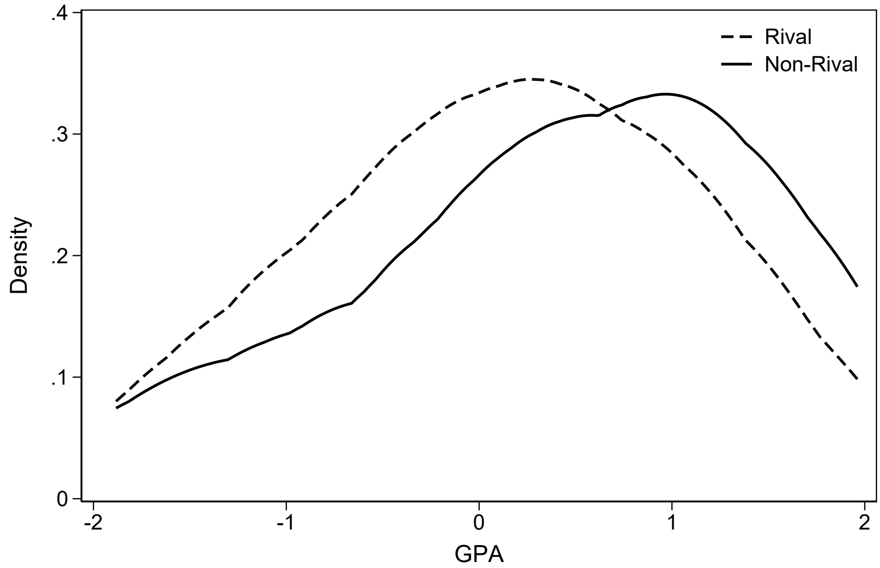
Notes: This table shows how the ability of students who hear (Column 1), apply (Column 2), are hired (Column 3), and their evaluation score (Column 4) changes when a job is rival/high-wage or not. The sample is restricted to respondents assigned to non-entry point group in week t and respondents who were entry points when the job was rival in week t. In Column (1), the sample is restricted to students who heard about the job, in Column (2) the sample is restricted to students who applied for the job, and in Columns (3) and (4), the sample is restricted to students who were hired. The dependent variable is the respondent's standardized GPA score in Columns (1)-(3) and the evaluation score (from 1-10) on the quality of submission in Column (4). Non-Rival$_{bt}$ takes the value 1 if the batch b was assigned to the non-rival treatment in week t and 0 otherwise. High-wage$_{bt}$ takes the value 1 if the batch b was assigned to the high-wage treatment in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$

Figures

Figure 1: Ability Distribution of Applicants and Hires



Panel A: Job Applicants

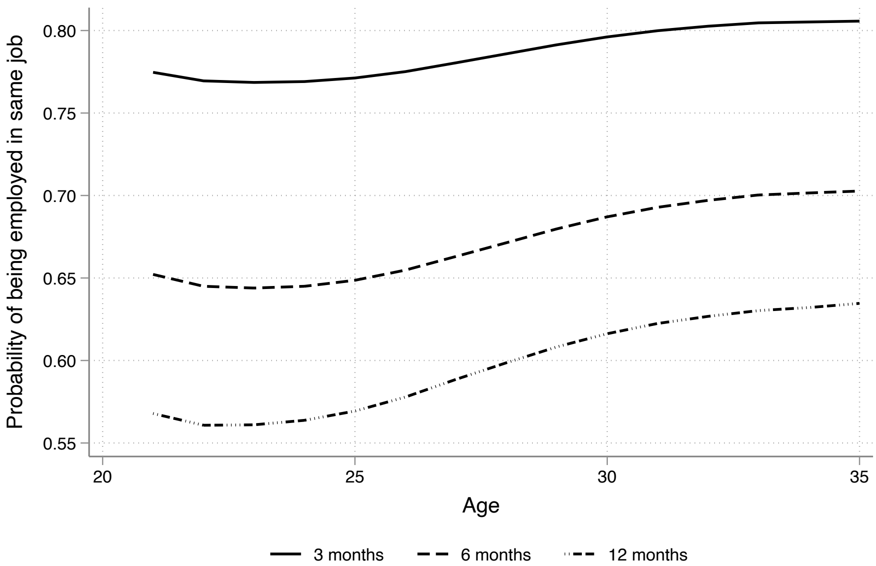


Panel B: Job Hires

Notes: This figure plots the densities of students' standardized GPAs for those who applied for jobs in Panel A and those who were hired in Panel B. In both panels, the distribution for rival jobs is shown by the dashed line and the distribution for non-rival jobs is shown by the solid line.

Appendix Figures and Tables

Figure A1: Probability of Remaining in the Same Job by Age



Notes: This figure uses monthly data on a panel of individuals between 21-35 years of age from the CPHS between 2017-2019. The graph shows a non-parameteric plot between the probability that an individual stays in the same occupation-industry pair (a proxy for the same job) after 3 months (solid line), 6 months (dashed line), and 12 months (dot-dashed line) and the age.

Table A1: Balance Across Entry-Point and Non-Entry Point students, All Weeks

	Control Students	Entry-Points	p-value	N
Age	20.5	20.4	0.10	2976
Female (%)	57.7	59.4	0.48	2976
GPA	6.9	6.9	0.71	2964
Religion: Hindu (%)	81.2	84.5	0.06*	2976
Caste: General (%)	61.5	61.4	0.97	2898
Mother completed college (%)	5.9	6.5	0.64	2976
Father completed college (%)	12.9	13.8	0.59	2976
Parents' monthly income > INR 30000 (%)	22.8	20.6	0.29	2604
Ever helped friend find jobs? (%)	53.6	56.0	0.30	2976
Rely on friends to find a job? (%)	41.8	41.7	0.97	2976
Ever talk to friends about jobs? (%)	86.6	85.9	0.63	2976
Speak to classmates about jobs? (%)	64.1	64.3	0.92	2976

Notes: This table pools all individuals across weeks and checks the balance across characteristics of entry-points and non-entry points across all weeks. The study sample is included. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Table A2: Comparison of Study Sample with a Nationally Representative Sample of Urban Youth

	Study	CMIE	p-value	N
	(1)	(2)	(3)	(4)
Panel A: All Individuals Between 16-25 Years				
In college (%)	100.0	12.7	0.00***	78817
Female (%)	59.4	40.3	0.00***	78817
Religion: Hindu (%)	82.0	81.4	0.73	78817
Caste: General (%)	60.6	36.1	0.00***	78804
Parents' monthly income > INR 30000 (%)	22.4	12.4	0.00***	78817
Panel B: All Individuals Between 16-25 Years | Enrolled in College				
Female (%)	59.4	35.7	0.00***	10417
Religion: Hindu (%)	82.0	86.3	0.01**	10417
Caste: General (%)	60.6	50.4	0.00***	10404
Parents' monthly income > INR 30000 (%)	22.4	20.5	0.34	10417

Notes: Panel A of this table compares characteristics of our study sample with a nationally representative sample of urban youth between ages 16-25 years from the CMIE. Panel B further restricts the CMIE sample to those enrolled in a college. Each outcome variable is a percentage. Columns (1) and (2) report the average in the study sample and CMIE respectively, while Column (3) reports the p-value that tests for the difference between Columns (1) and (2). $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Table A3: Job Sharing and Gender

	(1) Ability	(2) Close Friends	(3) Same Gender
Panel A: Males			
Rival_{jt}	0.229	0.132	0.238
	(0.047)***	(0.038)***	(0.056)***
$\text{Rival}_{jt} \times \text{X}$	-0.142	0.062	-0.107
	(0.047)***	(0.047)	(0.059)*
Non-Rival_{jt}	0.090	0.111	0.132
	(0.040)**	(0.038)***	(0.061)**
$\text{Non-Rival}_{jt} \times \text{X}$	0.117	0.102	0.036
	(0.075)	(0.057)*	(0.068)
$\beta_{1B} = \beta_{2B}$	0.00	0.51	0.12
Observations	1111	1491	1491
Panel B: Females			
Rival_{jt}	0.166	0.057	0.119
	(0.040)***	(0.022)**	(0.075)
$\text{Rival}_{jt} \times \text{X}$	-0.033	0.142	0.019
	(0.059)	(0.041)***	(0.077)
Non-Rival_{jt}	0.213	0.175	0.156
	(0.046)***	(0.043)***	(0.063)**
$\text{Non-Rival}_{jt} \times \text{X}$	0.073	0.081	0.073
	(0.070)	(0.061)	(0.081)
$\beta_{1B} = \beta_{2B}$	0.22	0.39	0.59
Observations	1670	1979	1979

Notes: This table shows whether individual characteristics affect how information disseminates when a job is rival or not separately for males (Panel A) and females (Panel B). The sample is restricted to ij pairs where individual i was assigned to the non-entry point group in week t. The dependent variable takes the value 1 if i heard about the job in week t from friend j, and 0 otherwise. (Non-)Rival_{jt} takes the value 1 if friend j was assigned to the (Non-)Rival treatment in week t and 0 otherwise. In Column (1), X is an indicator for $1(\text{Ability}_i > \text{Ability}_j)$, which takes the value 1 if individual i has a higher ability than j. In Column (2), X is an indicator for Same Gender_{ij}, which takes the value 1 if both i and j are of the same gender and 0 otherwise. Similarly, in Column (3), X is an indicator for Close Friend_j, which takes the value 1 if both i and j are "close friends" and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Table A4: Robustness by Definition of Close Friendship

	Threshold for Strength of Friendship		
	(1)	(2)	(3)
	= 3	= 4	= 5
Rival_{jt}	0.089	0.090	0.134
	(0.035)**	(0.022)***	(0.022)***
$\text{Rival}_{jt} \times$ X	0.070	0.108	0.074
	(0.039)*	(0.029)***	(0.042)*
Non-Rival_{jt}	0.125	0.143	0.171
	(0.046)***	(0.033)***	(0.027)***
$\text{Non-Rival}_{jt} \times$ X	0.080	0.093	0.101
	(0.053)	(0.045)**	(0.064)
$\beta_{1B} = \beta_{2B}$	0.88	0.76	0.69
Observations	3470	3470	3470

Notes: The outcome variable in the above table is a binary variable that takes the value 1 if a student hears about the job and 0 otherwise. Individuals were asked on a scale of 1 (not a lot) to 5 (a lot) how frequently they talked to their friend about other employment and job opportunities. Columns (1)-(3) then define a binary variable X that takes the value 1 if a respondent's frequency of interactions had a value of at least 3, 4, or 5 respectively. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Table A5: Job Performance Measures and High-Wage Jobs

	(1) Present	(2) Submitted	(3) Submitted Ontime	(4) Time Taken	(5) Eval. Score
High-wage_{bt}	0.122	0.109	0.120	-6.509	0.989
	(0.026)***	(0.036)***	(0.045)***	(1.348)***	(0.320)***
Non-Rival_{bt}	0.142	0.168	0.178	-4.388	1.723
	(0.062)**	(0.062)***	(0.099)*	(3.389)	(0.568)***
$\text{Non-Rival}_{bt} \times \text{High-wage}_{bt}$	-0.109	-0.050	0.020	2.913	-0.407
	(0.073)	(0.083)	(0.120)	(4.230)	(0.774)
$\beta_1 = \beta_2$	0.74	0.33	0.53	0.52	0.18
$\beta_2 + \beta_3 = 0$	0.44	0.03	0.00	0.46	0.01
Control Mean	0.77	0.69	0.59	41.98	6.80
Observations	304	304	304	304	304

Notes: The dependent variables in Columns (1)-(3) are binary variables that take the value 1 if a student showed up for a task, submitted, and submitted within the stipulated time limit (45 mins), and 0 otherwise. The dependent variables in Columns (4) and (5) are the time taken (in minutes) to complete the task and the quality of submission, which is a score from 1-10. Non-Rival_{bt} and High-wage_{bt} take the value 1 if the batch b was assigned to the non-rival or high-wage treatment in week t respectively, and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$

Table A6: Heard About and Applied to a Job: Robustness

	Heard		Applied	
	(1) Benchmark	(2) Robust	(3) Benchmark	(4) Robust
Panel A:				
Non-Rival$_{bt}$	0.053	0.058	0.047	0.050
	(0.020)**	(0.026)**	(0.022)**	(0.026)*
Control Mean	0.18	0.16	0.14	0.12
Observations	2535	2436	2535	2436
Panel B:				
Non-Rival$_{bt}$	0.030	0.056	0.020	0.044
	(0.017)*	(0.025)**	(0.017)	(0.025)*
Non-Rival$_{bt}$ $\times$ T$_{it}$	0.255	0.258	0.230	0.232
	(0.057)***	(0.057)***	(0.054)***	(0.055)***
Rival$_{bt}$ $\times$ T$_{it}$	0.241	0.242	0.188	0.189
	(0.048)***	(0.048)***	(0.044)***	(0.045)***
Control Mean	0.12	0.12	0.08	0.08
Observations	2388	2388	2388	2388

Notes: This table shows whether the rival/non-rival nature of the job affects the probability of hearing (Columns 1 and 2) or applying (Columns 3 and 4) to the job. The sample is restricted to non-entry point students in week t. Column 1 and 3 report the results from the benchmark specification in Table 1. Columns 2 and 4 additionally control for the treatment status of the individual and their batch in week $t-1$. By definition, everyone has lagged treatment status set to 0 in week 1. The dependent variable in Columns 1 and 2 take the value 1 if i has heard about the job in week t and 0 otherwise. The dependent variable in Columns 3 and 4 take the value 1 if i has applied to the job in week t and 0 otherwise. In Panel B, we drop the 147 respondents who were not in the baseline sample but applied for a job. (Non-)Rival$_{bt}$ takes the value 1 if batch b was assigned to the (Non-)Rival treatment in week t and 0 otherwise. T_{it} takes the value 1 if at least one friend of individual i was an entry-point in week t and 0 otherwise. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table A7: Heard About and Job-Seeker Characteristics: Robustness

	Ability		Close Friends		Same Gender	
	(1) Benchmark	(2) Robust	(3) Benchmark	(4) Robust	(5) Benchmark	(6) Robust
Rival_{jt}	0.191	0.191	0.090	0.091	0.190	0.189
	(0.036)***	(0.036)***	(0.022)***	(0.022)***	(0.048)***	(0.047)***
$\text{Rival}_{jt} \times \text{X}$	-0.075	-0.075	0.108	0.108	-0.053	-0.052
	(0.038)*	(0.038)*	(0.029)***	(0.029)***	(0.045)	(0.046)
Non-Rival_{jt}	0.165	0.164	0.143	0.143	0.143	0.142
	(0.033)***	(0.033)***	(0.033)***	(0.032)***	(0.041)***	(0.041)***
$\text{Non-Rival}_{jt} \times \text{X}$	0.085	0.085	0.093	0.094	0.057	0.057
	(0.061)	(0.061)	(0.045)**	(0.045)**	(0.049)	(0.049)
$\beta_{1B} = \beta_{2B}$	0.02	0.02	0.76	0.77	0.09	0.09
Observations	2781	2781	3470	3470	3470	3470

Notes: This table shows whether individual characteristics affect how information disseminates when a job is rival or not. The sample is restricted to ij pairs where individual i was assigned to the non-entry point group in week t. The dependent variable takes the value 1 if i heard about the job in week t from friend j, and 0 otherwise. (Non-)Rival_{jt} takes the value 1 if friend j was assigned to the (Non-)Rival treatment in week t and 0 otherwise. In Columns (1) and (2), X is an indicator for $1(\text{Ability}_i > \text{Ability}_j)$, which takes the value 1 if individual i has a higher ability than j. In Columns (3) and (4), X is an indicator for Same Gender_{ij}, which takes the value 1 if both i and j are of the same gender and 0 otherwise. Similarly, in Columns (5) and (6), X is an indicator for Close Friend_j, which takes the value 1 if both i and j are "close friends" and 0 otherwise. Columns (1), (3), and (5) report the results from the benchmark specification in Table 2. Columns (2), (4), and (6) additionally control for the treatment status of the individual and their batch in week $t-1$. By definition, everyone has lagged treatment status set to 0 in week 1. All regressions include batch and week fixed effects. Standard errors are clustered at the week-batch and individual level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$