Career Effects of Online Social Network Access at Labor Market Entry*

Moritz Seebacher†

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Abstract

Does access to online social networking platforms at labor market entry affect young workers' careers? Exploiting the staggered introduction of Facebook across U.S. colleges in a generalized difference-in-differences design, I estimate the causal impact of Facebook access before vs. after labor market entry on the career trajectories of U.S. business and economics students. Using detailed resume data from nearly 900,000 public LinkedIn profiles, I find that students with early access to Facebook are more likely to receive early-career promotions, work in higher-paying jobs, and reach senior leadership roles in their mid-30s to early 40s. I provide evidence that the long-run career effects can be explained by (i) a more successful college-to-work transition, driven by college peers helping each other in the early-career job search process, (ii) improved early-career worker-firm match quality, enabling students to climb up the career ladder within their organizations, and (iii) early-career sorting into higher-quality and career-supporting firms. The results highlight how access to online social networks during a sensitive period of a young worker's career can facilitate the college-to-work transition, reduce information frictions, and generate long-run career benefits.

Keywords: Online Social Networks, Facebook, College Graduates, Labor Market Entry, Career Development, Leadership, Management, Firms, Networking

JEL Codes: D83, I26, J24, J30, J61, J62, L86

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†ifo Institute – Leibniz Institute for Economic Research at the University of Munich, Poschingerstr. 5, 81679 Munich, Germany, `seebacher@ifo.de`

1 Introduction

Online social networking platforms have become an essential part of modern society, fundamentally reshaping how people access information and communicate. While more than 3 billion people report using these platforms for work-related purposes (Kemp (2025)), we still know surprisingly little about their labor market impacts, especially how they shape workers' job search and career trajectories.[1]

Platforms such as Facebook and LinkedIn increase the flow of information and reduce the cost of maintaining social connections. Given the well-established evidence that social connections are valuable for job search and career advancement (e.g., Simon and Warner (1992); Granovetter (1995); Calvó-Armengol and Jackson (2004); Topa (2011); Schmutte (2015); Pallais and Sands (2016); Gee *et al.* (2017); Rajkumar *et al.* (2022); Michelman *et al.* (2022); Cullen and Perez-Truglia (2023)), providing workers with access to these platforms may reduce information frictions and shape their career trajectories in the long run. This may be particularly relevant for younger workers, who have less experience with the job search process and face greater information frictions (e.g., Altonji and Pierret (2001); Pallais (2014)).

In this paper, I provide novel evidence on the causal impact of access to online social networking platforms on the career trajectories of young workers. To isolate plausibly exogenous variation, I exploit a unique natural experiment: the staggered rollout of Facebook across U.S. colleges between 2004 and 2006. Since Facebook became publicly available in 2006, this variation essentially captures the effect of having *early* access to Facebook right before vs. after labor market entry, a sensitive period of a young worker's career that can have long-lasting consequences on labor market outcomes (e.g., Kahn (2010); Oreopoulos *et al.* (2012); Altonji *et al.* (2016); Schwandt and Von Wachter (2019); Von Wachter (2020)).[2]

Using detailed resume data from nearly 900,000 public LinkedIn profiles of U.S. business and economics students combined with a generalized difference-in-differences design, I find that providing students with access to Facebook at labor market entry has a long-run positive impact on their career trajectories.[3] Affected students are more likely to receive early-career promotions, attain higher-paying jobs, and reach senior leadership roles in their mid-30s to early 40s. I provide evidence that part of these long-run career benefits can be explained by a more successful college-to-work transition, largely driven by college peers sharing work-related information and helping one another find high-quality early-career jobs.

[1]See Wheeler *et al.* (2022) and Armona (2023) for some first causal evidence on this topic.

[2]The labor market entry phase is also the point in time when many universities and career services recommend starting to use online social networking platforms for work-related purposes (e.g., Yuan (2010); School of Information, San Jose State University (2018)).

[3]I focus on business and economics students because their LinkedIn coverage is by far the highest among all fields for the graduation cohorts around Facebook's introduction in the mid-2000s. See Section 3 for more details.

I further show that the long-run career benefits can be explained by (i) Facebook improving the quality of early-career worker-firm matches, enabling students to move up the career ladder within their organizations and (ii) early-career sorting into higher-quality and career-supporting firms. In combination, the findings highlight how access to online social networks during a sensitive period of a young worker's career can smooth the college-to-work transition, lower information frictions, and create long-run career benefits.

I use two main datasets for the analysis. The first comprises the introduction dates of Facebook across the first 842 colleges (Armona (2023)), which allows me to identify the academic year in which each U.S. college received access. The second dataset is provided by Revelio Labs and contains detailed CV data from public LinkedIn profiles. The LinkedIn data include two critical pieces of information. First, the detailed education histories provide the name of the postsecondary institution as well as start and end dates, allowing me to identify which students were directly affected by Facebook's staggered introduction at U.S. colleges. Second, the employment histories contain detailed information on job titles, job-specific earnings, and company names, allowing me to track the career trajectories of each student.

To estimate the causal impact of Facebook access at labor market entry on career outcomes, I use a generalized difference-in-differences design. Founded at Harvard in February 2004, Facebook was gradually introduced to other U.S. colleges before going public in September 2006, creating sharp differences in availability across colleges and cohorts. Due to factors such as limited server capacity (Kirkpatrick (2011)) and the desire to cultivate a sense of exclusivity (Braghieri *et al.* (2022)), the rollout of Facebook was not random but targeted elite and highly selective colleges first.[4] In the main specification, I therefore exclusively rely on the plausibly exogenous within-college cross-cohort-selectivity-region variation, essentially narrowing the comparison to treated and not-yet-treated cohorts within the same college selectivity and region. This strategy accounts for various endogeneity concerns such as (i) spurious correlations with the non-random timing of the Facebook rollout, (ii) time-invariant college-specific characteristics (e.g., prestige), and (iii) cohort-specific shocks within the same region at colleges of similar selectivity (e.g., fluctuations in labor market entry conditions and returns to education). To address potential biases in staggered difference-in-differences estimation using two-way fixed effects (Goodman-Bacon (2021)), I apply the heterogeneity-robust two-stage estimator by Gardner (2022).[5]

The main finding of the paper is that access to Facebook at labor market entry has a long-run positive impact on the career trajectories of young workers. U.S. business and economics students with access to

[4]See Section 2 for more details on the adoption and rollout strategy of Facebook.

[5]Appendix F presents the main results using the heterogeneity-robust difference-in-differences estimators of Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020), which differ slightly in their identifying assumptions. The results are very similar.

Facebook are 5.1% more likely to receive early-career promotions and 3% more likely to reach senior leadership positions in their mid-30s to early 40s. They also tend to work in higher-paying jobs, leading to an economically meaningful increase in lifetime earnings of around 1.2%.[6]

Investigating the mechanisms behind these long-run career effects, I document several key factors. Consistent with the idea that online social network access at labor market entry facilitates the early-career job search process, I show that students with early access to Facebook have a more successful college-to-work transition. Students are, on average, 1.5% more likely to be employed in the first two years after graduation, 6.8% more likely to begin their careers in high-wage firms, and 8.8% more likely to obtain a job at a firm offering high career support.[7] In addition to the employment and firm quality margin, I also find that students with early access to Facebook are 4.8% more likely to start their career in high-paying occupations and 7% more likely to find early-career jobs with high chances of reaching a senior leadership position in the long run. The college-to-work transition effects are not explained by graduation timing or postgraduate education choices, and not apparent for lower-quality early-career jobs. In combination, these findings highlight that online social network access at labor market entry facilitates a successful transition into the labor market, which is a key determinant of long-run career success (Kahn (2010); Oreopoulos *et al.* (2012); Altonji *et al.* (2016); Schwandt and Von Wachter (2019); Von Wachter (2020); Arellano-Bover (2024)).

Using a proxy for information sharing and job help based on relational firm mobility patterns developed by Gee *et al.* (2017), I show that the improved college-to-work transition effect can largely be attributed to college peers helping each other access higher-quality early-career jobs.[8] In particular, students with access to Facebook at labor market entry are 17.1% (16.3%) more likely to receive job help from their college peers to obtain an early-career job at a high-wage (career-supporting) firm and 14.9% more likely to use their college network to secure an early-career job with high chances of reaching a senior leadership position. The results highlight that access to Facebook before exiting college increases the value of the college network as a referral system for accessing high-quality entry-level jobs and fundamentally shifts the early-career job search strategy of students towards the college network.

Looking at potential longer-run treatment dynamics, I do not find any evidence that the career benefits are explained by early access to Facebook leading to a long-run information advantage in the search for higher-paying jobs. While evidence by Armona and Bailey (2025) shows that early Facebook adopters

[6]The increase in lifetime earnings for the early Facebook adopters is roughly equivalent to 44% of the reduction in lifetime earnings college graduates were to expect when graduating in a typical recession (e.g., Von Wachter (2020)).

[7]To capture non-wage firm characteristics, I use the employer ratings by Glassdoor. See Data Section 3 for more details.

[8]In the baseline, I define college peers as students between three classes below and above the respective cohort.

have larger social networks in the long run, the estimated impact on between-firm mobility and promotion patterns is close to zero and insignificant, even when combining the between-firm mobility outcomes with job help indicators for the college network. In the spirit of traditional job search models (e.g., Burdett (1978)), this finding suggests that early access to Facebook did not lead to a permanent increase in the job offer arrival rate. This is consistent with the idea that students in the control group created a Facebook account shortly after their labor market entry, narrowing down the differences in the flow of work-related information in the long-run.[9]

Instead, I find evidence consistent with the idea that the career benefits are explained by early access to Facebook improving the quality of early-career worker-firm matches. In the first six years after graduation, students with early access to Facebook are 1% more likely to be in stable worker-firm matches and accumulate on average 0.37 months more firm tenure, with the firm tenure effect persisting in the longer run. Consistent with the interpretation of more stable and productive early-career worker-firm matches, treated students are 13.6% more likely to receive early-career promotions within their firm, while there is no impact on within-firm demotion patterns. In line with the finding by Armona (2023) on early access to Facebook improving the horizontal match between majors and occupations, the worker-firm match results highlight that access to Facebook at labor market entry enabled students to find stable and productive worker-firm matches early on, accelerating firm-specific human capital accumulation and facilitating climbing up the career ladder within their organization.

In addition to the worker-firm match quality channel, I also show that part of the documented career benefits can be explained by sorting into firms that provide better learning opportunities and career support. Consistent with the college-to-work transition effects on the firm quality margin, in the first six years after graduation, students with early access to Facebook accumulate on average 5.4% more work experience at higher-quality firms. They also accumulate more work experience in firms that offer better career support with the effect persisting in the long run. Given the recent evidence by Arellano-Bover (2022), Gregory (2023), and Arellano-Bover and Saltiel (2026) that (i) firms differ substantially in the learning opportunities they provide and (ii) the heterogeneous human capital accumulation across firms can explain a considerable part of life-cycle differences in career outcomes, the findings suggest that sorting into higher-quality firms and accumulating valuable on-the-job skills at a faster rate likely explains part of the documented long-run career benefits beyond the worker-firm match quality channel.

[9] Consistent with this finding, Armona and Bailey (2025) show that the positive network size effects are decaying over time, Facebook was also highly popular among the control group students, and there are no detectable long-run differences in terms of the intensity of Facebook usage between treatment and control group.

What are the implications of having access to online social networking systems for labor market inequality across gender? Estimating the treatment effects separately for men and women, I show that the career benefits are homogeneously shared across gender, suggesting that providing students with access to Facebook at labor market entry does not meaningfully impact gender gaps in career outcomes. However, consistent with the evidence by Armona and Bailey (2025) that early access to Facebook leads to a long-run reduction in gender homophily in social networks, I do find evidence that treated students are more likely to receive opposite-sex job help for finding high-quality early-career jobs. The finding suggests that access to online social networking systems may have facilitated women's access to otherwise male-dominated labor market networks (and vice versa).

The findings are robust to a series of sensitivity checks. One key concern with the identification strategy is that the selectivity-by-region cells are not sufficient to account for the non-random rollout strategy of Facebook and pick up spurious correlations within those cells.[10] To test the seriousness of this issue, I perform a randomization inference test by randomly reshuffling the Facebook introduction dates across colleges within each selectivity-by-region cell. The placebo estimates have a dense distribution around zero, and all of the statistically significant treatment effects are above the 95th percentile of the placebo distribution. Hence, the results strongly indicate that the remaining variation of the Facebook rollout is not spuriously correlated.

Another concern with the main estimation strategy is that the results are driven by treated students taking away jobs from students in the control group, upward biasing the treatment effects. To formally test this, I start by predicting the exposure to spillovers for the potential control cohorts based on the historical career overlap of U.S. business and economics students across colleges. Then, I drop every college that has at least one potential control cohort predicted to be highly exposed to the colleges where Facebook was first introduced. The results are very similar to the baseline estimates, suggesting that the documented career benefits of having early access to Facebook do not simply reflect a reallocation of high-quality jobs, but are rather consistent with a reduction in information frictions.

The results of this paper contribute to various strands of literature. To start with, the findings contribute to the emerging literature on the labor market effects of online social networking systems. Wheeler *et al.* (2022) show that providing job seekers with training to use LinkedIn improves their chances of finding a job and provide suggestive evidence that the effects are explained by workers accessing more information about potential employers and job opportunities. Armona (2023) shows that access to Facebook at labor

[10] E.g., due to differential cohort-specific trends in career outcomes across colleges *within* the same selectivity-by-region cell correlated with the timing of the Facebook rollout.

market entry increases the earning rank of affected college cohorts and provides indirect evidence that the positive earnings effect stems from stronger social ties among college peers and improved matching between major and occupation. Armona and Bailey (2025) shows that Facebook access during college has a long-run impact on the geographic location and occupational choice of students: students with early access to Facebook are more likely to sort into areas with higher economic opportunity and to work in higher-paying occupations. I extend this literature in several ways. First, in addition to the already documented employment and earnings gains due to online social network access, I show that providing access to online social networks during a sensitive period of a worker's career - the labor market entry phase - results in a long-lasting positive impact on career development and economic mobility to top jobs. Second, thanks to the rich career trajectory information on the LinkedIn profiles, I improve the understanding of the *dynamics* and *mechanisms* of the accumulated career benefits due to online social network access. The results of this paper show that the career benefits stem primarily from young workers successfully entering the labor market and finding high-quality jobs and stable worker-firm matches, ultimately climbing the career ladder within their organizations.

The findings also relate to the broader literature on the societal impacts of online social networking platforms. Some papers document negative consequences, such as increased mental health problems (Braghieri *et al.* (2022)), greater political polarization (Zhuravskaya *et al.* (2020)), the spread of misinformation (Allcott and Gentzkow (2017)), and the amplification of hate speech (Müller and Schwarz (2021)). Other work highlights benefits such as increased collective action and protest participation (Fergusson and Molina (2019); Enikolopov *et al.* (2020)). This paper contributes to the literature by showing that work-related usage of online social networks for young workers can generate long-run career benefits, with the effects not being explained by a reallocation of jobs but rather by a reduction in information frictions and increase in worker-firm match quality.

The documented effects in this paper speak to the extensive literature on the role of college networks for labor market outcomes. Marmaros and Sacerdote (2002) and Zhu (2022) provide evidence that social connections among U.S. college students affect career choices and job placement at labor market entry. Zimmerman (2019) and Fischer *et al.* (2023) show that for elite business programs, social ties among college students play an important role in accessing high-paying jobs. Ost *et al.* (2024) shows that college peers help mitigate the negative consequences of job loss due to layoffs. This paper highlights that the access to online social networking systems for college students (i) increases the *value* of the college network as an information system for accessing high-quality early-career jobs and (ii) fundamentally shifts the early-career job search strategy of students towards their college network.

Finally, this paper contributes to the literature on the college-to-work transition and long-run career success. Kahn (2010); Oreopoulos *et al.* (2012); Altonji *et al.* (2016); Schwandt and Von Wachter (2019); Von Wachter (2020) show that graduating in a recession hinders a successful transition to the labor market, reducing the likelihood of working in high-quality jobs and harming workers' careers in the long run. Arellano-Bover (2024) shows that starting a career at a large firm benefits workers' labor market success in the long run. The results of this paper demonstrate that access to online social networks at labor market entry facilitates the college-to-work transition and improves early-career job placement.

The rest of the paper is organized as follows. Section 2 provides a short history of the early expansion of Facebook and its work-related usage. Section 3 describes the data. Section 4 discusses the empirical strategy. Section 5 presents the results. Section 6 concludes.

2 Background

The Early Expansion of Facebook: Founded in February 2004 at Harvard, Facebook started as an exclusive social networking platform for college students, requiring a verified *.edu* email address to create an account. Over the following years, Facebook was gradually rolled out to other U.S. colleges and universities abroad until going public in September 2006. Appendix Figure A1 shows the rollout of Facebook across all selective U.S. colleges offering four-year business and economics degrees by academic year and college selectivity.[11] The rollout was not random but initially focused on highly selective colleges, driven by limited server capacity (Kirkpatrick (2011)), a deliberate strategy to launch in college networks where students already knew each other well offline (Aral (2021)), and the desire to cultivate a sense of exclusivity (Braghieri *et al.* (2022)). During the expansion period, Facebook was highly popular among college students, with around 85% of undergraduates creating an account (Arrington (2005)) and nearly three-quarters of users logging in daily (Hass (2006)), primarily to keep in touch with friends and to find out more about classmates (Lampe *et al.* (2006, 2008)).

Facebook in a Work-Related Context: While Facebook never fully specialized as a work-related online social networking platform, its features and immense popularity supported work-related activities, such as job search, professional networking, and recruiting, from the very beginning. As early as 2004, Facebook enabled targeted advertising, allowing employers to advertise jobs and products to specific

[11] College selectivity is measured using Barron's selectivity index (Barron's Educational Series (2008)).

colleges (Grynbaum (2004)).[12] To keep up with the changing demands of students transitioning into the labor market, Facebook enabled students to list their current workplace and introduced workplace networks in April 2006 (Facebook (2006)).[13] In 2007, Facebook launched *Facebook Marketplace*, allowing users to post job ads within their networks (Facebook (2008)), and *Facebook Pages*, enabling employers to create public company profiles (Facebook (2007)). While evidence on the use of individual features is scarce, a 2011 survey of U.S. job seekers shows that 48% used Facebook for job search and 16% obtained a job referral from a Facebook friend (Jobvite (2011)), making it the most important online social networking platform for job-seeking activities at that time.[14] With Facebook gaining further popularity in the U.S. and the addition of features such as *Jobs on Facebook*, which enabled companies to post vacancies (Facebook (2018)), the importance of Facebook for job-seeking activities continued to rise and remained high in the early 2020s.[15] The adoption of Facebook in a work-related context was also high on the firm side: in 2008, 36% of U.S. employers used or planned to use Facebook for recruiting (Jobvite (2009)). This number increased to 68% in 2021, making Facebook the most popular online social network recruiting channel among U.S. employers in that year (Jobvite (2021)).

3 Data

To assess the career effects of access to Facebook at labor market entry, this paper primarily combines four data sources: (i) LinkedIn data provided by the company Revelio Labs, (ii) the introduction dates of Facebook across the first 842 colleges, (iii) the number of awards and demographic composition of college graduation classes from the National Center for Education Statistics, and (iv) institutional college characteristics including Barron's selectivity index. This section provides an overview of the data sources, key variables, and descriptive statistics.

3.1 LinkedIn data

Information on the career trajectories of U.S. business students and firm characteristics comes from a snapshot of public LinkedIn data from November 2024. With more than 1 billion members and 67 million

[12]This feature was later expanded with the introduction of *Facebook Ads* in November 2007 (Facebook (2007)).

[13]Recent evidence by Armona and Bailey (2025) shows that around 20–25% of early-adopter U.S. students reported their employment history on their Facebook profiles.

[14]The second-largest platform during this period was LinkedIn, with substantially smaller usage numbers (26% and 9%) due to its lower adoption rate.

[15]In 2016, 67% of job seekers reported using Facebook for job-seeking activities (Jobvite (2016)). More recently, a 2021 U.S. study reports that 50% of job seekers used Facebook to find out more about companies (CareerArc and The Harris Poll (2022)).

companies, LinkedIn is currently the world's largest professional networking site (LinkedIn (2024)). In addition to its extensive global coverage, LinkedIn is particularly popular among U.S. college graduates (Auxier and Anderson (2021)). Users create profiles that resemble a CV and contain detailed information on employment history and educational background. Firms also create profiles containing information on firm characteristics to advertise open positions and increase their visibility.

The LinkedIn data come from the company Revelio Labs. Revelio Labs is a workforce intelligence company that provides an extensive human-resource database from various online sources. In the case of LinkedIn, Revelio Labs scrapes information from public user and company profiles and converts it into a structured database using proprietary algorithms.

The employment history section of public LinkedIn profiles contains information on job titles, start and end dates of employment, the name of the employer, and job location. The educational background section contains information on the postsecondary institution, degree, field of study, and start and end dates. The key advantage of using public LinkedIn profile data is that the vast majority of these variables is typically unavailable in public or administrative datasets. The start and end dates of each stage in the CV allow me to construct a retrospective yearly career panel for each U.S. business and economics student up to 19 years after graduation.[16] At the end of the career panel, students are typically in their early 40s, when career trajectories have largely stabilized (Chetty *et al.* (2017)). Below, I describe the key variables derived from the public LinkedIn data.

Job-specific earnings: A frequently used measure of workers' career trajectories is earnings (e.g., Bronson and Thoursie (2019); Von Wachter (2020)). While LinkedIn profiles do not report individual-level earnings, I can use Revelio Labs' job-specific earnings imputation to track whether students work in typically higher- or lower-paying jobs over their careers. To generate job-specific earnings, Revelio Labs employs a machine learning model that predicts the annual salary of each job stage using information on job title, company name, job location, tenure, and calendar year. The model is trained on publicly available online job postings and visa application data. Dorn *et al.* (2025) show that the imputed earnings align closely with official earnings data from the American Community Survey and serve as a reliable proxy for job-specific earnings. To make the job-specific earnings measure comparable across years and cohorts, I convert it into real 2024 dollars using the U.S. Consumer Price Index (CPI).

Job-specific promotions: To assess steps on the career ladder more formally, I use the job-specific earnings measure to construct a measure of promotions. Following Bronson and Thoursie (2019), I define

[16] To construct the yearly career panel, I take a snapshot on June 30 of each year, similar to Armona and Bailey (2025).

promotions as large relative real wage growth jumps of at least 10 log points by comparing the real annual wage growth of a worker to the predicted real annual wage growth the worker would have obtained had they remained in their previous position.[17] Since I do not observe within-job earnings differentials, this measure of promotions essentially captures job-specific promotions identified through changes in job titles, firms, or geographic location. Appendix Table A1 and Figure A2 investigate whether the job-specific earnings measure by Revelio Labs, combined with the "relative wage growth jump" methodology in Bronson and Thoursie (2019), is capable of detecting promotion patterns in the LinkedIn data. Appendix Table A1 exploits the availability of job titles on LinkedIn profiles to assess the most frequent job title changes coinciding with a promotion. The most common job title transitions closely reflect standard moves up the career ladder. For example, the most common promotion event in the early-career stage reflects a change in job title from "Staff Accountant" to "Senior Accountant," in the mid-career stage from "Financial Analyst" to "Senior Financial Analyst," and in the later-career stage from "Project Manager" to "Senior Project Manager." Appendix Figure A2 further supports the suitability of the promotion measure by showing that the distribution of the imputed real annual wage growth (in log points) closely mirrors the individual-level wage growth distribution in Bronson and Thoursie (2019). The majority of the real annual wage growth distribution is concentrated around zero with a slight skewness to the left. Similar to the evidence in Bronson and Thoursie (2019), the distribution has a large right tail, indicative of promotion events, with one-tenth of the observations having an imputed real annual wage growth above 10%.

Leadership positions: One key advantage of the employment history on LinkedIn profiles is the availability of job titles, which I can use to detect leadership positions as another measure of workers' career development.[18] To do so, I use the keyword-based approach from Hampole *et al.* (forthcoming), which maps job titles into the following managerial career pipeline: individual contributor, manager, director, vice president, senior vice president, and c-suite. Following Hampole *et al.* (forthcoming), I define senior leadership positions as director-level to c-suite-level positions. To validate the mapping, Appendix Table A2 shows some basic descriptive statistics for each category in the managerial career pipeline, while Appendix Table A3 shows the most commonly mapped job titles. Average job-based annual earnings are monotonically increasing along the career pipeline, starting from an average of $66,543 for individual contributor roles, to $170,116 for director-level jobs, and up to $250,123 for c-suite positions.

[17] Since the job-specific earnings measure predicts the same earnings trajectory for *all* workers in a given job, this definition coincides with the methodology in Bronson and Thoursie (2019), who use coworkers' earnings to predict counterfactual wage growth.

[18] Leadership positions are considered major career steps for workers, coming with a significant increase in responsibility, earnings, and prestige (e.g., Gibbons and Waldman (1999)).

Consistent with the literature (Lean In and McKinsey & Company (2020); Hampole *et al.* (forthcoming)), the share of female U.S. business graduates gradually decreases with each step on the career ladder. In addition, Appendix Table A3 demonstrates that the most commonly mapped job titles closely align with each concept in the managerial pipeline and show no sign of misclassification.[19]

Firm choice: Job stages on LinkedIn profiles also contain information on the company name with Revelio Labs linking each company to the corresponding LinkedIn company profile and Glassdoor amenity ratings. This unique feature of the data allows me to investigate the role of firm choice across various dimensions, which has been shown to be an important driver of workers' career trajectories (e.g., Oreopoulos *et al.* (2012); Von Wachter (2020); Arellano-Bover (2024)). To analyze firm choice, I focus on several measures of firm quality. Starting with firm pay as the first quality dimension, I combine information on company names with the job-specific earnings imputation to classify high-wage and non-high-wage firms following the approach in Oreopoulos *et al.* (2012); Haltiwanger *et al.* (2018); Von Wachter (2020). To do so, I use information from *all* LinkedIn profiles and companies that employ college students in my estimation sample and compute the average median log earnings at the firm level, net of year fixed effects. I then split the employment-weighted firm-earnings distribution into quartiles and define high-wage firms as all firms in the upper quartile of the distribution and non-high-wage firms as all firms below this threshold.[20]

As workers also highly value non-pecuniary aspects of work (e.g., Mas and Pallais 2017; Sorkin 2018; Sockin 2022; Maestas *et al.* 2023; Caldwell *et al.* 2026), I extend the firm quality measures to non-wage attributes using the information on Glassdoor employer ratings.[21] To do so, I use the same employment-weighted quartile split procedure after calculating the average employer rating, net of year fixed effects, to create firm quality proxies for the following dimensions: overall rating, compensation & benefits, career opportunities, culture and values, senior leadership, and work-life balance. Appendix Table A4 shows the coverage, distribution, and relation to the firm pay quality proxy in more detail. I am able to merge the firm amenity characteristics to slightly more than two thirds of the observed firm choices in the career panel with the upper quartile threshold for the different dimensions being around 3.5 to 4 on the Glassdoor rating scale from 1 to 5.[22] Looking at the correlation between the different firm

[19]For example, the most frequent terms for the c-suite category are "President" and "CEO," the most common terms for director-level positions are "Partner" and "Controller," and the most common terms for individual contributor positions are "Account Executive" and "Senior Accountant."

[20]Appendix Table A4 shows the coverage and distribution of the firm pay variable in more detail. Using alternative thresholds produces similar results.

[21]For a detailed discussion on the coverage and validation of the Glassdoor amenity ratings in the U.S., see Sockin (2022).

[22]Also here, using alternative thresholds for the classification of high-quality firms in the various amenity dimensions

quality margins provides several important insights. First, the firm pay variable is almost orthogonal to the Glassdoor amenity ratings, and if anything, slightly positively correlated (correlations of 0.04–0.1). This is in line with recent evidence by Sockin (2022) and Arellano-Bover and Saltiel (2026) showing that firm pay and non-wage amenities are slightly positively correlated. Second, there is a strong positive correlation between the different Glassdoor amenity rating dimensions (correlations of 0.63–0.87), highlighting that firms tend to offer amenities in a bundle instead of focusing on a single dimension.

Occupational choice: While LinkedIn profiles do not contain occupational codes, Revelio Labs infers 2018 SOC classifications using proprietary algorithms trained primarily on job titles, reported skills, and job descriptions. This measure allows me to analyze occupational choice as another important determinant of career trajectories (e.g., Keane and Wolpin (1997); Speer (2017)). Similar to the proxies of firm quality, I use the job-specific earnings imputation to construct a measure of occupational quality. To do so, I compute the average median log earnings for each 5-digit SOC occupation in the Revelio Labs data between 2000 and 2024 and perform an employment-weighted quartile split of the occupation-earnings distribution. I then classify the upper quartile of the occupation-earnings distribution, mainly reflecting white-collar professional and managerial jobs (e.g., top executives, financial managers, engineers, lawyers, and management analysts), as high-wage occupations.

Steep career ladder early-career jobs: The detailed employment history on LinkedIn profiles also enables me to assess whether students sort into early-career jobs with steep or flat career prospects. To do this, I follow the idea in Almar *et al.* (2025) and predict the long-run wage growth and likelihood of attaining a senior leadership position for each early-career job. To construct the measures, I aggregate early-career jobs at the occupation-by-firm level and perform a leave-one-cohort-out prediction of both measures 15 years later.[23] I then split both occupation-by-firm-level career prospect distributions at the upper quartile to define early-career jobs with steep career prospects.

Job help in the college network: LinkedIn profiles do not contain explicit information on whether students shared work-related information or helped one another access jobs. Nevertheless, the panel structure and the availability of firm names allow me to construct a proxy for the use of social ties in the job search process, following Gee *et al.* (2017). Suppose I observe two college peers in the data: person A and person B. If person A starts working at a firm where person B has already worked at for at least one year, this is taken as evidence that person A has received help from the college peer to access the new job

produces similar results.

[23]For occupation-by-firm cells with fewer than 30 observations, I collapse the career cells at the 5-digit SOC level to avoid small-sample bias. I define an early-career job as any job in the first two years after expected graduation.

at the connected firm.[24]

Degree, field of study, and postsecondary institution: The educational background section on LinkedIn profiles contains information on degree, field of study, and educational institution, enabling me to merge the Facebook introduction dates with the career outcomes of each student. To convert the raw text strings into standardized educational background characteristics, I follow the keyword approach in Dorn *et al.* (2025). For educational degrees, I map the raw degree input into six levels of education using a keyword approach based on several online sources on typical degree abbreviations (YourDictionary (2022); StudentNews Group (2024); Best Universities (2024)). The six levels are as follows: high school, associate, bachelor, master, professional degree, and doctorate. To classify field of study, I use the Classification of Instructional Programs (CIP) taxonomy provided by National Center for Education Statistics (2024a). As field-of-study entries on LinkedIn profiles are closely related to the CIP classification, I can map most entries to the respective CIP codes using regular expressions. For the most common non-mapped entries, I apply manual mapping. To standardize information on educational institutions, I use the clustering algorithm provided by Revelio Labs, which also takes into account common abbreviations. To further improve the accuracy of the clustering algorithm, I refine the mapping by manually dropping the most frequent false positive cases in the estimation sample.[25]

3.2 Further data sources

Facebook introduction dates: The second primary data source comes from Armona (2023) and contains information on Facebook's introduction dates for the first 842 postsecondary institutions. While the exact introduction date of Facebook is only known for all selective U.S. colleges up to August 2005, I can use the remaining selective U.S. colleges as a control group, as they did not have access to Facebook before the academic year 2005–2006. Using this information, I can determine for all selective U.S. colleges the academic year in which they received access to Facebook and merge the treatment information with the LinkedIn profiles.

IPEDS data: The third data source comes from the Integrated Postsecondary Education Data System (IPEDS) and contains detailed information on the demographic composition and degree counts of each

[24] This measure has been validated by Gee *et al.* (2017) and is considered the state-of-the-art approach to measuring relational job mobility (Rajkumar *et al.* (2022)).

[25] In most cases, the false positive matches result from colleges with similar names located in different countries (e.g., "assumption college, san Lorenzo" and "assumption college"). To distinguish between U.S. colleges with similar names located in different regions (e.g., Marian University), I exploit the geographic information from LinkedIn profiles at the corresponding education stage.

graduation class at a U.S. postsecondary institution (National Center for Education Statistics (2024b)). I use this information to investigate the representativeness of the LinkedIn sample and to merge information on the class size of each cohort.

Mobility Report Cards data: To merge institutional characteristics of all four-year colleges to the LinkedIn profiles, I utilize the Mobility Report Cards (MRC) data from the Equality of Opportunity Project (Chetty *et al.* (2017)). The MRC dataset provides information on the location of postsecondary institutions and their selectivity, measured by Barron's selectivity index (Barron's Educational Series (2008)).

3.3 Data merge, sample selection, and representativeness of LinkedIn profiles

To construct the final estimation sample, I start by linking the Facebook introduction dates, IPEDS data, and MRC data using the unitid identifier. Since I focus on undergraduate business and economics students at selective U.S. colleges, I limit the sample to selective four-year colleges that offered an undergraduate business or economics degree between 1999 and 2005, resulting in 1,242 potential colleges.[26] In the next step, I merge the college-level information to the LinkedIn profiles using the information on college names. Appendix Table A5 documents the sampling procedure in detail. I can match 1,235 colleges (99.4%) to at least one LinkedIn profile reporting a bachelor's degree in business and economics, resulting in 1,071,848 profiles. To ensure that the estimation sample does not contain any incomplete or stale profiles, I drop 23,271 observations reporting an invalid undergraduate graduation date (2.2%) and 133,601 (12.7%) observations that do not report any employment for more than half of the career panel.[27] Following Overgoor *et al.* (2020), I further restrict the sample to colleges with average LinkedIn coverage rates between 0.25 and 1.25 to maintain representative coverage across college cohorts.[28] This refinement leaves a final estimation sample with 1,154 colleges and 890,951 profiles. While the sample selection steps ensure that only sufficiently complete LinkedIn profiles and sufficiently representative college cohorts enter the final estimation sample, Appendix Table A5 shows that this refinement has little overall impact on the composition of the sample, in terms of age, gender, or college selectivity.

To assess the representativeness and coverage of the final estimation sample, I compare basic descriptive

[26] I define business and economics majors following the methodology used by U.S. News & World Report. Business majors are defined as any major with the two-digit CIP code 52, excluding 52.06. Economics majors are classified as any major with the CIP codes 45.06, 01.103, 03.0204, 51.2007, 52.06, 30.3901, and 30.4001 (Brooks (2025)).

[27] I define a valid undergraduate graduation date as any end date of the education spell that is not missing, strictly after the indicated start date, and implies a study duration of under 10 years. The employment filter ensures that LinkedIn profiles that a) did not indicate an early-career employment history and b) did not update their LinkedIn profile in recent years are not entering the estimation sample.

[28] Alternative thresholds do not affect the results.

statistics to the information in the IPEDS data. Appendix Table A6 shows that the final estimation sample covers 46.7% of all U.S. business and economics students during that time period. Consistent with other studies that use a LinkedIn sample of U.S. college graduates (e.g., Dorn *et al.* (2025)), females are slightly underrepresented, with 41.6% of the LinkedIn sample compared to 47.2% in IPEDS. The share of students coming from (i) colleges located in different U.S. regions and (ii) colleges from different selectivity tiers is more closely aligned across both data sets with very selective colleges being slightly overrepresented in the LinkedIn data (51.9%) compared to IPEDS (48.2%).[29]

3.4 Descriptive statistics

Table 1 presents descriptive statistics on the career trajectories of U.S. business and economics students, measured at the person-by-year level. In the first six years after expected graduation, 77.5% of students report being employed, with the average job-based real annual earnings accruing to around $76,000 (2024 USD). Consistent with the well-documented evidence on life cycle employment and earnings dynamics (e.g., Rubinstein and Weiss (2006)), the employment share of U.S. business and economics students quickly rises and stabilizes at around 94% with the average real annual earnings reaching $122,000, 13–19 years after expected graduation. Taking a closer look at job mobility patterns, Table 1 shows that the annual promotion rate in the sample is around 8%, with roughly two thirds of the promotions occurring between firms and one third within firms. Consistent with previously documented evidence on mobility patterns within- and across-firms (e.g., Belzil and Bognanno (2008); Frederiksen *et al.* (2016)), promotions occur more frequently than lateral job moves (3.5% to 4.1%) and demotions (4.4% to 5.9%), but are not the only type of job transitions occurring in the data. Investigating firm choice, Table 1 indicates that the share of students reporting to work at high-wage firms starts at 25.7% in the first six years after graduation and rises to 34.7% in the later career stage, indicating that roughly one third of the students are employed at high-wage firms. Looking at top jobs, the share of U.S. business and economics students holding a senior leadership position starts at 10% in the first six years of their careers and increases up to 27.2% 13–19 years after expected graduation.[30]

How important are college peers for job finding and career development?[31] The job help proxy by

[29]While the main analysis utilizes the LinkedIn sample composition for estimation, Appendix G shows that the results are very similar when reweighting the sample in terms of demographic and college characteristics using the official statistics from the IPEDS data.

[30]This pattern closely aligns with the findings in Hampole *et al.* (forthcoming) on the dynamics of holding senior leadership positions for MBA graduates with the levels shifted downwards as the sample here comprises undergraduate students.

[31]I define college peers as students between three classes below and three classes above the respective cohort.

Gee *et al.* (2017) shows that in the first 12 years, roughly 14% of U.S. business and economics students received job-related information from their college network to obtain their current job. While the share declines to 11.6% in the later career stage, the evidence suggests that more than 12.5% of the reported jobs in the career panel have been obtained with the help of college peers, emphasizing their relevance in the job search process. Interacting the job help proxy with firm quality and career development outcomes suggests that college peers are also an important source for career advancement. Between 4.3% and 5.4% of students used their college network to obtain a job at a high-wage firm, 0.7% to 1.3% to obtain a promotion at a connected firm, and around 0.2% to transition into a senior leadership position, with the relevance of college peers for career advancement slowly declining over time.

Table 1: Career Outcomes Over Time

	Years 1-6	Years 7-12	Years 13-19
Panel A: Career Development			
Employment	0.775	0.938	0.943
Annual Earnings	76,300	107,068	121,926
Promotion (≥10 log pts.)	0.081	0.088	0.074
Between-Firm Promotion (≥10 log pts.)	0.057	0.056	0.045
Within-Firm Promotion (≥10 log pts.)	0.024	0.031	0.030
Lateral Moves	0.035	0.041	0.037
Demotion	0.044	0.058	0.059
High-Wage Firm	0.257	0.329	0.347
Senior Leadership Positions	0.100	0.199	0.272
Panel B: College Network Outcomes			
College Job Help	0.137	0.144	0.116
College Job Help: High-Wage Firm	0.053	0.054	0.043
College Job Help: Promotion (≥10 log pts.)	0.013	0.011	0.007
College Job Help: Sr. Leadership	0.002	0.002	0.002
Observations	5,345,706	5,345,706	6,236,657

Notes: Descriptive statistics of career outcomes over time reported at the person*year level. Each value represents the mean outcome pooled over one of the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Sample: All business & economics undergraduates expected to graduate from 1999 to 2005 at selective 4-year colleges with valid LinkedIn profile and reasonable college-level coverage (1,154 colleges). Job mobility outcomes start at year 2 after expected graduation. *Data source:* Revelio Labs.

4 Empirical Strategy

4.1 Identification

To isolate the causal effect of access to Facebook at labor market entry on career outcomes, I exploit the sharp and staggered rollout of Facebook across U.S. colleges in a generalized difference-in-differences design. The variation in treatment timing allows me to compare the career outcomes of business and economics students from the same college across treated and untreated cohorts, while controlling for common cohort differences using not-yet-treated cohorts from colleges in the same region and selectivity tier. The baseline model in a two-way fixed effects (TWFE) setting can be specified as follows:

$$Y_{fs,c,t} = \alpha_1 \, Treat_{fs,c} + \delta_{fs,\text{tier,region}} + \phi_c + \epsilon_{fs,c,t} \, , \tag{1}$$

where $Y_{fs,c,t}$ represents various career outcome measures for freshman cohort fs at college c, t years after expected graduation. $Treat_{fs,c}$ is a binary variable indicating whether freshman cohort fs from college c had access to Facebook before the *expected* graduation date, avoiding a potentially endogenous relation between treatment and the actual graduation date.[32] Since Facebook became public in 2006, the treatment indicator essentially captures the intent-to-treat (ITT) effect of having access to Facebook before vs. after labor market entry. $\delta_{fs,\text{tier,region}}$ represents cohort-by-college-tier-by-region fixed effects, narrowing down the comparison in the difference-in-differences setting to college cohorts within the same region and selectivity cell. As the rollout of Facebook was not random but targeted elite and highly selective colleges first, the key idea behind $\delta_{fs,\text{tier,region}}$ is to absorb all systematic differences across college cohorts that might be spuriously correlated with the treatment timing and exclusively rely on the plausibly exogenous within-college cross-cohort-selectivity-region variation.[33] Examples of potential spurious correlations that are taken care of by $\delta_{fs,\text{tier,region}}$ are cohort-specific shocks in career outcomes within the same region at colleges of similar selectivity (e.g., fluctuations in labor market entry conditions and returns to education) or differential cohort-specific trends across those cells. ϕ_c denotes college fixed effects, accounting for time-invariant differences across colleges, such as prestige. To account for potential correlations in the error term across cohorts within the same college, I cluster standard errors at the college level (Athey and

[32] I follow Armona and Bailey (2025) and define access to Facebook before the *expected* graduation date as having access to Facebook at the respective U.S. college before June 30 of the expected graduation year (fourth year of the undergraduate).

[33] Since all but one elite college received early access to Facebook, I group elite and highly competitive institutions (Barron's tiers 1 and 2) into a single category for the fixed-effects estimation. To still allow for differential trends across cohorts within the broader group of highly selective colleges, I include linear cohort trends for Ivy Plus colleges, other elite colleges, and all highly competitive-by-region interactions. Appendix H shows that the results are robust to dropping Ivy Plus and elite colleges.

Imbens (2022)).

A growing body of literature emphasizes that in staggered adoption designs, the conventional two-way fixed effects (TWFE) model requires not only the parallel trends assumption but also treatment effect homogeneity to produce consistent estimates (Goodman-Bacon (2021); Sun and Abraham (2021); Roth *et al.* (2023)). Specifically, Goodman-Bacon (2021) shows that the estimate of the TWFE model is a weighted average of all possible 2×2 difference-in-differences comparisons, including comparisons of already-treated units to newly-treated units. If the treatment effect varies over time or by adoption cohort, this biases the treatment effect obtained with TWFE. Given that Facebook initially targeted more selective universities, it is possible that earlier adoption cohorts experienced different treatment effects compared to later cohorts, questioning the strong assumption of treatment effect homogeneity.

To ensure that the results are not driven by this bias, I estimate the treatment effect in the spirit of equation (1) using the two-stage heterogeneity-robust estimator proposed by Gardner (2022). The idea behind the two-stage approach is to first regress the outcome $Y_{fs,c,t}$ on the group ϕ_c and period $\delta_{fs,\text{tier},\text{region}}$ fixed effects using the not-yet-treated observations only and then regress the residualized outcome for all observations on the treatment indicator $Treat_{fs,c}$. This procedure effectively avoids using already-treated units as controls for newly-treated ones and is robust to heterogeneous treatment effects.[34]

4.2 Core threats to internal validity

The core identifying assumption behind the difference-in-differences model is that, in the absence of treatment, the career outcomes of students in treated colleges would have evolved in parallel to those in not-yet-treated colleges of similar selectivity located in the same U.S. region. To assess the plausibility of the parallel trends assumption for each career outcome, Appendix B shows estimates of an event-study version of equation (1), in which the event refers to the first freshman cohort expected to be exposed to the introduction of Facebook at the respective college.[35] Reassuringly, the pre-treatment coefficients are close to zero and the majority of the coefficients are individually as well as jointly insignificant at the 5% level, supporting the parallel trend assumption in this setting.

Another key concern is that access to Facebook may affect the probability of having a LinkedIn account or may change the composition of the sample. In this case, estimated treatment effects might simply

[34]Note that the two-stage heterogeneity-robust estimator is numerically equivalent to the imputation estimator of Borusyak *et al.* (2024). Appendix F presents the main results using two further heterogeneity-robust estimators: Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020). While these differ from the baseline in their identifying assumptions and precision, the results are very similar.

[35]See Appendix B for more details on the set up.

reflect sample selection bias. Using official statistics from the IPEDS data, Appendix Table A7 shows that Facebook access at labor market entry does not affect the likelihood of having a LinkedIn account and does not change the composition of the sample in terms of baseline demographic characteristics such as gender or age. I present further evidence supporting the identifying assumptions in Section 5.4.

5 Results

5.1 Career development

Does access to Facebook at labor market entry affect the career development of U.S. business and economics students? Table 2 investigates this question by tracking their career trajectories up to 19 years after graduation, when they are typically in their early 40s and careers have largely stabilized (e.g., Chetty *et al.* (2017)). Panel A shows the results using the job-based earnings measure. In the first six years after expected graduation, students with early access to Facebook earn on average $1,286 more than the control group with the earnings effect increasing to $1,343 in the years 6–12.[36] Comparing the treatment effect to the average job-based annual earnings of the control group indicates a relative effect size of 1.7% ($75,876) and 1.3% ($106,240) respectively, suggesting a moderate but economically meaningful shift in average annual earnings. While the earnings effect is fading out over time (see Column 3), the results in Panel A provide clear first evidence that the career trajectory of students with early access to Facebook has been positively affected. To better understand the extent to which the positive earnings effects are driven by labor supply vs. job pay decisions, Appendix Table A8 shows the estimated treatment effects for (i) employment and (ii) earnings conditional on employment. In the first six years after graduation, students with early access to Facebook are more likely to be employed and do not earn significantly more than the control group conditional on employment, suggesting that the unconditional early-career positive earnings effect is mainly driven by an increase in labor supply. The interpretation of the earnings effect changes in the long run, as the positive employment effect fades out over time, suggesting that the positive earnings effect 6–12 years after expected graduation comes from students with early access to Facebook obtaining higher-paying jobs.[37]

What does this imply for the lifetime earnings of U.S. business and economics students with early

[36] The estimated earnings effect 6–12 years after expected graduation is well in line with Armona (2023), who finds that each year of Facebook access during college increases average earnings in 2014 by $972 ($1,280 in 2024 dollars).

[37] The labor supply and earnings dynamics are very similar to the documented career patterns in the graduating in a recession literature for college graduates (e.g., Oreopoulos *et al.* (2012); Altonji *et al.* (2016); Von Wachter (2020)).

access to Facebook? Appendix Table A9 investigates this question by looking at the estimated treatment effect on the cumulative earnings in the first 19 years after graduation. Assuming a 5% discount rate, the estimated lifetime earnings increase of early access to Facebook is around $14,976, which is equivalent to a 1.2% increase compared to the control group. This corresponds to 44% of the reduction in lifetime earnings college graduates can expect when graduating in a typical recession (e.g., Von Wachter (2020)), highlighting that early Facebook access had an economically meaningful impact on the cumulated earnings gains for the affected U.S. business and economics students.

Table 2: Facebook Access and Career Development

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,286**	1,343*	768
	(479)	(556)	(649)
Dep. Var. Mean	75,876	106,240	121,452
Observations	48,252	48,252	56,294
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.004**	0.002	-0.0010
	(0.001)	(0.001)	(0.0010)
Dep. Var. Mean	0.078	0.085	0.075
Observations	40,210	48,252	56,294
Panel C: Senior Leadership Positions			
FB Access	0.002	0.006*	0.008*
	(0.002)	(0.003)	(0.004)
Dep. Var. Mean	0.101	0.199	0.270
Observations	48,252	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table 2, Panel B, uses the relative wage growth jump methodology by Bronson and Thoursie (2019) to analyze how early access to Facebook affects promotion patterns. Consistent with the positive earnings effect, Column 1 shows that students with early access to Facebook are 0.4% more likely to receive promotions in the first six years after graduation. Comparing the effect size to the average annual promotion rate of the control group (7.8%) indicates an economically meaningful relative effect size of 5.1%. While the positive effect on promotions fades out over time (see Columns 2 and 3), the point estimates remain positive though statistically insignificant, so the *cumulative* promotion gap over the first 19 years of a career is not reversed.[38] To better understand the impact on job mobility in general, Appendix Table A11 investigates whether early access to Facebook also impacted the likelihood of lateral job mobility and demotions. There is no impact on either margin, suggesting that the positive earnings effects are not explained by treated students being less likely to receive a demotion or receiving frequent small wage-growth jumps through an increase in lateral job mobility.

While the positive earnings effect is fading out over time, the positive cumulative promotion effect raises the question whether access to Facebook enabled some students to reach top jobs in the economy. Panel C investigates this question by looking at the senior leadership measure initially proposed by Hampole *et al.* (forthcoming). Consistent with the intuition that reaching a senior leadership position takes time, there is no impact in the first six years after expected graduation. However, Columns 2 and 3 show that Facebook access at labor market entry increases the likelihood of attaining a senior leadership position in the longer run. 13–19 years after graduation, students with early access to Facebook are 0.8 percentage points more likely to reach senior leadership positions, a 3% increase relative to the control group mean, suggesting that early access to Facebook enabled some students to reach top jobs in the economy.[39] Overall, the results in Table 2 indicate that Facebook access at labor market entry improved the long-run career trajectories of U.S. business and economics students in an economically meaningful way.

5.2 Mechanisms

Having shown that access to Facebook at labor market entry has a long-run positive impact on students' career trajectories, I next examine potential mechanisms. To do so, I split the treatment dynamics into three stages.

[38] Appendix Table A10 shows that the results are robust to alternative specifications of the promotion threshold.

[39] Appendix Table A12 repeats the estimation using management occupations (SOC 11), top executives (SOC 11-1), and board members as alternative definitions of top jobs. While the concepts differ slightly in the kinds of jobs they capture, the results for management and top executive occupations are very similar. There is no impact on the likelihood of becoming a board member.

5.2.1 During college

During college, students with early access to Facebook had the opportunity to sign up for the platform and expand their social networks. Well-documented evidence suggests that around 85% of undergraduate students created an account (Arrington (2005)), with one additional year of early Facebook access leading to a 4% increase in the likelihood of having a Facebook account and a 13.6% increase in the number of Facebook connections within the college network (Armona (2023)).[40] While students did not yet enter the labor market at this stage, the evidence clearly suggests that early Facebook access (i) positively affected Facebook adoption and (ii) enabled students to improve their connectedness within the college network, leading to greater accumulation of college-specific social capital.

5.2.2 The college-to-work transition

During the college-to-work transition, students may rely on improved information flows from their online social networks or work-related platform features to support the early-career job search process.[41] As an extensive literature emphasizes that a successful college-to-work transition is key to long-run career development (e.g., Kahn (2010); Oreopoulos *et al.* (2012); Altonji *et al.* (2016); Schwandt and Von Wachter (2019); Von Wachter (2020); Arellano-Bover (2024)), this mechanism could explain part of the documented career benefits. Table 3 investigates this channel by examining early-career employment and job-placement outcomes in the first two years after expected labor market entry.[42] Consistent with the estimated employment patterns in Appendix Table A8, Column 1 in Panel A shows that early Facebook access increases the probability of finding a job during the expected labor market entry phase by 1 percentage point (1.5%), providing first evidence of an improvement in the college-to-work transition. To assess whether the *job quality* margin was also affected, Columns 2–6 show results focusing on several indicators of high-quality entry-level jobs. Starting with firm quality, Columns 2 and 3 show that students with early access to Facebook are 1.4 percentage points more likely to start their careers at high-wage firms and in firms being highly rated in terms of career support. Compared to the control group, this implies a relative effect size of 6.8% and 8.8% respectively, suggesting an economically meaningful shift in the likelihood of obtaining a job at a high-quality firm.[43] Column 4 shows that students with early access to Facebook are

[40] Importantly, as Facebook solely required a verified *.edu* email address for creating an account, alumni could also sign up to the platform, leading to an increase in the connectedness between graduates and alumni (see Armona (2023) for more details).

[41] Note that the majority of employers were not actively using Facebook during the labor market entry phase of the first exposed college cohorts, essentially ruling out any demand-side information channels (e.g., employer screening, recruiters).

[42] Varying the definition of the labor market entry phase does not affect the results.

[43] Appendix Table A13 shows the results for access to high-quality firms using the other Glassdoor amenity dimensions. Consistent with the positive earnings effects documented in Table 2, students with early access to Facebook are also more likely

also 1.2 percentage points (4.8%) more likely to start working in a high-paying occupation, suggesting that next to the firm quality margin, early access to Facebook also enabled students to improve their early-career outcomes at the occupational margin.

Table 3: Facebook Access and The College-To-Work Transition

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.010**	0.014***	0.014***	0.012**	-0.001	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.653	0.206	0.159	0.249	0.159	0.201
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

To also consider the long-run perspective of early-career jobs on career development, Columns 5 and 6 investigate sorting into early-career jobs associated with *steep career prospects* in terms of wage growth and the likelihood of reaching a senior leadership position.[44] While Column 5 indicates that early access to Facebook did not increase the likelihood of obtaining an early-career job with a steep wage-growth profile, Column 6 shows that students are 1.4 percentage points (7%) more likely to access entry-level jobs with a high chance of reaching a senior leadership position later in their careers. Appendix Table A15 investigates whether the college-to-work transition effect is also apparent for *lower-quality* early-career jobs. The coefficients are close to zero and slightly negative, with non-steep wage growth jobs being the only outcome that is positively affected. Overall, the findings are consistent with the interpretation that early access to Facebook primarily enabled students to find *high-quality* early-career jobs after labor market entry, fundamentally shifting their career prospects not just in the short run, but also in the longer run.[45]

to sort into firms that have a high rating in terms of compensation and benefits. There is no effect on the other dimensions (overall rating, culture and values, senior leadership, work-life balance). Appendix Table A14 shows that the results are not driven by firms with missing information on amenities.

[44] See Section 3 for details on the variable construction.

[45] Note that in the task-specific human capital and career development model by Gibbons and Waldman (2006), even a temporary early-career shock in job quality can have long-lasting consequences on career development, as workers in lower-quality jobs lag behind on task-specific human capital that they need to perform higher-quality jobs later on in their career.

Graduation timing and postgraduate education choice: Appendix Table A16 investigates to what extent the college-to-work transition effects are driven by graduation timing and postgraduate education choices. Looking at the reported undergraduate study duration and likelihood of studying in the first two years after expected graduation, the effects are close to zero and insignificant, suggesting that students without early access to Facebook did not strategically delay their labor market entry by staying in college. Also, I do not find any impact on the likelihood of obtaining a postgraduate degree or an adjustment in the type of postgraduate degree, suggesting that the documented treatment effects are not mediated through postgraduate education decisions. Nevertheless, I do find evidence that students with early access to Facebook report their first stable job after expected graduation two thirds of a month earlier than the control group. While the effect is small in economic magnitude, the treatment effect suggests that part of the positive college-to-work transition effect might be explained by students with early access to Facebook finding their first stable job at a faster rate.[46]

Early-career job help in the college network: While the previous results indicate that Facebook access at labor market entry facilitated the college-to-work transition, it remains unclear where this effect comes from. Since students with early access to Facebook could increase their connectedness within the college network, maintain those connections after exiting college at a lower cost, and use the early-stage platform features of Facebook to quickly exchange information, the improved transition may stem from students sharing work-related information and helping one another in the early-career job search process. Consistent with this hypothesis, early survey evidence by Ellison *et al.* (2007) suggests that U.S. students expected Facebook to be useful for obtaining job referrals and learning more about jobs from their social network. To formally test this channel, Table 4 uses the job-help proxy of Gee *et al.* (2017) and interacts it with the early-career outcomes shown in Table 3.

Column 1 investigates whether early access to Facebook increased the likelihood that students would use their college network to find an early-career job. The documented treatment effect is positive and statistically significant with an estimated effect size of 1.1 percentage points. Relative to the control group mean, the estimated relative effect size is 10.2%, suggesting a considerable shift in the reliance on the college network for early-career job finding, supporting the hypothesis that early access to Facebook increased information sharing about jobs within the college network.

[46] This would be consistent with the idea that early access to Facebook increases the arrival of job offers at the college-to-work transition stage, enabling students to find a job that matches their expectations at a faster rate. Following Kramarz and Skans (2014), I define the first stable job here as the first reported employment spell active after the expected graduation with a duration of at least 4 months.

Table 4: Facebook Access and Early-Career Job Help in the College Network

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.011***	0.007***	0.008***	0.004*	0.004**	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Dep. Var. Mean	0.107	0.041	0.049	0.042	0.027	0.047
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

To investigate whether students with early access to Facebook also more intensively used the college network to find high-quality entry-level jobs, Columns 2–6 interact the job help proxy with the high-quality early-career job indicators. Columns 2 and 3 show that U.S. business and economics students with early access to Facebook are 0.7 percentage points (17.1%) more likely to receive job help from a college peer to obtain a job at a high-wage firm and 0.8 percentage points (16.3%) more likely to receive job help to access a highly career-supporting firm. Comparing the coefficients to the documented effect sizes in Table 3 suggests that at least half of the positive impact of early access to Facebook on the likelihood of obtaining a job at a high-quality firm can be explained by the college network providing relevant information in the early-career job search process. Columns 4–6 show that the improved information flow and job help pattern within the college network is also apparent for accessing high-paying occupations (0.4 percentage points), steep wage growth jobs (0.4 percentage points), and jobs associated with a high chance of reaching senior leadership positions (0.7 percentage points) at connected firms. To better understand which type of college peer is driving the results, Appendix Table A17 decomposes the early-career job help effect into below-cohort, same cohort, and above-cohort college peer ties. Consistent with the idea that peers with more labor market experience can provide more useful work-related information, the results in Table A17 show that the documented effects in Table 4 are almost exclusively driven by above-cohort college peer ties. In combination, the results highlight that early access to Facebook fundamentally shifted the early-career job search process for high-quality jobs towards the college network, with a large share of the improved college-to-work transition driven by information sharing and job help among college peers.[47]

Employer ads: Another potential reason behind the improved college-to-work transition effect is that students with early access to Facebook may have engaged more actively with employer ads, which were introduced as early as May 2004 (Grynbaum (2004)). If targeted ads increased the awareness of jobs and companies for treated students, this could have also facilitated their search for early-career jobs. However, there are two reasons to believe this channel is unlikely to explain a meaningful part of the college-to-work transition effects in Table 3. First, targeted ads were only temporarily available to a very small set of firms during the college-to-work transition phase of the early Facebook adopters.[48] Second, survey evidence from the late 2000s indicates that only 12% of U.S. students actively engaged with employer ads during their first job search (National Association of Colleges and Employers (2009)), suggesting that student engagement with this platform feature was quite low.

5.2.3 After the college-to-work transition

The results in Table 3 and Table 4 provide clear evidence that part of the documented career benefits stem from a more successful college-to-work transition driven by college peers helping each other in the early-career job search process. Another part may reflect longer-run treatment dynamics that unfold after labor market entry.

Long-run job search, firm mobility, and job help in the college network: While all U.S. business and economics students received access to Facebook in the long run, part of the documented career benefits for the early Facebook adopters could be explained by a long-run increase in the information access about job opportunities, facilitating their search for higher-paying jobs.[49] There are three reasons why this might be the case. First, students with early access to Facebook may continue to receive more information about job opportunities as they had more time to build their social network and were less likely to lose their college ties when transitioning into the labor market. In line with this idea, recent evidence by Armona and Bailey (2025) shows that students with early access to Facebook have larger online social networks and are more closely connected to their college peers in the long run. As workers rely heavily on their

[47] Appendix Table A18 shows that the increased likelihood of receiving job help within the college network is also apparent for attaining jobs in lower-paying occupations and jobs with non-steep wage growth prospects, but not apparent for attaining jobs in lower quality firms.

[48] To be precise, targeted ads were available to a small set of firms during May 2004 (Grynbaum (2004)). The importance and adoption of targeted ads changed with the official launch of *Facebook Ads* in November 2007 (Facebook (2007)), shortly after the college-to-work transition phase of the early Facebook adopters, which is here defined as the period until June 2007.

[49] In traditional job search models (e.g., Burdett (1978)), this channel would reflect a permanent (or slowly decaying) increase in the job offer arrival rate, allowing workers to draw from better job offers in the wage distribution.

social networks for information about job opportunities (e.g., Caldwell and Harmon (2019)) and larger networks predict a greater arrival rate of job offers from other firms, this channel could explain part of the long-run career benefits. Second, students with early access to Facebook may be more intensively using the later introduced work-related platform features, such as Facebook Marketplace, Pages, or Ads, to acquire job-related information. Third, due to a potentially higher visibility on the platform, students with early access to Facebook might receive more job-related information from employers and recruiters, which were increasingly using the platform from the demand-side.

Panel A in Table 5 starts investigating the joint significance of these channels by looking at the likelihood of receiving a between-firm promotion. If early access to Facebook increases access to information about job opportunities in the long run, job search models would predict an increase in the annual rate of between-firm promotions. However, columns 1 to 3 in Panel A show that the estimated treatment effect on between-firm promotion patterns is close to zero and insignificant across the entire career panel, suggesting that a long-run increase in the job offer arrival rate is not driving the documented career benefits. Appendix Table A19 shows that the documented treatment effects are also close to zero when looking at any between-firm switches or between-firm switches with no immediate promotion, supporting this conclusion.

To test more directly for the hypothesis that early access to Facebook leads to a long-run improvement in access to job opportunities through the more closely connected college network, Panels B and C provide estimates interacting the between-firm promotion measure with the job help proxy for college peers. Similar to the findings in Panel A, the results are close to zero and insignificant, indicating that while the social network size of the early Facebook adopters might be slightly larger than for the control group, the documented career benefits are not coming from a long-run improvement in information access about job opportunities through the college network.[50] Overall, the results in Table 5 suggest that the career benefits are not driven by students with early access to Facebook having a long-run information advantage about job opportunities, consistent with differences in the job offer arrival rate decaying quickly once the control group received access to Facebook.[51]

[50]Appendix Table A19 shows that the results for job help in the college network for accessing jobs at connected firms with no promotion is also close to zero and insignificant, providing further evidence that long-run information sharing within the college network does not explain the documented career benefits.

[51]This interpretation is consistent with several pieces of evidence by Armona and Bailey (2025): (i) the larger social network size of the early adopters of Facebook decreased over time, (ii) Facebook was also highly popular in the control group and was quickly adopted after Facebook went public, and (iii) there was no long-run difference in the overall platform activity between treatment and control group.

Table 5: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access	0.0005	0.0003	-0.001
	(0.001)	(0.0009)	(0.0008)
Dep. Var. Mean	0.055	0.055	0.045
Observations	40,210	48,249	56,294
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access	-0.00009	0.0005	-0.00004
	(0.0004)	(0.0004)	(0.0003)
Dep. Var. Mean	0.012	0.010	0.007
Observations	40,210	48,252	56,294
Panel C: Sequential College Sr. Leadership Tie			
FB Access	-0.00007	0.0002	0.000006
	(0.0002)	(0.0002)	(0.0001)
Dep. Var. Mean	0.002	0.002	0.002
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Match quality, skill accumulation, and long-run firm sorting: While the previous results show no impact on between-firm promotions patterns, another potential reason behind the documented career benefits could be that students with early access to Facebook use their initial information advantage during the college-to-work transition to sort into higher-quality worker-firm matches, enabling them to accelerate their human capital accumulation and move up the career ladder within their organizations. A higher-quality worker-firm match in this context could reflect two things. First, students with early access to Facebook being more likely to find *stable* and *productive* worker-firm matches, raising their productivity and enabling them to accumulate more firm-specific human capital. Second, students with early access to Facebook *sorting* into firms that provide better learning opportunities and career support, even if the match quality remains unchanged.

Starting with the worker-firm match quality channel, Table 6, Panel A, analyzes the fraction of students reporting to work at their current employer for at least 6 months as a measure of early-career worker-firm match stability.[52] Column 1 shows that in the first six years after expected graduation, students with early access to Facebook are 0.7 percentage points (1%) more likely to report working at their employer for at least 6 months, providing first evidence that early access to Facebook improved the worker-firm match stability. Consistent with that interpretation, Appendix Table A20 shows that there is no positive impact on the likelihood of working in an unstable worker-firm match. While Columns 2 and 3 show that the positive effect is fading out over time, this could be driven by the well-documented evidence that firm tenure is increasing with experience (e.g., Topel and Ward (1992)), making the longer run results sensitive to the early-career threshold choice.

To investigate whether the worker-firm match stability also improved in the longer run, Panel B therefore uses current firm tenure as a proxy for worker-firm match stability. Consistent with the evidence in Panel A, Column 1 shows a positive effect on firm tenure in the first six years after expected graduation. Compared to the average firm tenure of the control group (1.64 years or 19.68 months), students with early access to Facebook stay on average 0.031 (0.37) more years (months) with their current employer. Column 2 shows that the firm tenure effect persists in the longer run and is actually increasing over time, rising up to 0.07 (0.84) years (months) 6–12 years after graduation. While the firm tenure effect becomes insignificant in the long run, the findings in Panels A and B provide solid evidence that students with early access to Facebook were more likely to find stable early-career worker-firm matches with the match stability persisting in the longer run. The findings also imply that students with early access to Facebook were able to accumulate more firm-specific human capital, making them more valuable for their organization.

As a more stable worker-firm match does not automatically imply that students with early access to Facebook benefited in terms of career development, Panel C turns to the question whether early access to Facebook also improved the productivity of the worker-firm match, looking at the probability of within-firm promotions.[53]

[52] The results for alternative early-career worker-firm match stability thresholds are very similar (not shown here).

[53] In a world with labor market frictions, there could be lock-in effects, making it more costly for workers to switch employers

Table 6: Facebook Access and Job Match Quality

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.007*	0.001	-0.0004
	(0.003)	(0.002)	(0.002)
Dep. Var. Mean	0.688	0.866	0.881
Observations	48,252	48,252	56,294
Panel B: Current Firm Tenure (Years)			
FB Access	0.031**	0.070*	0.083
	(0.011)	(0.028)	(0.047)
Dep. Var. Mean	1.64	4.02	6.04
Observations	48,252	48,252	56,294
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.003***	0.002*	0.0002
	(0.0008)	(0.0008)	(0.0006)
Dep. Var. Mean	0.022	0.030	0.029
Observations	40,210	48,249	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Column 1 shows that in the first six years after graduation, students with early access to Facebook are 0.3 percentage points more likely to obtain an early-career within-firm promotion, which refers to a 13.6% increase in the within-firm promotion probability compared to the control group. The positive effect on within-firm promotions also persists 6–12 years after graduation (0.2 percentage points) and only fades out at the later career stage. Consistent with the interpretation of an improvement in match quality between workers and firms, Appendix Table A20 shows that there is no positive impact on within-firm demotions

(e.g., Adda and Dustmann (2023)). If students with early access to Facebook are placed in firms offering less support for career development, the stable worker-firm matches could go in the opposite direction and result in a career penalty.

and only a slight positive impact on within-firm lateral moves. Together, these results show that early access to Facebook enabled students to find stable and productive worker-firm matches early on, allowing them to accumulate firm-specific human capital and advance within their organizations.

While the previous results provide evidence of an improvement in the worker-firm match quality, another reason behind the positive career benefits could reflect sorting into firms that provide better learning opportunities and career support. Theoretical work by Rosen (1972), Gibbons and Waldman (2006) as well as more recent empirical evidence by Arellano-Bover (2022), Gregory (2023), and Arellano-Bover and Saltiel (2026) emphasizes that firms differ substantially in the learning opportunities they provide, rationalizing a sizable fraction of life-cycle differences in career outcomes. As the college-to-work transition results already indicate that early access to Facebook enabled students to start their career in higher-quality firms and jobs, longer-run sorting into training-intensive and career-supporting firms could therefore be a complementary mechanism explaining the documented career effects. Table 7, Panel A, starts investigating this channel by looking at the accumulated work experience at high-wage firms as a first proxy for sorting into firms that provide better learning opportunities.[54] Consistent with the college-to-work transition results, Column 1 shows that in the first six years after graduation, U.S. business and economics students with early access to Facebook accumulated on average 0.08 years (0.96 months) more work experience at high-wage firms, which reflects a 5.4% increase compared to the control group (1.48 years). While the positive effect is fading out over time, as students from the control group are more likely to switch into high-wage firms later in their career (see Appendix Table A21), the results provide first evidence that an acceleration of skill accumulation on-the-job due to early-career sorting into higher-quality firms might explain part of the positive career development effects beyond the improvement in worker-firm match quality.[55]

To capture the effect of sorting into firms providing better learning opportunities and career support more directly, Panel B analyzes the accumulated work experience in high-career-support firms using the career opportunity rating dimension from Glassdoor. Consistent with the work experience effects for high-wage firms, Column 1 shows that six years after graduation, students with early access to Facebook also accumulate on average 0.054 years more work experience in high-career-support firms, reflecting a 6.4% increase compared to baseline. Contrary to the effect fading out in Panel A, the results in Panel B

[54] While the findings of the literature on heterogeneous skill accumulation across firms suggest that it is difficult to predict learning opportunities based on observable firm characteristics, Arellano-Bover and Saltiel (2026) provide some evidence that there is a weak positive correlation between firm pay and learning opportunities.

[55] Note that increased switching rate into high-wage firms from the control group is very similar to the behavior of students graduating in a recession (e.g., Oreopoulos *et al.* (2012); Schwandt and Von Wachter (2019)).

(Columns 2 and 3) indicate that the accumulated work experience in career-supporting firms is increasing over time.

Table 7: Facebook Access, Firm Sorting, and Human Capital Accumulation

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.080***	0.076	0.044
	(0.024)	(0.049)	(0.080)
Dep. Var. Mean	1.48	3.45	5.88
Observations	8,042	8,042	8,042
Panel B: Work Experience at High-Career-Support Firms (Years)			
FB Access	0.054**	0.105**	0.145**
	(0.017)	(0.035)	(0.054)
Dep. Var. Mean	0.846	1.80	2.97
Observations	8,029	8,027	8,029
Panel C: Cumulative Work Experience (Years)			
FB Access	0.048**	0.054**	0.043
	(0.017)	(0.021)	(0.022)
Dep. Var. Mean	4.49	10.12	16.78
Observations	8,042	8,042	8,042
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Work experience at high-career-support firms: cumulative years employed at a high-career-support firm. Cumulative work experience: total years of employment. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Overall, the results support the hypothesis that an acceleration of skill accumulation on-the-job due to sorting into firms that provide better learning opportunities and career support likely explains part of the documented career benefits beyond the improved worker-firm match quality channel.

General labor market experience and long-run unemployment risk: Another potential reason behind the documented career benefits could be that students with early access to Facebook accumulated more general labor market experience and faced a lower risk of unemployment in the long run. Table 7, Panel C, investigates the relevance of this channel by looking at cumulative work experience. Consistent with the documented positive early-career employment effects in Appendix Table A8, students with early access to Facebook accumulate 0.048 years (0.58 months) more work experience in the first six years after expected graduation. The effect remains positive and significant 12 years after graduation (0.054 years) before fading out in the long run, suggesting that part of the positive career benefits may also come from an accumulation of more general labor market experience. However, the relative effect sizes are comparatively small (1% and 0.5% respectively), suggesting that the impact of general labor market experience on the documented career effects is likely to be small.[56] Consistent with this observation, Appendix Table A8 shows that the positive employment effects are quickly fading out after the first six years after graduation, suggesting that a long-run reduction in unemployment risk does not explain the documented career effects.

5.3 Heterogeneity by gender

This section examines how the documented career benefits differ by gender. Despite decades of progress, women still work in lower-paying jobs and are systematically underrepresented at the top of the corporate world (e.g., Goldin (2014); Hindlian *et al.* (2018); Olivetti *et al.* (2024)). While several studies highlight a range of explanations, including the role of labor supply (e.g., Bertrand *et al.* (2010)), family responsibilities (e.g., Kleven *et al.* (2019)), or preferences for risk and competition (Niederle and Vesterlund (2007); Buser *et al.* (2014); Wiswall and Zafar (2018); Mas and Pallais (2017)), another part of the literature emphasizes the role of social networks, homophily, and referrals (e.g., Lalanne and Seabright (2016); Beaman *et al.* (2018); Zeltzer (2020); Mengel (2020); Cullen and Perez-Truglia (2023); von Essen and Smith (2023); Hampole *et al.* (2025)). As Facebook reduces the costs of adding and maintaining social connections, this may have facilitated women's access to male-dominated networks, equalizing access to valuable labor

[56] This is especially true in light of the well-documented evidence of decreasing returns to general labor market experience over a worker's career (e.g., Mincer (1974); Rubinstein and Weiss (2006)).

market connections, and ultimately reducing gender gaps in career outcomes. Consistent with the first part of this hypothesis, the results by Armona and Bailey (2025) indicate that early Facebook adopters have online social networks with lower gender homophily.

Appendix C investigates to what extent this observation translates into differential career effects for men and women. Appendix Table C1 shows that the documented career benefits are homogeneously shared across gender. While the effects on job-based earnings are slightly larger for women, consistent with the cross-sectional evidence by Armona (2023), the coefficients do not differ in terms of statistical significance, suggesting that the more gender-diverse network structure induced by early access to Facebook did not significantly reduce the gender gap in career outcomes. Nevertheless, investigating gender differences in the mechanisms behind the documented career benefits for men and women provides several important insights. While Appendix Table C2 shows that for both sexes, online social network access considerably improved the college-to-work transition, the results in Appendix Table C5 show that the improved worker-firm match quality channel is particularly visible for male students. Also regarding firm sorting, Appendix Table C6 shows that male students more strongly sort into career-supporting firms while the effect for sorting into higher-wage firms is particularly pronounced for females. Lastly, consistent with the finding by Armona and Bailey (2025) of reduced gender homophily, Appendix Table C3 shows that during the college-to-work transition, students with early access to Facebook were more likely to receive job help from opposite-sex peers. Overall, the results indicate that early access to Facebook did not meaningfully affect the gender gap in career outcomes, but may have facilitated women's access to otherwise male-dominated labor market networks (and vice versa).

5.4 Robustness

This section presents a battery of robustness checks addressing concerns related to (i) remaining spurious correlations with the Facebook rollout, (ii) spillover effects, (iii) multiple hypothesis testing, (iv) the choice of heterogeneity-robust estimator, (v) the sample composition on LinkedIn, and (vi) empirical design choices for elite colleges.

Randomization inference: A key concern with the main empirical strategy is that even within narrow selectivity-by-region comparisons, there might be remaining spurious correlations with the timing of the Facebook rollout, biasing the main estimates. For example, Facebook may have (deliberately or not) expanded early to colleges *within* the same selectivity and U.S. region where career outcomes of U.S. business and economics cohorts were already on a differential trend. To formally test this, I implement a randomization inference test in which I randomly reshuffle the introduction year of Facebook across colleges within each selectivity-by-region cell, preserving the total number of treated colleges per cell and the overall distribution of treatment timing. Appendix D presents the results. The placebo estimates are densely distributed around zero, and virtually all statistically significant effects from the main specification fall above the 95th percentile of the placebo distribution. The remaining variation in the Facebook rollout is therefore unlikely to reflect spurious correlations.

Spillover analysis: A further concern is that the results are driven by spillovers. In particular, treated students might displace students in the control group from jobs, biasing the treatment effect upward and violating the stable-unit treatment value assumption (SUTVA). To assess the severity of this concern, I predict each potential control cohort's exposure to spillovers based on the historical career overlap of U.S. business and economics students across colleges prior to the Facebook rollout.[57] I then drop all colleges that have at least one potential control cohort with the highest exposure score from the estimation. Reassuringly, Appendix E shows that the main patterns are very similar to the baseline estimates. Combined with the previous findings, the results suggest that the treatment effects are not simply coming from a reallocation of jobs within the economy but are rather consistent with the idea that access to Facebook reduces information frictions about job opportunities.

Multiple hypothesis testing: Given the large number of main results, some statistically significant findings could simply arise by chance. Appendix Table A21 reports adjusted p-values controlling for the false discovery rate following Benjamini and Hochberg (1995). The main findings remain statistically significant after the correction, suggesting that the key results are unlikely to reflect false positive discoveries.

Further robustness: Appendix F examines whether the main effects are sensitive to the choice of heterogeneity-robust estimator, presenting results using the estimator of Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020) as two alternatives. While the standard errors tend to be slightly larger, the main patterns are very similar, indicating that the results are not driven by the choice of the estimator. Appendix G reweights the analysis sample by gender and cohort size using IPEDS enrollment data to make it representative in terms of baseline demographics and college characteristics. The results are nearly identical to the baseline estimates, indicating that the main findings are not driven by sample composition on LinkedIn. Appendix H excludes Ivy Plus and other elite colleges, which are among the earliest adopters and can only be modeled with linear cohort trends. The estimates remain similar,

[57] See Appendix E for details.

suggesting that the main findings are not driven by empirical design choices for elite colleges.

6 Conclusion

More than 3 billion people report using online social networking platforms for work-related purposes (Kemp (2025)), yet evidence on the labor market impacts of these platforms remains scarce. To improve understanding of the consequences of online social networking platforms in a work-related context, this paper analyzes how providing young workers with access to Facebook during a sensitive period of their career - the labor market entry phase - affects their long-run job search and career outcomes. Exploiting the staggered introduction of Facebook across U.S. colleges in a generalized difference-in-differences design, I find that access to Facebook at labor market entry has a long-run positive impact on career development and economic mobility to top jobs. U.S. business and economics students with early access to Facebook are 5.1% more likely to receive early-career promotions and 3% more likely to reach senior leadership positions in their mid-30s to early 40s. Consistent with these findings, they also tend to work in higher-paying jobs, leading to an economically meaningful increase in lifetime earnings of around 1.2%.

I provide direct evidence that part of these long-run career benefits can be explained by a more successful college-to-work transition, largely driven by college peers sharing work-related information and helping one another find high-quality early-career jobs. I further show that the long-run career benefits can be explained by (i) Facebook improving the quality of early-career worker-firm matches, enabling students to move up the career ladder within their organizations and (ii) early-career sorting into higher-quality and career-supporting firms. Overall, the findings highlight that the provision of online social networks during a sensitive period of a young worker's career can improve the college-to-work transition, mitigate information frictions, and produce long-run career benefits.

The career benefits are homogeneously shared across gender, suggesting that online social network access at labor market entry does not ultimately affect the gender gap in career outcomes. Moreover, I do find evidence that treated students are more likely to receive opposite-sex job help for finding high-quality early-career jobs, suggesting that access to online social networking systems may facilitate women's access to otherwise male-dominated labor market networks (and vice versa).

What can we learn from the findings about the role of online social networking platforms for job search and career development today? The share of people using online social networking platforms, such as Facebook, has increased considerably over recent decades, growing from a small set of college students to over 70% of U.S. adults by 2025 (Pew Research Center (2025)). With a higher job offer arrival rate for the entire population, traditional job search models (e.g., Burdett (1978)) would predict that the career benefits of using online social networking platforms likely become smaller as individuals increasingly hear about and compete for the same jobs.[58] Nevertheless, given (i) the finding of this paper that the career benefits do not simply reflect a reallocation of desirable jobs within the economy and (ii) the well-documented evidence of persistent information frictions in the labor market (e.g., Conlon *et al.* (2018); Heller and Kessler (2024)) with job-seekers being inaccurately informed about potential job opportunities (e.g., Belot *et al.* (2019); Jäger *et al.* (2024); Caldwell *et al.* (2026)), it is likely that some of the career benefits from an improved information flow due to online social networks are still present today.[59] Therefore, career services and unemployment agencies should actively encourage the use of online social networking platforms as a low-cost tool for job search and career development that can mitigate search frictions and improve labor market prospects for workers facing sensitive periods in their careers.

While the results in this paper improve our understanding of the relevance of online social networks for job finding and career development of young workers, several important questions for future research remain. In particular, examining how the career effects differ for lower-educated workers and workers at older ages, assessing the general equilibrium effects, and better understanding the relative importance of the different channels (e.g., referrals, recruiters, job ads, company profiles) and platforms (e.g., Facebook, LinkedIn, Twitter/X) are first-order questions for fully understanding the labor market impacts of online social networking platforms today.

[58]This is especially true for a single online social networking platform, as nowadays, more social networking platforms have gained popularity and provide work-related information (e.g., Facebook, LinkedIn, Twitter/X).

[59]See, for example, Wheeler *et al.* (2022) for evidence on positive labor market effects due to online social network usage for young work seekers in more recent years.

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Appendix A: Additional Tables and Figures

Table A1: Most Common Job Title Transitions for Promotion Events

Years Since Graduation	Top 10 Job Title Transitions (Promotion Events)
2-6 Years	Staff Accountant -> Senior Accountant, Financial Analyst -> Senior Financial Analyst, Analyst -> Associate, Associate -> Vice President, Consultant -> Senior Consultant, Accountant -> Senior Accountant, Account Executive -> Senior Account Executive, Account Executive -> Account Executive, Associate -> Associate, Associate -> Senior Associate
7-12 Years	Financial Analyst -> Senior Financial Analyst, Associate -> Vice President, Manager -> Senior Manager, Attorney -> Attorney, Associate -> Partner, Associate -> Associate, Staff Accountant -> Senior Accountant, Assistant Vice President -> Vice President, Project Manager -> Senior Project Manager, Senior Accountant -> Accounting Manager
13-19 Years	Project Manager -> Senior Project Manager, Vice President -> Senior Vice President, Associate -> Partner, Controller -> Chief Financial Officer, Assistant Controller -> Controller, Manager -> Senior Manager, Vice President -> President, Vice President -> Director, Attorney -> Partner, General Manager -> General Manager

Notes: Most common job title transitions for identified promotion events by years since graduation. Promotions are identified by large relative real annual wage growth jumps of at least 10 log points following Bronson and Thoursie (2019). *Data source:* Revelio Labs.

Table A2: Managerial Pipeline Validation - Earnings

Variable	Individual Contributor	Manager	Director	Vice president	Senior vice president	C-Suite
Job-based annual earnings	66,543	102,596	170,116	190,486	209,820	250,123
Share female	0.450	0.414	0.409	0.303	0.257	0.246
Observations	8,765,845	4,053,126	1,633,676	756,400	462,375	442,071

Notes: Descriptive statistics at the person–year level by managerial pipeline position. Sample: all U.S. business & economics undergraduates expected to graduate from 1999 to 2005 at selective 4-year colleges with a valid LinkedIn profile and reasonable college-level coverage (1,154 colleges). *Data source:* Revelio Labs

Table A3: Most Common Job Titles - Leadership Pipeline

Category	Top 10 job titles
Individual Contributor	Account Executive, Senior Accountant, Accountant, Associate, Financial Advisor, Attorney, Financial Analyst, Sales Representative, Staff Accountant, Senior Financial Analyst
Manager	Project Manager, Manager, Account Manager, Operations Manager, Sales Manager, Branch Manager, Store Manager, Accounting Manager, Senior Manager, Marketing Manager
Director	Partner, Controller, Director, Director of Operations, Assistant Vice President, Marketing Director, Director of Finance, Director of Marketing, Director of Sales, Director Of Operations
Vice President	Vice President, Principal, Regional Vice President, Vice President of Sales, Vice President of Operations, Senior Director, VP, Vice President Operations, Vice President of Finance, VP of Operations

Table A3: (continued)

Category	Top 10 job titles
Senior Vice President	General Manager, Managing Director, Executive Director, Managing Partner, Senior Vice President, Executive Vice President, Assistant General Manager, Senior Managing Director, Managing Principal, GM
C-Level	President, CEO, Chief Financial Officer, Chief Executive Officer, CFO, Chief Operating Officer, COO, President & CEO, President/CEO, General Counsel

Notes: Most common job titles by leadership pipeline category. *Data source:* Revelio Labs.

Table A4: Coverage, Distribution, and Correlation of Permanent Firm Characteristics

	Coverage (%)		Distribution (emp.-wtd.)			Correlation matrix						
	LinkedIn	Est. sample	p_{25}	Median	p_{75}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Firm pay	100.0	99.8	10.70	11.00	11.26	1.00	0.04	0.05	0.05	0.10	0.07	0.10
(2) Overall rating	43.8	69.4	3.34	3.65	3.94	0.04	1.00	0.77	0.84	0.73	0.84	0.69
(3) Career opportunities	43.2	68.8	3.01	3.35	3.63	0.05	0.77	1.00	0.77	0.65	0.79	0.73
(4) Culture & values	43.1	68.7	3.13	3.51	3.87	0.05	0.84	0.77	1.00	0.76	0.87	0.68
(5) Work-life balance	43.2	68.8	3.14	3.50	3.85	0.10	0.73	0.65	0.76	1.00	0.75	0.63
(6) Senior leadership	43.2	68.8	2.87	3.17	3.48	0.07	0.84	0.79	0.87	0.75	1.00	0.69
(7) Comp. & benefits	43.2	68.8	3.02	3.41	3.73	0.10	0.69	0.73	0.68	0.63	0.69	1.00

Notes: Descriptive statistics on the coverage, distribution, and correlation of all permanent firm characteristics. LinkedIn: coverage of the respective firm characteristic among all companies on LinkedIn that employ college students in the main estimation sample weighted by the average LinkedIn employee size. Est. sample: coverage of the respective firm characteristic among all person-year observations indicating an employer in the main estimation sample. Distribution columns: p_{25}, median, and p_{75} of each permanent firm characteristic among all companies on LinkedIn that employ college students in the main estimation sample weighted by the average LinkedIn employee size. Firm pay: average median log annual earnings, net of year fixed effects. Glassdoor amenity ratings are measured on a scale from 1–5: overall rating, career opportunities, culture & values, work-life balance, senior leadership, comp. & benefits. All Glassdoor amenity ratings are averaged across years, net of year fixed effects. Correlation matrix: Pearson correlations at the firm level between the different firm quality measures. *Data source:* Revelio Labs and Glassdoor.

Table A5: Sample Selection

Filtering step	Observations	Number of Colleges	Cumulative	Age	Female	At Least Very Selective College
All LinkedIn profiles, U.S. business and economics undergraduates	1,071,848	1,235	1.00	18.42	0.434	0.503
Valid undergraduate graduation date	1,048,577	1,235	0.978	18.41	0.433	0.504
Complete employment history	914,976	1,234	0.854	18.41	0.424	0.511
Reasonable college-level coverage	890,951	1,154	0.831	18.39	0.423	0.519

Notes: Each row reports the number of LinkedIn profiles remaining after the corresponding filtering step is applied. The final estimation sample covers all U.S. business & economics undergraduates expected to graduate from 1999 to 2005 at selective 4-year colleges with a valid LinkedIn profile and reasonable college-level coverage (1,154 colleges). *Data source:* Revelio Labs

Table A6: Comparison Table - Revelio Labs vs. IPEDS

Variable	Actual Graduation	Expected Graduation	Ipeds
Elite College	0.075	0.076	0.067
Highly Competitive College	0.161	0.162	0.150
Very Competitive College	0.280	0.281	0.265
Competitive College	0.394	0.392	0.415
Less Competitive College	0.090	0.089	0.103
Public College	0.638	0.640	0.643
Northeast	0.220	0.220	0.211
Midwest	0.276	0.275	0.266
South	0.342	0.342	0.351
West	0.162	0.162	0.173
Female	0.420	0.416	0.472
Observations	905,281	890,951	1,907,885

Notes: Descriptive statistics for various samples. Actual Graduation: All business & economics graduates from the 1,154 colleges in the graduation cohorts from 1999 to 2005 with a valid LinkedIn profile and reasonable college-level coverage. Expected Graduation: All business & economics students from the 1,154 colleges in the expected graduation cohorts from 1999 to 2005 with a valid LinkedIn profile and reasonable college-level coverage. Ipeds: All business & economics graduates from the 1,154 colleges in the graduation cohorts from 1999 to 2005 in the IPEDS data. *Data source:* Revelio Labs and IPEDS.

Table A7: Facebook Access, LinkedIn Sign-Up, and Balancing

	Coverage			Age at Entry	Female
	Overall	Male	Female		
FB Access	0.006	0.003	0.011	−0.010	−0.0008
	(0.010)	(0.013)	(0.012)	(0.020)	(0.005)
Dep. Var. Mean	0.453	0.505	0.397	18.42	0.417
Observations	8.042	7.827	7.953	8.042	8.042
College FE	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year or college*cohort*year*gender level. Coverage: fraction of students in the LinkedIn estimation sample compared to the official graduation counts in IPEDS. Coverage regressions are weighted using IPEDS graduation counts. Age at entry: imputed age at labor market entry. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs and IPEDS.

Table A8: Facebook Access, Employment, and Conditional Earnings

	1–6 Years	7–12 Years	13–19 Years
Panel A: Employment			
FB Access	0.007*	0.0001	-0.0009
	(0.003)	(0.001)	(0.002)
Dep. Var. Mean	0.768	0.937	0.943
Observations	48,252	48,252	56,294
Panel B: Conditional Earnings (Employed Only)			
FB Access	561	1,372*	973
	(504)	(555)	(635)
Dep. Var. Mean	98,787	113,411	128,820
Observations	48,200	48,239	56,284
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Panel A: share of graduates with a recorded employment spell. Panel B: average job-based annual earnings (2024 USD) conditional on employment. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A9: Facebook Access and Cumulative Earnings

	δ = 0%	δ = 2.5%	δ = 5%
FB Access	21,148*	17,660*	14,976**
	(8,989)	(7,105)	(5,771)
Dep. Var. Mean	1,942,861	1,528,716	1,229,694
Observations	8,042	8,042	8,042
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort level. The present discounted value of earnings is the discounted sum of average annual earnings over the 19-year observation window: $\text{PDV}(\delta) = \sum_{t=1}^{19} \bar{w}_{j,c,t}/(1+\delta)^{t-1}$, where $\bar{w}_{j,c,t}$ is the average job-based annual earnings of college j, cohort c, at year t after graduation, and δ is the discount rate. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A10: Facebook Access and Alternative Promotion Thresholds

	2–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Promotion (≥7.5 log pts.)			
FB Access	0.004**	0.002	-0.0008
	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.082	0.089	0.079
Observations	40,210	48,252	56,294
Panel B: Job-Based Promotion (≥12.5 log pts.)			
FB Access	0.003*	0.002	-0.0009
	(0.001)	(0.001)	(0.0010)
Dep. Var. Mean	0.074	0.080	0.070
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A11: Facebook Access, Lateral Moves, and Demotion

	2–6 Years	7–12 Years	13–19 Years
Panel A: Lateral Moves			
FB Access	0.001	0.0008	0.0002
	(0.001)	(0.0009)	(0.0009)
Dep. Var. Mean	0.034	0.040	0.037
Observations	40,210	48,252	56,294
Panel B: Job-Based Demotion (≤10 log pts.)			
FB Access	0.0002	-0.0009	-0.0007
	(0.0010)	(0.001)	(0.0010)
Dep. Var. Mean	0.042	0.057	0.059
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. Panel A: share of graduates transitioning to a job with relative real annual wage growth between -10 and $+10$ log points. Panel B: share of graduates transitioning to a job with relative real annual wage growth below -10 log points. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A12: Facebook Access and Alternative Top Jobs

	1–6 Years	7–12 Years	13–19 Years
Panel A: Management Occupations (SOC 11)			
FB Access	0.002	0.001	0.010*
	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.198	0.265	0.288
Observations	48,246	48,248	56,293
Panel B: Top Executives (SOC 11-1)			
FB Access	0.0007	0.003*	0.003
	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.020	0.034	0.042
Observations	48,246	48,248	56,293
Panel C: Member of the Board			
FB Access	-0.0003	-0.0003	0.00010
	(0.0002)	(0.0004)	(0.0004)
Dep. Var. Mean	0.0007	0.002	0.003
Observations	48,252	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Member of the board: indicator for working as a board member or member of the board of directors using a keyword search on job titles. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A13: Facebook Access and the College-to-Work Transition - Other High-Amenity Firm Dimensions

	Overall	Comp. & Benef.	Culture	Leadership	Work-Life
Panel A: Working at High-Amenity Firm [1–2Y]					
FB Access	0.003	0.010**	0.006	0.004	0.005
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Dep. Var. Mean	0.100	0.139	0.113	0.124	0.095
Observations	16,068	16,066	16,066	16,066	16,066
Panel B: Sequential Job Help into High-Amenity Firm [1–2Y]					
FB Access	0.002	0.003*	0.003	0.003*	0.0010
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.017	0.028	0.021	0.030	0.014
Observations	16,068	16,066	16,066	16,066	16,066
College FE	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-amenity firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor rating distribution for the given dimension (among firms with at least two ratings). The career opportunities dimension is shown separately in Tables 3, 4, and 7. Overall: overall rating on Glassdoor. Comp. & Benef.: compensation and benefits. Culture: company culture. Leadership: senior leadership. Work-Life: work-life balance. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A14: Facebook Access and Missing Glassdoor Rating – Balancing Check

	Overall	Comp. & Benef.	Career Opps.	Culture	Leadership	Work-Life
FB Access	0.003	0.004	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.208	0.212	0.212	0.213	0.212	0.212
Observations	16,084	16,084	16,084	16,084	16,084	16,084
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. Missing amenity: indicator for working at an employer with no Glassdoor rating in the respective dimension. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A15: Facebook Access and the College-to-Work Transition – Other Job Types

	Non-High-Wage Firm	Non-High-Career-Support Firm	Non-High-Wage Occupation	Non-Steep Wage Growth	Non-Sr. Leadership Track
FB Access	-0.004	-0.004	-0.001	0.012*	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Dep. Var. Mean	0.446	0.402	0.402	0.483	0.441
Observations	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate for the first two years after expected graduation. Non-High-Wage Firm: indicator for working at a firm not in the upper employment-weighted quartile of the average median log earnings distribution at the firm level. Non-High-Career-Support Firm: indicator for working at a firm not in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Non-High-Wage Occupation: indicator for working in an occupation not in the upper employment-weighted quartile of the average median log earnings distribution at the 5-digit SOC level. Non-Steep Wage Growth: indicator for an early-career job with a leave-one-cohort-out 15-year wage growth prediction at or below the 75th percentile. Non-Sr. Leadership Track: indicator for an early-career job with a leave-one-cohort-out prediction of reaching senior leadership 15 years after at or below the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A16: Facebook Access, Education Outcomes, and Time to First Stable Job

			Postgraduate Degree			
	Study Duration	In College	Any	Business & Economics	MBA	Time to First Stable Job
FB Access	0.007	-0.004	0.0007	0.0007	-0.004	-0.055**
	(0.012)	(0.002)	(0.005)	(0.005)	(0.004)	(0.020)
Dep. Var. Mean	3.83	0.055	0.326	0.259	0.147	1.49
Observations	8,042	16,084	8,042	8,037	8,042	8,042
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. Study Duration: total years from enrollment to completion of the bachelor's degree. Time to First Stable Job: time to the first active employment spell after expected graduation lasting at least 4 months, following Kramarz and Skans (2014). In College: indicator whether students report being enrolled in the first two years after expected graduation. Postgraduate Degree: reporting a master's, PhD, or professional degree as the highest degree on the LinkedIn profile. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A17: Facebook Access and Early-Career Job Tie by College Peer Type

	Early-Career Job Help via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
Panel A: Same-Cohort Tie						
FB Access	0.002	0.001	0.002	-0.0008	0.002	0.001
	(0.002)	(0.0009)	(0.001)	(0.001)	(0.0010)	(0.001)
Dep. Var. Mean	0.039	0.016	0.020	0.015	0.010	0.018
Observations	16,084	16,084	16,066	16,082	16,082	16,082
Panel B: Alumni Tie						
FB Access	0.010***	0.006***	0.008***	0.004*	0.004**	0.007***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Dep. Var. Mean	0.093	0.038	0.045	0.037	0.024	0.042
Observations	16,084	16,084	16,066	16,082	16,082	16,082
Panel C: Below-Cohort Tie						
FB Access	0.004*	0.003**	0.003	-0.001	0.003***	0.002*
	(0.002)	(0.0009)	(0.001)	(0.001)	(0.0009)	(0.001)
Dep. Var. Mean	0.040	0.014	0.017	0.015	0.011	0.015
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. Alumni: students 1 to 3 classes above the expected graduation cohort. Below-cohort peers: students 1 to 3 classes below the expected graduation cohort. Any Job: indicator for receiving job help from the respective college peer type, following Gee *et al.* (2017). High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distribution at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distribution at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching senior leadership 15 years after above the 75th percentile. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A18: Facebook Access and Early-Career Job Help in the College Network – Other Job Types

	Early-Career Job via College Network				
	Non-High-Wage Firm	Non-High-Career-Support Firm	Non-High-Wage Occupation	Non-Steep Wage Growth	Non-Sr. Leadership Track
FB Access	0.004	0.004	0.007***	0.006**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.066	0.075	0.064	0.081	0.061
Observations	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate for the first two years after expected graduation. Complement outcomes to Table 4. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). Non-High-Career-Support Firm: indicator for working at a firm not in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A19: Facebook Access and Between-Firm Job Changes

	2–6 Years	7–12 Years	13–19 Years
Panel A: Any Between-Firm Switch			
FB Access	0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.112	0.123	0.111
Observations	40,210	48,249	56,294
Panel B: Between-Firm Switches (No Promotion)			
FB Access	0.0006	-0.002	-0.0002
	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.057	0.068	0.065
Observations	40,210	48,249	56,294
Panel C: Sequential College Job (No Promotion)			
FB Access	0.0004	-0.008**	-0.001
	(0.002)	(0.003)	(0.003)
Dep. Var. Mean	0.108	0.125	0.106
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. Panel A: share of graduates who change employers in the given period. Panel B: share of graduates who change employers without a relative real annual wage growth jump of at least 10 log points. Panel C: share of graduates who change employers with the help of a college peer but no relative real annual wage growth jump of above 10 log points. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A20: Facebook Access, Job Stability, and Within-Firm Mobility

	1–6 Years	7–12 Years	13–19 Years
Panel A: Unstable Worker-Firm Match (<6 mo.)			
FB Access	0.0001	-0.0010	-0.0005
	(0.001)	(0.001)	(0.001)
Dep. Var. Mean	0.080	0.071	0.061
Observations	48,252	48,252	56,294
Panel B: Within-Firm Lateral Move			
FB Access	0.0006	0.001*	-0.0007
	(0.0005)	(0.0006)	(0.0005)
Dep. Var. Mean	0.010	0.015	0.015
Observations	40,210	48,249	56,294
Panel C: Within-Firm Demotion			
FB Access	0.0005	0.0007	0.0003
	(0.0005)	(0.0007)	(0.0005)
Dep. Var. Mean	0.009	0.014	0.015
Observations	40,210	48,249	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Panel A: share of graduates with a current employer tenure of less than 6 months. Panels B–C start in year 2 as within-firm transitions are only defined for ongoing employment spells. Panel B: share of graduates who transition to a different role at the same employer with a relative real annual wage growth jump between -10 and +10 log points. Panel C: share of graduates who transition to a role at the same employer with relative real annual wage growth jump below -10 log points. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A21: Facebook Access and High-Wage Firm Transitions

	1–6 Years	7–12 Years	13–19 Years
Panel A: High-Wage Firm			
FB Access	0.013***	-0.001	-0.005
	(0.004)	(0.005)	(0.005)
Dep. Var. Mean	0.251	0.325	0.342
Observations	48,252	48,250	56,294
Panel B: Entry into High-Wage Firm			
FB Access	0.0007	-0.002*	0.0004
	(0.001)	(0.0008)	(0.0006)
Dep. Var. Mean	0.051	0.037	0.029
Observations	40,210	48,250	56,294
Panel C: Exit from High-Wage Firm			
FB Access	0.0009	0.0007	-0.00001
	(0.0008)	(0.0006)	(0.0007)
Dep. Var. Mean	0.029	0.031	0.027
Observations	40,210	48,250	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Panel A: share of graduates employed at a high-wage firm (upper employment-weighted quartile of the firm wage distribution). Panel B: share of graduates who transition from a non-high-wage to a high-wage firm. Panel C: share of graduates who transition from a high-wage to a non-high-wage firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table A21: Multiple Hypothesis Testing Corrections

	Coefficient	Unadj. *p*-value	BH (1995) *p*-value
Panel A: Career Development (Table 2)			
Job-Based Real Annual Earnings [1–6Y]	1,286**	0.007	0.019
Job-Based Real Annual Earnings [7–12Y]	1,343*	0.016	0.033

	Coefficient	Unadj. p-value	BH (1995) p-value
Job-Based Real Annual Earnings [13–19Y]	768	0.237	0.334
Job-Based Promotion (≥10 log pts.) [2–6Y]	0.004**	0.008	0.021
Job-Based Promotion (≥10 log pts.) [7–12Y]	0.002	0.092	0.147
Job-Based Promotion (≥10 log pts.) [13–19Y]	-0.0010	0.326	0.448
Sr. Leadership Positions [1–6Y]	0.002	0.373	0.483
Sr. Leadership Positions [7–12Y]	0.006*	0.037	0.072
Sr. Leadership Positions [13–19Y]	0.008*	0.021	0.042
Panel B: College-to-Work Transition (Table 3)			
Employed [1–2Y]	0.010**	0.006	0.018
High-Wage Firm [1–2Y]	0.014***	0.0002	0.001
High-Career-Support Firm [1–2Y]	0.014***	0.0002	0.001
High-Wage Occupation [1–2Y]	0.012**	0.005	0.017
Steep Wage Growth [1–2Y]	-0.001	0.797	0.869
Steep Sr. Leadership [1–2Y]	0.014***	0.0005	0.003
Panel C: Early-Career Job Help in College Network (Table 4)			
Job Help x Any Job [1–2Y]	0.011***	0.00002	0.0003
Job Help x High-Wage Firm [1–2Y]	0.007***	0.00001	0.0003
Job Help x High-Career-Support Firm [1–2Y]	0.008***	0.00002	0.0003
Job Help x High-Wage Occ. [1–2Y]	0.004*	0.042	0.075
Job Help x Steep Wage Growth [1–2Y]	0.004**	0.001	0.005
Job Help x Sr. Leadership [1–2Y]	0.007***	0.000002	0.0001
Panel D: Firm Mobility, and Long-Run Job Help in the College Network (Table 5)			
Between-Firm Promotion (≥10 log pts.) [2–6Y]	0.0005	0.719	0.821
Between-Firm Promotion (≥10 log pts.) [7–12Y]	0.0003	0.758	0.846
Between-Firm Promotion (≥10 log pts.) [13–19Y]	-0.001	0.109	0.169
Job Help x Promotions [2–6Y]	-0.00009	0.825	0.880
Job Help x Promotions [7–12Y]	0.0005	0.178	0.259
Job Help x Promotions [13–19Y]	-0.00004	0.883	0.902
Job Help x Sr. Leadership [2–6Y]	-0.00007	0.676	0.811
Job Help x Sr. Leadership [7–12Y]	0.0002	0.369	0.483

	Coefficient	Unadj. p-value	BH (1995) p-value
Job Help x Sr. Leadership [13–19Y]	0.000006	0.963	0.963
Panel E: Job Match Quality (Table 6)			
Stable Worker-Firm Match (≥6 mo.) [1–6Y]	0.007*	0.013	0.028
Stable Worker-Firm Match (≥6 mo.) [7–12Y]	0.001	0.584	0.719
Stable Worker-Firm Match (≥6 mo.) [13–19Y]	-0.0004	0.883	0.902
Firm Tenure [1–6Y]	0.031**	0.003	0.013
Firm Tenure [7–12Y]	0.070*	0.012	0.027
Firm Tenure [13–19Y]	0.083	0.077	0.127
Within-Firm Promotion (≥10 log pts.) [2–6Y]	0.003***	0.0001	0.0010
Within-Firm Promotion (≥10 log pts.) [7–12Y]	0.002*	0.041	0.075
Within-Firm Promotion (≥10 log pts.) [13–19Y]	0.0002	0.699	0.818
Panel F: Work Experience (Table 7)			
Exp. at High-Wage Firm [6Y]	0.080***	0.0007	0.004
Exp. at High-Wage Firm [12Y]	0.076	0.123	0.184
Exp. at High-Wage Firm [19Y]	0.044	0.583	0.719
Exp. at High-Career-Support Firm [6Y]	0.054**	0.001	0.005
Exp. at High-Career-Support Firm [12Y]	0.105**	0.002	0.009
Exp. at High-Career-Support Firm [19Y]	0.145**	0.007	0.019
Work Experience [6Y]	0.048**	0.005	0.017
Work Experience [12Y]	0.054**	0.009	0.022
Work Experience [19Y]	0.043	0.053	0.090

Notes: Unadjusted and adjusted p-values for each coefficient in the main results section. Adjusted p-values are computed using the Benjamini and Hochberg (1995) adjustment procedure. *Data source:* Revelio Labs.

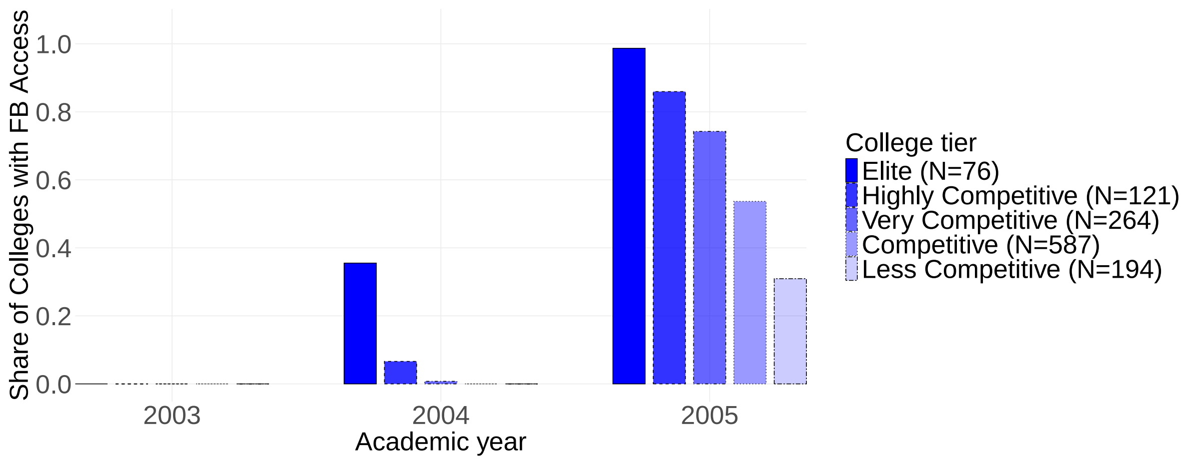


Figure A1: Facebook rollout across selective U.S. colleges with a business and economics undergraduate degree by college selectivity tier.

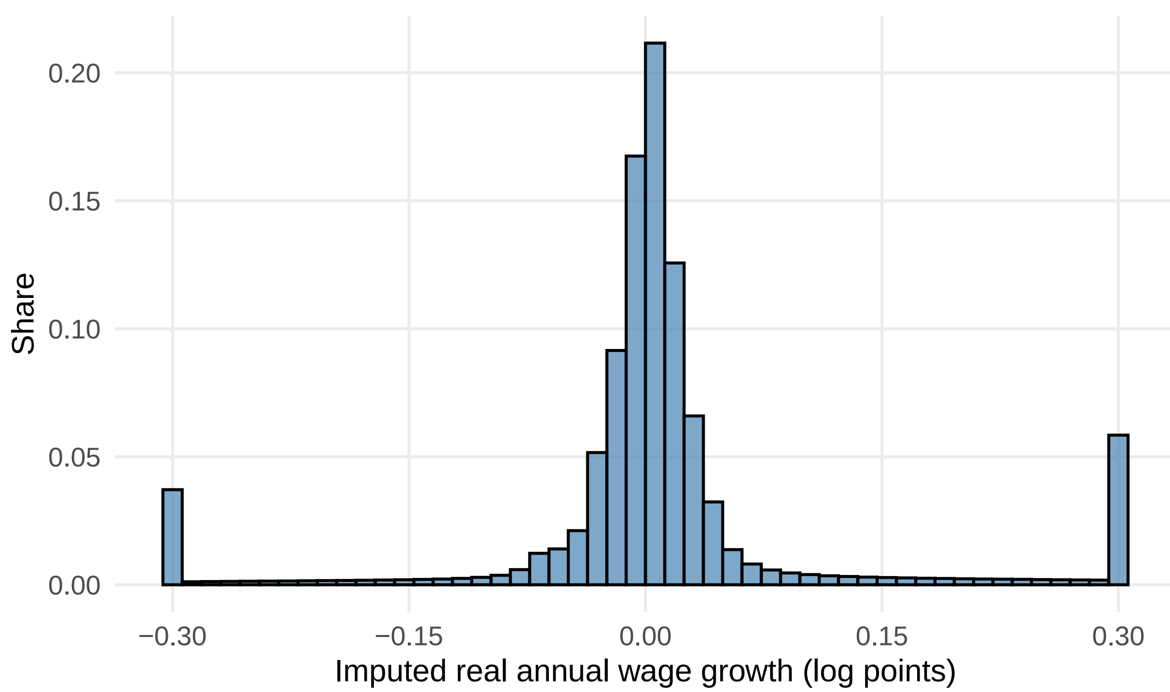


Figure A2: Imputed real annual wage growth distribution

Appendix B: Event-Study Specification

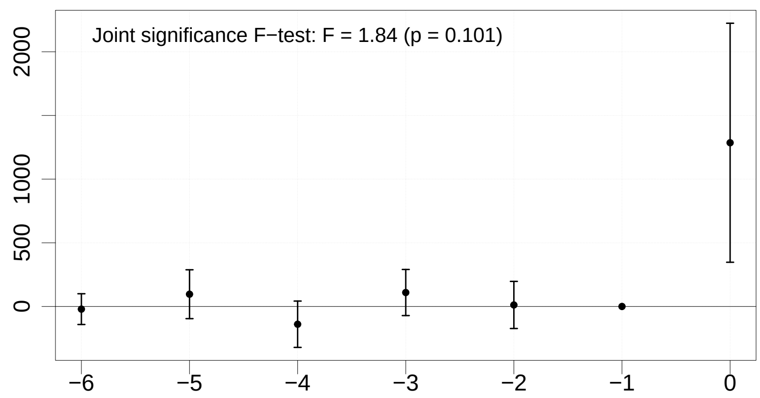
To assess the plausibility of the parallel trends assumption, I estimate an event-study version of equation (1), where the expected graduation year of the first freshman cohort to be affected by the introduction of Facebook in a given college is referred to as the *event*. The model, estimated using the heterogeneity-robust estimator proposed by Gardner (2022), can be specified as follows:

$$Y_{fs,c,t} = \sum_{k=-6}^{0} \mathbf{1}\{t_{fs,c} - t_c = k\} \beta_k + \delta_{fs,\text{tier,region}} + \phi_c + \epsilon_{fs,c,t}, \tag{2}$$

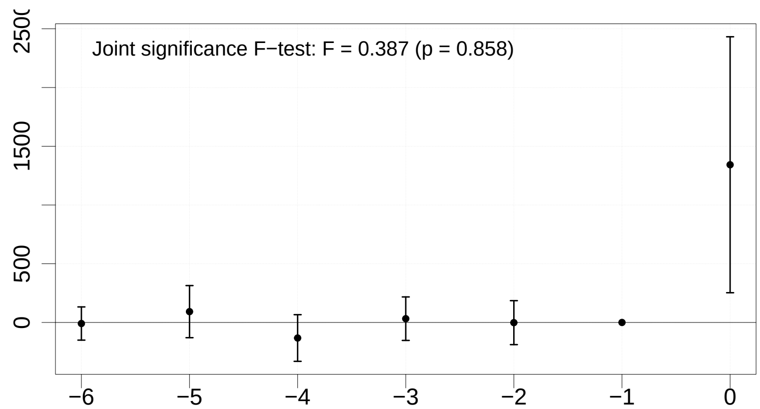
where t_c corresponds to the *event* in college c and $t_{fs,c}$ to the expected graduation year of freshman cohort fs in college c. The remaining components of equation (2) are the same as in the baseline model. The event-study specification allows me to investigate nonlinear pre-trends in the career outcome variables between treatment and control cohorts. To allow for separate identification of the dynamic treatment effect coefficients β_k and the cohort fixed effects in a setup that uses only not-yet-treated cohorts as comparison groups, I follow the recommendation by Schmidheiny and Siegloch (2023) and bin both endpoints of the event-time window. To be precise, I bin the event-time coefficients for $k \leq -7$ with $k = -6$, and for $k \geq 1$ with $k = 0$. Hence, β_0 in the event-study model captures the same ITT estimate as α_1 in the baseline specification. Event time $k = -1$ is omitted as the reference category.

Appendix Figures B2 to B16 show the results. Across all outcome variables, the pre-treatment coefficients are close to zero and the majority of the coefficients are individually as well as jointly insignificant at the 5% level. The flat pre-treatment coefficients support the parallel trends assumption and rule out the concerns that the documented treatment effects simply reflect pre-existing differential trends in career outcomes between treated and control cohorts.

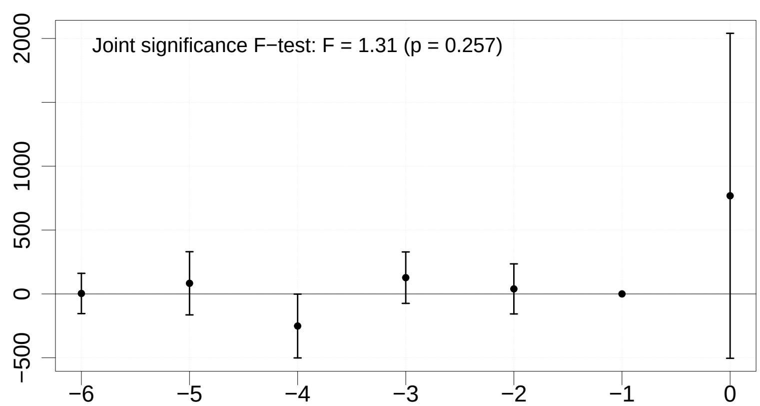
Figure B1: Facebook Access and Job-Based Real Annual Earnings – Event Studies



(a) 1–6 Years

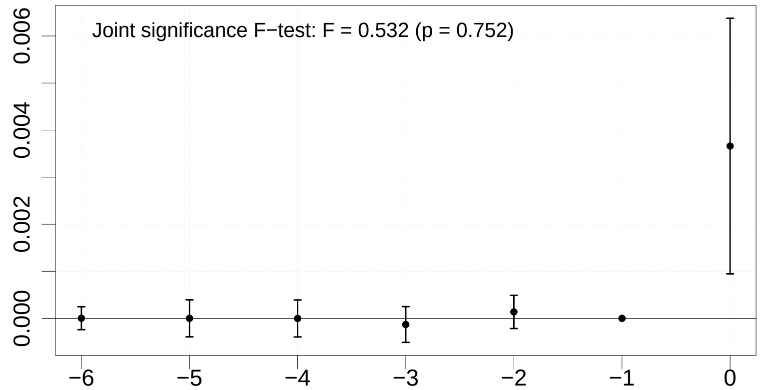


(b) 7–12 Years

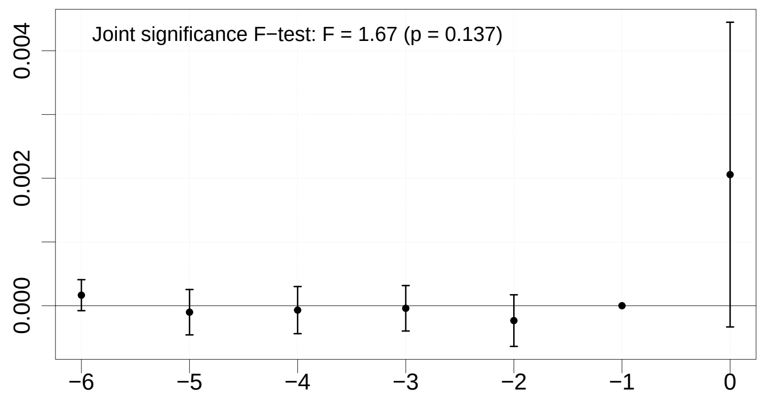


(c) 13–19 Years

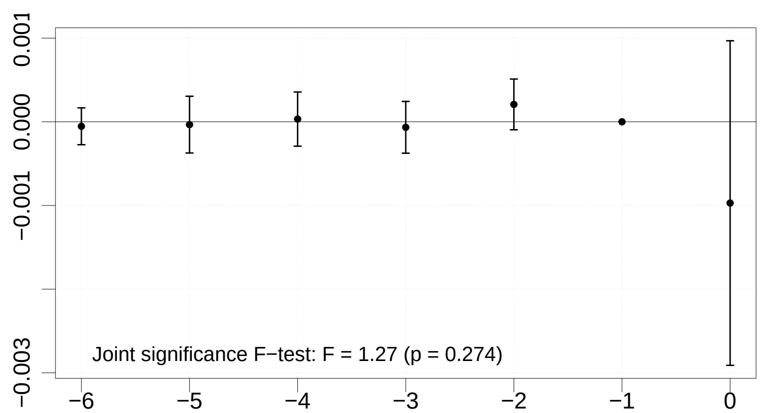
Figure B2: Facebook Access and Job-Specific Promotions – Event Studies



(a) 2–6 Years

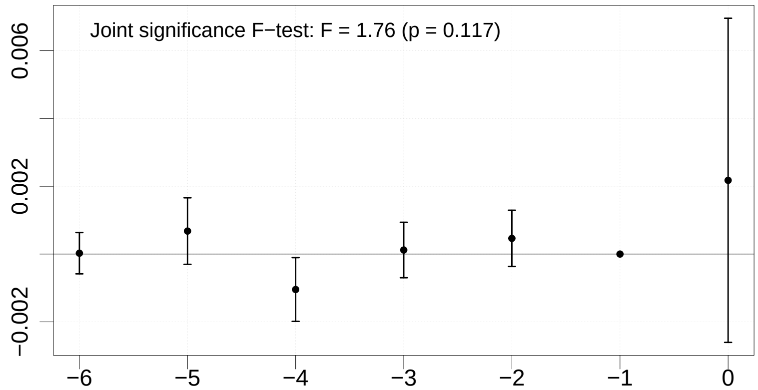


(b) 7–12 Years

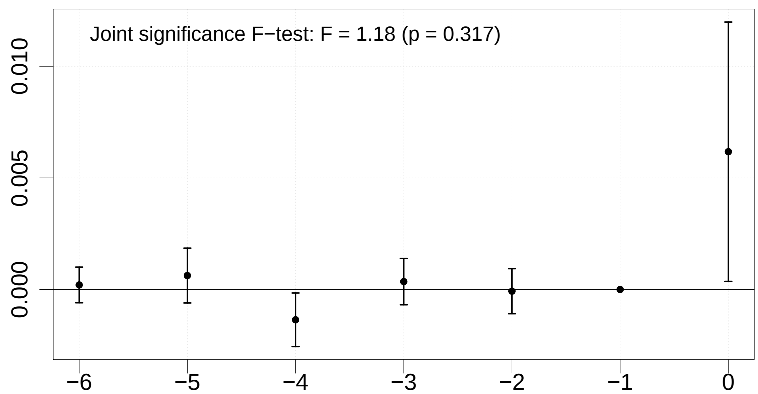


(c) 13–19 Years

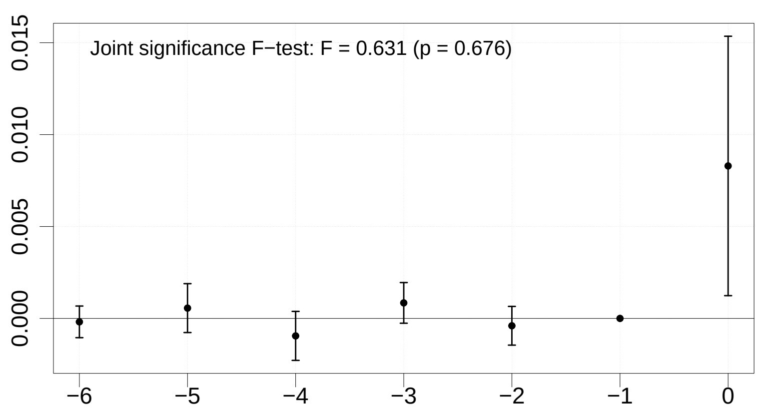
Figure B3: Facebook Access and Senior Leadership Positions – Event Studies



(a) 1–6 Years

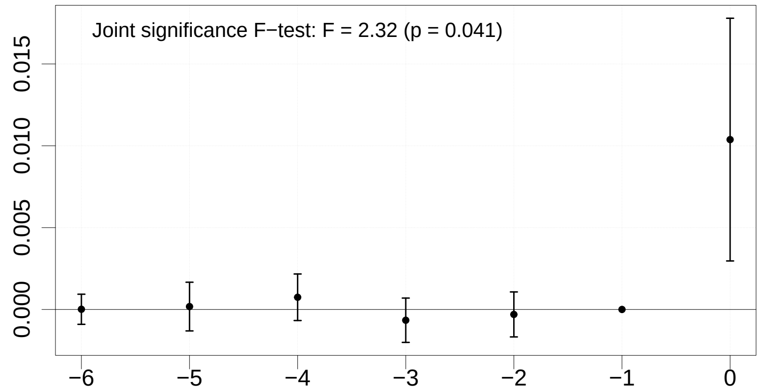


(b) 7–12 Years

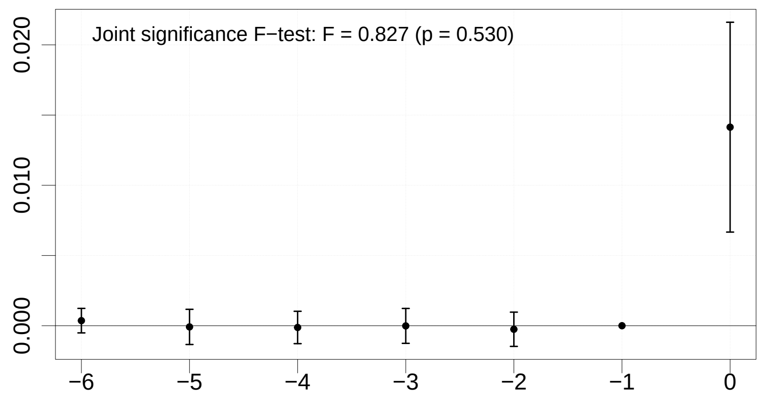


(c) 13–19 Years

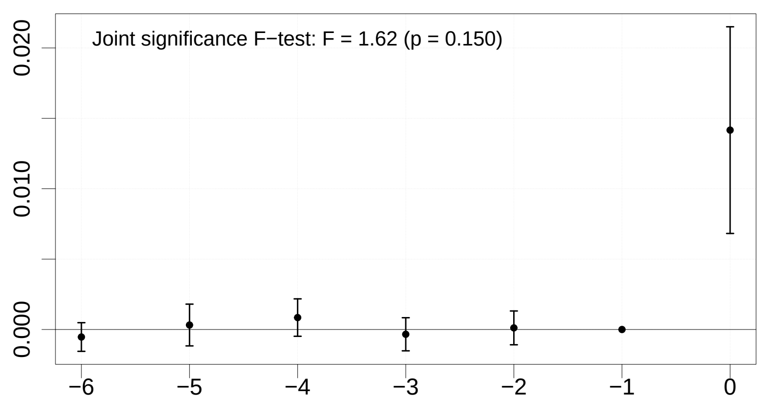
Figure B4: Facebook Access and The College-To-Work Transition (1) – Event Studies



(a) Employment

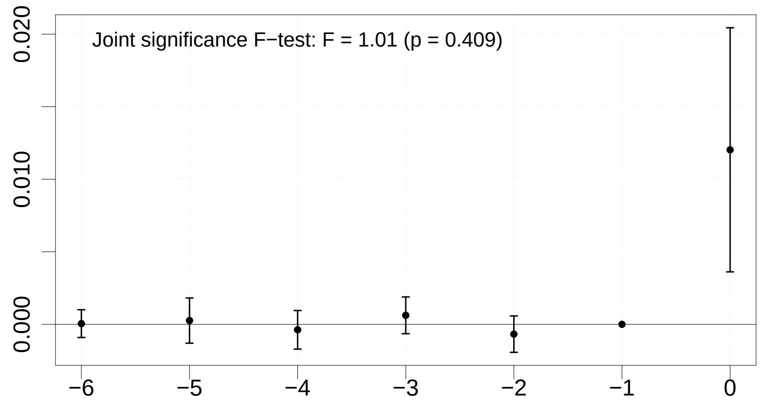


(b) High-wage firm

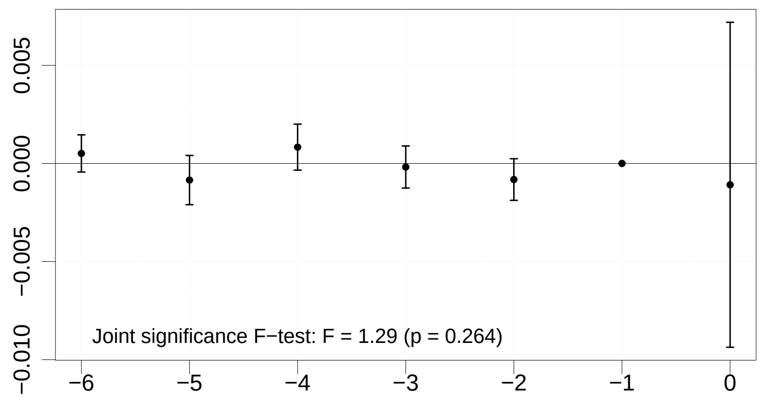


(c) High-career-support firm

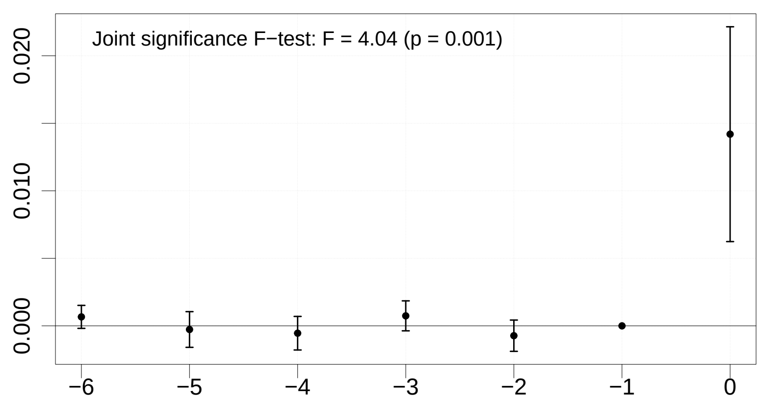
Figure B5: Facebook Access and The College-To-Work Transition (2) – Event Studies



(a) High-wage occupation

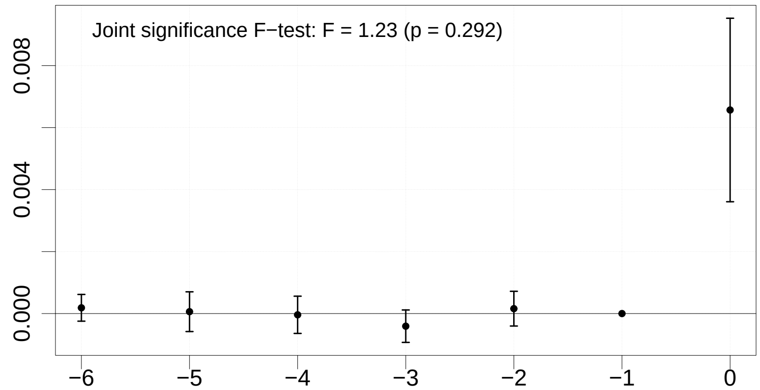


(b) Steep Wage Growth

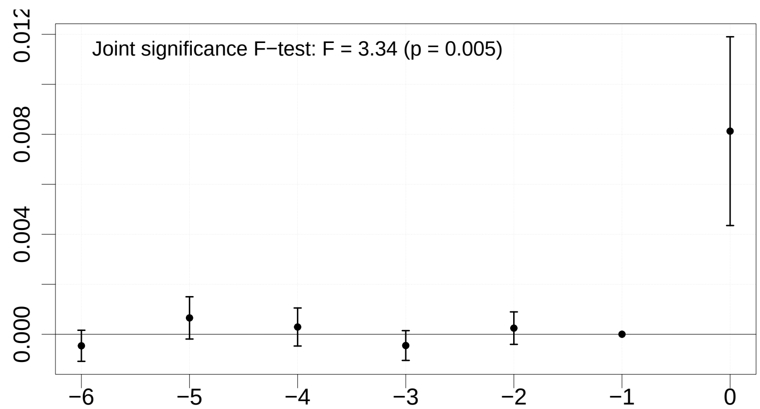


(c) Sr. Leadership Track

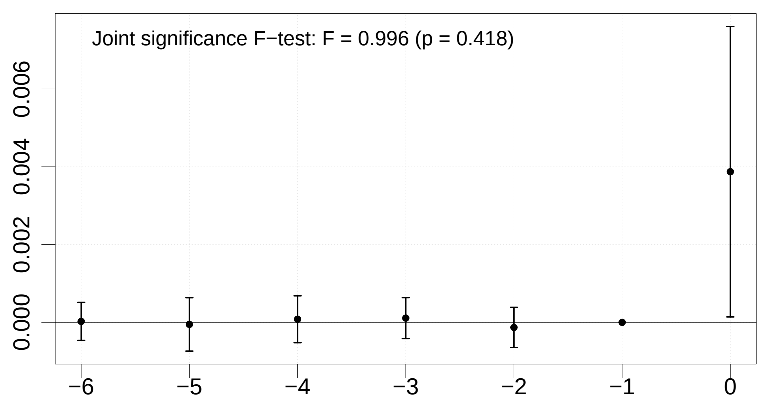
Figure B6: Facebook Access and Early-Career Job Help in the College Network (1) – Event Studies



(a) Sequential college job tie: High-wage firm

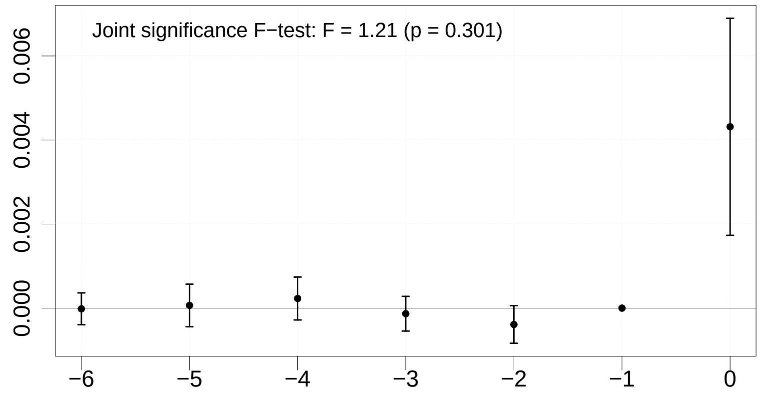


(b) Sequential college job tie: High-career-support firm

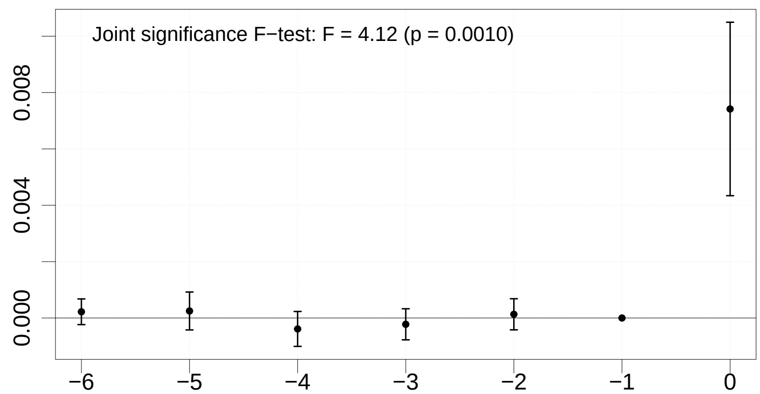


(c) Sequential college job tie: High-wage occupation

Figure B7: Facebook Access and Early-Career Job Help in the College Network (2) – Event Studies

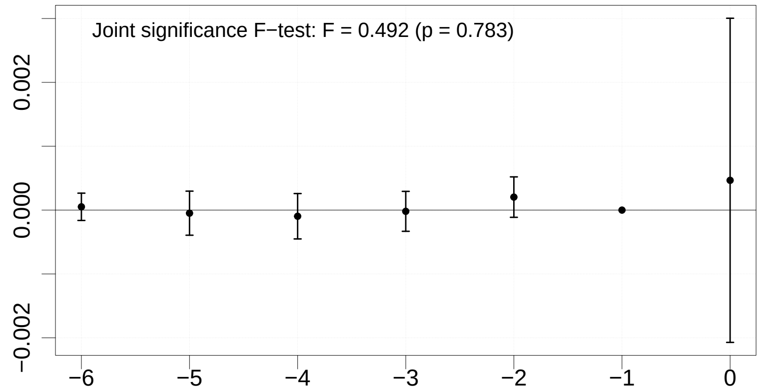


(a) Sequential college job tie: Steep Wage Growth

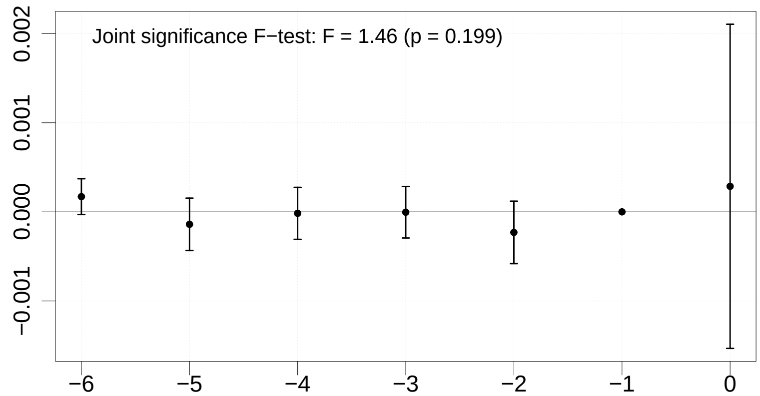


(b) Sequential college job tie: Sr. Leadership Track

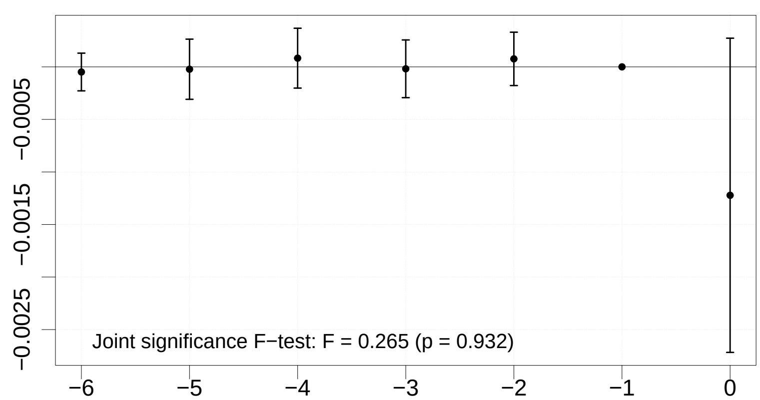
Figure B8: Facebook Access and Between-Firm Promotions – Event Studies



(a) 2–6 Years

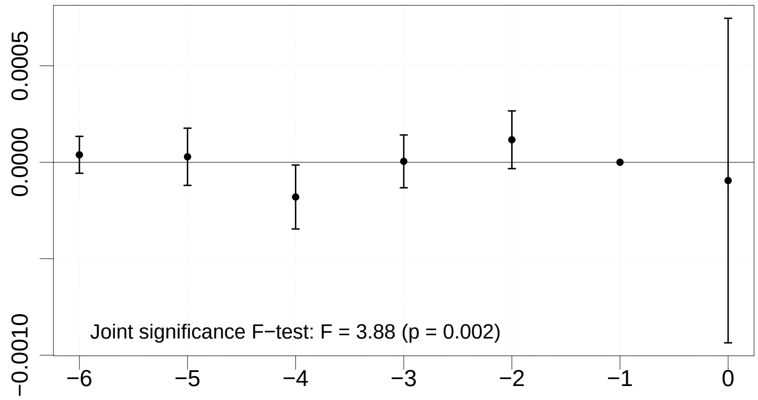


(b) 7–12 Years

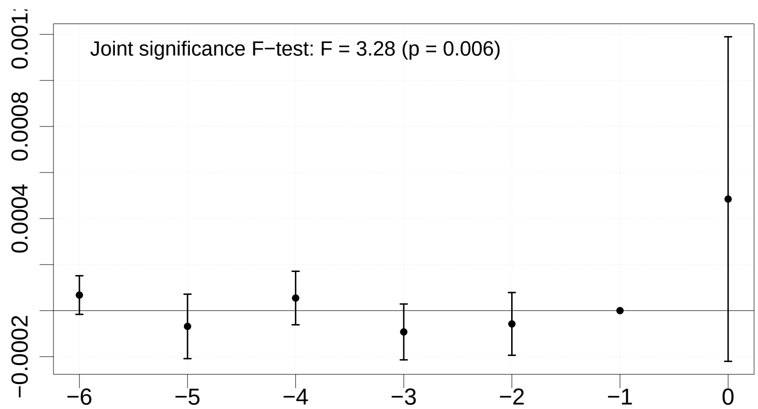


(c) 13–19 Years

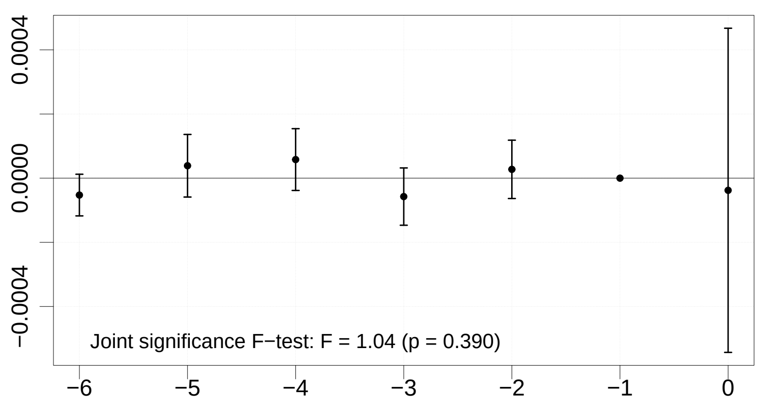
Figure B9: Facebook Access and Sequential College Job Promotion – Event Studies



(a) 2–6 Years

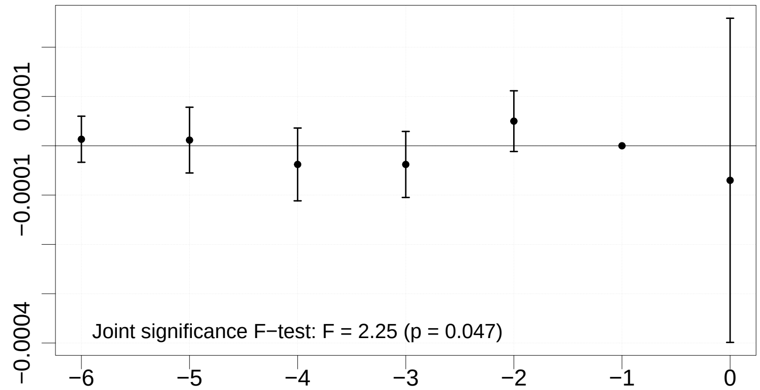


(b) 7–12 Years

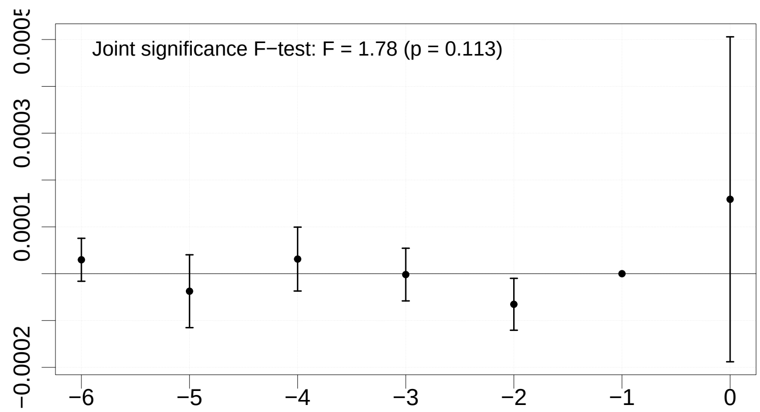


(c) 13–19 Years

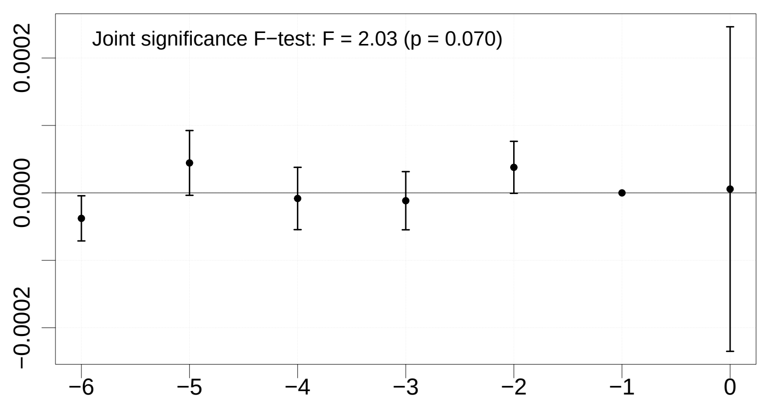
Figure B10: Facebook Access and Sequential College Sr. Leadership Tie – Event Studies



(a) 2–6 Years

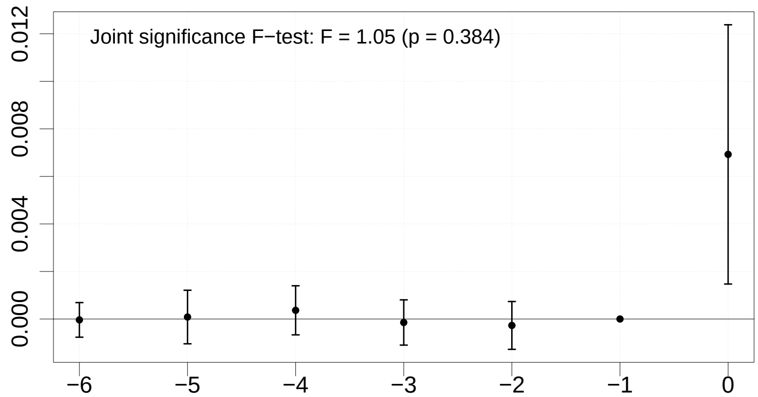


(b) 7–12 Years

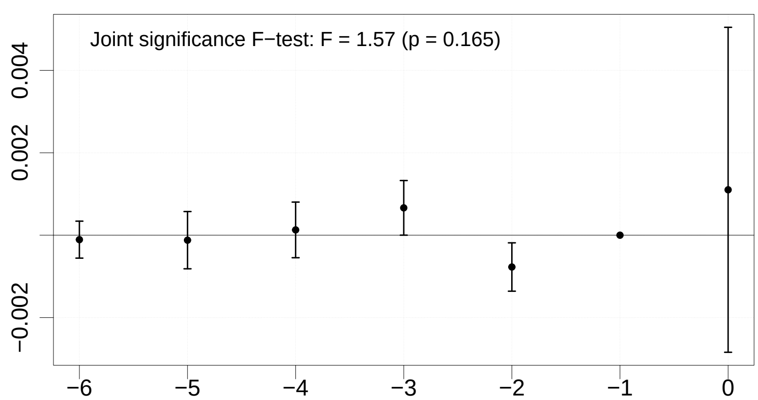


(c) 13–19 Years

Figure B11: Facebook Access and Stable Worker-Firm Match – Event Studies



(a) 1–6 Years



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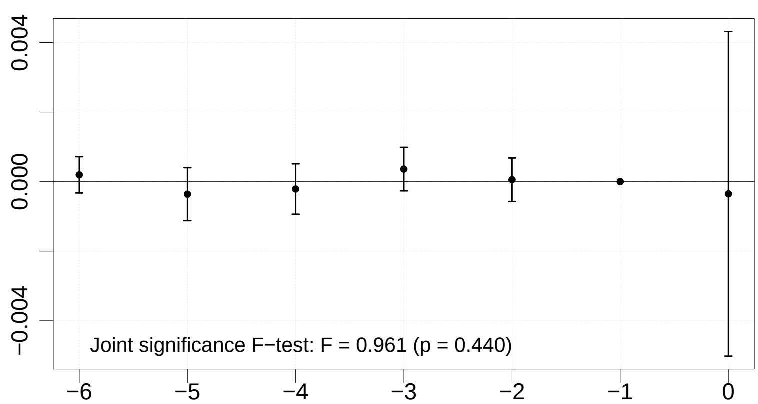
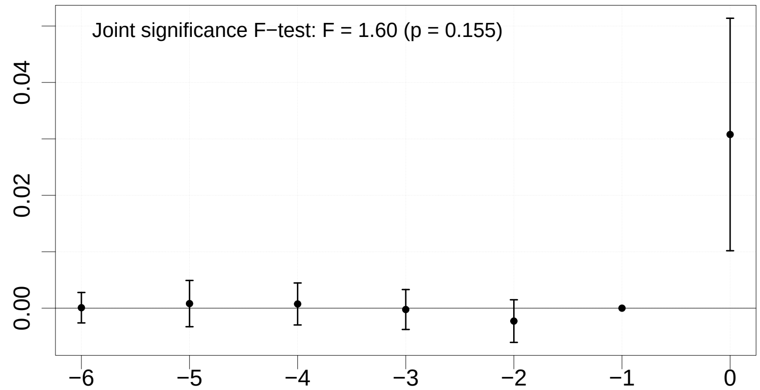
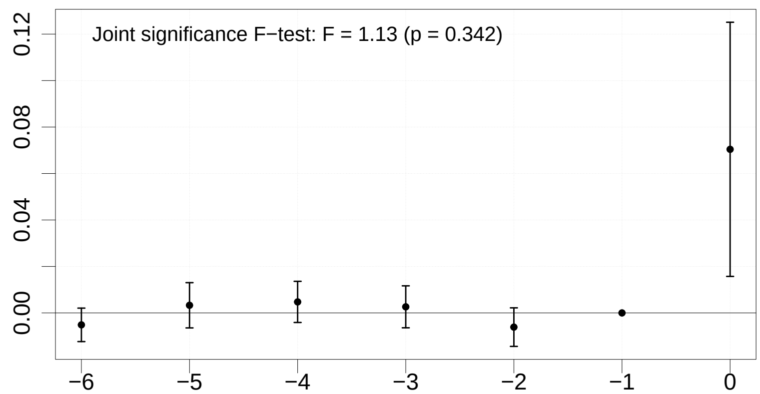


(c) 13–19 Years

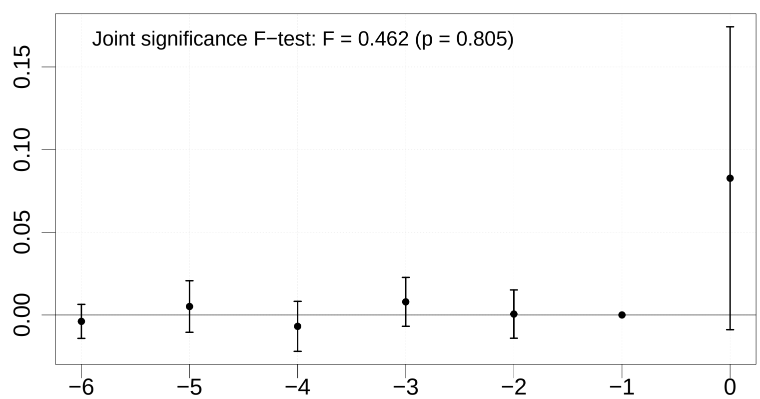
Figure B12: Facebook Access and Current Firm Tenure – Event Studies



(a) 1–6 Years

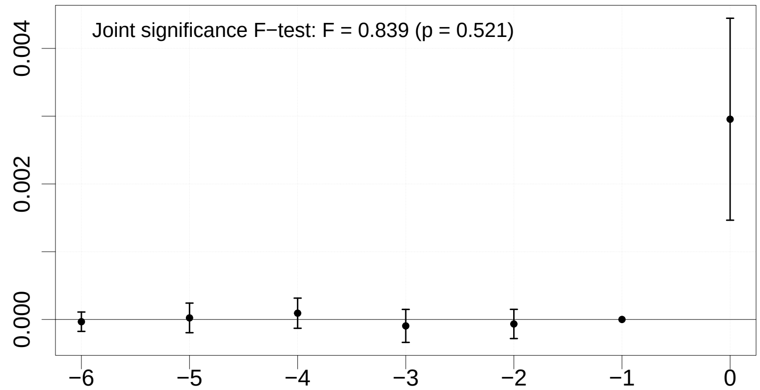


(b) 7–12 Years

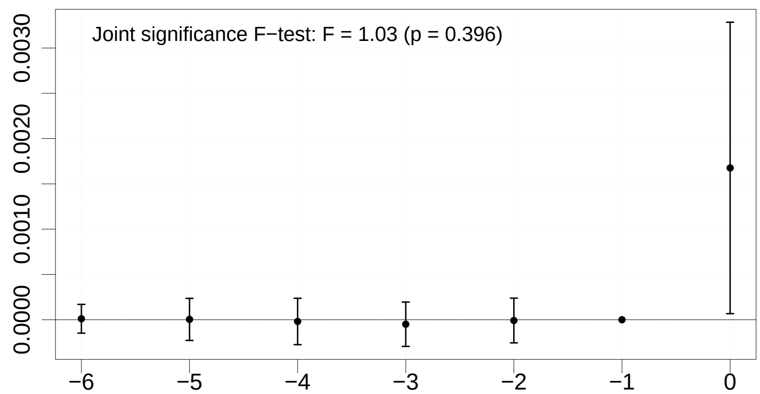


(c) 13–19 Years

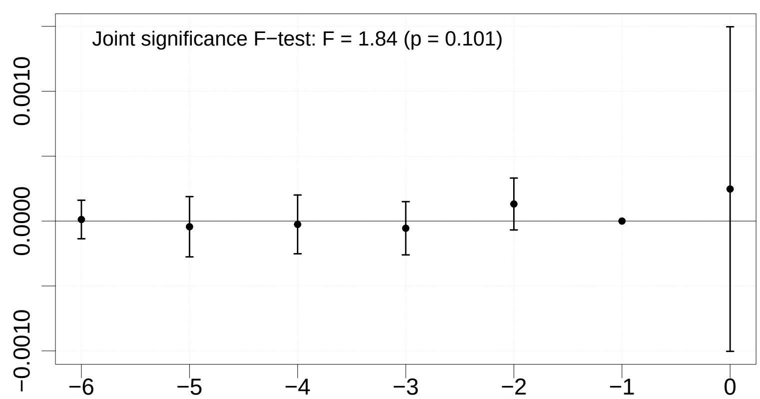
Figure B13: Facebook Access and Within-Firm Promotions – Event Studies



(a) 2–6 Years

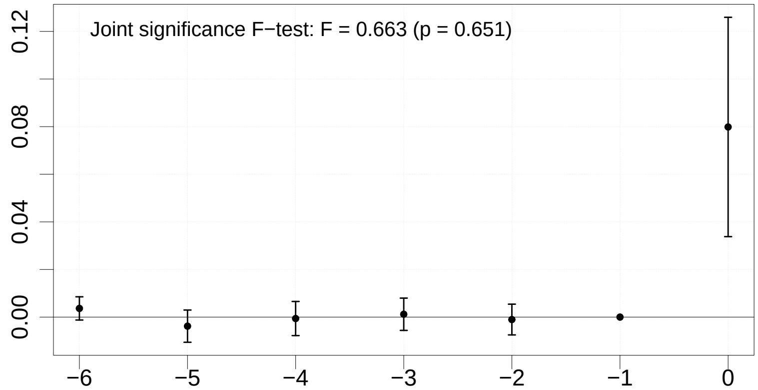


(b) 7–12 Years

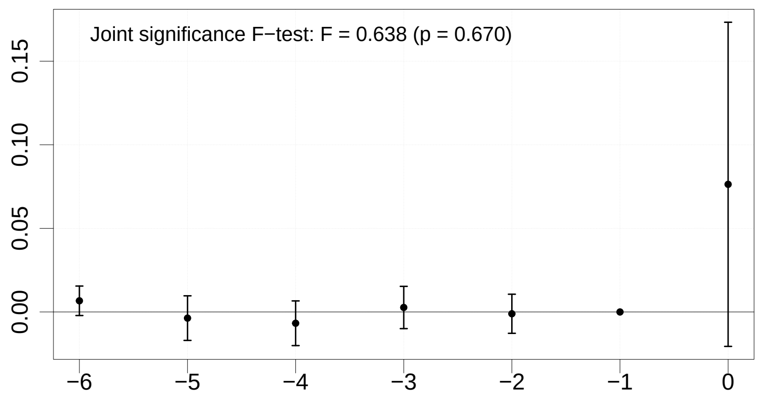


(c) 13–19 Years

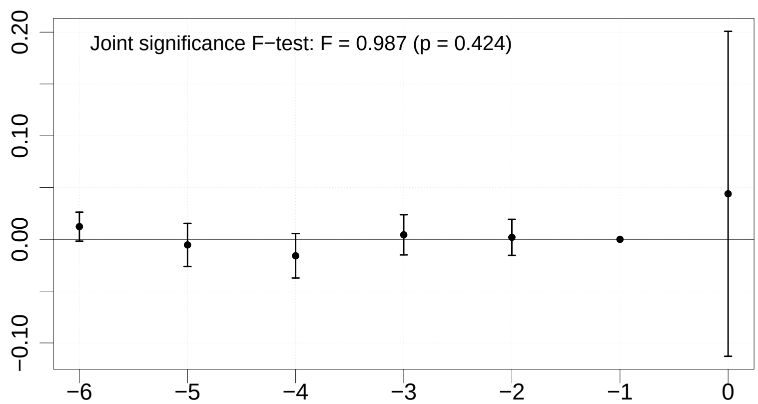
Figure B14: Facebook Access and Work Experience at High-Wage Firms – Event Studies



(a) Year 6

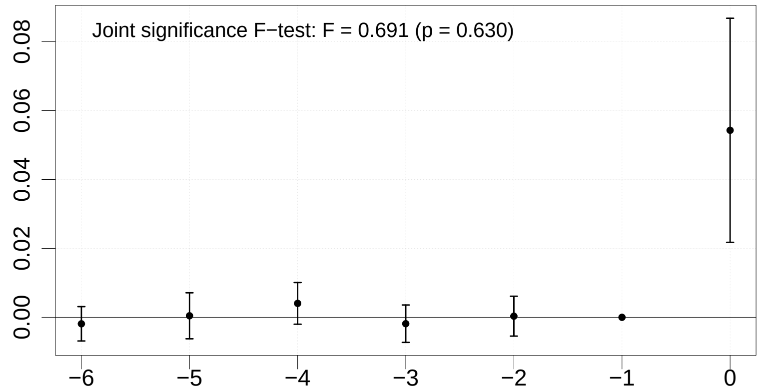


(b) Year 12

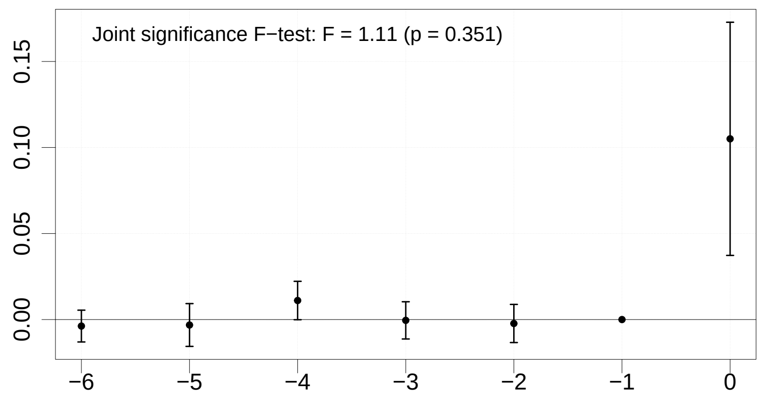


(c) Year 19

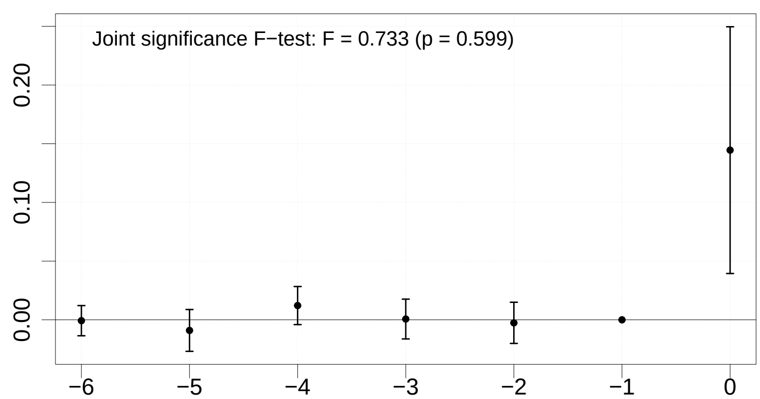
Figure B15: Facebook Access and Work Experience at High-Career-Support Firms – Event Studies



(a) Year 6

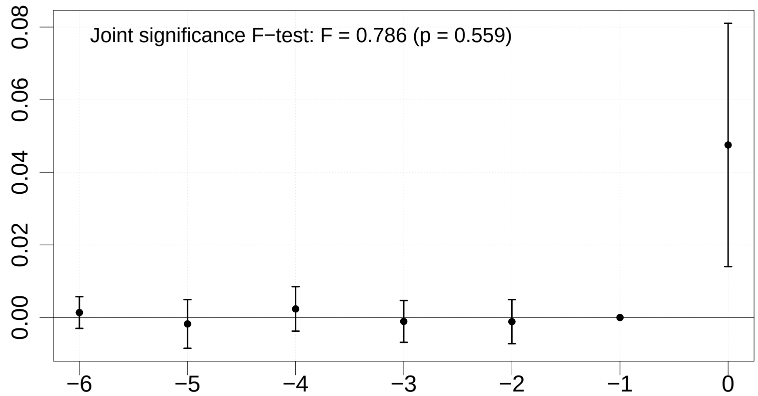


(b) Year 12

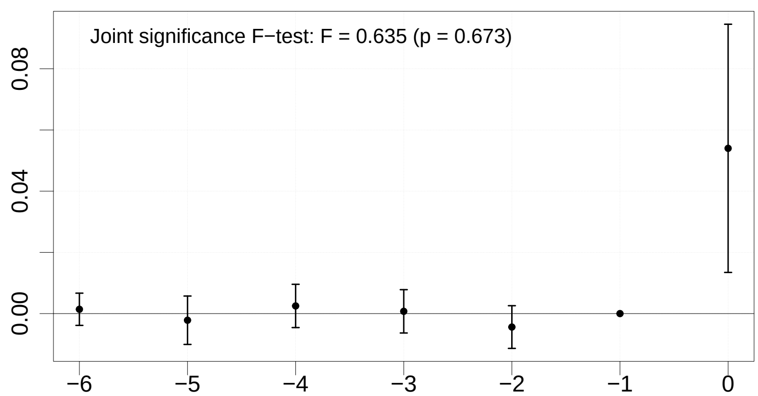


(c) Year 19

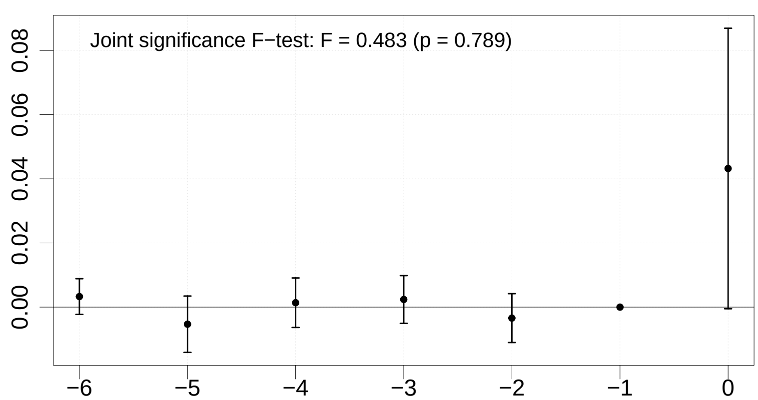
Figure B16: Facebook Access and Cumulative Work Experience – Event Studies



(a) Year 6



(b) Year 12



(c) Year 19

Appendix C: Gender Heterogeneity

Table C1: Facebook Access and Career Development – By Gender

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access*Male	1,319*	1,108	7.07
	(669)	(843)	(981)
FB Access*Female	1,131	1,639*	1,806
	(662)	(803)	(944)
Equality test (p-value)	0.842	0.648	0.186
Dep. Var. Mean (Male)	79,840	113,823	131,041
Dep. Var. Mean (Female)	70,330	95,628	108,035
Observations	94,680	94,680	110,460
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access*Male	0.003*	0.002	-0.00009
	(0.002)	(0.002)	(0.001)
FB Access*Female	0.004*	0.002	-0.002
	(0.002)	(0.002)	(0.001)
Equality test (p-value)	0.662	0.898	0.284
Dep. Var. Mean (Male)	0.078	0.087	0.076
Dep. Var. Mean (Female)	0.078	0.080	0.073
Observations	78,900	94,680	110,460
Panel C: Senior Leadership Positions			
FB Access*Male	0.001	0.007	0.009
	(0.003)	(0.005)	(0.005)
FB Access*Female	0.004	0.006	0.008
	(0.003)	(0.004)	(0.005)
Equality test (p-value)	0.623	0.889	0.896
Dep. Var. Mean (Male)	0.114	0.226	0.305
Dep. Var. Mean (Female)	0.084	0.161	0.221
Observations	94,680	94,680	110,460
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table C2: Facebook Access and The College-To-Work Transition – By Gender

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access*Male	0.013*	0.012*	0.015**	0.018**	-0.005	0.010
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
FB Access*Female	0.008	0.016**	0.013*	0.004	0.005	0.020**
	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Equality test (p-value)	0.563	0.636	0.825	0.095	0.239	0.244
Dep. Var. Mean (Male)	0.645	0.216	0.165	0.282	0.134	0.201
Dep. Var. Mean (Female)	0.665	0.192	0.150	0.203	0.194	0.201
Observations	31,560	31,558	31,446	31,556	31,546	31,546
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table C3: Facebook Access and Early-Career Job Help in the College Network – By Gender

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
Panel A: Same-Sex Early-Career Job Help						
FB Access*Male	0.009**	0.005*	0.008**	0.004*	0.004**	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
FB Access*Female	0.009**	0.006***	0.004*	0.003	0.004*	0.005*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Equality test (p-value)	0.998	0.536	0.251	0.716	0.978	0.641
Dep. Var. Mean (Male)	0.091	0.038	0.045	0.041	0.021	0.041
Dep. Var. Mean (Female)	0.079	0.028	0.037	0.025	0.023	0.035
Observations	31,560	31,558	31,446	31,556	31,546	31,546
Panel B: Opposite-Sex Early-Career Job Help						
FB Access*Male	0.006*	0.002	0.007**	0.0004	0.004**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
FB Access*Female	0.011**	0.008***	0.006*	0.003	0.004*	0.007**
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Equality test (p-value)	0.260	0.020	0.676	0.433	0.889	0.575
Dep. Var. Mean (Male)	0.072	0.030	0.036	0.031	0.017	0.034
Dep. Var. Mean (Female)	0.082	0.031	0.040	0.028	0.024	0.037
Observations	31,560	31,558	31,446	31,556	31,546	31,546
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table C4: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network – By Gender

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access*Male	0.0005	0.0007	-0.0001
	(0.001)	(0.001)	(0.0010)
FB Access*Female	0.0005	0.0002	-0.003*
	(0.002)	(0.002)	(0.001)
Equality test (p-value)	0.992	0.817	0.081
Dep. Var. Mean (Male)	0.056	0.057	0.048
Dep. Var. Mean (Female)	0.055	0.051	0.043
Observations	78,892	94,653	110,417
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access*Male	-0.00004	0.0009	-0.00006
	(0.0006)	(0.0005)	(0.0003)
FB Access*Female	-0.0002	0.00007	-0.0000005
	(0.0007)	(0.0006)	(0.0004)
Equality test (p-value)	0.898	0.265	0.894
Dep. Var. Mean (Male)	0.012	0.011	0.007
Dep. Var. Mean (Female)	0.012	0.009	0.006
Observations	78,900	94,680	110,460
Panel C: Sequential College Sr. Leadership Tie			
FB Access*Male	0.0001	0.0003	0.00004
	(0.0002)	(0.0002)	(0.0002)
FB Access*Female	-0.0003	0.00001	-0.00002
	(0.0003)	(0.0003)	(0.0002)
Equality test (p-value)	0.195	0.369	0.832
Dep. Var. Mean (Male)	0.002	0.003	0.002
Dep. Var. Mean (Female)	0.002	0.002	0.002
Observations	78,900	94,680	110,460
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table C5: Facebook Access and Job Match Quality – By Gender

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access*Male	0.010*	0.001	-0.003
	(0.004)	(0.002)	(0.002)
FB Access*Female	0.003	0.0006	0.003
	(0.004)	(0.003)	(0.004)
Equality test (p-value)	0.210	0.853	0.199
Dep. Var. Mean (Male)	0.685	0.873	0.891
Dep. Var. Mean (Female)	0.693	0.856	0.867
Observations	94,680	94,680	110,460
Panel B: Current Firm Tenure (Years)			
FB Access*Male	0.045**	0.119**	0.105
	(0.015)	(0.039)	(0.057)
FB Access*Female	0.014	0.007	0.052
	(0.017)	(0.041)	(0.062)
Equality test (p-value)	0.169	0.046	0.533
Dep. Var. Mean (Male)	1.63	4.03	6.08
Dep. Var. Mean (Female)	1.66	4.01	5.99
Observations	94,680	94,680	110,460
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access*Male	0.003*	0.001	0.00003
	(0.001)	(0.001)	(0.0009)
FB Access*Female	0.004**	0.002*	0.0005
	(0.001)	(0.001)	(0.0009)
Equality test (p-value)	0.517	0.469	0.725
Dep. Var. Mean (Male)	0.022	0.030	0.029
Dep. Var. Mean (Female)	0.023	0.029	0.030
Observations	78,892	94,653	110,417
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table C6: Facebook Access, Firm Sorting, and Human Capital Accumulation – By Gender

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access*Male	0.063	0.060	0.002
	(0.033)	(0.066)	(0.100)
FB Access*Female	0.097**	0.088	0.086
	(0.034)	(0.070)	(0.116)
Equality test (p-value)	0.463	0.769	0.583
Dep. Var. Mean (Male)	1.56	3.71	6.35
Dep. Var. Mean (Female)	1.35	3.10	5.23
Observations	15,780	15,780	15,780
Panel B: Work Experience at High-Career-Support Firms (Years)			
FB Access*Male	0.062**	0.140**	0.195**
	(0.023)	(0.045)	(0.068)
FB Access*Female	0.040	0.062	0.090
	(0.026)	(0.051)	(0.088)
Equality test (p-value)	0.519	0.249	0.345
Dep. Var. Mean (Male)	0.885	1.90	3.12
Dep. Var. Mean (Female)	0.792	1.68	2.77
Observations	15,692	15,674	15,677
Panel C: Cumulative Work Experience (Years)			
FB Access*Male	0.057*	0.064*	0.042
	(0.027)	(0.031)	(0.033)
FB Access*Female	0.036	0.044	0.049
	(0.025)	(0.030)	(0.035)
Equality test (p-value)	0.561	0.642	0.872
Dep. Var. Mean (Male)	4.46	10.13	16.86
Dep. Var. Mean (Female)	4.53	10.11	16.68
Observations	15,780	15,780	15,780
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level separately for male and female graduates. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Work experience at high-career-support firms: cumulative years employed at a high-career-support firm. Cumulative work experience: total years of employment. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Equality test: p-value for the null hypothesis $H_0 : \beta_{\text{male}} = \beta_{\text{female}}$. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Appendix D: Randomization Inference

A key concern in the main empirical strategy is that even within the narrow selectivity-by-region comparisons, there might be remaining spurious correlations with the timing of the Facebook rollout, biasing the main estimates. For example, this could be the case if Facebook (deliberately or not) expanded early to colleges *within the same selectivity and U.S. region* where the career outcomes of U.S. business and economics cohorts were on a differential trend.

To formally test this, I implement a randomization inference test where I randomly reshuffle the introduction year of Facebook across colleges within each selectivity-by-region cell (N = 1,000), preserving the total number of treated colleges per cell and the overall distribution of treatment timing. Appendix Tables D1–D6 show the results. The placebo estimates have a dense distribution around zero and virtually all of the statistically significant effects from the main specification fall above the 95th percentile of the placebo distribution. The remaining variation in the Facebook rollout is therefore unlikely to reflect spurious correlations.

Table D1: Permutation Test: Career Development

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
Baseline	1,286**	1,343*	768
Mean (placebo)	5.72	110	117
SD (placebo)	516	628	785
Percentile rank	99	97	80
Panel B: Job-Based Promotion (≥10 log pts.)			
Baseline	0.004**	0.002	-0.0010
Mean (placebo)	-0.00007	-0.00004	-0.00008
SD (placebo)	0.001	0.001	0.0009
Percentile rank	100	98	15
Panel C: Senior Leadership Positions			
Baseline	0.002	0.006*	0.008*
Mean (placebo)	0.00006	0.0002	0.0001
SD (placebo)	0.002	0.003	0.004
Percentile rank	84	97	99
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates ≤ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Table D2: Permutation Test: College-To-Work Transition

	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occ.	Steep Wage Growth	Sr. Leadership Track
Baseline	0.010**	0.014***	0.014***	0.012**	-0.001	0.014***
Mean (placebo)	-0.0002	0.0004	0.0004	0.0001	-0.00002	0.0005
SD (placebo)	0.004	0.004	0.004	0.004	0.004	0.005
Percentile rank	100	100	100	100	38	100
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates ≤ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Table D3: Permutation Test: Early-Career Job Help in the College Network

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occ.	Steep Wage Growth	Sr. Leadership Track
Baseline	0.011***	0.007***	0.008***	0.004*	0.004**	0.007***
Mean (placebo)	0.0004	0.0005	0.0003	0.0001	0.0001	0.0006
SD (placebo)	0.003	0.002	0.003	0.002	0.002	0.003
Percentile rank	100	100	100	96	100	100
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates $\leq$ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Table D4: Permutation Test: Promotion Ties

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
Baseline	0.0005	0.0003	-0.001
Mean (placebo)	-0.00004	0.00004	0.00002
SD (placebo)	0.001	0.0008	0.0007
Percentile rank	68	62	3
Panel B: Sequential College Job Promotion (≥10 log pts.)			
Baseline	-0.00009	0.0005	-0.00004
Mean (placebo)	0.00004	0.00005	-0.0000009
SD (placebo)	0.0005	0.0004	0.0003
Percentile rank	39	86	45
Panel C: Sequential College Sr. Leadership Tie			
Baseline	-0.00007	0.0002	0.000006
Mean (placebo)	0.000008	-0.00001	-0.000004
SD (placebo)	0.0002	0.0002	0.0001
Percentile rank	33	82	54
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates ≤ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Table D5: Permutation Test: Job Match Quality

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
Baseline	0.007*	0.001	-0.0004
Mean (placebo)	-0.0001	0.0002	0.00002
SD (placebo)	0.003	0.002	0.002
Percentile rank	99	72	42
Panel B: Current Firm Tenure (Years)			
Baseline	0.031**	0.070*	0.083
Mean (placebo)	-0.0002	0.001	0.001
SD (placebo)	0.010	0.021	0.040
Percentile rank	100	100	98
Panel C: Within-Firm Promotions (≥10 log pts.)			
Baseline	0.003***	0.002*	0.0002
Mean (placebo)	-0.00002	-0.00008	-0.0001
SD (placebo)	0.0008	0.0009	0.0006
Percentile rank	100	98	72
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates ≤ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Table D6: Permutation Test: Firm Sorting and Human Capital Accumulation

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
Baseline	0.080***	0.076	0.044
Mean (placebo)	0.002	0.005	0.008
SD (placebo)	0.021	0.042	0.063
Percentile rank	100	97	71
Panel B: Work Exp. at High-Career-Support Firms (Years)			
Baseline	0.054**	0.105**	0.145**
Mean (placebo)	0.002	0.003	0.003
SD (placebo)	0.017	0.031	0.047
Percentile rank	100	100	100
Panel C: Cumulative Work Experience (Years)			
Baseline	0.048**	0.054**	0.043
Mean (placebo)	-0.0004	-0.000005	-0.0003
SD (placebo)	0.016	0.019	0.020
Percentile rank	100	100	99
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: Each cell reports four quantities: (1) baseline Gardner (2022) two-stage DiD estimate (significance: *p<0.05; **p<0.01; ***p<0.001), (2) mean of the placebo distribution, (3) standard deviation of the placebo distribution, (4) percentile rank of the baseline estimate in the placebo distribution (share of permuted estimates $\leq$ the baseline). Permutations: $N = 1000$. Within each stratum (college selectivity * region), the vector of Facebook introduction years is randomly permuted across colleges; the number of treated colleges and the distribution of introduction timing per stratum are preserved. Standard errors clustered at the college level. *Data source:* Revelio Labs.

Appendix E: Spillovers

One key concern with the main specification is that the results are driven by spillovers. In particular, treated students might take away jobs from students in the control group, upward biasing the treatment effect and violating the stable-unit treatment value assumption (SUTVA). To assess the seriousness of this issue, I start by predicting the exposure to spillovers for each potential control cohort using the actual career overlap of U.S. business and economics students across colleges *before* the Facebook rollout. The main motivation behind this measure is that graduate placements are highly persistent over time (e.g., Hampole *et al.* (2025)) and therefore highly suitable for predicting future labor market competition across college cohorts. To account for the changing set of treated colleges over time, I define the predicted spillover exposure measure for each potential control cohort as follows:

$$J_{a,T_t} = \frac{\left|C_a^{1999\text{–}2003} \cap \left(\bigcup_{b \in T_t} C_b^{1999\text{–}2003}\right)\right|}{|C_a^{1999\text{–}2003}|}$$

where J_{a,T_t} measures the share of graduates from college a working in the same job as graduates from the set of colleges T that already had access to Facebook in the academic year t. To ensure that the prediction is not contaminated by potential treatment effects, I use the cohorts from 1999–2003 *before* the Facebook rollout for computation. To closely reflect career overlap and labor market competition between college graduates, I define the same job as working in the same firm*2-digit SOC*year cell.[60]

Table E1 investigates the predicted spillover exposure measure for the potential control group cohorts in detail. In 2004, the average predicted fraction of control group cohorts competing for the same jobs as graduates from the treated colleges was around 15%, consistent with the small number of highly selective institutions given early access to Facebook. By 2005, this share increased to around 33% as Facebook expanded to a broader set of colleges. Table E1 regresses the exposure score on college characteristics to identify which control cohorts are most susceptible to spillovers. In 2004, institutions in the highest selectivity tiers and those in the Northeast have substantially higher predicted exposure scores, consistent with the idea that these colleges are the most likely to compete for the same jobs as the elite colleges Facebook targeted first. By 2005, as more colleges across the U.S. get access to Facebook, the differences across selectivity and region reduce considerably with the colleges in the West and with the lowest selectivity being slightly less exposed. Table E2 shows the twenty college cohorts with the

[60]Note that the ideal labor market competition measure would use information on job applications instead of realized outcomes. While this information is not available, the derived measure from the LinkedIn profiles data can be seen as a meaningful but lower bound proxy for this.

highest predicted exposure scores. All twenty come from the 2005 graduation cohort, consistent with spillovers being more severe at the later stage of the Facebook expansion. The most-exposed college cohorts come predominantly from HBCUs (e.g., Johnson C. Smith University, Central State University, Cheyney University of Pennsylvania) and Catholic colleges (e.g., College of Saint Elizabeth, College of Mount St. Joseph, College of Saint Benedict).

To probe the robustness of the main results to potential spillovers, I then drop every college that has at least one potential control cohort with a predicted exposure score above the population-weighted upper quartile of the 2005 exposure distribution ($Q^{\text{pop}}_{0.75}(J_{a,2005}) = 0.369$).[61] This removes 97 colleges, or 25% of the potential control student body graduating in 2005. Tables E3 to E6 present the results. Reassuringly, the results are very similar to the baseline estimates. Combined with the baseline findings, the results suggest that the treatment effects are not simply coming from a reallocation of jobs within the economy but are rather consistent with the idea that access to Facebook reduces information frictions about job opportunities.

Table E1: Predicted Spillover Exposure Score and Observable College Characteristics

	Predicted Spillover Exposure Score (J_{a,T_t})	
	$J_{a,2004}$	$J_{a,2005}$
U.S. Region (ref.: West)		
Midwest	0.009*	0.049***
	(0.004)	(0.011)
Northeast	0.028***	0.046***
	(0.004)	(0.012)
South	0.005	0.045***
	(0.004)	(0.010)
Selectivity (ref.: Less competitive)		
Competitive	0.009*	0.004
	(0.003)	(0.007)
Very competitive	0.030***	0.019
	(0.004)	(0.010)
Highly competitive	0.056***	0.032
	(0.005)	(0.017)
Elite	0.118***	0.178**
	(0.006)	(0.063)
Dep. Var. Mean (pop.-wtd.)	0.157	0.332
Upper Quartile (pop.-wtd.)	0.177	0.369
Observations	1.118	422
R^2	0.360	0.086

Notes: OLS regressions at the college-cohort level. Sample: all potential control college-cohorts during the Facebook expansion period by academic year. Dependent variable: predicted spillover exposure score in each academic year. *p<0.05; **p<0.01; ***p<0.001. *Data source:* Revelio Labs.

[61] The results are robust to using different thresholds.

Table E2: Top Twenty Control College-Cohorts with Highest Predicted Spillover Exposure

College	Cohort	Exposure score
johnson c smith university	2005	0.523
barnard college	2005	0.500
lane college	2005	0.488
st catherine university	2005	0.485
eureka college	2005	0.470
central state university	2005	0.469
williams baptist college	2005	0.461
gwynedd mercy university	2005	0.460
college of saint benedict	2005	0.452
westminster college	2005	0.448
mount saint joseph university	2005	0.448
missouri university of science and technology	2005	0.446
cheyney university of pennsylvania	2005	0.439
university of arkansas at pine bluff	2005	0.438
university of michigan-dearborn	2005	0.436
fisk university	2005	0.434
saint johns university	2005	0.434
union college	2005	0.434
southern university and a & m college	2005	0.434
university of michigan-flint	2005	0.434

Notes: Potential control college-cohorts with the twenty highest predicted spillover exposure scores. *Data source:* Revelio Labs.

Table E3: Facebook Access and Career Development – Excluding Spillover-Exposed Colleges

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,537*	1,657*	1,033
	(673)	(688)	(886)
Dep. Var. Mean	76,108	106,652	122,017
Observations	44,178	44,178	51,541
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.003*	0.002	-0.002*
	(0.002)	(0.002)	(0.001)
Dep. Var. Mean	0.078	0.085	0.075
Observations	36,815	44,178	51,541
Panel C: Senior Leadership Positions			
FB Access	0.004	0.008*	0.012**
	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.102	0.201	0.272
Observations	44,178	44,178	51,541
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table E4: Facebook Access and The College-To-Work Transition – Excluding Spillover-Exposed Colleges

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.013*	0.012*	0.010*	0.015*	0.0008	0.016**
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Dep. Var. Mean	0.653	0.207	0.160	0.250	0.159	0.202
Observations	14,726	14,726	14,711	14,724	14,724	14,724
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table E5: Facebook Access and Early-Career Job Help in the College Network – Excluding Spillover-Exposed Colleges

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.011**	0.006***	0.007***	0.002	0.006***	0.008***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Dep. Var. Mean	0.108	0.042	0.050	0.043	0.027	0.047
Observations	14,726	14,726	14,711	14,724	14,724	14,724
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table E6: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network – Excluding Spillover-Exposed Colleges

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access	-0.0009	0.0009	-0.002*
	(0.002)	(0.001)	(0.0009)
Dep. Var. Mean	0.056	0.055	0.046
Observations	36,815	44,175	51,541
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access	-0.0003	0.001**	-0.00002
	(0.0005)	(0.0004)	(0.0003)
Dep. Var. Mean	0.012	0.010	0.007
Observations	36,815	44,178	51,541
Panel C: Sequential College Sr. Leadership Tie			
FB Access	-0.00003	0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)
Dep. Var. Mean	0.002	0.002	0.002
Observations	36,815	44,178	51,541
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table E7: Facebook Access and Job Match Quality – Spillover Robustness

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.010*	0.003	-0.002
	(0.004)	(0.002)	(0.003)
Dep. Var. Mean	0.688	0.866	0.881
Observations	44,178	44,178	51,541
Panel B: Current Firm Tenure (Years)			
FB Access	0.043**	0.090**	0.060
	(0.013)	(0.035)	(0.059)
Dep. Var. Mean	1.64	4.01	6.03
Observations	44,178	44,178	51,541
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.004***	0.0008	-0.0003
	(0.001)	(0.001)	(0.0009)
Dep. Var. Mean	0.022	0.030	0.029
Observations	36,815	44,175	51,541
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table E8: Facebook Access, Firm Sorting, and Human Capital Accumulation – Spillover Robustness

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.076**	0.060	0.004
	(0.027)	(0.055)	(0.086)
Dep. Var. Mean	1.48	3.47	5.92
Observations	7,363	7,363	7,363
Panel B: Work Exp. at High-Career-Support Firms (Years)			
FB Access	0.024	0.056	0.080
	(0.021)	(0.048)	(0.080)
Dep. Var. Mean	0.851	1.81	2.99
Observations	7,351	7,349	7,351
Panel C: Cumulative Work Experience (Years)			
FB Access	0.059*	0.067*	0.051
	(0.025)	(0.030)	(0.030)
Dep. Var. Mean	4.48	10.12	16.78
Observations	7,363	7,363	7,363
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. Cumulative work experience: total years of employment. Colleges with any control cohort whose predicted spillover exposure score exceeds the population-weighted upper quartile of the 2005 distribution (0.369) are excluded entirely. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Appendix F: Alternative Heterogeneity-Robust DiD Estimators

Table F1: Facebook Access and Career Development - Callaway and Sant'Anna (2021)

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,480**	655	128
	(553)	(588)	(733)
Dep. Var. Mean	75,876	106,240	121,452
Observations	48,252	48,252	56,294
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.004**	-0.002	-0.001
	(0.001)	(0.002)	(0.001)
Dep. Var. Mean	0.078	0.085	0.075
Observations	40,210	48,252	56,294
Panel C: Senior Leadership Positions			
FB Access	0.002	0.001	0.004
	(0.003)	(0.003)	(0.004)
Dep. Var. Mean	0.101	0.199	0.270
Observations	48,252	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Callaway and Sant'Anna (2021), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F2: Facebook Access and The College-To-Work Transition - Callaway and Sant'Anna (2021)

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.009*	0.013**	0.015***	0.008	-0.003	0.010*
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Dep. Var. Mean	0.653	0.206	0.159	0.249	0.159	0.201
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Callaway and Sant'Anna (2021), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F3: Facebook Access and Early-Career Job Help in the College Network - Callaway and Sant'Anna (2021)

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.011***	0.006***	0.009***	0.003	0.004*	0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.107	0.041	0.049	0.042	0.027	0.047
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Callaway and Sant'Anna (2021), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F4: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network - Callaway and Sant'Anna (2021)

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions ($\geq$10 log pts.)			
FB Access	0.001	-0.002	-0.002*
	(0.001)	(0.001)	(0.0008)
Dep. Var. Mean	0.055	0.055	0.045
Observations	40,210	48,249	56,294
Panel B: Sequential College Job Promotion ($\geq$10 log pts.)			
FB Access	0.0004	-0.0003	-0.0001
	(0.0005)	(0.0004)	(0.0003)
Dep. Var. Mean	0.012	0.010	0.007
Observations	40,210	48,252	56,294
Panel C: Sequential College Sr. Leadership Tie			
FB Access	0.00004	-0.00003	0.00010
	(0.0002)	(0.0002)	(0.0002)
Dep. Var. Mean	0.002	0.002	0.002
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Callaway and Sant'Anna (2021), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F5: Facebook Access and Job Match Quality — Callaway and Sant'Anna (2021)

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.006	-0.0004	0.0007
	(0.003)	(0.002)	(0.002)
Dep. Var. Mean	0.688	0.866	0.881
Observations	48,252	48,252	56,294
Panel B: Current Firm Tenure (Years)			
FB Access	0.021	0.074*	0.154**
	(0.013)	(0.032)	(0.052)
Dep. Var. Mean	1.64	4.02	6.04
Observations	48,252	48,252	56,294
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.002**	0.0005	0.0004
	(0.0008)	(0.0010)	(0.0008)
Dep. Var. Mean	0.022	0.030	0.029
Observations	40,210	48,249	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Callaway–Sant'Anna (2021) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F6: Facebook Access, Firm Sorting, and Human Capital Accumulation — Callaway and Sant'Anna (2021)

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.070**	0.046	0.0009
	(0.027)	(0.060)	(0.099)
Dep. Var. Mean	1.48	3.45	5.88
Observations	8,042	8,042	8,042
Panel B: Work Exp. at High-Career-Support Firms (Years)			
FB Access	0.051**	0.096*	0.121
	(0.019)	(0.042)	(0.064)
Dep. Var. Mean	0.846	1.80	2.97
Observations	8,029	8,027	8,029
Panel C: Cumulative Work Experience (Years)			
FB Access	0.041*	0.033	0.026
	(0.020)	(0.025)	(0.026)
Dep. Var. Mean	4.49	10.12	16.78
Observations	8,042	8,042	8,042
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Callaway–Sant'Anna (2021) estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. Cumulative work experience: total years of employment. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F7: Facebook Access and Career Development — De Chaisemartin and d'Haultfoeuille (2020)

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,362*	719	474
	(557)	(602)	(685)
Dep. Var. Mean	75,876	106,240	121,452
Observations	48,252	48,252	56,294
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.003*	-0.001	-0.0006
	(0.001)	(0.002)	(0.001)
Dep. Var. Mean	0.078	0.085	0.075
Observations	40,210	48,252	56,294
Panel C: Senior Leadership Positions			
FB Access	0.002	0.0008	0.005
	(0.003)	(0.004)	(0.004)
Dep. Var. Mean	0.101	0.199	0.270
Observations	48,252	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Non-parametric region-by-selectivity strata trends are included. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F8: Facebook Access and The College-To-Work Transition — De Chaisemartin and d'Haultfoeuille (2020)

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.009	0.011*	0.012**	0.006	-0.003	0.009
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Dep. Var. Mean	0.653	0.206	0.159	0.249	0.159	0.201
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. Non-parametric region-by-selectivity strata trends are included. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F9: Facebook Access and Early-Career Job Help in the College Network — De Chaisemartin and d'Haultfoeuille (2020)

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.010***	0.006**	0.007***	0.003	0.003*	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.107	0.041	0.049	0.042	0.027	0.047
Observations	16,084	16,084	16,066	16,082	16,082	16,082
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. Non-parametric region-by-selectivity strata trends are included. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F10: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network — De Chaisemartin and d'Haultfoeuille (2020)

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access	0.001	-0.002	-0.0010
	(0.001)	(0.001)	(0.0008)
Dep. Var. Mean	0.055	0.055	0.045
Observations	40,210	48,249	56,294
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access	0.0005	-0.0004	0.00002
	(0.0005)	(0.0005)	(0.0003)
Dep. Var. Mean	0.012	0.010	0.007
Observations	40,210	48,252	56,294
Panel C: Sequential College Sr. Leadership Tie			
FB Access	0.00006	-0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)
Dep. Var. Mean	0.002	0.002	0.002
Observations	40,210	48,252	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. Non-parametric region-by-selectivity strata trends are included. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F11: Facebook Access and Job Match Quality — De Chaisemartin and d'Haultfoeuille (2020)

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.006	-0.001	0.0008
	(0.003)	(0.002)	(0.003)
Dep. Var. Mean	0.688	0.866	0.881
Observations	48,252	48,252	56,294
Panel B: Current Firm Tenure (Years)			
FB Access	0.018	0.046	0.123*
	(0.012)	(0.031)	(0.052)
Dep. Var. Mean	1.64	4.02	6.04
Observations	48,252	48,252	56,294
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.002*	0.0001	0.0005
	(0.0008)	(0.001)	(0.0007)
Dep. Var. Mean	0.022	0.030	0.029
Observations	40,210	48,249	56,294
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Non-parametric region-by-selectivity strata trends are included. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table F12: Facebook Access, Firm Sorting, and Human Capital Accumulation — De Chaisemartin and d'Haultfoeuille (2020)

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.062*	0.050	0.028
	(0.025)	(0.053)	(0.080)
Dep. Var. Mean	1.48	3.45	5.88
Observations	8,042	8,042	8,042
Panel B: Work Exp. at High-Career-Support Firms (Years)			
FB Access	0.043*	0.079*	0.084
	(0.018)	(0.037)	(0.057)
Dep. Var. Mean	0.846	1.80	2.97
Observations	8,029	8,027	8,029
Panel C: Cumulative Work Experience (Years)			
FB Access	0.037	0.028	0.026
	(0.020)	(0.024)	(0.026)
Dep. Var. Mean	4.49	10.12	16.78
Observations	8,042	8,042	8,042
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. de Chaisemartin and D'Haultfœuille (2020) estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Non-parametric region-by-selectivity strata trends are included. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. Cumulative work experience: total years of employment. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Appendix G: IPEDS Weights

Table G1: Facebook Access and Career Development – IPEDS-Weighted

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,193*	965	545
	(484)	(568)	(666)
Dep. Var. Mean	75,362	104,709	119,172
Observations	94,686	94,686	110,467
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.004*	0.003*	-0.0002
	(0.001)	(0.001)	(0.0010)
Dep. Var. Mean	0.076	0.082	0.073
Observations	78,905	94,686	110,467
Panel C: Senior Leadership Positions			
FB Access	0.002	0.006	0.009*
	(0.003)	(0.003)	(0.004)
Dep. Var. Mean	0.101	0.194	0.261
Observations	94,686	94,686	110,467
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table G2: Facebook Access and The College-To-Work Transition – IPEDS-Weighted

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.011**	0.014***	0.014***	0.010*	-0.002	0.014**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Dep. Var. Mean	0.654	0.204	0.156	0.243	0.160	0.197
Observations	31,562	31,560	31,448	31,558	31,548	31,548
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table G3: Facebook Access and Early-Career Job Help in the College Network – IPEDS-Weighted

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.011***	0.006***	0.007***	0.003	0.004**	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Dep. Var. Mean	0.102	0.039	0.046	0.040	0.026	0.044
Observations	31,562	31,560	31,448	31,558	31,548	31,548
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table G4: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network – IPEDS-Weighted

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access	0.00009	0.0006	-0.0006
	(0.001)	(0.001)	(0.0007)
Dep. Var. Mean	0.054	0.054	0.045
Observations	78,897	94,659	110,417
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access	0.0001	0.0007	-0.00002
	(0.0004)	(0.0004)	(0.0003)
Dep. Var. Mean	0.012	0.010	0.007
Observations	78,905	94,686	110,467
Panel C: Sequential College Sr. Leadership Tie			
FB Access	-0.0001	0.0001	-0.00006
	(0.0002)	(0.0002)	(0.0001)
Dep. Var. Mean	0.002	0.002	0.002
Observations	78,905	94,686	110,467
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table G5: Facebook Access and Job Match Quality – IPEDS Weighted

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.008**	0.001	-0.001
	(0.003)	(0.002)	(0.003)
Dep. Var. Mean	0.689	0.865	0.879
Observations	94,686	94,686	110,467
Panel B: Current Firm Tenure (Years)			
FB Access	0.035***	0.078**	0.069
	(0.010)	(0.029)	(0.049)
Dep. Var. Mean	1.66	4.04	6.05
Observations	94,686	94,686	110,467
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.003***	0.002*	0.0004
	(0.0008)	(0.0009)	(0.0006)
Dep. Var. Mean	0.022	0.028	0.028
Observations	78,897	94,659	110,417
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table G6: Facebook Access, Firm Sorting, and Human Capital Accumulation – IPEDS Weighted

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.073**	0.057	0.014
	(0.023)	(0.047)	(0.076)
Dep. Var. Mean	1.46	3.40	5.78
Observations	15,781	15,781	15,781
Panel B: Work Exp. at High-Career-Support Firms (Years)			
FB Access	0.053**	0.115**	0.176**
	(0.017)	(0.036)	(0.059)
Dep. Var. Mean	0.826	1.76	2.91
Observations	15,692	15,675	15,677
Panel C: Cumulative Work Experience (Years)			
FB Access	0.054**	0.060**	0.047
	(0.017)	(0.021)	(0.024)
Dep. Var. Mean	4.49	10.11	16.76
Observations	15,781	15,781	15,781
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. Cumulative work experience: total years of employment. Observations are weighted by gender and cohort size using IPEDS enrollment data. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Appendix H: Excluding Elite Colleges

Table H1: Facebook Access and Career Development – Excluding Elite Colleges

	1–6 Years	7–12 Years	13–19 Years
Panel A: Job-Based Real Annual Earnings (2024, USD)			
FB Access	1,519**	1,518**	1,143
	(487)	(556)	(635)
Dep. Var. Mean	74,659	103,734	118,123
Observations	45,102	45,102	52,619
Panel B: Job-Based Promotion (≥10 log pts.)			
FB Access	0.004**	0.002	-0.001
	(0.001)	(0.001)	(0.0010)
Dep. Var. Mean	0.077	0.084	0.074
Observations	37,585	45,102	52,619
Panel C: Senior Leadership Positions			
FB Access	0.004	0.006*	0.009**
	(0.002)	(0.003)	(0.003)
Dep. Var. Mean	0.099	0.191	0.259
Observations	45,102	45,102	52,619
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. For the job-specific promotion measure, the first time interval refers to 2–6 Years after expected graduation. Elite colleges are excluded from the sample. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table H2: Facebook Access and The College-To-Work Transition – Excluding Elite Colleges

		Early-Career Job Placement				
	Employment	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.013***	0.013***	0.014***	0.011**	-0.0007	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.652	0.197	0.152	0.242	0.157	0.190
Observations	15,034	15,034	15,016	15,032	15,032	15,032
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. High-wage firm: indicator for working at a firm in the upper employment-weighted quartile of the average median log earnings distributions at the firm level. High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). High-wage occupation: indicator for working in an occupation in the upper employment-weighted quartile of the average median log earnings distributions at the 5-digit SOC level. Steep wage growth job: indicator for working in an early-career job with a leave-one-cohort-out 15-year wage growth prediction above the 75th percentile. Sr. leadership track job: indicator for working in an early-career job with a leave-one-cohort-out prediction of reaching a senior leadership position 15 years after above the 75th percentile. Elite colleges are excluded. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table H3: Facebook Access and Early-Career Job Help in the College Network – Excluding Elite Colleges

	Early-Career Job via College Network					
	Any Job	High-Wage Firm	High-Career-Support Firm	High-Wage Occupation	Steep Wage Growth	Sr. Leadership Track
FB Access	0.012***	0.007***	0.010***	0.003*	0.005***	0.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Dep. Var. Mean	0.103	0.038	0.045	0.039	0.026	0.042
Observations	15,034	15,034	15,016	15,032	15,032	15,032
College FE	X	X	X	X	X	X
Cohort*Tier*Region FE	X	X	X	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate of the first two years after expected graduation. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Tie: indicator for receiving job help from a college peer following Gee *et al.* (2017). High-career-support firm: indicator for working at a firm in the upper employment-weighted quartile of the Glassdoor career opportunities rating distribution (among firms with at least two ratings). Elite colleges are excluded. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table H4: Facebook Access, Firm Mobility, and Long-Run Job Help in the College Network – Excluding Elite Colleges

	2–6 Years	7–12 Years	13–19 Years
Panel A: Between-Firm Promotions (≥10 log pts.)			
FB Access	0.001	0.0003	-0.001
	(0.001)	(0.0009)	(0.0007)
Dep. Var. Mean	0.055	0.054	0.045
Observations	37,585	45,099	52,619
Panel B: Sequential College Job Promotion (≥10 log pts.)			
FB Access	0.0002	0.0005	-0.0001
	(0.0004)	(0.0004)	(0.0002)
Dep. Var. Mean	0.012	0.010	0.007
Observations	37,585	45,102	52,619
Panel C: Sequential College Sr. Leadership Tie			
FB Access	-0.00007	0.00010	0.00006
	(0.0001)	(0.0002)	(0.0001)
Dep. Var. Mean	0.002	0.002	0.002
Observations	37,585	45,102	52,619
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 2–6 Years, 7–12 Years, 13–19 Years. College peers: students up to 3 classes above and below the expected graduation cohort. Sequential College Job Promotion: indicator for receiving job help from a college peer following Gee *et al.* (2017) coupled with an immediate promotion at a connected firm. Sequential College Sr. Leadership Tie: indicator for receiving job help from a college peer coupled with a transition from non-senior leadership to senior leadership role at a connected firm. Elite colleges are excluded. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table H5: Facebook Access and Job Match Quality – Excluding Elite Colleges

	1–6 Years	7–12 Years	13–19 Years
Panel A: Stable Worker-Firm Match (≥6 Months)			
FB Access	0.008**	0.0008	0.00002
	(0.003)	(0.002)	(0.002)
Dep. Var. Mean	0.690	0.867	0.881
Observations	45,102	45,102	52,619
Panel B: Current Firm Tenure (Years)			
FB Access	0.035***	0.062*	0.091*
	(0.011)	(0.028)	(0.046)
Dep. Var. Mean	1.66	4.06	6.08
Observations	45,102	45,102	52,619
Panel C: Within-Firm Promotions (≥10 log pts.)			
FB Access	0.003***	0.001	0.00006
	(0.0007)	(0.0008)	(0.0006)
Dep. Var. Mean	0.022	0.030	0.029
Observations	37,585	45,099	52,619
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a pooled coefficient estimate within the following time intervals after expected graduation: 1–6 Years, 7–12 Years, 13–19 Years. Stable worker-firm match: indicator equal to one if the individual is employed at the same firm for at least 6 months. Current firm tenure: years at current employer. Within-firm promotions: indicator for upward title transition within the same firm. Elite colleges are excluded. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.

Table H6: Facebook Access, Firm Sorting, and Human Capital Accumulation – Excluding Elite Colleges

	6Y	12Y	19Y
Panel A: Work Exp. at High-Wage Firms (Years)			
FB Access	0.082***	0.089*	0.077
	(0.022)	(0.045)	(0.071)
Dep. Var. Mean	1.42	3.32	5.67
Observations	7,517	7,517	7,517
Panel B: Work Exp. at High-Career-Support Firms (Years)			
FB Access	0.059***	0.110***	0.152**
	(0.016)	(0.032)	(0.048)
Dep. Var. Mean	0.815	1.75	2.89
Observations	7,505	7,504	7,504
Panel C: Cumulative Work Experience (Years)			
FB Access	0.059***	0.065**	0.057**
	(0.017)	(0.020)	(0.021)
Dep. Var. Mean	4.49	10.14	16.80
Observations	7,517	7,517	7,517
College FE	X	X	X
Cohort*Tier*Region FE	X	X	X

Notes: *p<0.05; **p<0.01; ***p<0.001. Two-stage DiD using Gardner (2022), estimated at the college*cohort*year level. Each value represents a point-in-time coefficient estimate at 6, 12, and 19 years after expected graduation. Work experience at high-wage firms: cumulative years employed at a firm in the upper quartile of the average median log earnings distribution. Cumulative work experience: total years of employment. Elite colleges are excluded. Dep. Var. Mean: average outcome for the not-yet-treated college cohorts. Standard errors are clustered at the college level. *Data source:* Revelio Labs.