Misaligned Calendars, Missed Internships: Labor Market Costs of Coordination Frictions in Higher Education*

Xinyao Qiu†

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Abstract

Administrative choices in higher education can have unintended consequences for students' careers. This paper examines the choice of academic calendar and the coordination frictions it creates when universities deviate from the prevailing norm. Using quasi-experimental variation in academic calendars across Ohio universities and data from LinkedIn profiles, I find that switching to the more prevalent semester calendar increases summer internship participation by 27%, with gains concentrated in labor markets where the semester calendar dominates. These additional internships improve students' post-college outcomes, including higher seniority and starting salaries. The findings highlight the labor market consequences of seemingly internal institutional choices.

JEL classification: I23, I28, J24, J31

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†University of Hong Kong Business School. Email: xinyaoq@hku.hk

1 Introduction

Colleges and universities make many administrative choices that appear purely academic, from curriculum design to degree requirements to the structure of the academic year. Yet these choices do not occur in isolation: they interact with labor market institutions in ways that can meaningfully shape students' career opportunities. This paper examines one such choice, the academic calendar, focusing on how deviating from the prevailing norm can create frictions that affect students' access to internships, a key early career opportunity.

Internships have become an increasingly important gateway to the labor market, with over two-thirds of graduating seniors in the U.S. reporting internship experience in 2024 (NACE, 2024). Securing an internship, however, requires coordination between students and firms, and a key dimension of this coordination is timing. Students need to be available when firms are recruiting and running their internship programs. In the United States, most universities follow a semester system that concludes in May, while a significant share operate on quarter systems that end several weeks later in June.[1] Since firms typically design their summer internship programs around the more prevalent semester schedule, quarter-system students may become available too late to participate in many of these opportunities. This paper shows that this timing friction is real and costly: universities deviating from the prevailing calendar face a coordination friction that restricts their students' access to internships and imposes lasting costs on their labor market outcomes.

The coordination challenges posed by the coexistence of two major academic calendars have drawn the attention of policymakers and universities. The Ohio Department of Higher Education mandated that all public universities switch to the semester system primarily to ease student transfers between institutions. More recently, the University of California system, where most campuses operate on the quarter system, has been debating whether to adopt a common semester calendar, driven largely by a desire for better coordination within the system and with California's community college system.[2] However, transitioning to the semester system can be costly, both academically, with negative impacts on four-year graduation rates

[1] As of 2023, 167 U.S. degree-granting institutions at the baccalaureate level or higher use quarter systems.

[2] A recent survey of over 1,200 UC faculty reveals sharply divided views on this question. While most concerns center on research productivity and teaching disruption, some faculty believe switching would improve student access to summer internships. Many call for empirical evidence before committing to such a major change. `https://cucfa.org/2025/02/common-calendar-survey-results/`.

(Bostwick et al., 2022), and financially.[3] These discussions have focused primarily on academic and financial considerations, leaving the potential labor market consequences of calendar choices largely unexamined.

This paper leverages quasi-experimental variation in academic calendars among colleges and universities in Ohio, the state with the highest number of calendar system transitions over the past 30 years. Using data from public LinkedIn profiles, I match students to the academic calendars they experienced and collect their self-reported internship experiences and post-college employment histories. Exploiting the staggered timing of academic calendar transitions in a difference-in-differences framework, I estimate the effects of switching to the more prevalent semester system on students' internship participation during college and their labor market outcomes after graduation.

Switching to the semester system substantially increases students' internship participation. Students are 1.17 percentage points more likely to participate in summer internships in a given year after their institution switches, representing a 28% increase relative to the sample mean, with a small offsetting decline in off-cycle internships taken during the academic term. At the individual level, fully exposed students graduate with 27% more summer internships and a net increase in their total number of internships. To understand whether these gains reflect the coordination mechanism or some inherent feature of the semester calendar, I examine when in the summer and in which labor markets the additional internships occur. The gains are concentrated in May, the month in which quarter-system students are still in class, while internships beginning in June decline. Roughly half of the May increase reflects internships shifted earlier from June and half reflects internships that would not otherwise have occurred. The gains are concentrated in labor markets dominated by semester-system institutions, where employers are more likely to structure their internship programs around the semester calendar. In contrast, effects are close to zero in regions with non-negligible quarter-system presence, where employers likely already accommodate both calendar types. This regional pattern confirms that the benefits of switching stem from resolving a coordination friction rather than from any inherent feature of the semester calendar. These gains do not appear to come at

[3]The estimated cost of converting the University of California's quarter campuses to semesters ranges from $288 million to $371 million (`https://www.ucop.edu/institutional-research-academic-planning/content-analysis/academic-planning/final-apc-common-calendar-workgroup-report.pdf`).

the expense of students at institutions that had already adopted the semester calendar, whose internship participation does not respond when later institutions transition.

These additional internships under the semester system translate into meaningful labor market benefits. Fully exposed students are 1.2 percentage points more likely to land a non-entry-level first job after graduation and earn starting salaries that are $846 higher.[4] They are also more likely to enter high-paying occupations such as business, management, and engineering, and report having broader skill portfolios on their LinkedIn profiles. These salary gains persist at least two to four years after college graduation. Taken together, these findings illustrate how an institutional choice that appears purely academic, i.e., the structure of the academic year, can shape students' career trajectories in ways that extend well beyond their college years.

This study contributes to the literature as the first to document how institutional frictions causally affect college students' internship participation, a key channel through which higher education institutions may influence students' labor market outcomes. Existing surveys and interviews (Hora et al., 2019, 2021) highlight academic, financial, and social barriers to securing college internships. This paper demonstrates that coordination frictions between higher education systems and labor markets reduce students' access to internships, thereby limiting an important pathway into the labor market.

This study specifically examines the role of academic calendars. It relates to the literature on the effects of calendar systems on postsecondary students.[5] Existing research has primarily focused on academic outcomes, showing that switching to semester systems negatively affects students' enrollment (Rosenthal, 2000) and academic performance (Gibbens et al., 2015), reduces students' credit hour loads and increases course withdrawals (Coleman et al., 1984). In their comprehensive analysis using panel data on nearly all four-year institutions in the U.S., Bostwick et al. (2022) find that transitioning from a quarter system to a semester system

[4] I discuss whether and how these reduced-form estimates can shed light on the magnitude of labor market returns to internship experience, but I do not take a stance on the underlying mechanisms through which internships improve labor market outcomes.

[5] Broadly speaking, this study also relates to the literature that explores different school calendars in primary and secondary education. The school structures discussed in the literature include four-day school weeks (e.g., Anderson and Walker, 2015; Fischer and Argyle, 2018; Morton, 2021; Thompson, 2021), extended school days (Battistin and Meroni, 2016; Figlio et al., 2018), extended or shortened school years (Pischke, 2007; Parinduri, 2014; Aucejo and Romano, 2016), and year-round academic calendars (Graves, 2010, 2011; McMullen and Rouse, 2012; Graves, 2013; Depro and Rouse, 2015).

reduces on-time graduation rates by 3.7 percentage points.[6]

In this study, I examine whether and how the academic calendar affects students' employment, including internship participation during college and labor market outcomes after graduation. While not the primary focus, Bostwick et al. (2022) also explores the relationship between academic calendars and summer internship participation. They use whether students earned positive income during the summer from non-food-service and non-retail industries as a proxy for summer internships, finding limited evidence of positive effects. In contrast, this study identifies internship experiences directly from LinkedIn profiles. As a professional networking platform, LinkedIn allows students to share their education and employment history with connections and potential employers, providing a comprehensive record of career-relevant employment, including both paid and unpaid internships.[7] Beyond improving the measurement of internships, this study extends the analysis by examining the downstream effects of increased internship participation on post-graduation outcomes, contributing to the literature on the benefits of internships.

Finally, this study contributes to the literature on causal estimates of returns to internship participation. Using variation from mandatory internships at German universities, Margaryan et al. (2022) finds that internships reduce unemployment and increase earnings by 6%. Bolli et al. (2021) also reports positive income effects, while Klein and Weiss (2011) and Weiss et al. (2014) find no wage impact. Research from Yemen and Finland shows that students randomly offered internships or internship subsidies gain more work experience and earn more after graduation (McKenzie et al., 2016; Virkola, 2021), with similar findings in Portugal and Brazil (Silva et al., 2016, 2018; Della Rocca et al., 2025).[8] This study adds new causal evidence from the United States, leveraging quasi-experimental variation in internship participation due to changes in academic calendars.[9]

[6]Scheduling within the term matters as well. Bostwick and Nguyen (2026) find that students earn lower grades and are less likely to continue in a field when its courses meet three times a week rather than twice, with the largest effects in STEM.

[7]Unlike Bostwick et al. (2022), which captures only paid employment, LinkedIn includes both paid and unpaid internships and covers students from both public and private institutions, whereas Bostwick et al. (2022) includes only public institutions.

[8]Complementary evidence from resume audit studies suggests that internship experience improves perceived employability (Pinto and Pereira, 2019; Jaeger et al., 2023) and increases the likelihood of receiving job interview invitations (Nunley et al., 2016; Baert et al., 2021).

[9]It also relates to research on the academic costs of student employment (e.g., Neyt et al., 2019), which documents that working during college may negatively affect academic performance.

2 Background and Data

2.1 Academic Calendar Systems

In the United States, colleges and universities operate under different academic systems, with the semester system and the quarter system being the most common. The semester system, adopted by the majority of institutions, organizes the academic year into two 15- to 16-week terms (fall and spring), followed by a summer break. The quarter system splits the academic year into four 10-week terms. Students typically attend three quarters (fall, winter, and spring) and may take the summer as an optional quarter. There are two other systems that are much less common: the trimester system, which divides the year into three terms, and the four-one-four system, which includes two four-month blocks separated by a one-month block. Following the categorization in Bostwick et al. (2022), I classify the trimester system as the quarter system and the four-one-four system as the semester system in the analysis due to their relative similarities in scheduling.[10]

Compared to the semester system, the quarter system features shorter terms with fewer courses taken simultaneously, making it more flexible for course scheduling but also resulting in an increased pace and more frequent evaluations. More relevant to this study, the two systems also differ in the timing of the summer break. Under the semester system, the academic year typically concludes in May and resumes in late August. In contrast, under the quarter system, the school year ends in June and recommences in September. If many firms structure their internship programs according to the more prevalent semester system schedule, students on the quarter system could miss these opportunities because their summer break starts about a month later.[11]

The data on the academic calendar of each institution are obtained from the Integrated Postsecondary Education Data System (IPEDS). IPEDS is maintained by the U.S. Department of Education's National Center for Education Statistics. It gathers information from every institution that participates in federal student financial aid programs. Specifically, for each academic year, all institutions report their predominant calendar system. The options

[10] The empirical results are robust to excluding the three institutions in the sample that have ever used the trimester or four-one-four systems.

[11] For example, approximately 40% of internships started in the month of May in Ohio in 2019, while around 15% started in the month of June.

include semester, quarter, trimester, four-one-four, other nontraditional academic systems, or calendars that differ by program.

In this study, the analyses focus on institutions in Ohio, as it is the state that has experienced the most transitions from quarter systems to semester systems over the past 30 years.[12] This is mainly because the Ohio Department of Higher Education mandates that all public universities and colleges in Ohio switch to semester systems. Specifically, the policy required all public institutions that were operating under quarter systems to adopt the semester system by the fall of 2012.[13] The goal of the policy is to make it easier for students to transfer between institutions. Using records from IPEDS, I constructed a panel that includes the academic calendars of all degree-granting institutions in Ohio that are at the baccalaureate level or higher, spanning from 1990 to 2019. To study the impact of the transition from quarter to semester systems, I restrict the sample to institutions that initially operated under quarter systems between 1990 and 1995.[14] For each institution, I identify the academic year in which it transitioned to a semester system, and exclude those that used non-traditional calendars or underwent multiple calendar transitions.

Appendix Table A1 lists the 17 colleges and universities in the final analysis sample. All but one transitioned from the quarter system to the semester system between 1996 and 2013; the exception is Franklin University, which remains on the trimester system. Several of these universities operate multiple campuses across the state, with all campuses of a given university sharing the same transition year. Together, these institutions enrolled approximately 55% of Ohio's undergraduate population as of 2019. Because the Ohio sample contains few never-treated institutions, I show that the main results are robust to adding comparable never-treated universities from Oregon and Washington as a control group.

2.2 LinkedIn Profiles

Students' educational and employment records are obtained from their public LinkedIn profiles through Revelio Labs. LinkedIn is a business- and employment-focused social media platform.

[12] Appendix Figure A1 compares the prevalence of quarter systems between 1995 and 2019. The share of institutions using quarter systems in Ohio decreased from above 30% to below 5%.

[13] `https://transfercredit.ohio.gov/educational-partners/educational-partner-resources/academic-calendar-conversion/overview`.

[14] The results remain robust when including the "always treated" units.

It first launched in 2003 and now has 200 million users in the U.S. The platform is more commonly used by college-educated white-collar workers, the sample this study intends to focus on. Through Revelio Labs, I have access to all public profiles created by LinkedIn users as of early 2023. LinkedIn profiles serve as online resumes where individuals share their education and employment histories with their connections, recruiters, and the general public. The education section includes the institutions users have attended or are currently attending, years of attendance, and degrees obtained or in progress. The employment section includes users' past and current employers, employment start and end dates (year and month), job titles, and brief job descriptions.

Revelio Labs preprocesses the raw data. First, they predict users' genders by feeding their first names into a model trained on the Social Security Administration data. Similarly, they predict users' race and ethnicity using a model trained on U.S. Census data, which considers users' first names, last names, and locations. For each employment record, Revelio Labs assigns a seniority level and an O*NET code based on the job title, company, and industry. Finally, Revelio Labs imputes the salary for each position using information specific to the position, including job title, seniority level, company, and location, as well as user-specific information such as years of experience. The model is trained on salary data from publicly available labor certification applications, self-reported data, and information from online job postings.[15]

The main sample of analysis includes college students with public LinkedIn profiles who were enrolled in the 17 Ohio colleges and universities between 1990 and 2019.[16] For each student, I observe their imputed demographics, duration and field of study, and post-graduation outcomes. The post-graduation outcomes include whether they enroll in advanced degree programs, when they start their first job, as well as the imputed salary, seniority level, and occupation of their first job. Most importantly, I identify all their internship experiences while enrolled in college. An employment record is classified as an internship if the job title includes the keyword "intern" or "internship." Following Bostwick et al. (2022), I classify an internship experience as a "summer internship" if it begins between April and September of

[15]The imputed wage data have been validated and used by Amanzadeh et al. (2024) and Dorn et al. (2024).
[16]Years after 2020 are excluded to avoid the impact of the COVID-19 pandemic.

the year.[17] I refer to the remaining ones as "off-cycle internships." Appendix Table A2 provides the summary statistics. On average, a student reports completing a total of 0.28 internships while in college, with the majority being summer internships.[18] Comparing the number of students observed on LinkedIn at each institution each fall with the institution's undergraduate enrollment reported to IPEDS, the sample covers 40% of undergraduates enrolled at these institutions between 2000 and 2019. Coverage exceeds a third at twelve of the seventeen institutions, reaching 57% at the highest.

3 Internship Participation: Individual-by-Year Level Analysis

3.1 Empirical Strategy

I exploit the staggered transitions from quarter to semester systems to estimate the impact of the academic calendar on students' internship participation. Specifically, I build a panel dataset with students enrolled at the 17 Ohio institutions between 1990 and 2019, recording whether they participated in internships in each calendar year. As a baseline specification, I estimate the following two-way fixed-effect (TWFE) event study model with staggered adoption:

$$Y_{ist} = \sum_{k=-6}^{7} \theta_k SemSys_{stk} + \gamma_s + \eta_t + \rho_{g(s)} \times t + \varepsilon_{ist}, \tag{1}$$

for student i who enrolls at institution s in calendar year t. The outcome variable Y_{ist} denotes whether student i from institution s participates in internships in calendar year t. In particular, I consider three different measures: (1) whether a student participates in a summer internship, (2) whether a student participates in an off-cycle internship, and (3) whether a student participates in any internship during the year. For example, for a student enrolled at Ohio State University from 2010 to 2014, I examine whether the student participated in internships in each calendar year t—2010, 2011, $\cdots$, and 2014—and distinguish between summer and off-cycle internships. I measure internships by calendar year rather than academic year because the start and end dates of academic years differ across academic calendar systems

[17] This definition of summer is broad enough to cover the summer break for students on both semester and quarter systems.

[18] Appendix Figure A2 plots the share of students who report internship participation on LinkedIn, by year of college entry. The rapidly growing trend reflects both the increased reporting on LinkedIn and a rise in internship participation.

and are endogenous to the calendar switch.

The variable $SemSys_{stk}$ is an indicator for k years since institution s transitioned to the semester system in calendar year t. For Ohio State University, which transitioned to the semester system in the fall of 2012, $k = 0$ in the calendar year $t = 2012$, $k = -1$ in calendar year 2011, and $k = 1$ in 2013. I normalize the coefficient in the year immediately preceding the switch (θ_{-1}) to zero. θ_ks are the coefficients of interest. Following Bostwick et al. (2022), I assume the treatment effect is constant at least six years before and seven years after the shift, with the average effects captured by θ_{-6} and θ_7. γ_s and η_t denote the institution and calendar year fixed effects, respectively. I additionally control for group-specific linear time trends $\rho_{g(s)} \times t$, where a group includes the institutions that made the transition in the same year. The standard errors are clustered at the institution level.

To better quantify the average treatment effect, I also estimate the TWFE staggered difference-in-differences model:

$$Y_{ist} = \beta SemSys_{st} + \gamma_s + \eta_t + \rho_{g(s)} \times t + \varepsilon_{ist}. \tag{2}$$

The model includes similar covariates as in equation (1), but instead of examining each year relative to the transition separately, it uses a single dummy variable, $SemSys_{st}$, indicating whether institution s operates under the semester system in calendar year t. The coefficient β captures the average treatment effect of transitioning to semester systems, assuming (1) parallel trends and (2) treatment effect homogeneity.

The identification of the causal effect of the calendar switch rests on two assumptions: parallel trends and treatment effect homogeneity. I discuss each in turn, along with evidence that both the institutional setting and the LinkedIn data support these assumptions.

Parallel trends. The parallel trends assumption requires that students' internship participation across different institutions would have followed the same trend if they had all continued using the quarter system. I control for institution-specific, time-invariant variation by including institution fixed effects, and I account for time trends in internship participation common across institutions by including year fixed effects. By additionally including adoption group-specific linear trends, I allow institutions adopting the semester system in different years to

follow differential linear trends in the absence of treatment. I also present results without group-specific linear trends and with institution-specific linear trends instead.

Three additional concerns could threaten the parallel trends assumption in this setting. First, the calendar switch could coincide with other institutional changes that independently affect students' outcomes. Appendix Table A3 examines this possibility by testing whether the transition is associated with changes in undergraduate enrollment, total enrollment, faculty size, undergraduate demographic composition, the share of Pell recipients, or per-student instructional and student services expenditures. None of the eight coefficients is statistically significant, indicating that the calendar transition is not accompanied by broader institutional changes that could drive the results.

Second, the calendar switch could shift the composition of students enrolled at these institutions, either because students select into institutions based on the calendar or because of other unobserved sorting. The institutional placebo in Appendix Table A3 also speaks to this concern using IPEDS data on the universe of enrolled undergraduates, showing that the share of female students, the share of minority students, and the share of students from low-income backgrounds do not respond to the calendar transition.

Third, because I rely on self-reported information from LinkedIn profiles, the parallel trends assumption also requires that students' engagement with LinkedIn is uncorrelated with the calendar transition. Institution-level heterogeneity and overall time trends in LinkedIn usage are absorbed by the institution and year fixed effects. I further test this assumption in two ways. Appendix Table A4 examines the rate of LinkedIn engagement at the institution-cohort level, measured by the share of the entering cohort who maintain a public profile, the share who report details about their first post-college job, the share with recent profile updates, and the average number of connections. None of these measures responds to the calendar switch.[19] The result on first-job reporting is especially relevant for the individual-level analysis of post-graduation outcomes in Section 4, where identification requires that the calendar switch does not change selection into reporting first-job information. Appendix Table A5 then examines the composition of profile-holders, testing whether the demographic and field-of-study mix of LinkedIn users changes with the calendar switch. The characteristics of LinkedIn users

[19]The number of connections is a snapshot as of 2023; I do not observe when or how a user's connections were formed.

are largely stable, with one marginally significant coefficient on minority share. To address any residual concern about compositional shifts, all subsequent analyses control for student characteristics, including gender, racial minority status, and fields of study.

Finally, to rule out anticipation effects, I visually examine the estimates of equation (1) prior to the calendar transition and find no evidence that students delayed their internships in anticipation of the future switch to semester systems or any other forms of pretrends.

Treatment effect homogeneity. Interpreting the coefficient of interest β in equation (1) as the average treatment effect on the treated additionally requires that treatment effects are homogeneous across institutions and over time (e.g., De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Borusyak et al., 2024; De Chaisemartin and d'Haultfoeuille, 2024). I address this in two ways. First, I include universities outside Ohio that used quarter systems throughout the sample period as additional never-treated control units, which mitigates concerns about heterogeneous treatment effects driven by the use of treated units as controls (Goodman-Bacon, 2021). Second, I re-estimate the event study using the heterogeneity-robust imputation estimator proposed by Borusyak et al. (2024).

3.2 Graphical Results

Figure 1(a) presents the estimates of θ_k from equation (1) for the three measures of internship participation. The coefficients before the transition are near zero and statistically insignificant, indicating no differential pre-trends across institutions with different transition timings. In the calendar year of the transition ($k = 0$), we find no impact on internship participation. This is unsurprising: all universities switched in the fall of that calendar year, after the summer had ended, so the transition could not affect summer internships in the transition year itself,[20] and had only limited scope to affect off-cycle internships.

We observe a significant increase in summer internship participation in the year immediately following the adoption of semester systems. The treatment effects remain stable, with a slight increase over time, possibly due to an overall rise in internship participation

[20] If anything, we might expect a decline in summer internship participation in the transition year, since the summer break is shortest during the transition.

and reporting on LinkedIn. Meanwhile, internship participation during non-summer seasons decreases after the transition to the semester system. This may be because students under semester systems take more courses concurrently, making it harder to add an internship to their schedules during the academic term. It could also reflect a crowding-out effect, as students may be less likely to pursue off-cycle internships when more summer opportunities are available.

Despite the decline in off-cycle internships, students experience a net increase in overall internship participation under semester systems. The fact that summer internships rise while off-cycle internships fall also speaks against differential trends in LinkedIn usage or reporting as a driver of the results. If semester-system students were simply more likely to report internships on LinkedIn, the natural expectation would be increases in both types of internships rather than offsetting movements.

The baseline TWFE estimates in Figure 1(a) rely on comparisons among Ohio institutions, nearly all of which transition from the quarter to the semester system between 1996 and 2013.[21] Recent econometric work shows that the TWFE estimates can be biased when treatment effects are heterogeneous across units or over time (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). I address this concern in two ways. First, I expand the sample to include never-treated universities from Oregon and Washington, two states with a large number of colleges and universities that have long used quarter systems and are comparable to institutions in Ohio. Appendix Table A6 lists these institutions. In the expanded sample, 41.52% of students are enrolled in universities that used the quarter system throughout the period. The larger pool of clean control units helps address concerns about heterogeneous treatment effects (Goodman-Bacon, 2021). Second, I re-estimate the event study using the imputation estimator of Borusyak et al. (2024), which is robust to heterogeneous treatment effects across cohorts and over time.

Figures 1(b)–(d) present the results separately for the three measures of internship participation, comparing the baseline TWFE estimates with the two alternatives. Although different estimators are not perfectly comparable to one another due to differences in sample selection and methodology, the estimates from both alternatives are quantitatively similar to

[21] The one exception is Franklin University, which remains on a trimester system.

the baseline TWFE results.

3.3 Regression Results

Panel A of Table 1 reports the results from equation (2), where I control for adoption group-specific linear time trends. Columns (2), (4), and (6) also control for student characteristics, including imputed gender, imputed race and ethnicity, and fields of study in college. The estimates remain unchanged with the inclusion of student characteristics. Column (2) suggests that, under the semester system, students are 1.17 percentage points (pp) more likely to undertake internships *each summer*, which represents a 28% increase relative to the sample mean. Meanwhile, column (4) indicates a slight, statistically insignificant decrease in off-cycle internship participation under the baseline specification. Overall, according to column (6), students are 1.00 pp (18%) more likely to have internship experiences *each year* after their institutions transition to semester systems.[22]

The magnitude of the average treatment effect should be interpreted with caution because we only observe internship experiences listed on LinkedIn profiles. Given that not everyone reports every internship experience they had, especially individuals who were in college many years before LinkedIn became available, it is not possible to directly map the sample mean or the estimates one-to-one to actual internship participation. However, the 18% *relative* increase compared to the sample mean is informative and suggests that academic calendars can have large impacts on internship participation.[23]

3.4 Mechanism

Table 1 shows that switching to the semester system raises summer internship participation. This is not obvious. The academic calendar governs only when students are free to intern, so its most direct effect is on the timing of internships rather than their number. If employers set start dates flexibly and accommodated the schedules of all qualified candidates, the calendar

[22] I code the treatment indicator $SemSys_{st}$ as equal to one in the calendar years following the transition (that is, $k \geq 1$). The calendar year of transition itself ($k = 0$) is not coded as treated, since Figure 1 shows no effect in that year: the switch occurs in the fall, after the summer internship season has ended. Appendix Table A7 confirms this by including a separate indicator for the transition year, which is near zero and statistically insignificant, while the estimated effect of the semester system is similar to the baseline.

[23] Appendix Table A8 shows that the additional internships are distributed across a variety of industries, including high-paying ones such as Information, Finance and Insurance, and Professional, Scientific, and Technical Services.

switch would shift summer internships earlier but leave their number unchanged. The observed increase in internship participation instead reflects the existence of a scheduling friction. Employers do not fully accommodate the later availability of the minority quarter-system students, so these students lose access to internships that begin before their summer break starts. Switching to the semester system relaxes this friction and generates internships that would not otherwise have occurred.

To investigate how academic calendars affect both the timing and number of summer internships, Table 2 decomposes summer internship participation by the month in which the internship begins. I re-estimate equation (2) using separate indicators for holding an internship that starts in April, in May, in June, and between July and September. Semester-system students are free from mid-May, whereas quarter-system students remain in class until after mid-June, so the switch makes students newly available for internships beginning in May.[24] The other months serve as placebos. In April, students on both calendars are still in class; by July, both are free and the summer internship season is largely underway. Neither period should respond to the switch.

Panel A of Table 2 presents the results. Participation in internships starting in May rises by 1.91 pp, roughly doubling relative to the sample mean of 1.87 pp. Participation in internships starting in June falls by 0.85 pp, a 67% decline relative to its mean. April and the July-through-September window show no significant change, and the four month-specific coefficients sum to approximately the pooled summer effect in Table 1. Appendix Figure A4 presents the corresponding event study plot. The rise in May starts and the decline in June starts both appear in the first year following the transition and persist thereafter, while participation in internships starting between July and September remains flat across the entire window.

The May and June coefficients indicate both reallocation of internship timing and creation of new internship matches. The fall in June starts reflects reallocation: a student who would have interned in June instead interns in May, for the same or a different employer, because the academic year now ends earlier. Reallocation alone would leave summer participation unchanged, with the May increase matching the June decline. Instead, the May increase

[24] LinkedIn records only the year and month of employment start dates, so we cannot distinguish whether a June internship begins before or after mid-June.

substantially exceeds the June decline, so internships are not merely shifted earlier but added. Of the May gain, roughly 45% offsets the decline in June starts and the remaining 55% represents newly created matches. This net increase is inconsistent with the frictionless benchmark and points to the resolution of a coordination friction, as students who could not previously align with programs beginning in May are now able to do so.

If the net increase in internships reflects the resolution of a scheduling friction, it should be larger in markets where that friction is more severe. Panels B and C of Table 2 test this by splitting internships according to the quarter-system presence of the state where the internship takes place. Consider first the markets where the friction is likely to be weaker. Panel B examines states where at least 10% of undergraduates attend quarter-system institutions. In these states, employers accustomed to hiring from both calendars are less likely to organize their programs around a single set of start dates, so the switch to semester systems should reallocate internships without creating them. That is what the data show. May starts rise by 0.18 pp and June starts fall by 0.14 pp, and the two nearly cancel, leaving a net effect on summer participation that is close to zero and statistically insignificant.

The net increase in summer participation comes instead from markets where the friction is more severe. Panel C restricts to states where quarter-system institutions are rare, accounting for no more than 10% of undergraduates. In these states, employers have less reason to accommodate quarter-system schedules, so the switch should create new matches and not merely reallocate them. Consistent with this, May starts rise by 0.44 pp while June starts fall by only 0.18 pp, so the June decline offsets 41% of the May gain and the rest represents newly created matches. The net effect on summer participation is 0.30 pp, a 34% increase relative to the sample mean.[25]

Taken together, the decomposition shows that switching to the semester system affects summer internships in two ways. It shifts the timing of internships, and it creates new student-employer matches that schedule misalignment would otherwise have prevented. The timing shift appears in all markets, whereas the new matches arise almost entirely where quarter-system institutions are rare and the friction is therefore most severe. Alternative explanations,

[25] Appendix Table A9 reports two further location splits: internships within the state of Ohio and internships outside the United States. Internships within Ohio, which does not belong cleanly to either group because its quarter-system presence changes over the sample period, show a relative magnitude of 26%. Internship participation outside the United States rises by 57%.

such as an inherent advantage of the semester calendar, differential LinkedIn reporting, or selection into institutions, would raise participation across all markets rather than only where the friction binds. The evidence instead reflects the resolution of a coordination friction: switching aligns students' availability with the schedules that employers have built around the dominant calendar.

3.5 Potential Crowding-Out Effects

The analyses so far focus on students whose own institution switches. If the supply of summer internships is not perfectly elastic, part of what these students gain may come at the expense of students who already had access to such positions, namely those at institutions that had already adopted the semester calendar. This has two implications. First, if part of the gain is a transfer between institutions, the benefit to an entire system is smaller than the benefit to any one switching institution. Second, it biases the TWFE estimates, since under the standard TWFE model, the early switchers serve as the control group for the later ones. If the early switchers lose internships when later institutions transition, the estimates are upward biased.

Quantifying the crowding-out effect is inherently difficult. I begin by comparing the TWFE estimate, which is most prone to the upward bias, against two alternatives that are less prone to it, both shown in Figure 1(b). The first alternative still uses the TWFE model but expands the sample to include 16 never-treated institutions in Oregon and Washington as additional controls. Because these institutions are far from Ohio and remain on the quarter calendar throughout, their students do not compete for the May-start positions that Ohio's transitions affect, which helps dilute the contamination from using already-switched Ohio institutions as controls. The second alternative, the imputation estimator of Borusyak et al. (2024), fits the counterfactual on untreated observations alone and never uses already-treated institutions as controls.[26] If crowding out were substantial, the baseline TWFE estimate would exceed both alternatives. Figure 1(b) shows that it does not: the estimates from both alternatives are similar to, if not slightly larger than, the baseline. This indirect evidence suggests that already-treated units do not experience substantial crowding out.

[26] If anything, the untreated observations may benefit when treated institutions switch away from the quarter calendar, since fewer students then compete for the later-starting positions available under the quarter schedule. This would push their outcomes up rather than down, making the comparison conservative.

A more direct test uses the transition of the four largest public universities in Ohio, which adopted the semester calendar together in the fall of 2012 and together enroll a large share of the state's undergraduates. Their transition sharply raises the number of students available for May-start internships in Ohio, and could generate crowding out within the Ohio internship market. I test whether students at the already-switched institutions become less likely to intern in Ohio relative to elsewhere, either finding fewer summer internships or substituting toward internships in other states. For students at the ten Ohio institutions that had been on the semester system for at least five years, I estimate

$$Y_{isdt} = \beta \left(Post_t \times Ohio_d \right) + \alpha_{sd} + \lambda_{st} + \rho \left(Ohio_d \times t \right) + \varepsilon_{isdt}, \tag{3}$$

where d indexes whether the internship is located in Ohio or elsewhere, $Post_t$ equals one from 2013 onward, and Y_{isdt} denotes whether student i from institution s holds a summer internship in location d and year t. α_{sd} denotes institution-by-location fixed effects, λ_{st} denotes institution-by-year fixed effects, and $\rho \left(Ohio_d \times t \right)$ allows the two locations to follow different linear trends. Standard errors are clustered at the institution level. The institution-by-location fixed effects absorb each institution's time-invariant propensity to place students in either location, and the institution-by-year fixed effects absorb anything that varies at the institution-year level and affects both locations equally.

The coefficient β therefore compares the change in participation in Ohio-located internships after 2012 with the change in participation in internships located elsewhere, under the assumption that, absent the transition, the gap between the two locations would have continued along its linear trend. Table 3 reports the estimates, decomposed by start month. If the 2012 transitions crowd out incumbent students, it should show up in May, the month in which those transitions make additional students available. The estimated coefficient β for May is near zero in magnitude and statistically insignificant. There is thus no evidence that the transition of Ohio's four large public universities makes students at already-switched institutions less likely to intern in Ohio, or leads them to shift their internships toward other states. The supply of summer positions may be elastic enough to absorb the new entrants, or the inflow may be modest relative to the size of the overall internship market. What this exercise does not rule out is the possibility that students from already-switched institutions become equally

less likely to intern in both Ohio and elsewhere, but Figure 1(b) suggests this uniform decline in internship participation is highly unlikely. Therefore, the empirical evidence indicates that existing semester-system institutions are not adversely affected by later transitions.

3.6 Robustness

Appendix Figure A3 and Appendix Table A10 show the results under alternative specification. Appendix Figure A3(a) presents the estimates without group-specific linear time trends, showing slight differences in the trends that different institutions followed prior to the calendar change, which leads to an overestimated average treatment effect (Panel A of Appendix Table A10). Figure A3(b) and Panel B of Appendix Table A10 report the results with institution-specific linear trends instead of group-specific trends, which do not impact the estimates. Figure A3(c) and Panel C of Appendix Table A10 report the results excluding the first and fifth or later years of college enrollment for each student. For a typical student who enrolls in the fall of their first year and graduates before the summer of their final year, internship participation during those partial years is unlikely to be affected by the academic calendar. By focusing only on the three full calendar years in college, this specification also addresses the concern that students who do not graduate on time are more heavily weighted in the baseline sample. The average treatment effects are larger after excluding the partial and extra years. Finally, Appendix Figure A3(d) and Panel D of Table A10 include graduate students in the analysis and find a smaller treatment effect than when focusing only on undergraduate students in the baseline specification.

Appendix Table A11 addresses the uneven coverage of LinkedIn across institutions and years. Panel A restricts the sample to cohorts entering between 2000 and 2015, for which IPEDS enrollment is available, and therefore coverage can be measured. Panel B weights each institution-year by the inverse of its LinkedIn coverage, so that institutions with sparser coverage are not underweighted relative to their actual size. Panel C excludes the five institutions whose coverage falls below one third. The estimated effect on summer internship participation is quantitatively similar across the three panels and to the main specification, while the effect on any-internship participation attenuates under the coverage weights.

Additionally, in Appendix Table A12, I estimate the impact of switching to semester

systems on internship participation *separately* for the summers following years 1, 2, and 3 of college. The point estimate is strongest in the summer before senior year, driven entirely by the higher baseline internship participation during that summer. Appendix Table A13 shows that the results are robust to excluding the three institutions in the sample that were ever on trimester or four-one-four systems. Appendix Table A14 examines how switching to semester systems affects the *joint* distribution of students' summer and off-cycle internship participation.

Because identification relies on only 17 institutions, I assess the sensitivity of the results to small-cluster inference in Appendix Table A15. The table reports wild cluster bootstrap p-values (Cameron et al., 2008; Roodman et al., 2019) and re-estimates the model on the expanded sample that has a larger number of clusters by adding the never-treated institutions from Oregon and Washington (Panel B). The estimated increase in summer internship participation remains statistically significant under both the wild cluster bootstrap and the expanded control group, while the smaller effect on any-internship participation is more sensitive to the choice of inference method. Appendix Table A16 reports the same bootstrap p-values for every coefficient of Table 2. The increase in May internships and the decline in June internships are both significant at the 5% level in the full sample and in states where quarter-system institutions are rare, and the two placebo bins remain insignificant throughout.

4 Post-Graduation Outcomes: Individual Level Analysis

4.1 Empirical Design

To estimate the impact of semester systems on students' total number of internships while in college and on their post-graduation outcomes, I conduct an individual level analysis that leverages the variation in their entry years relative to the year of the calendar change. Specifically, I consider a student as fully exposed to the semester system if she enters college in the year of or after the transition to semester systems. I consider a student as partially exposed if she enters college one or two years before the transition, meaning that her institution transitions to semester systems during her sophomore or junior years. I do not consider students who are in their senior year at the transition as treated because, if they graduate on time, there are no

summers left for them to do internships while in college. Some students do not graduate on time, so they become de facto exposed by spending extra years in college. However, as shown in Bostwick et al. (2022), the on-time graduation rate is endogenous to academic calendars. Therefore, rather than using their actual exposure, I define it as "intended" exposure assuming everyone graduates on-time and estimate the intent-to-treat effects.

I estimate the same TWFE event study model as in equation (1) but at the individual level, with t now denoting the college entry year of student i. The outcome variable Y_{ist} represents the number of internships or some post-graduation outcomes of student i who enters institution s in year t. The θ_ks are the coefficients of interest: θ_0 captures the treatment effect for students who enter college in the year of the calendar change, and θ_{-1} (θ_{-2}) captures the effect for students who are in their sophomore (junior) year when the institution transitions to a semester system. I normalize θ_{-3} to zero. Similarly, I control for institution and entry year fixed effects and group-specific linear trends, and cluster standard errors at the institution level.

I also estimate the difference-in-differences model that is parallel to equation (2):

$$Y_{ist} = \beta_1 Partial_{st} + \beta_2 Full_{st} + \gamma_s + \eta_t + \rho_{g(s)} \times t + \varepsilon_{ist}, \tag{4}$$

where $Partial_{st}$ denotes whether students who enter institution s in year t are partially exposed to semester systems if they graduate on time, and $Full_{st}$ denotes whether they are fully exposed. The sample for analysis includes college students who entered the 17 institutions in Ohio between 1990 and 2015, and is restricted to students who spent four to six years in college. Since Bostwick et al. (2022) finds that transitioning to semester systems reduces four-year graduation rates but has no significant impact on six-year graduation rates, a six-year window retains students whose graduation the transition delays. The results are similar when I include all undergraduate students regardless of their duration of study.[27] I conduct a placebo analysis and show in Appendix Table A5 that students' characteristics, including gender, racial minority status, and fields of study, do not change in response to the transition to semester systems. This helps alleviate concerns that students select institutions based on their academic calendars. The post-graduation outcomes Y_{ist} are observed for the 85% of

[27] Panel C of Appendix Table A24 presents the results.

students whose first job after college is recorded on LinkedIn. Appendix Table A17 estimates equation (4) with an indicator for observing the first job as the outcome, using all students who spent four to six years in college, and finds no change with either partial or full exposure.

4.2 Results

Figure 2 presents the estimates from the event study model. Figure 2(a) overlays the coefficients for three internship measures: the total number of internships undertaken throughout college that are (1) summer internships, (2) off-cycle internships, and (3) both types combined. There are no differential pretrends in internship participation across institutions that transitioned to semesters in different years. The coefficients suggest that students graduate with significantly more summer internships if their institutions transition to a semester system in their junior or sophomore years. The effects are stronger if the transition occurs in their freshman year or before they enroll. Meanwhile, we observe a small and marginally significant decrease in off-cycle internship participation for students who are partially or fully exposed to semester systems. The increase in summer internships outweighs the decrease in off-cycle internships, leading to more overall internship experiences, especially for students who are fully exposed.

Figure 2(b) shows the impact of semester systems on the share of students with a non-entry-level first job after college. Specifically, I use the seniority levels imputed by Revelio Labs, which characterize positions such as assistants, clerks, and trainees as entry level. The coefficients suggest that students exposed to semester systems are more likely to have their first non-internship job after college classified as non-entry-level, although the estimates are noisier and only marginally significant. Figure 2(c) shows the impact of semester systems on students' starting salaries. The outcome variable is the imputed starting salary of students' first non-internship job after college, adjusted to 2010 dollars. Students who are partially exposed to semester systems earn higher starting salaries, and the effects are larger and statistically significant for students who are fully exposed.

The same concerns about TWFE bias under heterogeneous treatment effects apply to the individual-level specification. Appendix Figure A5 conducts analogous robustness checks, comparing the baseline TWFE estimates to two alternatives: a TWFE specification that adds

never-treated universities from Oregon and Washington as a control group, and the imputation estimator of Borusyak et al. (2024).[28] Across all outcomes (the number of summer internships, the total number of internships, the likelihood of a non-entry-level first job, and the starting salary), the estimates from both alternatives are quantitatively similar to the baseline TWFE results. This consistency suggests that the baseline TWFE estimates provide a reasonable summary of the effects of semester systems on internship participation and post-graduation outcomes.

Table 4 presents the regression results from equation (4). According to column (1), students who are partially exposed to semester systems complete 0.034 more summer internships throughout college, while fully exposed students complete 0.068 more summer internships—a 27% increase relative to the sample mean. However, column (2) suggests that the transition to a semester system decreases the number of off-cycle internships by 0.014 for fully exposed students. Overall, when institutions transition to semester systems, students who are partially exposed have 0.025 more internships in college (statistically insignificant), and fully exposed students have 0.054 more internships, a 16% increase relative to the sample mean of 0.339 internships. As the effect on the total number of internships nets the robust increase in summer internships against the decline in off-cycle internships, it is therefore less precisely estimated.[29] These results are consistent with the findings from the individual-by-year level analyses. For post-graduation outcomes, column (4) shows that partial exposure to semester systems makes students 0.8 pp more likely to land a non-entry-level job after college, while full exposure increases this likelihood by 1.2 pp, or 2.2% relative to the sample mean. Column (5) shows a positive but statistically insignificant change in starting salary for partially exposed students, and a significant $846 (1.5%) increase in salary for fully exposed students.

Table 4 finds that when institutions adopt semester systems, students gain more (summer) internship experiences and see improved labor market outcomes after college. Descriptively, this finding is consistent with the literature, which suggests that internship participation

[28] Compared with the TWFE specifications, the imputation estimator omits the group-specific linear time trends and is estimated with the additional never-treated institutions from Oregon and Washington. Because the estimator fits the model on untreated observations alone, the Ohio sample provides too few pre-switch cohorts to estimate the group-specific trends precisely, and too few untreated observations in the later entry cohorts to identify the cohort fixed effects. The additional never-treated institutions supply untreated observations in every entry cohort.

[29] Appendix Table A18 shows that, as the number of internships changes, exposure to semester systems increases students' earnings from summer internships and decreases earnings from off-cycle internships.

increases labor market opportunities and boosts earnings. However, caution is needed in interpreting these reduced-form estimates as a causal quantification of the impact of internships on labor market outcomes, for two main reasons. First, the exclusion restriction is not satisfied if we use calendar changes as an instrument for internship participation. Specifically, academic calendars can influence students' labor market outcomes through channels other than internships, such as academic performance. For instance, Bostwick et al. (2022) finds that students have worse academic performance and lower on-time graduation rates under semester systems.[30] Assuming that academic performance is positively correlated with labor market outcomes, this implies that IV estimates will *underestimate* the benefits of internship participation on labor market outcomes.

Second, the magnitudes should be interpreted with caution because LinkedIn profiles do not necessarily include all internship experiences or complete employment histories. To the extent that LinkedIn records only a fraction of students' summer internships, the point estimate of the effect of full exposure on the number of summer internships (0.068) understates its true magnitude, and, even if the exclusion restriction holds, the implied return to one additional summer internship ($846/0.068) overstates the true per-internship effect.

Therefore, I rely on the relative magnitudes to interpret the results, focusing on summer internships. According to column (1), students' summer internship participation increases by 27% (0.068/0.250) if they are fully exposed to semester systems. Assuming the exclusion restriction holds, this increase leads to an $846 increase in their starting salaries. By linear extrapolation, the results suggest that students' starting salaries would increase by $3,133 if their number of summer internships in college were to double.[31] Similarly, the likelihood of students finding a non-entry-level job after college would increase by 4.4 percentage points if their number of summer internships doubled. Finally, considering the likely violation of the exclusion restriction, it is possible that these labor market benefits of internships are underestimated and may actually be stronger.

The analyses do not take a position on the specific mechanisms through which internships improve labor market outcomes. The positive effects may reflect human capital accumulation,

[30] Student employment may also affect academic performance. Neyt et al. (2019) provides a comprehensive review.

[31] The $3,133 salary increase substantially exceeds the typical return to a few months of work experience, indicating that internships generate benefits beyond simple experience accumulation.

signaling, expanded professional networks, or a combination of these factors. Appendix Figure A6 examines medium-term outcomes. I track students' employment positions eight years after college entry and find that the salary gains associated with semester systems persist, while the effect on seniority diminishes.

4.3 Additional Outcomes

I explore whether increased internship experience under semester systems affects other post-graduation outcomes. Appendix Table A19 illustrates how students enter different occupations when their institutions transition to semester systems. Based on the O*NET code of their first job after college, I find that more students enter high-paying occupations (i.e., business and management, engineering, and mathematics) when they are exposed to semesters. This may help explain the positive impact on students' earnings after college. The benefits in the labor market could be further amplified in the long run if we consider the network effects of having more alumni holding senior positions in high-paying occupations.

Appendix Table A20 examines the likelihood that students' first post-college employment is in the same company, industry, or occupation as one of their internships. The estimates suggest that under semester systems, students are more likely to receive and accept "return offers," i.e., jobs at the same companies where they complete internships.

Using self-reported skills from LinkedIn profiles, I examine whether exposure to semester systems affects students' skill accumulation. Despite being self-reported and potentially noisy, skills listed on LinkedIn profiles provide an informative measure of individual human capital (Dorn et al., 2024). Appendix Table A21 shows that students fully exposed to semester systems are more likely to report any skills on their profiles and list on average 0.3 more skills overall. The higher likelihood of reporting any skills could partly reflect that these students are more adept at using professional platforms, which is itself a form of soft skill. Classifying skills along two dimensions, hard versus soft and practical versus research,[32] fully exposed students list significantly more soft and practical skills, while the effect on hard skills is positive but

[32]Hard skills are specific, teachable, and job-specific (e.g., Python, accounting, AutoCAD), while soft skills are interpersonal and transferable (e.g., leadership, communication, teamwork). Practical skills are hands-on and industry-focused (e.g., sales, marketing, Salesforce), while research skills are scholarly or theoretical (e.g., statistics, laboratory methods, curriculum development).

imprecisely estimated. The null result on research skills is consistent with the expectation that internship exposure drives industry-relevant rather than academic skill accumulation. Since skills are observed as of 2023 without information on when they were acquired, they could reflect human capital built during internships, skills developed through the more senior and higher-paying jobs that internship experience helped students access, or both.

I also explore whether academic calendars affect students' pursuit of advanced degrees. Appendix Table A22 shows that exposure to semester systems does not affect the gap between college graduation and students' first job. The likelihood of students pursuing advanced degrees (one year, three years after graduation, or ever) remains unchanged. However, semester systems appear to reduce the likelihood of earning a doctorate degree by 0.6 pp (8.3%, statistically insignificant). It suggests that semester systems may be less academically beneficial, consistent with Bostwick et al. (2022).

Appendix Table A23 shows little impact of academic calendars on students' participation in non-internship positions, such as teaching or research assistant roles, while in college.

Robustness Appendix Table A24 reports the results of alternative specifications of equation (4). Panel A excludes student characteristics (gender, race and ethnicity, and field of study) as covariates in the regression. Panel B controls for institution-specific linear trends instead of group-specific trends, and Panel C includes all undergraduate students regardless of their duration of study. The results are quantitatively similar to the baseline results in Table 4. In particular, the estimates in Panel C are close to the baseline, so the results are not sensitive to the duration restriction. Appendix Table A25 further assesses small-cluster inference, reporting standard errors clustered by institution, multiway clustered standard errors, and wild cluster bootstrap p-values (Cameron et al., 2008), both for the Ohio sample and for the expanded sample that includes the never-treated Oregon and Washington institutions. Following Bostwick et al. (2022), who study the same quarter-to-semester transitions, the multiway standard errors allow for arbitrary correlation between the outcomes of any two students who enroll at the same institution within five years of one another (Cameron et al., 2011). This structure captures overlapping cohorts of students who share the same campus environment, and is less conservative than clustering by institution, which assumes that any two students who ever attend the same institution have correlated outcomes. The effects on

the number of summer internships, non-entry-level employment, and starting salary remain statistically significant across inference methods, whereas the effect on the total number of internships is less precisely estimated.

Heterogeneity Appendix Tables A26, A27, and A28 present the heterogeneity of individual-level analyses by gender, racial minority status, and fields of study. Overall, the adoption of semester systems increases internship participation across all student backgrounds, especially for female and racial minorities, and for students who major in business, economics, and engineering. However, it seems that male and white students enjoy larger benefits for labor market outcomes, along with students majoring in business and economics.

5 Conclusion

Colleges and universities routinely make administrative decisions that appear to have little bearing on students' career prospects. This paper shows that the academic calendar is one such decision with consequences that are far from trivial. Using quasi-experimental variation in calendar transitions across Ohio institutions and data from public LinkedIn profiles, I find that switching to the more prevalent semester system resolves a coordination friction that meaningfully expands students' internship opportunities. Fully exposed students graduate with 27% more summer internships and a net increase in their total number of internships, are more likely to land non-entry-level jobs, earn higher starting salaries, and accumulate broader skill portfolios over their careers. Part of this reflects internships shifted earlier within the summer, but the larger part reflects matches that would not otherwise have been made. These gains stem from schedule alignment with the broader labor market rather than any inherent feature of the semester calendar, implying that the costs of calendar misalignment fall disproportionately on students at minority-calendar institutions.

These findings speak directly to ongoing policy debates. The University of California system, currently weighing whether to adopt a common semester calendar, has identified the lack of evidence on labor market consequences as a key gap in its deliberations. This paper suggests that calendar alignment carries labor market benefits that deserve to be weighed alongside the well-documented academic and financial costs of transition. A rough accounting

for Ohio suggests the benefits are of the same order as the costs. On the cost side, Bostwick et al. (2022) attribute a 2.9 percentage point decline in on-time graduation to the calendar switch, which amounts to $1,185 per student in 2010 dollars.[33] The administrative cost of conversion is smaller and incurred only once. The $12.6 million Ohio State spent (Pant, 2012) amounts to roughly $265 per undergraduate and is shared by every subsequent cohort. Against these, the $846 gain in starting salaries ($649 with additional never-treated universities in the control group) offsets more than half of the graduation cost in the first year of earnings alone, and would cover it in full within two years.

It is worth noting that the magnitude of these labor market benefits will vary across settings. It depends on the prevalence of the quarter system in the local labor market and the severity of the resulting scheduling friction, and on whether a single institution switches or an entire system converts at once. But the qualitative takeaway from the Ohio experience is more general: the design of the academic year, typically treated as an internal institutional matter, also shapes students' access to the labor market.

[33] According to Bostwick et al. (2022), the cost of a one-year delay of college graduation can be approximated as one year of tuition at a four-year public institution plus one year of forgone starting salary, or $44,327 in 2014 dollars. Applied to the 2.9 percentage point decline in on-time graduation and converted to the 2010 dollars used in this paper, this is approximately $1,185 per student.

References

Amanzadeh, Naser, Amir Kermani, and Timothy McQuade, "Return Migration and Human Capital Flows," *NBER Working Paper 32352*, 2024.

Anderson, D Mark and Mary Beth Walker, "Does Shortening the School Week Impact Student Performance? Evidence from the Four-Day School Week," *Education Finance and Policy*, 2015, *10* (3), 314–349.

Aucejo, Esteban M and Teresa Foy Romano, "Assessing the Effect of School Days and Absences on Test Score Performance," *Economics of Education Review*, 2016, *55*, 70–87.

Baert, Stijn, Brecht Neyt, Thomas Siedler, Ilse Tobback, and Dieter Verhaest, "Student Internships and Employment Opportunities After Graduation: A Field Experiment," *Economics of Education Review*, 2021, *83*, 102141.

Battistin, Erich and Elena Claudia Meroni, "Should We Increase Instruction Time in Low Achieving Schools? Evidence from Southern Italy," *Economics of Education Review*, 2016, *55*, 39–56.

Bolli, Thomas, Katherine Caves, and Maria Esther Oswald-Egg, "Valuable Experience: How University Internships Affect Graduates' Income," *Research in Higher Education*, 2021, *62* (8), 1198–1247.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event-Study Designs: Robust and Efficient Estimation," *Review of Economic Studies*, 2024, p. rdae007.

Bostwick, Valerie and Tuan D. Nguyen, "More Often or Longer? The Effects of the Academic Schedule on Postsecondary Academic Outcomes," *Economics of Education Review*, 2026, *113*, 102812.

_ , Stefanie Fischer, and Matthew Lang, "Semesters or Quarters? The Effect of the Academic Calendar on Postsecondary Student Outcomes," *American Economic Journal: Economic Policy*, 2022, *14* (1), 40–80.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-Based Improvements for Inference with Clustered Errors," *The Review of Economics and Statistics*, 2008, *90* (3), 414–427.

_ , _ , and _ , "Robust Inference with Multiway Clustering," *Journal of Business & Economic Statistics*, 2011, *29* (2), 238–249.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 2020, *110* (9), 2964–2996.

_ and _ , "Difference-in-Differences Estimators of Intertemporal Treatment Effects," *Review of Economics and Statistics*, 2024, pp. 1–45.

Coleman, Daniel, John R Bolte, and Leroy Franklin, "Academic Calendar Change Impact on Enrollment Patterns and Instructional Outcomes," *Research in Higher Education*, 1984, *20*, 155–166.

Depro, Brooks and Kathryn Rouse, "The Effect of Multi-Track Year-Round Academic Calendars on Property Values: Evidence from District Imposed School Calendar Conversions," *Economics of Education Review*, 2015, *49*, 157–171.

Dorn, David, Florian Schoner, Moritz Seebacher, Lisa Simon, and Ludger Woessmann, "Multidimensional Skills as a Measure of Human Capital: Evidence from LinkedIn Profiles," *arXiv preprint arXiv:2409.18638*, 2024.

Figlio, David, Kristian L Holden, and Umut Ozek, "Do Students Benefit from Longer School Days? Regression Discontinuity Evidence from Florida's Additional Hour of Literacy Instruction," *Economics of Education Review*, 2018, *67*, 171–183.

Fischer, Stefanie and Daniel Argyle, "Juvenile Crime and the Four-Day School Week," *Economics of Education Review*, 2018, *64*, 31–39.

Gibbens, Brian, Mary A Williams, Anna K Strain, and Courtney DM Hoff, "Comparison of Biology Student Performance in Quarter and Semester Systems," *College & University*, 2015, *90* (3).

Goodman-Bacon, Andrew, "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Graves, Jennifer, "The Academic Impact of Multi-Track Year-Round School Calendars: A Response to School Overcrowding," *Journal of urban Economics*, 2010, *67* (3), 378–391.

_ , "Effects of Year-Round Schooling on Disadvantaged Students and the Distribution of Standardized Test Performance," *Economics of Education Review*, 2011, *30* (6), 1281–1305.

_ , "School Calendars, Child Care Availability and Maternal Employment," *Journal of Urban Economics*, 2013, *78*, 57–70.

Hora, Matthew T, Matthew Wolfgram, Zi Chen, and Changhee Lee, "Closing the doors of opportunity: A field theoretic analysis of the prevalence and nature of obstacles to college internships," *Teachers College Record*, 2021, *123* (12), 180–210.

_ **, Zi Chen, Emily Parrott, and Pa Her**, "Problematizing College Internships: Exploring Issues with Access, Program Design, and Developmental Outcomes in Three US Colleges," *Wisconsin Center for Education Research Working Paper*, 2019.

Jaeger, David A, John M Nunley, R Alan Seals Jr, Carrie L Shandra, and Eric J Wilbrandt, "The Demand for Interns," *Journal of Economic Behavior & Organization*, 2023, *209*, 372–390.

Klein, Markus and Felix Weiss, "Is Forcing Them Worth the Effort? Benefits of Mandatory Internships for Graduates from Diverse Family Backgrounds at Labour Market Entry," *Studies in Higher Education*, 2011, *36* (8), 969–987.

Margaryan, Shushanik, Nils Saniter, Mathias Schumann, and Thomas Siedler, "Do Internships Pay Off? The Effects of Student Internships on Earnings," *Journal of Human Resources*, 2022, *57* (4), 1242–1275.

McKenzie, David, Nabila Assaf, and Ana Paula Cusolito, "The demand for, and impact of, youth internships: evidence from a randomized experiment in Yemen," *IZA Journal of Labor & Development*, 2016, *5*, 1–15.

McMullen, Steven C and Kathryn E Rouse, "The Impact of Year-Round Schooling on Academic Achievement: Evidence from Mandatory School Calendar Conversions," *American Economic Journal: Economic Policy*, 2012, *4* (4), 230–252.

Morton, Emily, "Effects of Four-Day School Weeks on School Finance and Achievement: Evidence from Oklahoma," *Educational Researcher*, 2021, *50* (1), 30–40.

NACE, "2024 Student Survey Report," *National Association of Colleges and Employers*, 2024.

Neyt, Brecht, Eddy Omey, Dieter Verhaest, and Stijn Baert, "Does Student Work Really Affect Educational Outcomes? A Review of the Literature," *Journal of economic surveys*, 2019, *33* (3), 896–921.

Nunley, John M, Adam Pugh, Nicholas Romero, and R Alan Seals Jr, "College Major, Internship Experience, and Employment Opportunities: Estimates from a Résumé Audit," *Labour Economics*, 2016, *38*, 37–46.

Pant, Meagan, "Colleges Spend Millions to Switch to Semesters," *Dayton Daily News*, March 2012.

Parinduri, Rasyad A, "Do Children Spend Too Much Time in Schools? Evidence from a Longer School Year in Indonesia," *Economics of Education Review*, 2014, *41*, 89–104.

Pinto, Luísa Helena and Pedro Capa Pereira, "'I wish to do an internship (abroad)': investigating the perceived employability of domestic and international business internships," *Higher Education*, 2019, *78*, 443–461.

Pischke, Jörn-Steffen, "The Impact of Length of the School Year on Student Performance and Earnings: Evidence from the German Short School Years," *The Economic Journal*, 2007, *117* (523), 1216–1242.

Rocca, Lucas Della, Fernanda Estevan, and Gabriel G Leite, "Internships, Academic Achievement, and Labor Market Outcomes," *SSRN Working Paper 5148139*, 2025.

Roodman, David, Morten Ørregaard Nielsen, James G. MacKinnon, and Matthew D. Webb, "Fast and Wild: Bootstrap Inference in Stata Using boottest," *The Stata Journal*, 2019, *19* (1), 4–60.

Rosenthal, Dan, "Transition to Semesters: Effects on Enrollment and FTE Students," Working Paper, ERIC 2000.

Silva, Patrícia, Betina Lopes, Marco Costa, Ana I Melo, Gonçalo Paiva Dias, Elisabeth Brito, and Dina Seabra, "The Million-Dollar Question: Can Internships Boost Employment?," *Studies in Higher Education*, 2018, *43* (1), 2–21.

_ , _ , _ , Dina Seabra, Ana I Melo, Elisabeth Brito, and Gonçalo Paiva Dias, "Stairway to Employment? Internships in Higher Education," *Higher Education*, 2016, *72*, 703–721.

Sun, Liyang and Sarah Abraham, "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Thompson, Paul N, "Is Four Less than Five? Effects of Four-Day School Weeks on Student Achievement in Oregon," *Journal of Public Economics*, 2021, *193*, 104308.

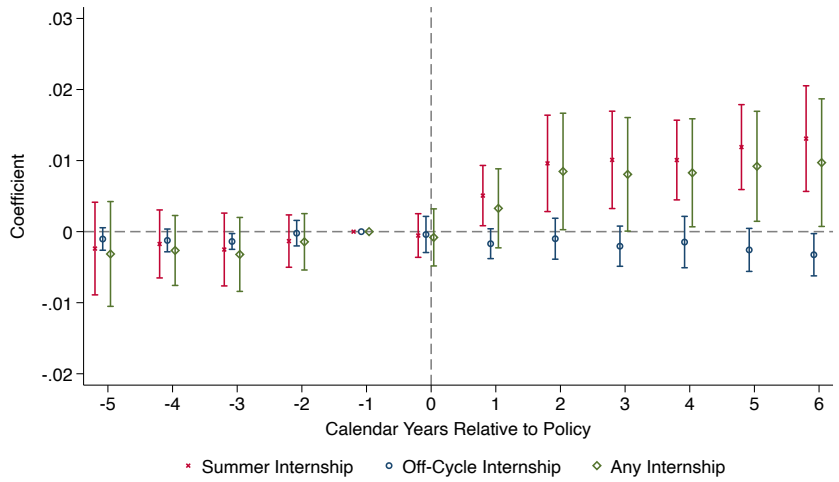
Virkola, Tuomo, "Internships and the Allocation of Talent," *Essays in Applied Economics*, 2021, p. 4.

Weiss, Felix, Markus Klein, and Thomas Grauenhorst, "The effects of work experience during higher education on labour market entry: learning by doing or an entry ticket?," *Work, Employment and Society*, 2014, *28* (5), 788–807.

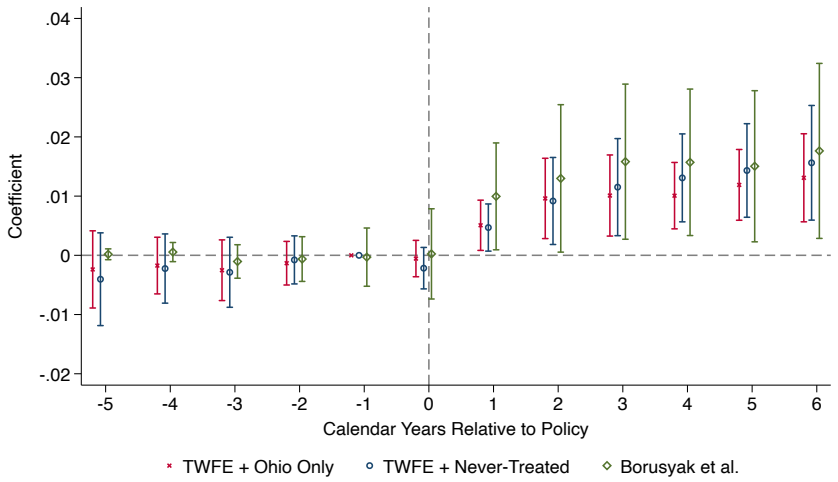
Figures and Tables

Figure 1: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis

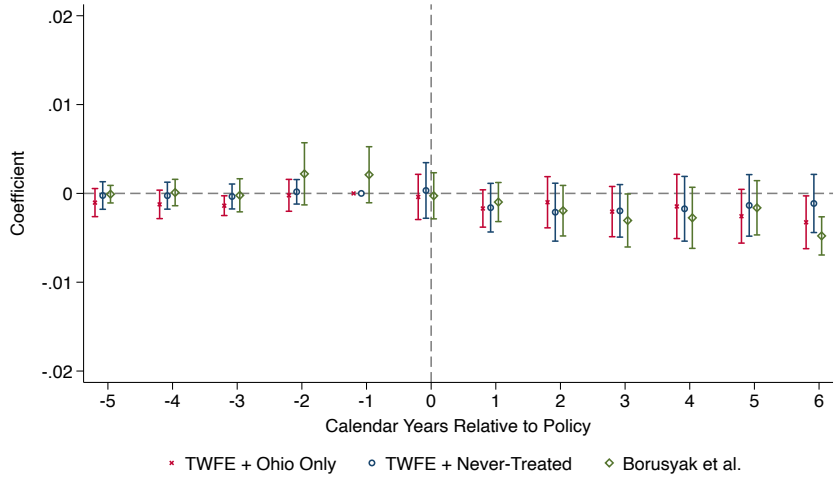
(a) TWFE Estimators



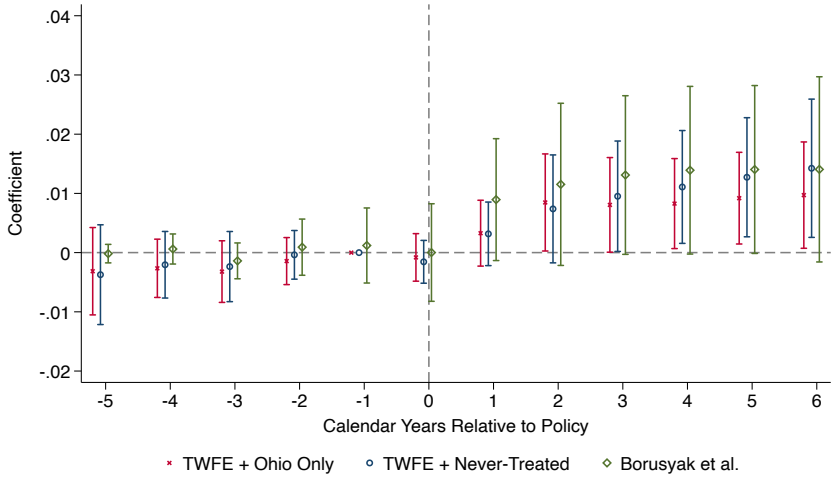
(b) Robustness: Summer Internship



(c) Robustness: Off-Cycle Internship



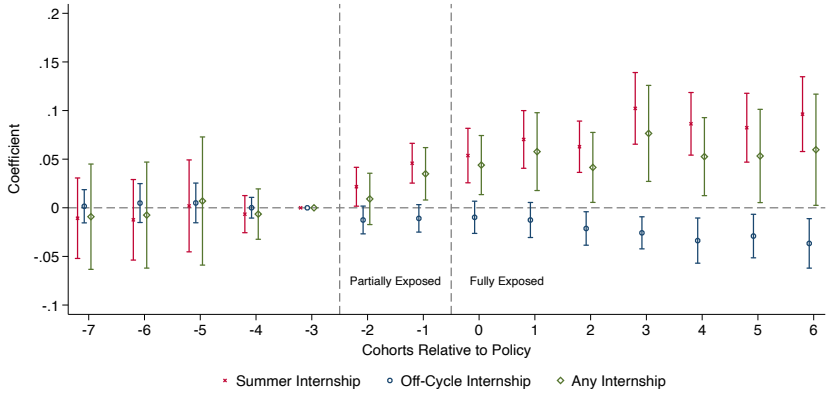
(d) Robustness: Any Internship



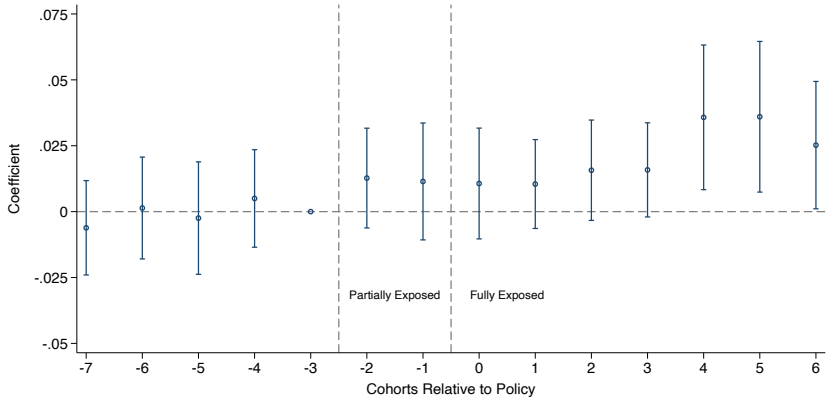
Notes: Sub-figure (a) presents the estimated coefficients, θ_k, of equation (1). The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. Sub-figures (b)-(d) overlay the event-study plots constructed using different estimators for the three outcomes. The estimators include the TWFE model with the main sample of Ohio institutions, the TWFE model with additional never-treated institutions from Oregon and Washington, and the model proposed by Borusyak et al. (2024) with the main sample of Ohio institutions. All specifications control for institution and year fixed effects, along with group-specific linear time trends. The 95% confidence intervals are calculated based on standard errors clustered at the institution level.

Figure 2: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis

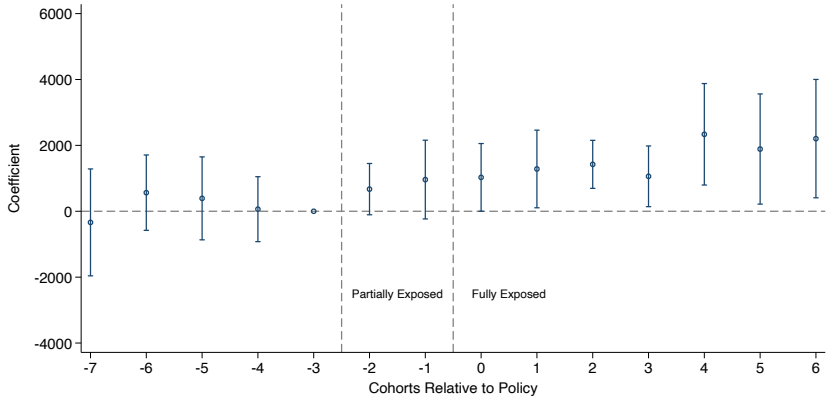
(a) Internship Participation



(b) Non-Entry-Level Job



(c) Starting Salary (in 2010 Dollars)



Notes: This figure presents the estimated coefficients of equation (1) but at the individual level. The outcome variables in sub-figure (a) are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, and (3) the total number of internships undertaken throughout college. The outcome variable in sub-figure (b) is whether the student has a non-entry-level first job after college. The outcome variable in sub-figure (c) is the imputed starting salary in 2010 dollars. All specifications control for institution and year fixed effects, along with group-specific linear time trends. I normalize the coefficients to zero for the cohort that enter college three years prior to the switch. The 95% confidence intervals are calculated based on standard errors that are clustered at the institution level.

Table 1: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Semester	0.0116**	0.0117**	-0.0014	-0.0012	0.0098*	0.0100*
	(0.0044)	(0.0044)	(0.0011)	(0.0010)	(0.0049)	(0.0049)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.014	0.014	0.053	0.053
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2). The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 2: Effect of Switching to Semesters on Internship Participation, by Internship Start Month

	(1) April	(2) May	(3) June	(4) July–September	(5) All Summer (April–Sept.)
Panel A: All Internships					
Semester	0.0001	0.0191***	-0.0085***	0.0014	0.0117**
	(0.0001)	(0.0051)	(0.0013)	(0.0010)	(0.0044)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0017	0.0187	0.0127	0.0101	0.0417
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel B: Internships in States with High Quarter-System Presence					
Semester	-0.0001*	0.0018*	-0.0014***	0.0002	0.0005
	(0.0001)	(0.0010)	(0.0004)	(0.0002)	(0.0011)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0001	0.0024	0.0018	0.0010	0.0052
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel C: Internships in States with Low Quarter-System Presence					
Semester	0.0001	0.0044***	-0.0018***	0.0003	0.0030**
	(0.0001)	(0.0010)	(0.0005)	(0.0004)	(0.0011)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0003	0.0039	0.0030	0.0018	0.0088
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2), with the summer internship outcome of Table 1 decomposed by the month in which the internship begins. The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are as follows: (1) whether the student participates in an internship starting in April, (2) whether the student participates in an internship starting in May, (3) whether the student participates in an internship starting in June, (4) whether the student participates in an internship starting between July and September, and (5) whether the student participates in an internship starting between April and September. Semester-system students are available from mid-May, while quarter-system students are in class until mid-June; LinkedIn records only the year and month of employment start dates, so June cannot be divided at the middle of the month. Panel B limits internships to those in states where more than 10% of undergraduate students are enrolled in quarter-system institutions. Panel C limits internships to those in states where no more than 10% of undergraduate students are enrolled in quarter-system institutions. The share of undergraduate students enrolled in quarter-system institutions is based on fall 2012 data. States where over 10% of undergraduates attended quarter-system institutions in 2012 include Oregon, Washington, Arizona, California, Utah, Illinois, Rhode Island, Delaware, Michigan, Georgia, Florida, New Hampshire, and Nevada. All regressions control for institution and year fixed effects, group-specific linear time trends, and students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 3: Effect of the 2012 Transitions on Internship Participation at Institutions That Had Already Adopted the Semester Calendar

	(1) April	(2) May	(3) June	(4) July–September	(5) All Summer (April–Sept.)
Post 2012 × Ohio Internship	-0.0002	-0.0002	0.0007	0.0019*	0.0021
	(0.0003)	(0.0007)	(0.0008)	(0.0010)	(0.0012)
Institution × Destination FE	x	x	x	x	x
Institution × Year FE	x	x	x	x	x
Destination-Specific Trend	x	x	x	x	x
Mean(Y)	0.0009	0.0149	0.0056	0.0066	0.0273
N	771,784	771,784	771,784	771,784	771,784

Notes: This table presents the estimates of equation (3). The sample includes undergraduate students enrolled between 2008 and 2019 at the ten Ohio institutions that adopted the semester calendar in or before 2007, at least five years before the four largest public universities transitioned in the fall of 2012. The window begins in 2008, the first year in which all ten had completed their own transition. Each student-year is observed twice, once for internships located in Ohio and once for internships located elsewhere; the latter includes internships outside the United States, which account for 23% of that group. The outcome variables are as follows: (1) whether the student participates in an internship starting in April, (2) whether the student participates in an internship starting in May, (3) whether the student participates in an internship starting in June, (4) whether the student participates in an internship starting between July and September, and (5) whether the student participates in an internship starting between April and September, in each case in the indicated location. Post 2012 equals one from 2013 onward, the first summer following the transition. All regressions control for institution-by-location and institution-by-year fixed effects, as well as location-specific linear time trends. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 4: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Partial	0.034*	-0.010	0.025	0.008*	508.033
	(0.018)	(0.006)	(0.021)	(0.004)	(364.543)
Full	0.068**	-0.014*	0.054*	0.012***	845.645**
	(0.023)	(0.008)	(0.027)	(0.003)	(315.569)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.250	0.089	0.339	0.548	54966.181
N	255,441	255,441	255,441	255,441	255,441

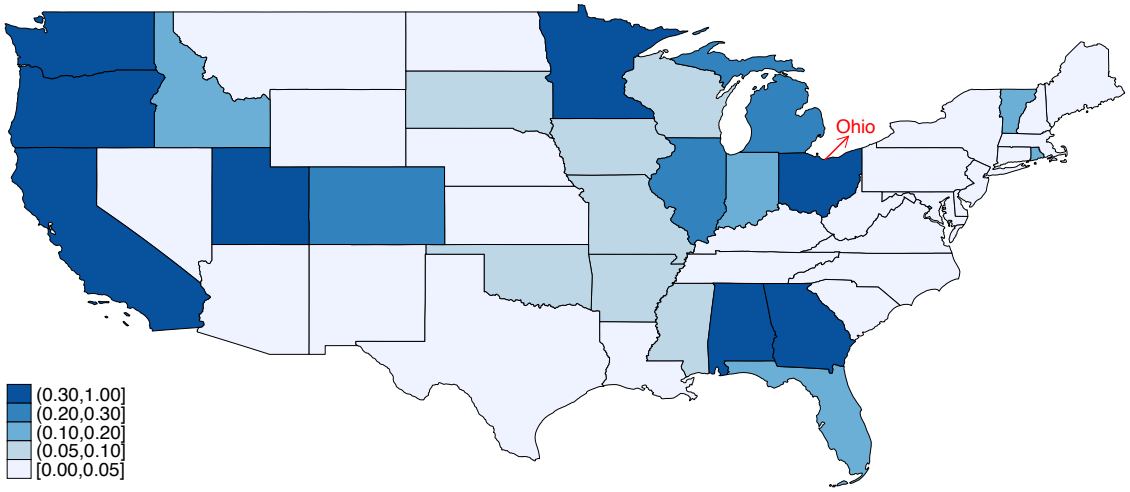
Notes: This table presents the estimates of equation (4). The sample includes college students who entered 17 institutions in Ohio between 1990 and 2015. I exclude students who spent fewer than four years or more than six years in college, those without information on their first job after college, and students from Antioch University due to its small sample size. The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

ONLINE APPENDIX

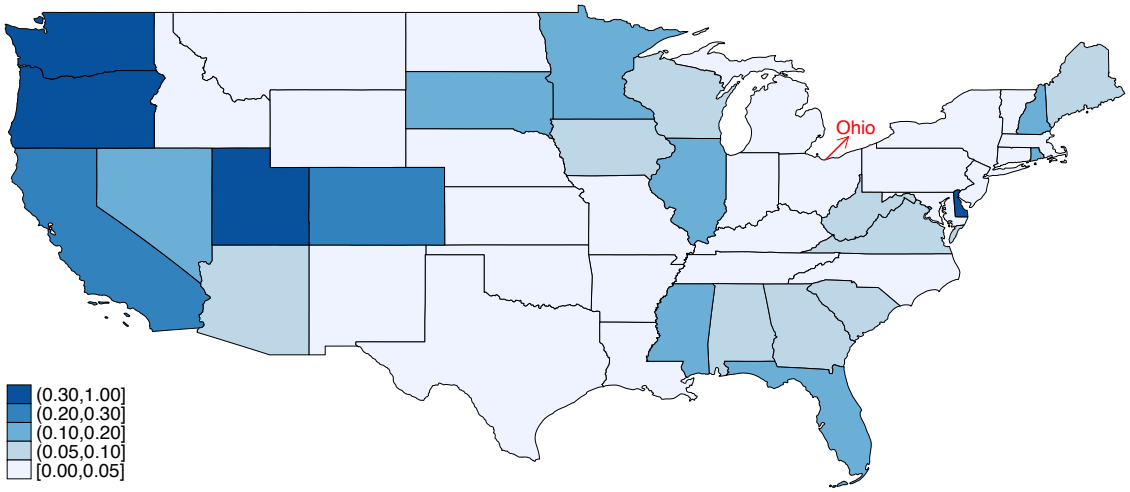
A Additional Figures and Tables

Figure A1: Share of Colleges and Universities Operating under Quarter Systems by State

(a) 1995

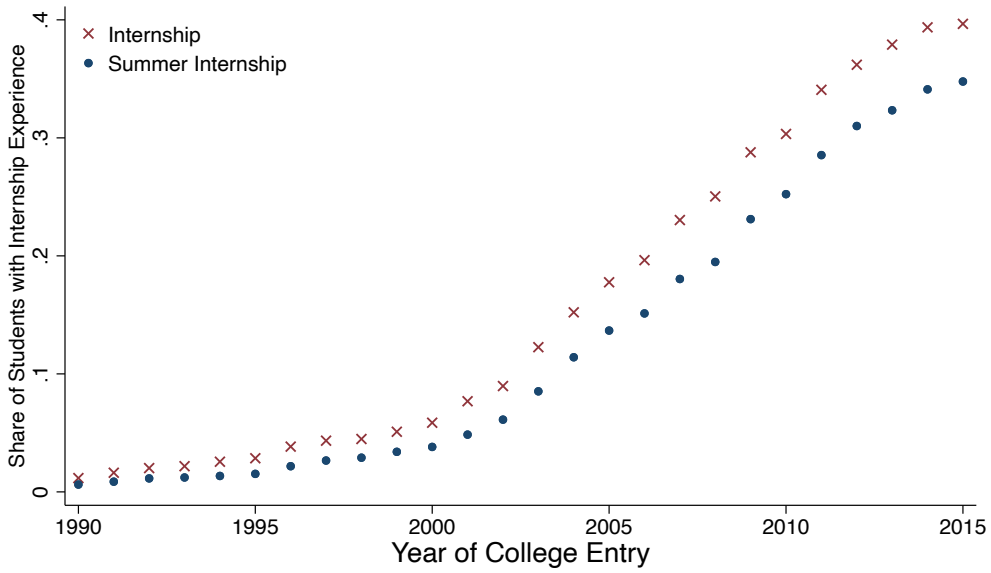


(b) 2019



Notes: This figure shows the share of colleges and universities operating under quarter systems by state in 1995 (a) and 2019 (b). The sample includes degree-granting institutions at the baccalaureate level or higher. Alaska and Hawaii are excluded from the map.

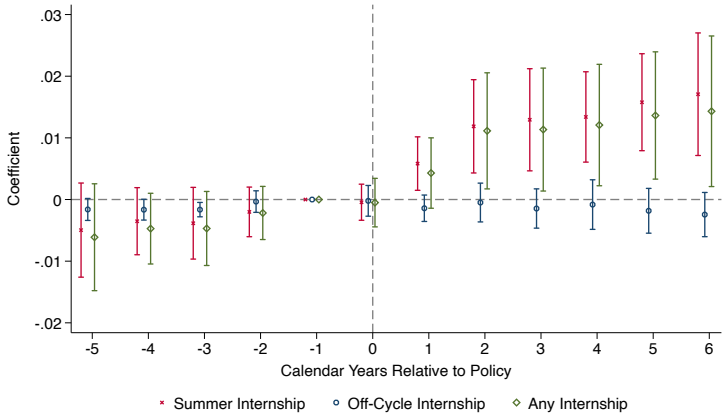
Figure A2: Share of Students with Internship Experience by Year of College Entry



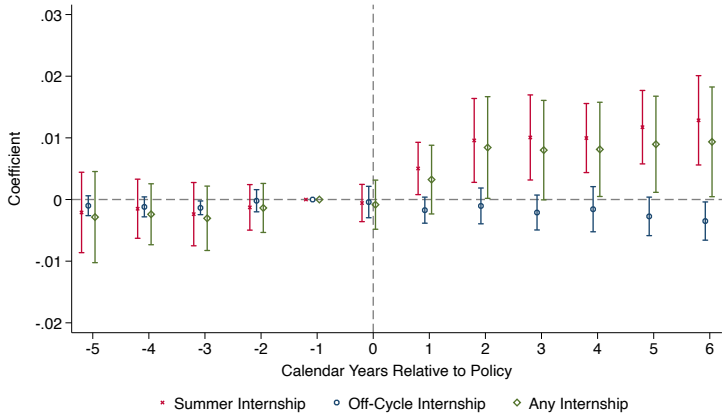
Notes: This figure presents the share of students with at least one internship and at least one summer internship during their years of college enrollment, by year of college entry. The sample includes students who entered 17 institutions in Ohio between 1990 and 2015. I exclude students who spent fewer than four or more than six years in college.

Figure A3: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis

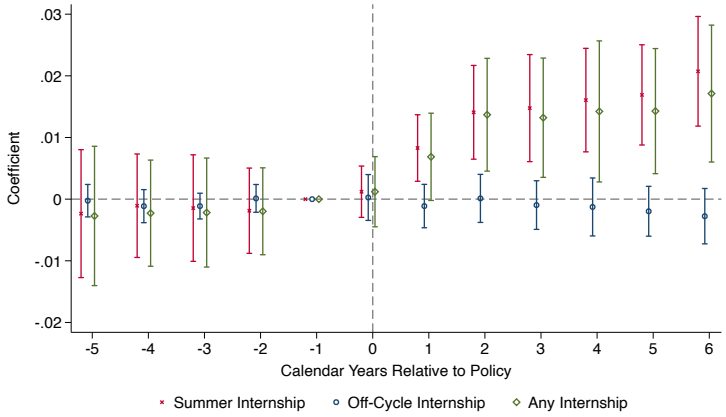
(a) No Group-Specific Linear Trend



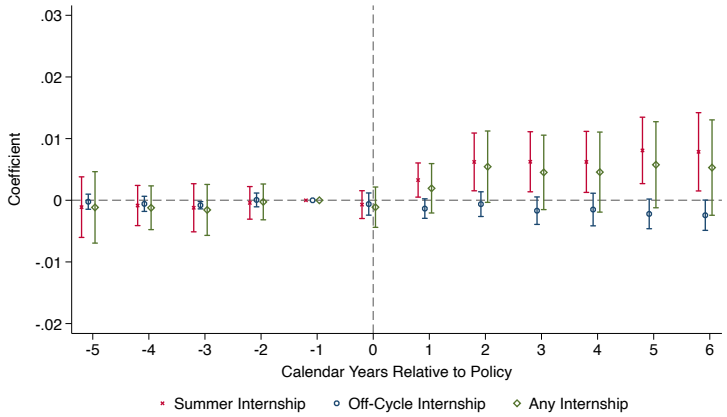
(b) Institution-Specific Linear Trend



(c) Excluding the First and Fifth or Later Calendar Years of Enrollment

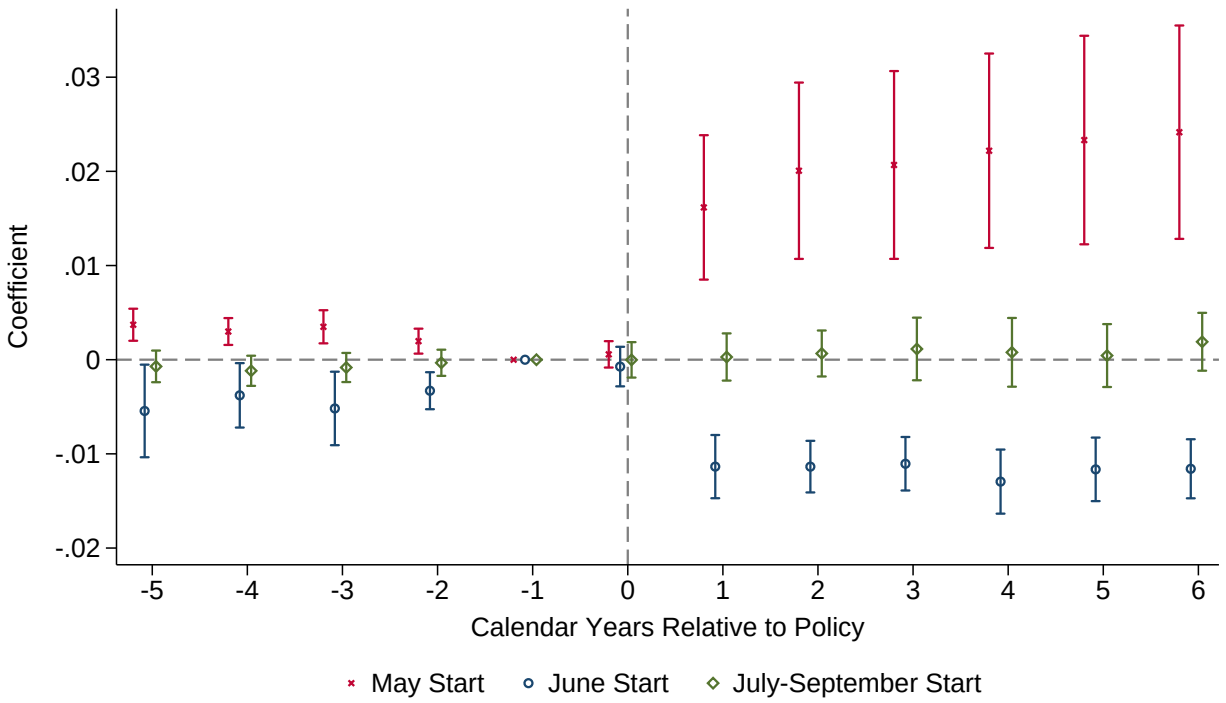


(d) Including Graduate Students



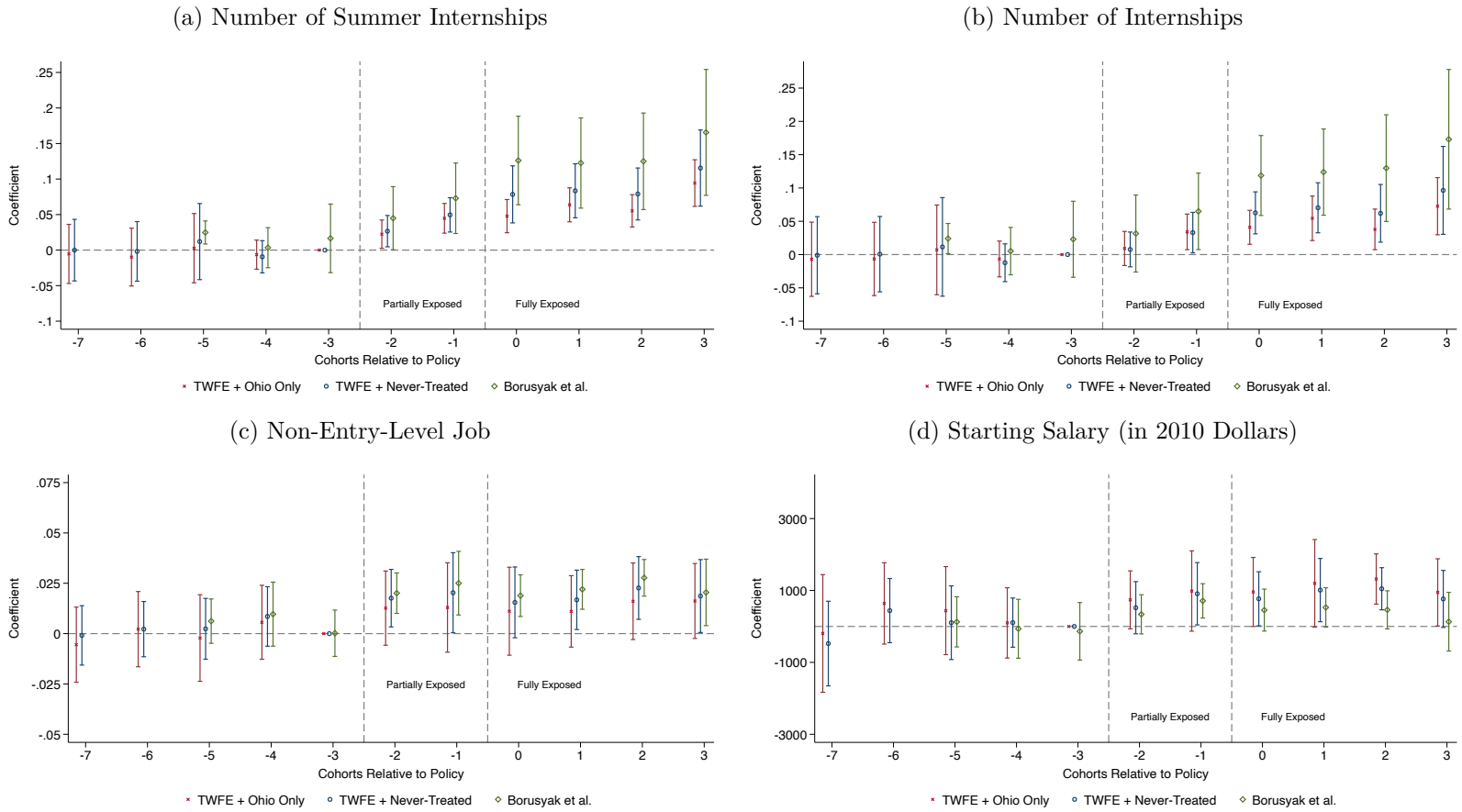
Notes: This figure presents the estimated coefficients, θ_k, of equation (1). The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All specifications control for institution and year fixed effects, along with group-specific linear time trends for sub-figures (c) and (d). I normalize the coefficients to zero in the year immediately preceding the switch to semester systems. The 95% confidence intervals are calculated based on standard errors that are clustered at the institution level. Sub-figure (a) does not control for the group-specific linear time trend. Sub-figure (b) controls for the institution-specific linear time trends. Sub-figure (c) excludes the first and fifth or later calendar years of enrollment. Sub-figure (d) includes both undergraduate and graduate students in the sample.

Figure A4: Effect of Switching to Semesters on Internship Participation, by Internship Start Month



Notes: This figure presents the estimated coefficients, θ_k, of equation (1), with the summer internship outcome decomposed by the month in which the internship begins. The outcome variables are as follows: (1) whether the student participates in an internship starting in May, (2) whether the student participates in an internship starting in June, and (3) whether the student participates in an internship starting between July and September. The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. All specifications control for institution and year fixed effects, along with group-specific linear time trends. I normalize the coefficients to zero in the year immediately preceding the switch to semester systems. The 95% confidence intervals are calculated based on standard errors that are clustered at the institution level. The coefficients for May and June internships differ modestly from zero before the switch, by up to 0.4 and 0.5 percentage points respectively, an order of magnitude smaller than the post-switch estimates. The coefficients for internships starting between July and September, the months available to students under both calendars, are close to zero throughout the window.

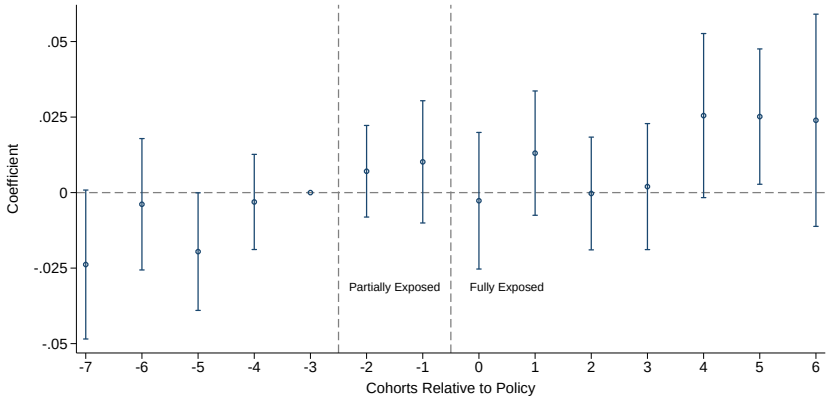
Figure A5: Effect of Switching to Semesters on Internship Participation: Individual Level Analysis, Robustness



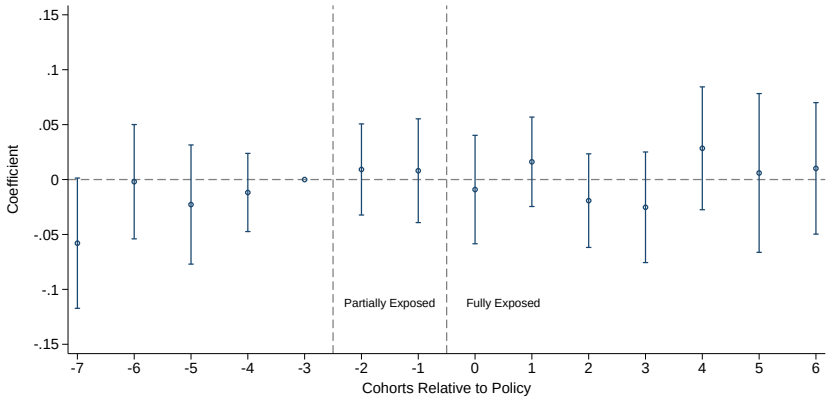
Notes: This figure overlays the event-study plots constructed using different estimators for the following outcomes: (a) the number of summer internships undertaken throughout college; (b) the total number of internships undertaken throughout college; (c) whether the student has a non-entry-level first job after college; and (d) the imputed starting salary in 2010 dollars. The estimators include the TWFE model with the main sample of Ohio institutions, the TWFE model with additional never-treated institutions from Oregon and Washington, and the model proposed by Borusyak et al. (2024) with additional never-treated institutions from Oregon and Washington. The two TWFE specifications control for institution and entry-year fixed effects, along with group-specific linear time trends, and I normalize their coefficients to zero for the cohort that enters college three years prior to the switch. The model proposed by Borusyak et al. (2024) controls for institution and entry-year fixed effects without group-specific linear time trends; see footnote 28. The 95% confidence intervals are calculated based on standard errors clustered at the institution level.

Figure A6: Effect of Switching to Semesters on Medium-Term Outcomes: Individual Level Analysis

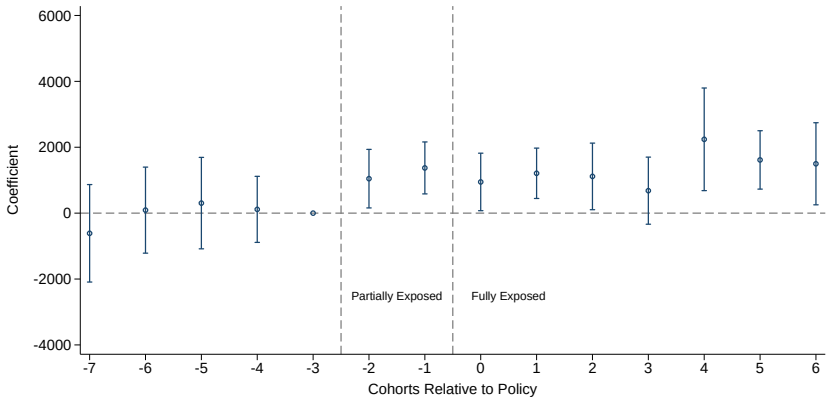
(a) Non-Entry-Level Job



(b) Job Seniority



(c) Imputed Salary (in 2010 Dollars)



Notes: This figure presents the estimated coefficients of equation (1) but at the individual level. It tracks students' employment positions eight years after college entry. The outcome variable in sub-figure (a) is an indicator for whether the student holds a non-entry-level job at that time. The outcome variable in sub-figure (b) is the seniority level on a 7-point scale. The outcome variable in sub-figure (c) is the imputed salary in 2010 dollars. All specifications control for institution and year fixed effects, along with group-specific linear time trends. I normalize the coefficients to zero for the cohort that enter college three years prior to the switch. The 95% confidence intervals are calculated based on standard errors that are clustered at the institution level.

Table A1: Year of Switch to Semesters

Institution	Year
Hiram College	1996
Baldwin Wallace University	1998
University of Toledo	1998
Bluffton University	1999
Cleveland State University	1999
Youngstown State University	2000
Cedarville University	2002
Central State University	2005
University of Dayton	2005
Shawnee State University	2007
Otterbein University	2011
Ohio State University	2012
Ohio University	2012
University of Cincinnati	2012
Wright State University	2012
Antioch University	2013
Franklin University	–

Notes: This table presents the 17 colleges and universities in Ohio that are included in the analysis sample, along with the academic year in which they transitioned from quarter to semester systems.

Table A2: Summary Statistics

Variable	Mean	Std Dev	Num of Obs
Panel A: Student Characteristics			
Female	0.488	0.500	407,517
White	0.855	0.352	407,517
Black	0.086	0.281	407,517
Asian Pacific Islander	0.039	0.193	407,517
Hispanic	0.018	0.132	407,517
Duration of Study: $<$ 4 yrs	0.242	0.428	407,517
Duration of Study: 4 yrs	0.501	0.500	407,517
Duration of Study: 5 yrs	0.199	0.399	407,517
Duration of Study: 6 yrs	0.038	0.191	407,517
Duration of Study: $>$ 6 yrs	0.019	0.138	407,517
Field of Study: Biz & Econ	0.261	0.439	407,517
Field of Study: Engineering	0.141	0.348	407,517
Field of Study: Other	0.598	0.490	407,517
Panel B: Internship Uptake			
Number of Internships: Summer	0.207	0.566	407,517
Number of Internships: Off-Cycle	0.075	0.309	407,517
Number of Internships	0.282	0.704	407,517
Panel C: Post-Graduation Outcomes			
Enrollment in Advanced Degree Program in 1 Year	0.146	0.353	407,517
Enrollment in Advanced Degree Program in 3 Years	0.205	0.404	407,517
Enrollment in Advanced Degree Program at Any Time	0.338	0.473	407,517
Enrollment in Doctorate Degree Program at Any Time	0.070	0.255	407,517
Gap to 1st Job (in Months)	22.545	39.602	342,345
Starting Salary (in Thousands, 2010 Dollars)	54.788	25.801	342,345
Non-Entry Level	0.549	0.498	342,345
Occupation: Biz & Mgmt	0.242	0.428	342,345
Occupation: Eng & Math	0.151	0.358	342,345
Occupation: Sales & Adm	0.166	0.372	342,345
Occupation: Education	0.086	0.280	342,345
Occupation: Healthcare	0.074	0.262	342,345

Notes: This table presents the mean, standard deviation, and number of observations for the key variables. The sample includes college students who entered 17 institutions in Ohio between 1990 and 2015.

Table A3: Placebo Test: University Characteristics Around the Quarter-to-Semester Switch

	(1) UG Enrollment	(2) Total Enrollment	(3) Num of Faculty	(4) Share of Female	(5) Share of Minority	(6) Share of Pell	(7) Instr. Exp. per Student	(8) Student Serv. Exp. per Student
Semester	-285.7644	-249.0725	2.0319	-0.0097	0.0049	0.0297	247.5765	89.6557
	(240.8426)	(293.3815)	(7.4332)	(0.0113)	(0.0122)	(0.0220)	(338.6961)	(206.3452)
Group-Specific Trend	x	x	x	x	x	x	x	x
Mean(Y)	11374.43	14343.24	522.44	0.56	0.23	0.20	8149.31	2650.69
N	357	357	357	357	357	367	356	356

Notes: This table presents TWFE estimates of the association between the quarter-to-semester calendar switch and university institutional characteristics, serving as a placebo test for the main analysis. The sample includes all Ohio universities in the main analysis sample observed in IPEDS between 2002 and 2022. Undergraduate enrollment and total enrollment are head counts from the IPEDS Fall Enrollment survey. Faculty count is the number of full-time instructional staff across all academic ranks from the IPEDS Human Resources survey. Share female and share minority are computed among undergraduate students; share minority excludes non-resident aliens and students with unknown race/ethnicity from the denominator. Share Pell is the fraction of full-time, first-time degree-seeking undergraduates receiving Pell grants, from the IPEDS Student Financial Aid survey. Instruction and student services expenditures per student are from the IPEDS Finance survey (F1A for public institutions, F2 for private non-profits) divided by total enrollment. All regressions control for institution and year fixed effects, as well as group-specific linear time trends. Standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A4: Effect of Switching to Semesters on LinkedIn Usage: Entering Cohort Level Analysis

	Share with LinkedIn Profiles		Share with First Job Details		Share with Updates Since '23		Avg Number of Connections	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Partial	0.020	0.019	0.016	0.017	0.010	0.002	3.918	-0.683
	(0.028)	(0.031)	(0.024)	(0.025)	(0.008)	(0.004)	(15.011)	(13.642)
Full	0.031	-0.006	0.021	-0.010	0.004	0.004	0.636	-0.679
	(0.030)	(0.043)	(0.026)	(0.036)	(0.006)	(0.006)	(13.177)	(13.985)
Group-Specific Trend	x	x	x	x	x	x	x	x
Weight by Avg Cohort Size		x		x		x		x
Mean(Y)	0.533	0.633	0.441	0.524	0.888	0.884	222.682	246.001
N	225	225	225	225	225	225	225	225

Notes: This table presents the TWFE estimates of the effect of switching to semesters on students' LinkedIn usage. I consider a cohort as fully exposed to the semester system if they enter college in the year of or after the transition to semester systems. I consider a cohort as partially exposed if they enter college one or two years before the transition. The sample includes entering cohorts of undergraduate students from 2000 to 2015, excluding Antioch University and Franklin University due to their small cohort sizes. To measure students' LinkedIn usage by each institution's entering cohort, I calculate the share of college graduates who have LinkedIn profiles (columns (1) and (2)) and those who provide detailed information about their first employment after college (columns (3) and (4)). The denominator is the number of full-time, first-time, degree-seeking undergraduate students in each entering cohort from 2000 to 2015, as obtained from IPEDS. The outcomes in columns (5) and (6) are the share of college graduates who have updated their profiles since 2023, conditional on having a public LinkedIn profile, while the outcomes in columns (7) and (8) are the average number of LinkedIn connections. In columns (2), (4), (6), and (8), observations are weighted by the average size of the entering cohorts at each institution. All regressions control for institution and year fixed effects, as well as group-specific linear time trends. Standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A5: Effect of Switching to Semesters on Students' Characteristics: Individual Level Placebo Analyses

	(1) Female	(2) Minority	(3) Biz & Econ	(4) Engineering	(5) Other Majors
Partial	-0.002	-0.001	-0.001	0.012	-0.011
	(0.005)	(0.006)	(0.010)	(0.008)	(0.008)
Full	0.007	0.011*	0.006	0.005	-0.011
	(0.008)	(0.006)	(0.010)	(0.009)	(0.015)
Group-Specific Trend	x	x	x	x	x
Mean(Y)	0.475	0.132	0.249	0.164	0.587
N	255,441	255,441	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) whether the student is female, (2) whether the student is a racial minority, (3) whether the student studies business and economics majors, (4) whether the student studies engineering majors, and (5) whether the student studies majors other than business, economics, or engineering. All regressions control for institution and year fixed effects, and group-specific linear time trends. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A6: List of "Never-Treated" Universities as a Control Group

Institution	State
Eastern Oregon University	OR
Oregon State University	OR
Portland State University	OR
Southern Oregon University	OR
University of Oregon	OR
Western Oregon University	OR
Antioch University Seattle	WA
Central Washington University	WA
City University of Seattle	WA
Eastern Washington University	WA
Seattle Pacific University	WA
Seattle University	WA
The Evergreen State College	WA
University of Washington	WA
Walla Walla University	WA
Western Washington University	WA

Notes: This table presents the 16 colleges and universities from Oregon and Washington that used the quarter system throughout the sample period and are included in the supplementary analysis.

Table A7: Effect of Switching to Semesters on Summer Internship Participation: Individual-by-Year Level Analysis, Separate Indicator for the Transition Year

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Year of Transition	0.0005	0.0008	0.0008	0.0010	0.0010	0.0014
	(0.0032)	(0.0030)	(0.0011)	(0.0010)	(0.0037)	(0.0034)
Semester	0.0117**	0.0118**	-0.0012	-0.0011	0.0100*	0.0103*
	(0.0050)	(0.0049)	(0.0013)	(0.0012)	(0.0056)	(0.0055)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.014	0.014	0.053	0.053
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2), augmented with a separate indicator for the calendar year of the transition to the semester system ($k = 0$). The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A8: Effect of Switching to Semesters on Summer Internship Participation: Individual-by-Year Level Analysis, by Industry of Internship Companies

	(1) Information	(2) Finance	(3) Professional, Scientific Services	(4) Manufacturing	(5) Education	(6) Healthcare	(7) Publicly Listed
Semester	0.0011***	0.0017**	0.0015**	0.0006	0.0007**	0.0003	0.0018
	(0.0003)	(0.0006)	(0.0006)	(0.0011)	(0.0003)	(0.0002)	(0.0012)
Group-Specific Trend	x	x	x	x	x	x	x
Student Characteristics	x	x	x	x	x	x	x
Mean(Y)	0.0023	0.0034	0.0040	0.0074	0.0022	0.0016	0.0071
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2). The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are the industries of the summer internship companies, classified using NAICS codes provided by Revelio Labs. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A9: Effect of Switching to Semesters on Internship Participation: Internships in Ohio and Outside the United States

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Internships in Ohio						
Semester	0.0065***	0.0067***	-0.0009	-0.0008	0.0056**	0.0059**
	(0.0021)	(0.0023)	(0.0008)	(0.0008)	(0.0026)	(0.0027)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.025	0.025	0.010	0.010	0.034	0.034
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel B: Internships Outside the United States						
Semester	0.0019**	0.0017**	-0.0000	-0.0000	0.0019**	0.0016**
	(0.0008)	(0.0006)	(0.0001)	(0.0001)	(0.0008)	(0.0006)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.003	0.003	0.000	0.000	0.003	0.003
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2). The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. Panel A limits internships to those in Ohio. Panel B limits internships to those outside the United States. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A10: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis, Robustness

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Group-Specific Linear Trend						
Semester	0.0178**	0.0177***	-0.0003	-0.0001	0.0167**	0.0168**
	(0.0062)	(0.0060)	(0.0016)	(0.0015)	(0.0072)	(0.0069)
Group-Specific Trend						
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.014	0.014	0.053	0.053
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel B: Institution-Specific Linear Trend						
Semester	0.0114**	0.0115**	-0.0015	-0.0014	0.0096*	0.0098*
	(0.0044)	(0.0044)	(0.0012)	(0.0011)	(0.0050)	(0.0050)
Institution-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.014	0.014	0.053	0.053
N	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel C: Excluding the First and Fifth or Later Calendar Years of Enrollment						
Semester	0.0164**	0.0165**	-0.0010	-0.0009	0.0148**	0.0150**
	(0.0062)	(0.0062)	(0.0013)	(0.0012)	(0.0068)	(0.0067)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.055	0.055	0.016	0.016	0.067	0.067
N	1,357,581	1,357,581	1,357,581	1,357,581	1,357,581	1,357,581
Panel D: Including Graduate Students						
Semester	0.0073*	0.0074*	-0.0013	-0.0013	0.0056	0.0058
	(0.0035)	(0.0036)	(0.0009)	(0.0008)	(0.0041)	(0.0041)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.033	0.033	0.012	0.012	0.042	0.042
N	4,215,816	4,215,816	4,215,816	4,215,816	4,215,816	4,215,816

Notes: This table presents the estimates of equation (2). The sample includes undergraduate students enrolled in the 17 institutions between 1990 and 2019. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All regressions control for institution and year fixed effects, along with group-specific linear time trends for Panels C and D. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. Panel A does not control for the group-specific linear time trend. Panel B controls for institution-specific linear time trend. Panel C excludes each student's first and fifth or later calendar years of enrollment. Panel D includes both undergraduate and graduate students in the sample. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A11: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis, LinkedIn Coverage

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Entering Cohorts 2000–2015						
Semester	0.0100**	0.0102**	-0.0012	-0.0012	0.0084*	0.0087*
	(0.0037)	(0.0039)	(0.0018)	(0.0017)	(0.0041)	(0.0043)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.051	0.051	0.018	0.018	0.066	0.066
N	1,535,593	1,535,593	1,535,593	1,535,593	1,535,593	1,535,593
Panel B: Weighted by Inverse LinkedIn Coverage						
Semester	0.0086**	0.0088**	-0.0024	-0.0024	0.0059	0.0062
	(0.0037)	(0.0038)	(0.0018)	(0.0018)	(0.0042)	(0.0043)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.044	0.044	0.017	0.017	0.057	0.057
N	1,535,593	1,535,593	1,535,593	1,535,593	1,535,593	1,535,593
Panel C: Excluding Institutions Covered Below One Third						
Semester	0.0111**	0.0114**	-0.0007	-0.0007	0.0100**	0.0103*
	(0.0041)	(0.0044)	(0.0018)	(0.0018)	(0.0045)	(0.0047)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.055	0.055	0.019	0.019	0.070	0.070
N	1,361,014	1,361,014	1,361,014	1,361,014	1,361,014	1,361,014

Notes: This table presents the estimates of equation (2) for students entering the 17 institutions between 2000 and 2015, observed over calendar years 2000 to 2019. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. LinkedIn coverage at an institution in a given year is the number of students in the sample whose enrollment spell covers that fall, divided by the institution's undergraduate enrollment at the same fall census as reported to IPEDS. Panel A is the baseline over this sample. Panel B weights each observation by the inverse of that coverage, so that institutions enter in proportion to the students they enroll rather than the number of profiles they generate. Panel C excludes the five institutions where fewer than a third of enrolled undergraduates appear on LinkedIn: Wright State University (32%), Central State University (29%), Youngstown State University (27%), Shawnee State University (16%), and Antioch University (6%). All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.

Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A12: Effect of Switching to Semesters on Summer Internship Participation: Individual-by-Year Level Analysis, Separately for Summers Following Years1, 2, and 3

	Summer After Year 1		Summer After Year 2		Summer After Year 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Semester	0.0095***	0.0094***	0.0148**	0.0148**	0.0212**	0.0214**
	(0.0028)	(0.0028)	(0.0066)	(0.0068)	(0.0073)	(0.0073)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.019	0.019	0.050	0.050	0.088	0.088
N	308,836	308,836	308,836	308,836	308,836	308,836

Notes: This table presents the estimates of equation (2). The sample includes college students who entered 17 institutions in Ohio between 1990 and 2015. I exclude students who spent fewer than four years, and students from Antioch University due to its small sample size. The outcome variables are as follows: (1) whether the student has an internship in the summer after their first year in college; (2) whether the student has an internship in the summer after their second year in college; and (3) whether the student has an internship in the summer after their third year in college. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.

Table A13: Effect of Switching to Semesters on Summer Internship Participation: Individual-by-Year Level Analysis, Excluding the Institutions Ever Under the 4-1-4 System or Trimester System

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Semester	0.0116**	0.0118**	-0.0022*	-0.0020*	0.0091	0.0094
	(0.0047)	(0.0047)	(0.0011)	(0.0010)	(0.0053)	(0.0053)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.015	0.015	0.054	0.054
N	2,125,103	2,125,103	2,125,103	2,125,103	2,125,103	2,125,103

Notes: This table presents the estimates of equation (2). The sample excludes Otterbein University, which used the 4-1-4 system between 2011 and 2014, Franklin University, which remained on the trimester system from 1984 to 2022, and University of Dayton, which used the trimester system from 1990 to 2004. The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A14: Effect of Switching to Semesters on Summer and Off-Cycle Internship Participation: Individual-by-Year Level Analysis

	(1) Summer Only	(2) Off-Cycle Only	(3) Both	(4) Neither
Semester	0.0112**	-0.0017*	0.0004	-0.0100*
	(0.0044)	(0.0010)	(0.0003)	(0.0049)
Group-Specific Trend	x	x	x	x
Student Characteristics	x	x	x	x
Mean(Y)	0.039	0.012	0.003	0.947
N	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2). The sample includes college students who entered 17 institutions in Ohio between 1990 and 2015. The outcome variables are: (1) whether the student participates in a summer internship but not an off-cycle internship; (2) whether the student participates in an off-cycle internship but not a summer internship; (3) whether the student participates in both summer and off-cycle internships; and (4) whether the student participates in neither a summer nor an off-cycle internship. All regressions control for institution and year fixed effects, group-specific linear time trends, and students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A15: Effect of Switching to Semesters on Internship Participation: Individual-by-Year Level Analysis, Small-Cluster Inference

	Summer Internship		Off-Cycle Internship		Any Internship	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Ohio Institutions Only						
Semester	0.0116	0.0117	-0.0014	-0.0012	0.0098	0.0100
SE clustered by institution	(0.0044)	(0.0044)	(0.0011)	(0.0010)	(0.0049)	(0.0049)
Wild cluster bootstrap p-value	[0.076]	[0.074]	[0.262]	[0.290]	[0.184]	[0.171]
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.042	0.042	0.014	0.014	0.053	0.053
Observations	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel B: Including Never-Treated Institutions from Oregon and Washington						
Semester	0.0131	0.0131	-0.0017	-0.0016	0.0110	0.0111
SE clustered by institution	(0.0051)	(0.0051)	(0.0011)	(0.0011)	(0.0057)	(0.0057)
Wild cluster bootstrap p-value	[0.006]	[0.015]	[0.163]	[0.160]	[0.168]	[0.166]
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.038	0.038	0.013	0.013	0.049	0.049
Observations	3,781,672	3,781,672	3,781,672	3,781,672	3,781,672	3,781,672

Notes: This table presents the estimates of equation (2). The outcome variables are as follows: (1) whether the student participates in a summer internship, (2) whether the student participates in an off-cycle internship, and (3) whether the student participates in any internship during the year. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally control for students' gender, race and ethnicity, as well as their fields of study in college. Below each coefficient, I report the standard error clustered at the institution level (in parentheses) and the wild cluster bootstrap p-value (in brackets), computed following Cameron et al. (2008) with Rademacher weights and 9,999 replications (Roodman et al., 2019). Panel A includes only the 17 Ohio institutions; Panel B additionally includes the never-treated institutions from Oregon and Washington, for 33 clusters in total.

Table A16: Effect of Switching to Semesters on Internship Participation by Start Month: Small-Cluster Inference

	(1) April	(2) May	(3) June	(4) July–September	(5) All Summer (April–Sept.)
Panel A: All Internships					
Semester	0.0001	0.0191	-0.0085	0.0014	0.0117
SE clustered by institution	(0.0001)	(0.0051)	(0.0013)	(0.0010)	(0.0044)
Wild cluster bootstrap p-value	[0.384]	[0.020]	[0.001]	[0.198]	[0.074]
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0017	0.0187	0.0127	0.0101	0.0417
Observations	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel B: Internships in States with High Quarter-System Presence					
Semester	-0.0001	0.0018	-0.0014	0.0002	0.0005
SE clustered by institution	(0.0001)	(0.0010)	(0.0004)	(0.0002)	(0.0011)
Wild cluster bootstrap p-value	[0.111]	[0.162]	[0.000]	[0.361]	[0.718]
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0001	0.0024	0.0018	0.0010	0.0052
Observations	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765
Panel C: Internships in States with Low Quarter-System Presence					
Semester	0.0001	0.0044	-0.0018	0.0003	0.0030
SE clustered by institution	(0.0001)	(0.0010)	(0.0005)	(0.0004)	(0.0011)
Wild cluster bootstrap p-value	[0.340]	[0.011]	[0.001]	[0.549]	[0.084]
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.0003	0.0039	0.0030	0.0018	0.0088
Observations	2,356,765	2,356,765	2,356,765	2,356,765	2,356,765

Notes: This table presents the estimates of equation (2) reported in Table 2. The outcome variables are as follows: (1) whether the student participates in an internship starting in April, (2) whether the student participates in an internship starting in May, (3) whether the student participates in an internship starting in June, (4) whether the student participates in an internship starting between July and September, and (5) whether the student participates in an internship starting between April and September. Panel B limits internships to those in states where more than 10% of undergraduate students are enrolled in quarter-system institutions. Panel C limits internships to those in states where no more than 10% of undergraduate students are enrolled in quarter-system institutions. All regressions control for institution and year fixed effects, group-specific linear time trends, and students' gender, race and ethnicity, as well as their fields of study in college. Below each coefficient, I report the standard error clustered at the institution level (in parentheses) and the wild cluster bootstrap p-value (in brackets), computed following Cameron et al. (2008) with Rademacher weights and 9,999 replications (Roodman et al., 2019). The sample includes only the 17 Ohio institutions.

Table A17: Effect of Switching to Semesters on Observing a Student's First Job after College

	First Job Observed	
	(1)	(2)
Partial	0.0049	0.0050
	(0.0056)	(0.0058)
Full	0.0062	0.0073
	(0.0081)	(0.0084)
Group-Specific Trend	x	x
Student Characteristics		x
Mean(Y)	0.8489	0.8489
N	300,911	300,911

Notes: This table presents the estimates of equation (4). The sample includes college students who entered the 17 institutions in Ohio between 1990 and 2015 and who spent four to six years in college, before the restriction to students whose first job after college is observed. The outcome variable is an indicator for observing an imputed starting salary for the first non-internship job after college, which is the restriction used in Table 4. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Column (2) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A18: Effect of Switching to Semesters on Internship Earnings: Individual Level Analysis

	(1) Summer	(2) Off-Cycle	(3) Total
Partial	350.540	-177.283	173.256
	(326.644)	(156.429)	(411.766)
Full	1050.608**	-319.885*	730.723
	(436.485)	(172.446)	(573.406)
Group-Specific Trend	x	x	x
Student Characteristics	x	x	x
Mean(Y)	5285.703	2330.392	7616.094
N	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are the total earnings from internships undertaken throughout college that are (1) summer internships, (2) off-cycle internships, and (3) both types combined. Earnings are calculated based on the imputed monthly salary for the internships and their duration. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A19: Effect of Switching to Semesters on Occupation of the First Job: Individual Level Analysis

	(1) Biz & Mgmt	(2) Eng & Math	(3) Sales & Adm	(4) Education	(5) Healthcare
Partial	0.012***	-0.000	0.000	0.002	-0.002
	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)
Full	0.011**	0.008**	0.002	-0.001	-0.003
	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.238	0.164	0.161	0.087	0.066
N	255,441	255,441	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables include whether their first job is in the occupation of business and management, engineering and mathematics, sales and administration, education, or healthcare. The occupation is defined by the first two digits of the O*NET code. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A20: Effect of Switching to Semesters on First Job Match in Internship's Company, Industry, and Occupation: Individual Level Analysis

	Same Company		Same Industry		Same Occupation	
	(1)	(2)	(3)	(4)	(5)	(6)
Partial	0.001	0.001	0.002	0.001	0.005	0.004
	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)	(0.006)
Full	0.007**	0.007*	0.009	0.009	0.009	0.009
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.045	0.045	0.075	0.075	0.116	0.116
N	255,441	255,441	255,441	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are whether the first job after graduation is in the same company, industry, and occupation as at least one internship. The occupation is defined by the first two digits of the O*NET code, and the industry is defined by the first two digits of the NAICS industry code. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A21: Effect of Switching to Semesters on Skill Accumulation: Individual Level Analysis

	(1) Any	(2) Number	(3) Hard	(4) Soft	(5) Practical	(6) Research
Partial	-0.004	-0.022	0.008	-0.027	-0.018	-0.000
	(0.008)	(0.150)	(0.153)	(0.058)	(0.143)	(0.018)
Full	0.016*	0.300*	0.170	0.127**	0.301*	-0.004
	(0.009)	(0.142)	(0.132)	(0.058)	(0.147)	(0.027)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics	x	x	x	x	x	x
Mean(Y)	0.618	10.667	9.146	1.494	9.946	0.694
N	255,441	255,441	255,441	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) whether the student reports any skills on their LinkedIn profile, (2) the total number of self-reported skills, (3) the number of hard skills, (4) the number of soft skills, (5) the number of practical skills, and (6) the number of research skills. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A22: Effect of Switching to Semesters on Gap to the First Job and Enrollment in Advanced Degrees: Individual Level Analyses

	Gap to 1st Job	Enrollment in Advanced Degree			Doctorate
	(1) In Months	(2) In 1 Year	(3) In 3 Years	(4) Ever	(5) Ever
Partial	0.560	0.007	0.006	0.001	-0.004
	(0.409)	(0.006)	(0.007)	(0.005)	(0.003)
Full	-0.125	-0.000	-0.001	0.003	-0.006
	(0.393)	(0.006)	(0.006)	(0.007)	(0.004)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	21.385	0.154	0.217	0.335	0.072
N	255,442	300,911	300,911	300,911	300,911

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. I include students without information on their first job after college for columns (2)–(5). The outcome variables are (1) the gap between college graduation and the first job in months, (2) whether students enroll in advanced degree programs within one year of college graduation, (3) within three years of college graduation, (4) ever, and (5) whether they ever enroll in doctorate degree programs. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A23: Effect of Switching to Semesters on Participation in Non-Internship Positions: Individual Level Analysis

	Any Non-Intern Jobs		Number of Non-Intern Jobs		Duration of Non-Intern Jobs	
	(1)	(2)	(3)	(4)	(5)	(6)
Partial	-0.000	-0.001	-0.012	-0.013	-0.309	-0.285
	(0.009)	(0.010)	(0.018)	(0.019)	(0.449)	(0.463)
Full	0.016	0.017	0.037	0.037	0.239	0.285
	(0.014)	(0.015)	(0.025)	(0.026)	(0.568)	(0.576)
Group-Specific Trend	x	x	x	x	x	x
Student Characteristics		x		x		x
Mean(Y)	0.359	0.359	0.649	0.649	12.855	12.855
N	255,441	255,441	255,441	255,441	255,441	255,441

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables include whether students have any non-internship jobs while in college, as well as the total number and duration of these jobs. The first and final calendar years, during which they are not enrolled for the full year, are excluded. Examples of non-internship jobs include positions such as teaching and research assistants, peer mentoring and private tutoring roles, and co-op positions. All regressions control for institution and year fixed effects, along with group-specific linear time trends. Columns (2), (4), and (6) additionally controls for students' gender, race and ethnicity, as well as their fields of study in college. The standard errors are clustered at the institution level. Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A24: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis, Robustness

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Panel A: No Student Characteristics					
Partial	0.035*	-0.010	0.025	0.011*	693.176
	(0.019)	(0.006)	(0.022)	(0.006)	(405.658)
Full	0.068**	-0.015*	0.054*	0.013**	935.298**
	(0.023)	(0.008)	(0.027)	(0.005)	(359.859)
Group-Specific Trend	x	x	x	x	x
Student Characteristics					
Mean(Y)	0.250	0.089	0.339	0.548	54966.181
N	255,441	255,441	255,441	255,441	255,441
Panel B: Institution-Specific Linear Trend					
Partial	0.034*	-0.010	0.024	0.007*	470.795
	(0.018)	(0.006)	(0.021)	(0.004)	(364.593)
Full	0.066**	-0.015*	0.052*	0.012***	800.886**
	(0.024)	(0.008)	(0.028)	(0.003)	(317.545)
Institution-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.250	0.089	0.339	0.548	54966.181
N	255,441	255,441	255,441	255,441	255,441
Panel C: All Undergraduate Students, Regardless of Duration of Study					
Partial	0.025	-0.006	0.019	0.004	475.482
	(0.016)	(0.005)	(0.020)	(0.005)	(346.655)
Full	0.063**	-0.010	0.053*	0.012**	903.030***
	(0.026)	(0.007)	(0.030)	(0.005)	(284.851)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.219	0.079	0.299	0.549	54779.119
N	342,039	342,039	342,039	342,039	342,039

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, and group-specific linear time trends. Panels B and C control for students' gender, race and ethnicity, as well as their fields of study in college. Panel B controls for institution-specific linear time trends instead of group-specific linear trends. Panel C includes all undergraduate students, regardless of their duration of study. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A25: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis, Small-Cluster Inference

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Panel A: Ohio Institutions Only					
Partial Exposure	0.034	-0.010	0.025	0.008	508.033
SE clustered by institution	(0.018)	(0.006)	(0.021)	(0.004)	(364.543)
SE multiway clustered	(0.019)	(0.007)	(0.023)	(0.005)	(371.011)
Wild cluster bootstrap p-value	[0.164]	[0.122]	[0.415]	[0.098]	[0.243]
Full Exposure	0.068	-0.014	0.054	0.012	845.645
SE clustered by institution	(0.023)	(0.008)	(0.027)	(0.003)	(315.569)
SE multiway clustered	(0.023)	(0.008)	(0.025)	(0.004)	(273.291)
Wild cluster bootstrap p-value	[0.057]	[0.139]	[0.184]	[0.006]	[0.043]
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.250	0.089	0.339	0.548	54966.181
Observations	255,441	255,441	255,441	255,441	255,441
Panel B: Including Never-Treated Institutions from Oregon and Washington					
Partial Exposure	0.035	-0.015	0.020	0.011	486.014
SE clustered by institution	(0.020)	(0.006)	(0.024)	(0.004)	(278.591)
SE multiway clustered	(0.021)	(0.007)	(0.024)	(0.005)	(284.568)
Wild cluster bootstrap p-value	[0.234]	[0.028]	[0.688]	[0.013]	[0.121]
Full Exposure	0.086	-0.015	0.070	0.012	649.082
SE clustered by institution	(0.030)	(0.007)	(0.034)	(0.003)	(270.434)
SE multiway clustered	(0.028)	(0.009)	(0.029)	(0.004)	(247.667)
Wild cluster bootstrap p-value	[0.025]	[0.054]	[0.141]	[0.008]	[0.058]
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.232	0.082	0.314	0.524	54110.171
Observations	392,336	392,336	392,336	392,336	392,336

Notes: This table presents the estimates of equation (4). The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. Below each coefficient, I report the standard error clustered at the institution level, the multiway clustered standard error along five overlapping institution-by-five-year-entry-cohort dimensions following Cameron et al. (2011) (both in parentheses, in that order), and the wild cluster bootstrap p-value (in brackets), computed following Cameron et al. (2008) with Rademacher weights and 9,999 replications (Roodman et al., 2019). The multiway clustering follows the implementation of Bostwick et al. (2022) in the same institutional setting. Panel A includes only the 17 Ohio institutions; Panel B additionally includes the never-treated institutions from Oregon and Washington, for 33 clusters in total.

Table A26: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis, Heterogeneity by Gender

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Panel A: Male Students					
Partial	0.024	-0.007	0.017	0.004	750.429*
	(0.017)	(0.006)	(0.019)	(0.005)	(416.717)
Full	0.058**	-0.011*	0.048*	0.016**	1009.805***
	(0.025)	(0.005)	(0.025)	(0.006)	(283.468)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.245	0.080	0.325	0.621	59316.599
N	134,071	134,071	134,071	134,071	134,071
Panel B: Female Students					
Partial	0.046**	-0.013*	0.033	0.013**	244.539
	(0.020)	(0.006)	(0.025)	(0.004)	(338.266)
Full	0.079***	-0.018	0.062*	0.009	655.316
	(0.025)	(0.012)	(0.035)	(0.006)	(419.524)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.256	0.099	0.355	0.467	50160.506
N	121,370	121,370	121,370	121,370	121,370

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, group-specific linear time trends, students' race and ethnicity, as well as their fields of study in college. Panel A includes only male students, and Panel B includes only female students. Students' gender are predicted based on their names. The standard errors are clustered at the institution level.

Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A27: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis, Heterogeneity by Race

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Panel A: White Students					
Partial	0.031*	-0.011*	0.020	0.009	546.310
	(0.017)	(0.006)	(0.021)	(0.005)	(418.195)
Full	0.065**	-0.014*	0.050*	0.010***	713.204**
	(0.024)	(0.008)	(0.028)	(0.003)	(275.733)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.245	0.088	0.333	0.548	54978.504
N	221,761	221,761	221,761	221,761	221,761
Panel B: Minority Students					
Partial	0.055*	-0.000	0.055	-0.000	244.519
	(0.027)	(0.011)	(0.033)	(0.014)	(940.069)
Full	0.086***	-0.012	0.073**	0.025	1836.776*
	(0.023)	(0.007)	(0.026)	(0.018)	(967.976)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.284	0.095	0.379	0.546	54885.042
N	33,680	33,680	33,680	33,680	33,680

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. Panel A includes only white students, and Panel B includes black, Hispanic, Asian, and Pacific Islander students. Students' race and ethnicity are predicted based on their names and locations. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table A28: Effect of Switching to Semesters on Internship Participation and Post-Graduation Outcomes: Individual Level Analysis, Heterogeneity by Fields of Study

	Number of Internships			Post-Graduation Outcomes	
	(1) Summer	(2) Off-Cycle	(3) Any	(4) Non-Entry Level	(5) Starting Salary
Panel A: Business and Economics Majors					
Partial	0.065**	-0.004	0.061**	0.011	931.563*
	(0.025)	(0.013)	(0.025)	(0.012)	(476.598)
Full	0.110***	-0.015	0.095***	0.026**	1730.142***
	(0.020)	(0.019)	(0.023)	(0.010)	(570.555)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.320	0.104	0.424	0.614	57906.151
N	63,623	63,623	63,623	63,623	63,623
Panel B: Engineering Majors					
Partial	0.026	-0.010	0.015	-0.006	-479.725
	(0.023)	(0.008)	(0.025)	(0.007)	(444.519)
Full	0.082***	-0.014**	0.068**	0.010	1215.998*
	(0.024)	(0.006)	(0.024)	(0.011)	(579.836)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.374	0.094	0.468	0.753	66991.335
N	41,922	41,922	41,922	41,922	41,922
Panel C: Other Majors					
Partial	0.029*	-0.011	0.017	0.013*	794.547*
	(0.014)	(0.008)	(0.019)	(0.007)	(430.856)
Full	0.047**	-0.011	0.036	0.009	500.467
	(0.017)	(0.008)	(0.023)	(0.006)	(371.837)
Group-Specific Trend	x	x	x	x	x
Student Characteristics	x	x	x	x	x
Mean(Y)	0.186	0.081	0.267	0.463	50355.197
N	149,896	149,896	149,896	149,896	149,896

Notes: This table presents the estimates of equation (4). See notes under Table 4 for more information on the analysis sample. The outcome variables are as follows: (1) the number of summer internships undertaken throughout college, (2) the number of off-cycle internships undertaken throughout college, (3) the total number of internships undertaken throughout college, (4) finding a non-entry-level job after college, and (5) imputed starting salary in 2010 dollars. All regressions control for institution and year fixed effects, group-specific linear time trends, students' gender, race and ethnicity, as well as their fields of study in college. Panel A includes students who study business and economics majors. Panel B includes students who study engineering majors. Panel C includes students who study majors other than business, economics, or engineering. The standard errors are clustered at the institution level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.